

# Utility Factor (UF) and Charging Preferences of Plug-in Hybrid Electric Vehicles (PHEVs): Insights from Real World Data

Seshadri Srinivasa Raghavan, Gil Tal

Corresponding author ([sraghav@ucdavis.edu](mailto:sraghav@ucdavis.edu))

Plug-in Hybrid and Electric Vehicle Research Center

Institute of Transportation Studies (ITS), University of California –Davis (UCD)

1590 Tilia Street, Davis CA - 95616

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## Summary

Using yearlong high resolution driving and charging data of 153 PHEVs in California, we identified driving style, daily vehicle miles traveled (DVMT), and charging behavior as the major causes for disparities between the sticker label UF and observed UF. These differences are attributable to PHEVs having higher DVMT compared to mainstream vehicles, accomplishing higher share of distance at higher speeds that are not represented in certification cycles, and being used as a HEV. Analysis revealed that the magnitude and direction of difference between observed UF and label UF depends on the impact of charging frequency on DVMT and electric range.

*Keywords:* charging, demand, plug-in hybrid electric vehicles (PHEV), user behavior

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## 1. Introduction

Plug-in electric vehicles (PHEVs) are an integral component within the larger context of mitigating light duty vehicle (LDV) sector greenhouse gas (GHGs) emissions. PHEVs are equipped with a larger battery pack compared to conventional HEV that could be charged using grid electricity and also have an internal combustion engine (ICE). PHEVs combine the advantages of engine downsizing, minimal energy losses due to engine idling, and regenerative braking capabilities of a HEV with the all-electric capabilities of a battery electric vehicle (BEV) [1]. The flexibility in fuel use allows them to be driven on three distinct modes: i) electricity alone in the charge depleting (CD) or zero emission (ZE) mode where the engine is never turned on and the entire motive demand is met by the electric motor; ii) charge depleting blended (CDB) mode where the motive demand is met by the electric motor and the ICE; and iii) charge sustaining (CS) mode where the motive demand is met entirely by the ICE. This unique flexibility of PHEVs enables them to substitute gasoline use with electricity and to be immune from range anxiety concerns. Gasoline is entirely and partially substituted by electricity in the CD and CDB modes respectively. Significant emission benefits are realized when the PHEVs are operated in the CD mode since electricity is much cleaner than gasoline [2]. Assuming a fully charged battery, the maximum distance a PHEV drives in the CD mode until the battery is depleted without engine being turned on is called the CD range or the all-electric range(AER). The CD range depends on the battery capacity and under ideal conditions the CD range is same as the AER capabilities of the PHEV. Even though the AER is directly related to the battery capacity, it is not always possible to recover the entire AER in CD mode since it depends on host of other factors such as the drivetrain architecture, powertrain control and battery management strategies, propulsion demand, road conditions, driving and charging behavior, and driving style[3, 4].

A critical aspect in assessing the performance of PHEVs thus depends on how much do we know about their real-world operation, particularly fuel economy and exhaust emissions. In this context, the concept of Utility

Factor (UF) has been developed, which represents the proportion of VMT travelled on electricity (eVMT). The formal procedures and test conditions under which the UF and the “sticker fuel economy” is estimated are outlined in *Society of Automotive Engineers (SAE) J1711- Recommended Practice for Measuring the Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-in Hybrid Vehicles* [5] and SAE J2841 - *Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data* [6] standards respectively. In order to ensure a fair comparison between different PHEV types, standardized certification cycles [7] are recommended in SAE J1711 in order to test the PHEV in both CD and CS modes. CD mode per-mile electricity consumption and CS mode per-mile gasoline consumption are the important outputs of SAE J1711 [8]. Since driving behavior, DVMT, road network conditions varies geographically, the distribution of per mile energy consumption by mode is weighted against national driving statistics such as the National Household Travel Survey (NHTS)[9] in order to determine at an aggregate level, how much of a vehicle’s driving can be accomplished on CD mode and the CS mode respectively in SAE J2841. The significance of UF estimated using SAE J1711/SAE J2841 cannot be understated since it is the most important performance metric on which vehicle emissions and label fuel economy estimates [10, 11] credit allocation under the zero emission vehicle(ZEV) mandate and the Low Carbon Fuel Standards (LCFS) in California, Corporate Average Fuel Economy, and Pavley GHG emission standards rely significantly [12, 13].

Majority of contemporary studies on the economic, environmental, market potential, and value proposition of PHEVs are based on expectations about PHEV use. In the context of this paper, “expected” PHEV use refers to the set of assumptions made about PHEV’s daily driving and charging behavior in SAE J2841, the driving style of PHEVs which is reflected in the standardized certification drive cycles[7, 14] that are used to determine the energy consumption, and label UF listed on the fuel economy database [15]. More recently, efforts have been undertaken to observe real-world PHEV driving and charging behavior over a year through GPS enabled data loggers [16, 17] to gather a better understanding of their real-world use.

The objective of this paper is twofold, first we compare and contrast how the observed PHEV driving and charging differs from expected PHEV use. Then, using k-means clustering algorithm we identify specific driving and charging behavior which caused these differences. Rest of the paper is organized as follows. Section 2 provides an overview of contemporary UF and eVMT estimation. Section 3 outlines the dataset analysed in this study. In Section 4 we compare and contrast observed PHEV use with the expected PHEV use from the perspectives of driving style, DVMT, and charging frequency. In Section 5 we present the results of k-means clustering of daily driving and charging behavior and describe how it influences the observed UF and eVMT and what aspects of driving and charging behavior contributed to its observed UF and eVMT differing their respective label values. Finally, we present our conclusions and future extensions of this work.

## 2. UF Estimation in Practice

The SAE J2841 methodology for UF estimation is based on certain assumptions about the driving and charging behavior of PHEVs which may not be generalizable. Specifically it is assumed that i) PHEV owners charge at least once per day at home; ii) travel day begins with a fully charged battery; iii) PHEV owners ubiquitous home charger access; iv) ICEs and PHEVs are perfect substitutes and travel patterns of an ICE based on a single day travel diary in the NHTS sufficiently characterizes PHEV travel ; v) travel behavior has no impact on the PHEV type a consumer decides to purchase; vi) PHEVs are always fully charged at their home; and vii) any existing or planned charging infrastructure has no incremental impact on the eVMT [8, 18, 19]

The normative daily distance based UF definition is represented using Eq. (1), where  $d(k)$  is the distance travelled on travel day  $k$ . It denotes the probability that a geographically weighted vehicle based on the NHTS will be driven less than or equal to the AER. In other words, the daily distance based UF is the fraction of DVMT that could be travelled on electricity alone and the rest of the travel is accomplished using gasoline (gVMT). If the DVMT is less than or equal to the AER of the PHEV then the UF is 1 and if DVMT is greater than the AER, then UF is  $R_{CD}/d(k)$  [20].

$$UF_{distance}(R_{CD}) = \frac{\sum_{k=1}^N \min(d(k), R_{CD})}{\sum_{k=1}^N d(k)} \quad (1)$$

The SAE J2841 UF estimation is defined based on the 2001 NHTS and there have been more recent studies that used the 2009 NHTS [8]. In order to determine  $R_{CD}$ , standardized certification cycles such as the Urban Dynamometer Driving Schedule, Federal Test Procedure, Highway Fuel Economy Test, US06 or Supplemental FTP, and the California Air Resources Board (CARB) Unified Driving Schedule (LA92) are

commonly used. The tests beings with the PHEV being fully charged and then subject to a sequence of 4-5 UDDS cycles [13] to first determine the AER and the sequence is repeated in the CS mode when the battery is fully depleted. There are additional criteria under which the PHEV is tested such as the soak time, pre and post-test vehicle preparation. The UF weighted fuel economy (FE in km/L) and fuel consumption (FC in L/km) of a PHEV fleet over a specific drive cycle in CD and CS modes is then estimated according to Eq. (2)-(3) [8].

$$FE_{UFweighted} = \frac{1}{(UF/FE_{CD}) + (UF/FE_{CS})} \quad (2)$$

$$FC_{UFweighted} = FC_{CD} \cdot UF + FC_{CS} \cdot (1 - UF) \quad (3)$$

More recently, various empirical studies have demonstrated that the UF is sensitive to charging behavior, vehicle characteristics, vehicle age, vehicle class, vehicle fuel economy, and the annual VMT, and alternative definitions of UF have been proposed that factors the sensitivity of PHEV performance to the aforementioned vehicle attributes, driving and charging behavior [8, 18, 21].

Table 1: Data Overview

PHEV	N Veh	N Veh Days	Total Trips	ZE Trips	CS Trips	VMT miles	gVMT miles	Charging Sessions	Energy (MWh)
Prius	22	6981	31473	3226	11184	314231	268113	7773	18
CMax Fusion	52	14650	64076	25004	18276	667656	437710	19621	732
Volt16	44	13088	51419	37936	6206	566354	204645	15942	100
Volt18	35	10564	43966	33836	2743	403425	130923	9797	74
Total	153	45283	190934	100002	38409	1951666	910252	53127	263.8

Table 2: Observed and Label UF and eVMT

PHEV Type	eVMT miles	Observed UF	Label UF	eVMT from Label UF	Δ eVMT miles
Prius	46116	0.147	0.29	91127	44935
CMaxFusion	229926	0.344	0.452	301781	72107
Volt-16	361708	0.639	0.652	369263	7363
Volt-18	27250	0.675	0.761	307007	34695

### 3. Data Description

Table 1 summarizes the driving and charging data of 153 PHEVs. 22 Toyota Plug-in Prius (2012-2014), 28 Ford CMax Energi (2013-2017), 24 Ford Fusion Energi (2013-2017), and 79 Chevrolet Volt (2012-2017) are in the data set. The data acquisition happened during 05/2015-10/2018 in California. CMax and Fusion Energi have rated battery capacity of 7.7 kWh and identical UF, except for the negligible difference between 2017 versions, so they have been combined together and addressed as CmaxFusion. 2016-2017 Volts have a slightly bigger battery capacity of 18.4 kWh compared to the earlier versions which have rated battery capacity of up to 16.5 kWh, they are separately considered in our analysis and addressed as Volt-16 and Volt-18 respectively. The dataset has close to 45,300 vehicle days (driving only, charging only, or driving and charging), 191,000 trips, 1.95 million VMT, 53,000 charging sessions, and 264 MWh of charging energy. The percentage share of zero emission (ZE) trips driven on electricity alone was 10% and 39% for the Prius and CMaxFusions respectively. Close to 75% of the Volts (Volt-16 and Volt-18) trips were ZE trips. Approximately 36% of Prius trips were driven entirely on gasoline in the charge sustaining (CS) mode, whereas for the CMaxFusions, 29% of trips were in CS model. The Volt-18 had the lowest share (6%) of trips in CS mode and 12% of Volt-16 trips were in CS mode. Table 2 presents the observed eVMT and UF and the EPA label combined city/highway UF [15] and eVMT calculated based on the label UF. The difference between label and observed UF is expressed in terms of eVMT ( $\Delta$  eVMT). Fig. 1a depicts the box plot and histogram of observed UF. Fig. 1b shows the ratio of observed UF to the combined city/highway label UF for every individual vehicle by PHEV type in the dataset. Referring to Fig. 1b, the observed UF of 80% of the Prius (18 out of 22), 63% of CMaxFusions (33 out of 52), 43% of Volt-16 (19 out of 44), and 69% of Volt-18 (24 out of 35) is lower than the label UF.

## 4. Comparison of Observed PHEV Use With Expectations

In this section, we systematically compare how observed PHEV use varies from expected PHEV use from the perspective of driving style, DVMT, and charging frequency. First we compare the percentage share of driving distance as a function of driving speeds between certification cycles and observed PHEVs. Then, we look at how the DVMT of observed PHEVs is markedly different from mainstream vehicles in the NHTS, followed by to what extent the travel day assumptions of fully charged battery are valid and how the DVMT impacts the UF on these days. Finally, we look at the effect of DVMT and charging frequency separately on the observed UF.

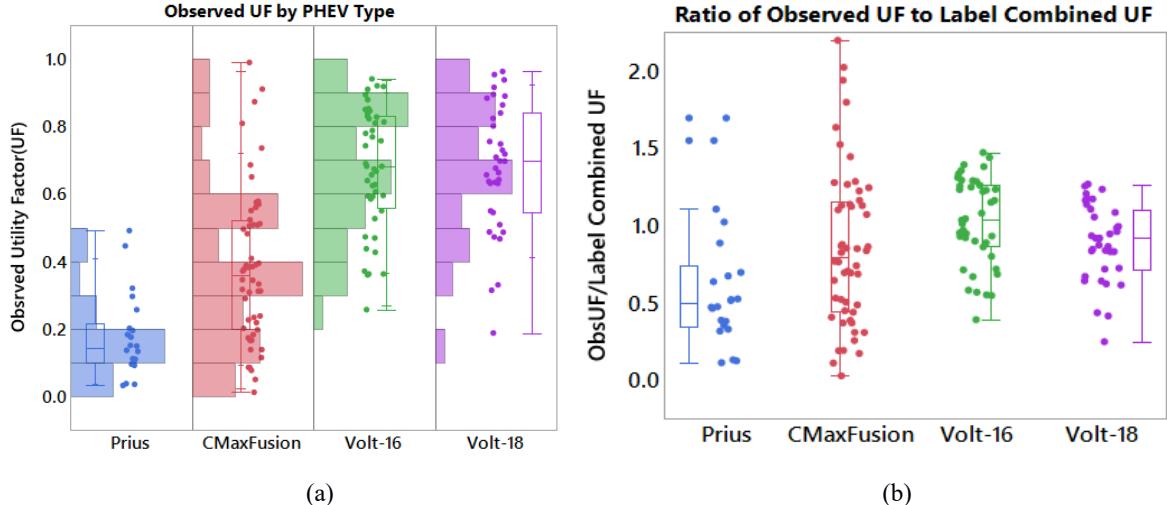


Figure 1: (a) Observed UF of individual PHEVs ; (b) Ratio of observed UF to label combined UF

### 4.1. Effect of Driving Style

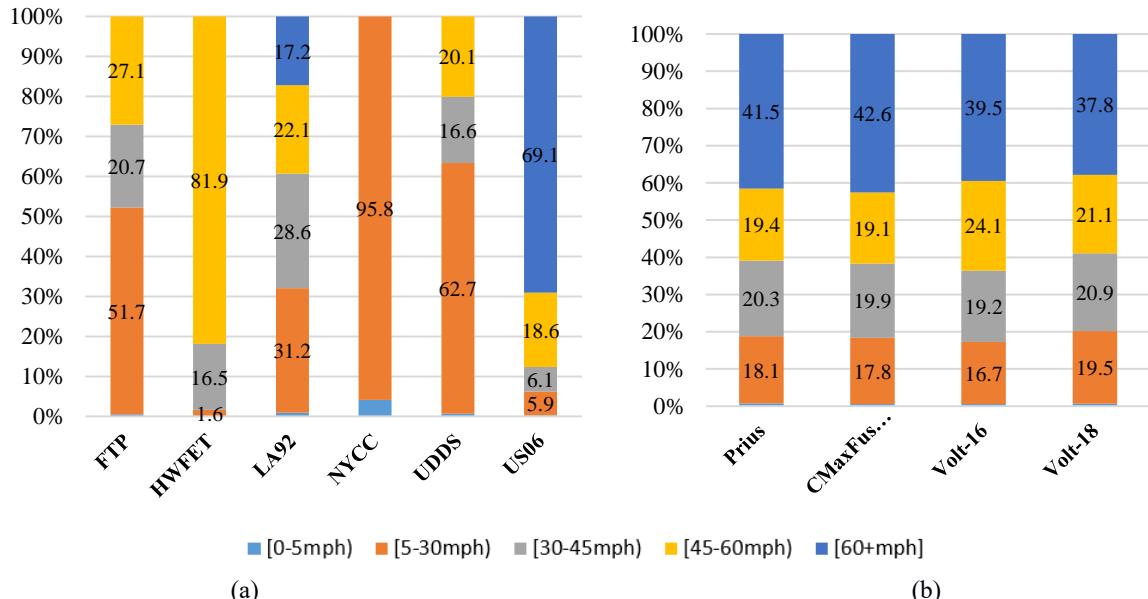


Figure 2: (a) Percentage of distance driven under EPA certification cycles at different speeds; (b) Percentage of distance driven by observed PHEVs at different speeds

As mentioned in Section 2, UDDS is the widely used drive cycle to determine the urban AER. The UDDS is representative of stop and go urban traffic of 7.45 miles, maximum speed of 56.7 mph, and average speed of 27.7 mph. FTP is similar to UDDS, HWFET represents highway style driving, and the NYCC represents congested stop and go city driving. The maximum speed of LA92 and US06 are 67.2 mph and 80.2 mph respectively. CARB uses FTP and US06 for its LDV particulate matter (PM) emission testing and ZEV credit allocation of PHEVs. Fig. 2a. and Fig. 2b shows the compares the percentage of distance travelled in different speed bins between certification cycles and observed PHEVs. We can clearly observe that the LA92 and UDDS closely resemble the distance travelled by the PHEVs in the 45-60mph speed bin and the FTP closely

resembles the distance travelled by the PHEVs in the 30-45mph speed bin. Other than these, none of the standard drive cycles adequately characterize the impact of driving speed on the share of total VMT, especially at highway speeds (60mph or more). In addition, the UDDS and FTP has a disproportionately higher percentage share of distance travelled in 5-30 mph speed bins when we compare it with the observed PHEVs.

#### 4.2. Daily VMT of Mainstream Vehicles and Observed PHEVs

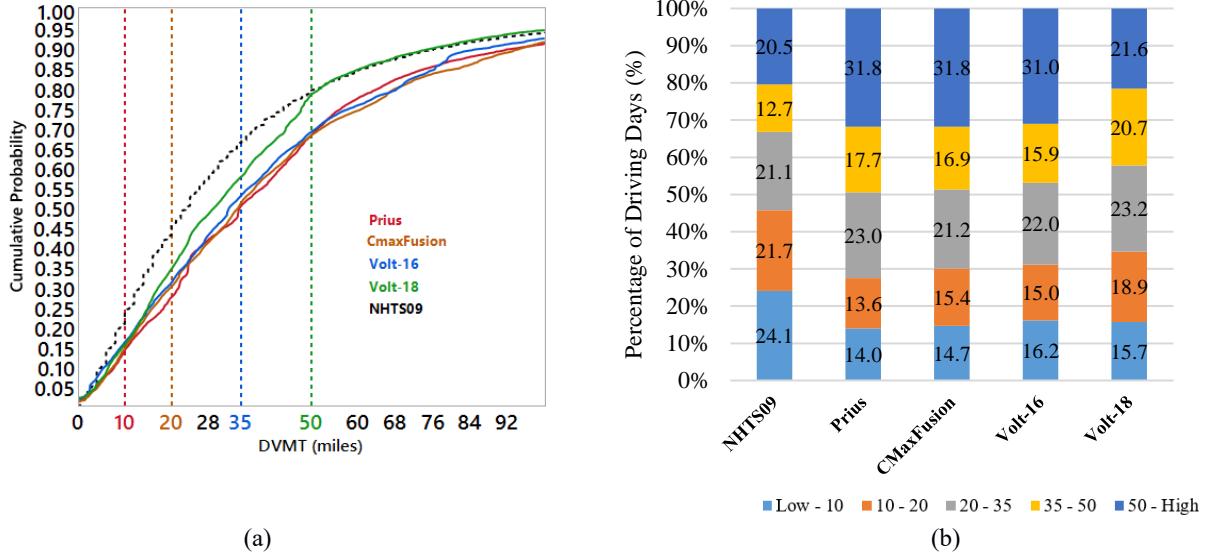


Figure 3: (a) Truncated 2009 NHTS and observed PHEV DVMT CDF (a) 2009 NHTS and observed PHEVs percentage of driving days by DVMT binned (miles)

Fig. 3a shows the truncated (0-100 miles) cumulative distribution plot of DVMT of 2009 NHTS (only LDVs with DVMT greater than zero) and the observed PHEVs. Fig. 3b shows the percentage of driving days by DVMT binned (miles). The NHTS oversamples driving days where DVMT is less than 10 miles or between 10-20 miles but under samples the driving days when DVMT was 50 miles or more compared to the observed PHEVs. The 2009 NHTS and observed PHEVs align well only when the DVMT is between 20-35 miles. The 2009 NHTS average DVMT was 37 miles, however all of the four PHEV types have a higher average DVMT. Average DVMT of Prius and CmaxFusion was 46 miles, Volt-16 and Volt-18 have average DVMT of 44 miles and 39 miles respectively. We can posit that the Prius, CmaxFusion, and Volt-16 have a higher annual VMT than mainstream vehicles represented in the NHTS.

#### 4.3. SAE J2841 Travel Day Assumptions

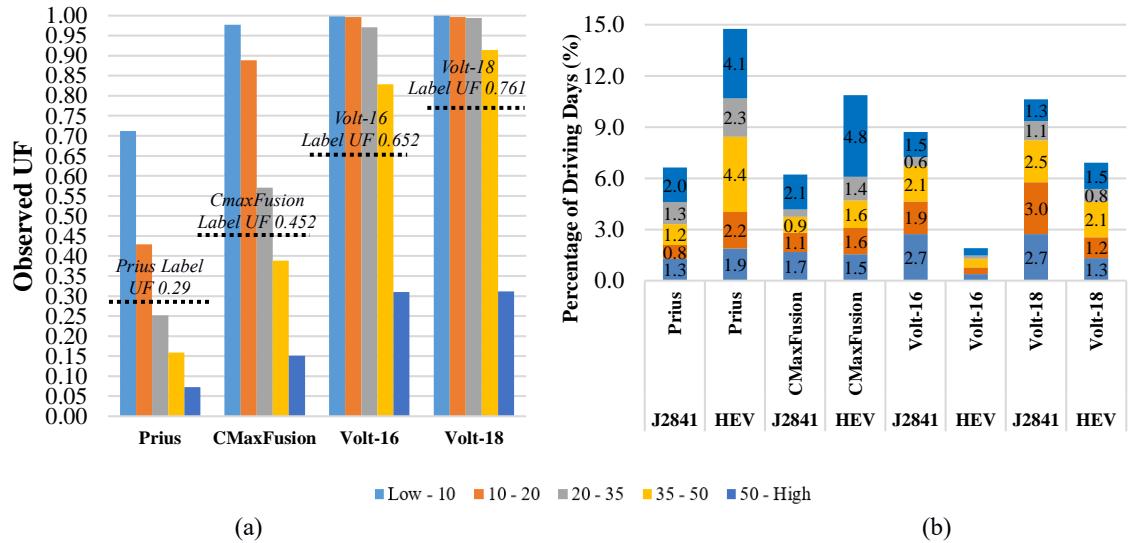


Figure 4: (a) UF on SAE J2841 compliant days ; (b) Percentage of driving days that were SAE J2841 compliant and when used as HEV

Fig. 4a shows the how the observed UF varies with DVMT on days when the PHEV was fully charged, consistent with the SAE J2841 travel day assumptions. Fig. 4b compares the percentage share of SAE J2841 days and the days on which the PHEV was strictly used as a HEV where the travel day started and ended on an empty battery and the vehicles were not charged at all. The observed could be either higher or lower than the label UF depending on the DVMT and the AER. There is a trend in UF declining with increase in DVMT, but on days when the DVMT was no more than twice their respective AER, the observed UF was higher than the label UF for the Prius and CmaxFusion. For the Volt-16 and the Volt-18, the observed UF drops below the label UF only when the DVMT 50 or more miles. The awareness and perception of remaining range could have influenced the driving style of the PHEVs on days when the observed UF was higher than the label UF even though the DVMT was more than their AER. From Fig. 4b we could observe that the Prius and CmaxFusion are used as a HEV on a higher percentage of driving days compared to days when their travel day began with a fully charged battery. This observation further strengthens the rationale presented in related studies[22] that report low correlation between needed and actual charging of shorter range PHEVs (Prius and CMaxFusions) due to lack of charger accessibility, which results in suboptimal utilization of the AER.

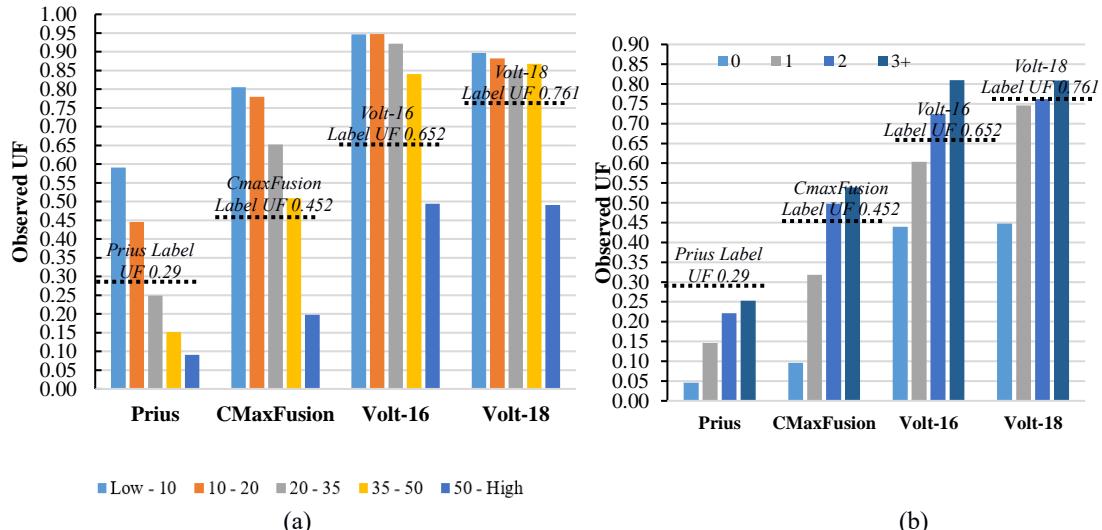


Figure 5: (a) Impact of Daily VMT binned (miles) on the UF; (b) Impact of charging frequency on UF

#### 4.4. Impact of DVMT and Charging Frequency on UF

Fig. 5a and Fig. 5b shows the specific impacts of DVMT and charging frequency on the UF. From a DVMT perspective the observed UF of CmaxFusion and Volts (Volt-16 and Volt-18) is higher than the label UF when the DVMT is less than 50 miles but the UF noticeably drops below the label UF when the DVMT exceeds 50 miles. In the case of Prius, the observed UF is higher (lower) than the label UF when the DVMT is less (more) than 20 miles. Referring to Fig. 3b we can see that the Prius and CmaxFusion have the highest share of driving days when the DVMT exceeded 50 miles. From Fig. 5b, we can see that the observed UF of Prius is lower than label UF irrespective of the number of charging sessions/day. However for the CMaxFusions and Volts (Volt-16 and Volt-18), the observed UF exceeds the label UF only when the number of charging sessions/day is 2 or more.

### 5. k-Means Clustering of Driving and Charging

The previous subsection outlined how DVMT and charging frequency independently influence the UF. In order to better understand how driving and charging behavior together influence the eVMT and how it varies with the AER of the PHEV, we utilized k-means clustering algorithm. The objective of the clustering algorithm is to uncover underlying patterns in driving and charging behavior. The driving and charging data were combined together into a single dataset by matching the vehicle ID and the day of event from the driving or charging dataset. For any data that was missing, we have assumed that the vehicle was observed during but not used and imputed with zeros. The combined dataset has 45,283 samples of vehicle-days (charging only or driving only or charging and driving), of which Prius Plug-in accounted for 15%, CMaxFusion accounted for 32%, and the Volts accounted for 52% ( 29% from Volt-16 and 23% from Volt-18). Clustering

is done to group these 45,283 samples into type of day that reflects the driving and charging behavior. This will then be used to understand how much of a time in terms of percentage of total vehicle days each of the PHEV type spends in each of these clusters and subsequently how the observed UF and eVMT of each PHEV differs from the label UF and eVMT calculated based on the label UF. The ten variables that were chosen for the clustering and the cluster means summaries are summarized in Table 3. Using the cubic clustering criterion (CCC), the optimal number of clusters was found to be 7. The k-means clustering algorithm reduced the 45,283 to seven driving and charging behavior profiles. Table 4 characterizes these driving and charging behavior profiles in the respective clusters.

Table 3: Cluster Means Summaries

Cluster	N Days	SOC Level		Daily Charging		Daily Driving			Daily Trips		
		Start	End	Sessions	kWh	VMT	<sup>e</sup> VMT	<sup>g</sup> VMT	ZE	CS	Blend
C1	848	36	95	1.05	5.17	0.0	0.0	0.0	0.0	0.0	0.0
C2	3543	99	41	0.0	0.0	35.5	16.4	19.1	2.4	0.5	0.8
C3	2321	0.8	1	0.0	0.0	47.8	0.6	47.2	0.0	3.2	1.9
C4	14406	80	81	1.3	6.6	23.1	23.1	0.0	3.9	0.0	0.0
C5	22476	73	75	1.5	7.2	56.0	22.9	33.1	1.6	1.1	2.0
C6	1565	1	23	0.3	1.5	45.0	0.0	45.0	0.0	3.1	0.0
Outlier	124	52	38	1.3	3.61	419	18.9	400.5	0.5	3.0	2.64

Table 4: Driving and Charging Behavior Profiles

Cluster	Characteristics
C1	Did not drive but charged at least once
C2	Travel day starts with a fully charged battery
C3	Strictly used as a HEV and CS day
C4	Travel day starts and ends at same SOC, lowest VMT (excluding outliers) and ZE day
C5	Travel day starts and ends at same SOC, highest VMT (excluding outliers) and charging frequency
C6	HEV dominant use , CS day, and minimal charging at the end of last trip
Outlier	Top 0.1 percentile of DVMT

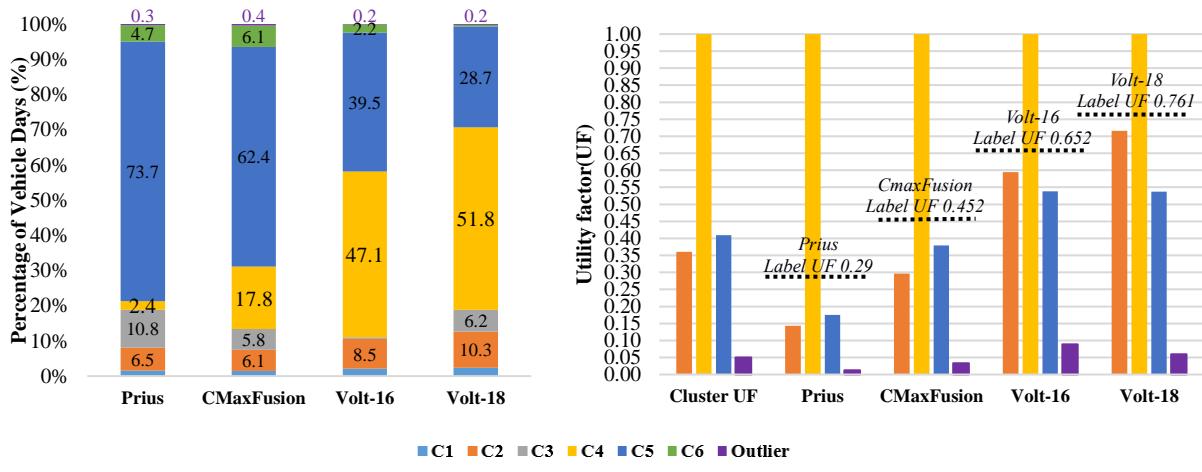


Figure 6: (a) Percentage of vehicle-days spent in each cluster by PHEV type ; (b) UF of PHEVs in the individual clusters

Fig. 6a shows the percentage of vehicle days spent in each of the cluster by the PHEV type and Fig. 6b shows the overall cluster UF and the UF of the PHEV in the six clusters. The label UF is indicated in Fig. 6b to highlight how driving and charging behavior profiles revealed by the clustering affects the UF for different PHEVs. Since the UF in C1, C3 and C6 is zero, they have been omitted from Fig. 6b for the sake of clarity. Prius and CMaxFusions spend a majority of their vehicle days in C5 which is associated with highest DVMT

(excluding the outlier cluster) and the highest recharging frequency, whereas the Volts (Volt-16 and Volt-18) spend a majority of their vehicle days in C4 which has the lowest DVMT (excluding the outlier cluster). In C4, on average the travel day starting and ending SOC are identical, indicative of intraday charging since the daily number of charging sessions is greater than 1. Since the DVMT of C4 is lower than the AER of the Volts and only slightly more than the AER of the CmaxFusion coupled with the fact that the travel day starts with 80% charged battery, the UF of these PHEVs on these vehicle days is 1 (ZE day). The Volts (Volt-16 and Volt-18) spend close to 50% of their time in C4 and the CMaxFusions spend close to 18% of their vehicle days in C4. In C3 and C6, the PHEVs are used as a conventional HEV (CS day). Though PHEVs charge in C6, it is negligible and happened after last trip ended as evidenced by the fact that the charging had no bearing on the daily eVMT in C6. Prius spend a combined 12% of its vehicle days and CmaxFusion spend 15% of its vehicle days in C3 and C6. Volt-16 spends 10% more of its vehicle days in C5 compared to the Volt-18. C2 is representative of a travel day that begins with a fully charged battery. The Prius and CmaxFusion spend a higher percentage of their vehicle days as a HEV (in C3 and C6) compared to C2. The outlier cluster represents the rarest travel days where the DVMT of the PHEVs was in the top 0.1 percentile (greater than 400 miles) of the DVMT distribution. The outlier cluster accounts for only 0.27% (124) of the total vehicle-days. The CmaxFusion spent the highest number of days (55 days) in the outlier cluster followed by Volt-16 (24 days), Volt-18 (23 days), and Prius (22 days).

Table 5: Average DVMT and charging sessions and energy in clusters causing observed eVMT OE

Cluster	Average DVMT (miles)					Outlier	Daily Average Charging Sessions and Energy							
	C2	C3	C4	C5	C6		C4		C5		C6		Outlier	
							Sess	kWh	Sess	kWh	Sess	kWh	Sess	kWh
Prius	44	45	5	47	30	450	1.20	1.71	1.44	3.33	0.18	0.49	0.73	1.6
CMax Fusion	44	58	15	52	52	396	1.56	4.48	1.64	6.34	0.24	1.12	2.07	4.3
Volt16	32	50	24	70	43	408	1.34	6.77	1.41	10.8	0.38	3.65	0.54	3.1
Volt18	29	38	27	62	22	458	1.12	7.53	1.11	10.19	0.09	1.24	0.83	4.3

### 5.1. Over (OE) and Under Estimation (UE) of Observed eVMT and UF Compared to Label Values

Referring to Fig. 6b, we can see that except in C4, the observed UF is noticeably lower than the label UF for all the PHEV types. In order to gather a deeper understanding of how and daily driving and/or charging behavior contributes to the deviation of observed UF from label UF and by how much the observed eVMT differs from the eVMT calculated from the label UF ( $\Delta$ eVMT), in each of the cluster, we first calculate  $\Delta$ eVMT. If  $\Delta$ eVMT is positive then the label UF overestimates (OE) the eVMT and when  $\Delta$ eVMT is negative, the label UF underestimates (UE) the eVMT. The sum of OE eVMT and UE eVMT is essentially the  $\Delta$ eVMT for each PHEV type listed in Table 2. Fig. 7a depicts the OE and UE eVMT for each PHEV type and we can identify five major reasons for the eVMT OE. From Fig. 7a we can clearly see that across all PHEV types irrespective of their AER, a majority of the eVMT OE is due to the driving and charging behavior characterized by C5, followed by C3, C6, outliers, and C2. The average DVMT, charging sessions and charged energy in these clusters for each PHEV type is shown in Table 5.

From Table 5, we can observe that the OE in C5 is due to the fact that the PHEVs drove much longer than their AER and did not fully charge even though they charged more than once per day, which resulted in the PHEVs being unable to recover even their AER share of DVMT. The second reason for eVMT OE across all PHEV types except the Volt-16 is due to C3 where they are used as conventional HEVs. The third reason for eVMT OE across all PHEV types except the Volt-18 is due to C6 where they are used as a conventional HEV with negligible end of travel day charging. It is interesting to note that the Volt-18 have a higher percentage of eVMT OE due to C3 compared to all other PHEV types. Also, from Table 5 we can see that the average DVMT of the PHEVs in C3 is higher than that of C6. The fourth reason for eVMT OE is due to the outliers in driving and charging behavior. The outlier driving and charging behavior cluster has only 124 days. These outliers in driving and charging behavior represent less than 0.3% of the total vehicle days for the four PHEV types, Fig. 6a. The average DVMT in the outlier cluster belongs to the top 0.1 percentile of the DVMT

distribution which causes eVMT OE. The final reason for the eVMT OE is due to C2 wherein the travel day begins with a fully charged battery but the average DVMT was higher than the AER of Prius and CmaxFusion. In C2, the Volt-16 did not fully utilize their AER since the average daily VMT was less than the AER. Even though the outlier cluster accounts only for 0.3% of the total vehicle-days, on an absolute eVMT and percentage of total eVMT OE basis, the OE from outlier driving and charging behavior is higher than that of C2, where the short range PHEVs (Prius and CmaxFusion) drove longer than their AER.

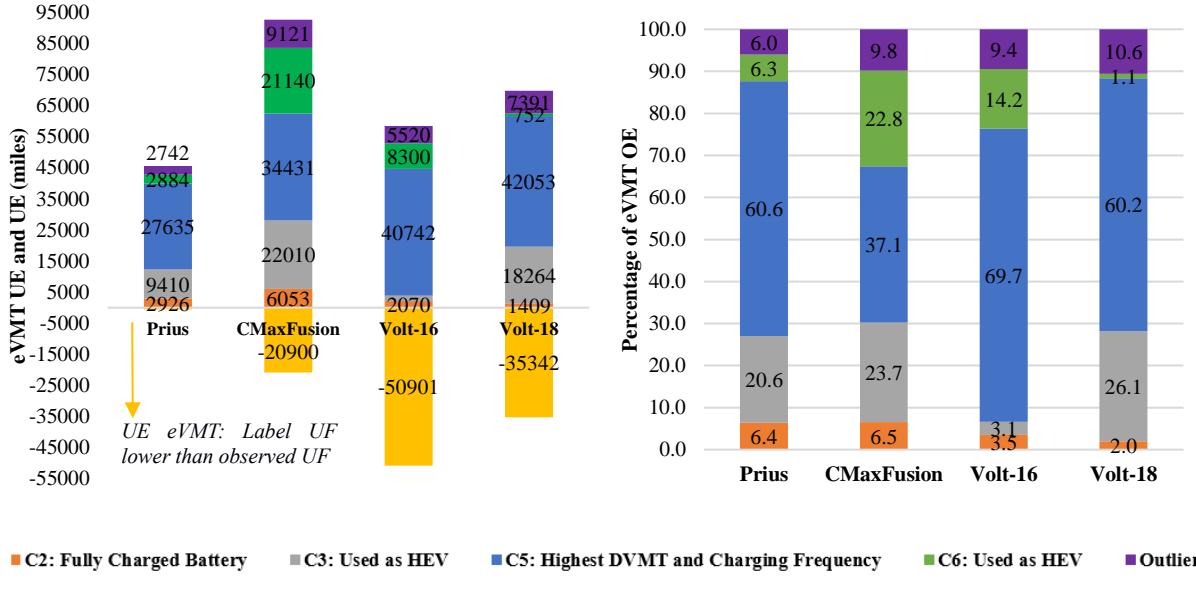


Figure 7: (a) Total eVMT in miles OE and UE by cluster; (b) Percentage of total eVMT OE by cluster

Referring to Fig. 7a and Table 5, only C4 contributes to eVMT UE where the PHEVs charged more than once and drove less than their AER. On a mileage basis, the eVMT UE was highest for the Volt-16, followed by the Volt-18, CmaxFusion, and the Prius which was negligible (only -587 miles) compared to the rest of the eVMT UE. Referring to Table 2, since almost an equal number of Volt-16 observed UF was either higher or lower than the label UF, at an aggregate level the nett effect of OE and UE eVMT is minimal and the observed UF of Volt-16 is therefore very close to its label UF. However for the CmaxFusion and Prius, since they are used as a conventional HEV on a higher percentage of their vehicle days compared to the Volts (Volt-16 and Volt-18), coupled with the fact that they have higher average DVMT than the Volts (Volt-16 and Volt-18) and have lower AER, their observed UF is only 50% and 70% of their respective label UF. The eVMT UE of the Volt-18 is mainly due to the fact that they were used as an HEV on days when the average DVMT was less than their AER, which explains why the observed UF of Volt-18 is only 88% of their label UF.

Table 6: Individual PHEV Level eVMT OE and UE

Cluster	C2	C3	C4	C5	C6	Outlier	Total OE eVMT	Total UE eVMT	Nett eVMT OE
Prius	133	428	-27	1256	131	125	2073	-27	2046
CMaxFusion	116	423	-402	662	407	175	1784	-402	1382
Volt16	47	41	-1157	926	189	125	1329	-1157	172
Volt18	40	522	-1010	1202	21	211	1996	-1010	986

In order to account for the sample size of different PHEVs in our dataset, we scaled the total fleet level eVMT OE and UE shown in Fig. 7a by the number of PHEVs of each type and Table 6 shows these values. It is worthwhile to note that the Nett eVMT OE for the CMaxFusion and Volt-18 are relatively close. However, this is due to two entirely divergent driving and charging behavior patterns. The CmaxFusion has the highest average DVMT (46 miles) whereas the Volt-18 has the lowest average DVMT (39 miles). Also, the Volt-18 is not fully utilizing their AER and not charging as often as evidenced by the fact that close to 25% of the eVMT OE comes from days on which it was used as a regular HEV. Volt-18 underutilization of AER could

be either due to lack of charging need because of their AER or lack of charging availability. In the case of CmaxFusion, the incremental gain in eVMT for every additional charging session is not sufficient enough to compensate for their higher average DVMT simply because of their AER capabilities.

## 6. Conclusions and Future Work

This study examined how observed PHEV use markedly differs from our expectations and how it contributes to the observed UF and eVMT being over or under estimated compared to their label values. Results indicated that PHEVs drive longer on average daily and have a higher share of miles driven on highway speeds (60 mph) compared to national travel statistics and certification cycles respectively. Analyses highlighted how DVMT and charging frequency independently and jointly cause the observed UF and eVMT to differ from their label values. For the short range PHEVs, label UF is higher than the observed UF due to the fact that they are used as a conventional HEV on a higher percentage of driving days compared to days when their travel begins with a fully charged battery. For the Volt-16, the observed UF and the label UF were very close to each other since the observed eVMT overestimated and underestimated offset each other. The observed UF of Volt-18 was lower than the label UF because the Volt-18 has a lower average DVMT compared to rest of the PHEV types and used as a HEV on a comparable percentage of vehicle days as the CmaxFusion, suggesting that Volt-18 is underutilizing its AER. Furthermore, we observed that just a tiny fraction of 0.27% of total vehicle days on which the PHEVs demonstrated outlier behavior accounted for 33% of the total observed eVMT overestimation compared to the label values. At an aggregate level, we showed that observed UF and eVMT is only 50% of label UF and eVMT for the Prius, 76% for the CmaxFusion, 89% for the Volt-18 and 98% for the Volt-16.

The study highlighted the importance and value of understanding how real-world driving and charging behavior of PHEVs deviates from assumptions about PHEV use. These assumptions are often used as the foundation to shape consumer expectations, inform policies, and evaluate performance of current and anticipated PHEV designs. As the PHEV design capabilities evolve, accompanied by changes in purchase behavior of prospective PHEV owners, and expansion of charging infrastructure, it is worthwhile to have the usage metric on which the PHEVs are evaluated, namely the UF, adequately capture or account for disparities between assumptions and their revealed usage.

While the study does not advocate or recommend moving away from relying on the UF, it does point out that there are indeed noticeable differences between actual driving and charging behavior and the assumptions made. In spite of the relatively small sample size of 153 PHEV, our analysis indicates that the existing method of UF estimation rewards short range PHEVs with a higher share of eVMT than what they actually accomplished. Even though assuming that travel day starts with a fully charged battery is feasible, it could be over-optimistic especially in the case of short-range PHEVs. Our data also indicated that the incremental gains in UF and eVMT levels off with increase in battery capacity as evidenced by the fact that the observed UF of Volt-18 is not significantly different from that of Volt-16. In addition, we also observed that a small subset of PHEVs exhibited extremities in their driving behavior. This is indicative of the fact that UF estimation at an aggregate level dilutes how different consumers value range and how the travel needs and usage patterns of two consumers who purchase the same PHEV could be drastically different. The marginal changes in UF and eVMT do not have to necessarily move in the same direction in response to marginal changes in battery capacity, since range utilization and range maximization are a function of driving and charging behavior which could be heterogeneous between different PHEV types and also within the same PHEV type.

From the perspective of GHG mitigation, a critical question facing the policy maker is to decide whether to push for more long-range PHEVs on the market or invest in increasing not just the number of chargers but also charger utilization. Future work will precisely tackle this question and expand upon the observations gathered from this study by looking deeper into driving style to characterize every trip as a highway, city, stop and go, or congested city driving, segmenting consumers by their charging frequency and VMT, and the inclusion of additional PHEV models (Toyota Prius Prime and Chrysler Pacificas).

## Authors



Seshadri Srinivasa Raghavan is a Doctoral Candidate in Transportation Technology and Policy at UCD. His research is on understanding plug-in electric vehicle usage at a vehicle and household level from GHG reduction potential, charging infrastructure adequacy, and grid impacts perspectives. He holds a M.S. in Electrical Engineering from University of Maryland, College Park.



Dr. Gil Tal is the Director of the Plug-in Hybrid & Electric Vehicle Research Center at the University of California, Davis (UCD). He is also the admission adviser for the Graduate Groups in Transportation Technology, and Policy at UCD. Dr. Tal is a leading expert on electric vehicle travel behavior, as well as understanding the role that incentives and infrastructure play in the electric vehicle market worldwide. He also researches the electrification of new mobility services and their impact on the electric grid. Dr. Tal holds a Ph.D. in Transportation Technology and Policy from UCD and a M.A. in geography and environmental policy and planning from the Hebrew University in Jerusalem.

## References

- [1] A. Poullikkas, "Sustainable options for electric vehicle technologies," *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 1277-1287, 2015.
- [2] D. Gohlke and Y. Zhou, "Impacts of Electrification of Light-Duty Vehicles in the United States, 2010-2017," Argonne National Lab.(ANL), Argonne, IL (United States)2018.
- [3] M. Duoba and H. Lohse-Busch, "Advanced Vehicle Performance Assessment. Nikowitz M. (eds) Advanced Hybrid and Electric Vehicles., " in *Lecture Notes in Mobility* Springer International Publishing Switzerland 2016, 2016, pp. 65-85.
- [4] S. Kamguia Simeu, J. Brokate, T. Stephens, and A. Rousseau, "Factors Influencing Energy Consumption and Cost-Competitiveness of Plug-in Electric Vehicles," *World Electric Vehicle Journal*, vol. 9, no. 2, p. 23, 2018.
- [5] *Society of Automotive Engineers (SAE) J1711\_201006: Recommended Practice for Measuring the Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-in Hybrid Vehicles*, 2010.
- [6] *Society of Automotive Engineers (SAE) J2841\_201009 : Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data*, 2010.
- [7] U.S. Environmental Protection Agency (EPA). (2018, Jan. 1). *Dynamometer Drive Schedules*. Available: <https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules>
- [8] T. H. Bradley and B. M. Davis, "Alternative Plug in Hybrid Electric Vehicle Utility Factor," SAE Technical Paper0148-7191, 2011.
- [9] FHWA. National Household Travel Survey [Online]. Available: <https://nhts.ornl.gov/>
- [10] M. Duoba, "Design of an On-Road PHEV Fuel Economy Testing Methodology with Built-In Utility Factor Distance Weighting," *SAE International Journal of Alternative Powertrains*, vol. 1, no. 1, pp. 349-353, 2012.
- [11] J. Gonder, A. Brooker, R. B. Carlson, and J. Smart, "Deriving in-use PHEV fuel economy predictions from standardized test cycle results," in *2009 IEEE Vehicle Power and Propulsion Conference*, 2009, pp. 643-648: IEEE.
- [12] *Advanced Clean Cars and Regulatory Development of the ZEV Program*, California Air Resources Board, 2010.
- [13] CARB, "California's Advanced Clean Cars Midterm Review," 2017.
- [14] *Special procedures related to electric vehicles and hybrid electric vehicles.* , EPA 76 FR 39548, July 6, 2011, as amended at 76 FR 57380, Sept. 15, 2011. , 2012.
- [15] U.S. Environmental Protection Agency (EPA). (2019, January 1). *Fuel Economy Data*. Available: <https://www.fueleconomy.gov/feg/download.shtml>

- [16] INL. (2014). *2014 DOE Vehicle Technologies Office Review - EV Project Data & Analytic Results*. Available: [https://energy.gov/sites/prod/files/2014/07/f18/vss137\\_francfort\\_2014\\_o.pdf](https://energy.gov/sites/prod/files/2014/07/f18/vss137_francfort_2014_o.pdf)
- [17] T. Turrentine and G. Tal, "Advanced Plug-In Electric Vehicle Usage and Charging Behavior," ed: CARB and CEC, 2015.
- [18] E. Paffumi, M. De Gennaro, and G. Martini, "Alternative utility factor versus the SAE J2841 standard method for PHEV and BEV applications," *Transport Policy*, vol. 68, pp. 80-97, 2018.
- [19] X. Wu, M. Aviquzzaman, and Z. Lin, "Analysis of plug-in hybrid electric vehicles' utility factors using GPS-based longitudinal travel data," *Transportation Research Part C: Emerging Technologies*, vol. 57, pp. 1-12, 2015.
- [20] T. H. Bradley and C. W. Quinn, "Analysis of plug-in hybrid electric vehicle utility factors," *Journal of Power Sources*, vol. 195, no. 16, pp. 5399-5408, 2010.
- [21] M. Aviquzzaman, *Analysis of Plug-In hybrid Electric Vehicles' utility factors using GPS-based longitudinal travel data*. Lamar University-Beaumont, 2014.
- [22] G. Tal, M. A. Nicholas, J. Davies, and J. Woodjack, "Charging behavior impacts on electric vehicle miles traveled: who is not plugging in?," *Transportation Research Record*, vol. 2454, no. 1, pp. 53-60, 2014.