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Empirical recharging behavior of plug-in hybrid vehicles

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Summary

In this paper, we investigated the recharging behavior of Chevy Volt (a plug-in hybrid electric vehicle) users. The dataset used is from volstats.net and contains data from 9,987 Chevrolet Volt driven with 3.7 million total driving days in the US and Canada, from April 2011 to May 2019. Results show that additional over-day recharging happens on average on 3-8 % of the days and no recharging overnight happens on average less often 3-6 % of the days. Furthermore, users with more than 30,000 annual vehicle kilometers traveled recharge over-day more than three times compared to the rest of the group.

Keywords: PHEV (plug in hybrid electric vehicle), charging, user behavior

1 Introduction

Plug-in hybrid electric vehicles (PHEVs) can play an important role in reducing the greenhouse gas emissions in the transport sector, and their impact is enhanced if the electricity used to recharge their batteries is generated from low-carbon sources [1]. In order to understand the extent of the role they can play, empirical studies that analyze the recharging behavior of PHEV users are needed. Analyzing the over-day recharging behavior of PHEV users is important for several reasons. (1) Recharging behavior provides insights on how future charging infrastructure policies should be developed. (2) It adds to the understanding of the relationship between more public charging infrastructure and users' charging behavior. (3) It clarifies the relation between battery size and charging behavior and whether people choose the vehicle they purchased based on their driving needs [2]–[5]. The main variable to analyze the environmental performance of PHEV is the utility factor (UF), i.e. the share of electric kilometers travelled within total vehicle km travelled.

Here, we use a dataset from an online database (volstats.net) that collects real-world fuel economy data of Chevrolet Volt, a plug-in hybrid electric vehicle. We estimate (1) the frequency of over-day recharging which is defined as the share of days per vehicle where the observed UF is significantly higher than the simulated UF, and (2) the frequency of no overnight charging which is defined as the share of days per vehicle where the observed UF is significantly lower than the simulated UF.

Following the frequency estimates for over-day recharging and no overnight charging, a characterization of the most frequent over-day recharging and no overnight charging users is made. For this characterization, we analyze the top 10% of most frequent over-day rechargers and top 10% of most frequent no overnight chargers and compare their behavior to their respective bottom 90%. Finally, we analyze intense vehicle users whom we define as users with more than 30,000 km annual vehicle kilometers travelled (VKT) and investigate how their charging behavior differs from the rest.

The outline of the paper is as follows: The data and methods are described in Section 2. Results are presented in Section 3 followed by the discussion in Section 4 and we close with the conclusions in Section 5.

2 Data and Methods

For our analysis, we use publicly available data representing real-world driving behavior from an online source: Voltstats.net. Voltstats.net is an online database that collects automatically (from an additional device) real-world fuel consumption performance data of Chevrolet Volt, in the United States and Canada with 9,987 reported Chevrolet Volts. The data was retrieved from the voltstats.net website. Every user profile on the website contains cumulative daily data on the electric and gasoline mileage including the number of gallons burnt per day by driving. The data was pre-processed, cleaned and cumulative mileage values were converted to daily driven km. Data cleaning comprised the exclusion of values with daily VKT greater than 1500 km and with higher electric VKT than total VKT per day.

The data set comprises data from registered users with a comprehensive set of user specific performance data from April 2011 to May 2019, with 3.7 million driving days. After data cleaning, the average number of days observed per vehicle is 442 days with a median of 330, and maximum of 2,507 days; and average number of driving days per vehicle is 378 with a median of 281 and maximum of 2,342 days. Based on the available data, we calculated the following parameters: electric vehicle kilometers travelled (eVKT), gasoline vehicle kilometers travelled (gVKT) and total vehicle kilometers travelled (VKT). The average distance travelled was extrapolated to annual values. The individual UF per user is obtained by dividing all electric km by total km driven during the observation period.

We analyze the frequency of additional over-day recharging and the frequency of no overnight charging using descriptive and inductive statistical methods. The dataset does not contain the model year of the vehicle, so for this analysis we use the base assumption that the date of the first logged trip for a vehicle indicates the model year of that vehicle. Based on our assumption for the model year, the following all-electric-ranges (AER) are used in our analysis: 56 km (35 US miles) for model years 2011-2012, 61 km (38 US miles) for model years 2013-2015 and 85 km (53 US miles) for model years from 2016 onwards. We also tested a single model year assumption of AER equal to 61 km (38 US miles) for all vehicles, in order to see the effect of our model year assumption on our results. Only the users with at least 28 driving days were included in the analysis.

In order to estimate the frequency of additional over-day recharging and the frequency of no overnight charging, we compare simulated and observed UF for each day and user, for which the definitions are given in Equation 1 and 2 respectively.

$$\mathrm{UF_{sim}} = \begin{cases} {AER}/{daily\ VKT}, & \text{if } daily\ VKT > AER \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

$$\mathrm{UF_{obs}} = {daily\ eVKT}/{daily\ VKT} \tag{2}$$

The simulation implicitly assumes a full recharge overnight, as we do not specifically simulate charging. If the observed UF is much higher than the simulated UF, the vehicle must have had at least one additional recharge during the day. For the occurrence of such an additional over-day recharging event, we use the assumption that the observed UF for a vehicle for that given day is at least 1.5 times higher than the simulated UF. Similarly, for the occurrence of no overnight charging, we use the assumption that the observed UF is smaller than half the simulated UF. These assumptions are summarized in Equation 3 and 4 below.

$$\text{Over-day recharging} = \begin{cases} \text{true}, & \text{if } \frac{UF_{obs}}{UF_{sim}} > 1.5 \\ \text{false}, & \text{otherwise} \end{cases} \tag{3}$$

$$\text{No overnight charging} = \begin{cases} \text{true}, & \text{if } \frac{UF_{obs}}{UF_{sim}} < 0.5 \\ \text{false}, & \text{otherwise} \end{cases} \tag{4}$$

The frequency of additional over-day recharging is defined as the share of days with an over-day recharging event within the total number of driving days for a given user. Similarly, the frequency of no overnight charging is defined as the share of days with no overnight charging within the total number of driving days.

Our assumptions regarding additional over-day recharging and no overnight charging are rather conservative, which further increases the robustness of our estimates. For instance, if a vehicle drives less than the AER on a given day and recharges during the day, this occurrence will not be captured. Accordingly, some additional recharging events during the day cannot be captured by our method and the obtained frequencies of additional recharging are conservative estimates.

3 Results

3.1 Descriptive Statistics of Charging Frequency

Table 1 summarizes vehicle usage and recharging statistics for all users and all subgroups (top 10 % and bottom 90% over-day rechargers, top 10 % and bottom 90 % no overnight chargers, intense vehicle users). With respect to the median and mean values for all users, we observe that additional over-day recharging happens on 3 – 8 % of the days and no recharging overnight happens less often 3 – 6 % of the days. There are on average 378 driving days recorded per user and the observed average UF for all users is 73.9 %.

Mean annual VKT for all users is 22,094 km; mean daily eVKT and mean daily VKT are 42.39 km and 60.49 km, respectively. We observe that top 10 % of most frequent over-day rechargers have a higher average daily eVKT, daily VKT, UF and annual VKT compared to the bottom 90 %. The top 10 % most frequent no overnight chargers have a lower average number of driving days, lower eVKT and higher VKT which results in a lower UF compared to the bottom 90 %. Intense vehicle users recharge over-day more than three times compared to the rest of the group, and also do not charge overnight twice as much; they have on average a lower UF, meaning their increased over-day recharging behavior falls short of matching the increased total VKT.

Table 1: Summary statistics of daily driving, UF, annual VKT and recharging behavior for different user groups

	Min	0.25-quantile	Median	Mean	0.75-quantile	Max
All Users (N=9,987)						
Number of driving days	29	133	281	378.76	518	2,342
Daily eVKT	0.0	30.8	40.7	42.4	52.1	149.1
Daily VKT	4.5	41.5	55.4	60.5	73.6	309.6
UF	0.0%	63.4%	77.4%	73.9%	87.7%	100.0%
Annual VKT	1,654	15,168	20,252	22,094	26,875	113,072
Frequency of over-day recharging	0.0%	0.6%	3.4%	8.2%	10.2%	86.1%
Frequency of no overnight charging	0.0%	1.4%	3.2%	6.3%	7.1%	100.0%
Top 10% of over-day rechargers (N=999)						
Number of driving days	29	106.5	254	391.23	568	2,126

Daily eVKT	20.0	59.4	67.9	70.0	78.3	149.1
Daily VKT	21.8	72.9	86.2	92.4	105.4	309.6
UF	23.4%	71.1%	81.7%	78.8%	89.3%	99.8%
Annual VKT	7,951	26,610	31,486	33,744	38,481	113,072
Frequency of over-day recharging	23.2%	28.2%	36.1%	39.0%	47.5%	86.1%
Frequency of no overnight charging	0.0%	0.7%	2.1%	3.2%	4.1%	33.8%
Bottom 90% of over-day rechargers (N=8,988)						
Number of driving days	29	136	282.5	377.37	515	2,342
Daily eVKT	0.0	29.5	38.9	39.3	48.5	106.2
Daily VKT	4.5	40.0	52.8	56.9	68.6	298.1
UF	0.0%	62.6%	76.7%	73.4%	87.4%	100.0%
Annual VKT	1,654	14,617	19,268	20,799	25,063	108,886
Frequency of over-day recharging	0.0%	0.5%	2.6%	4.8%	7.3%	23.2%
Frequency of no overnight charging	0.0%	1.4%	3.4%	6.7%	7.6%	100.0%
Top 10% of no overnight rechargers (N=999)						
Number of driving days	29	105.5	236	291.74	410	1,564
Daily eVKT	0.0	21.2	31.3	31.7	41.1	77.5
Daily VKT	4.5	51.1	71.3	77.8	99.4	298.1
UF	0.0%	34.3%	44.7%	44.3%	55.3%	93.3%
Annual VKT	1,654	18,677	26,044	28,413	36,299	108,886
Frequency of over-day recharging	0.0%	0.0%	0.6%	3.1%	3.6%	47.5%
Frequency of no overnight charging	14.9%	17.6%	22.5%	28.9%	34.0%	100.0%
Bottom 90% of no overnight rechargers (N=8,988)						
Number of driving days	29	136	286	388.43	536	2,342
Daily eVKT	5.6	32.0	41.7	43.6	53.1	149.1
Daily VKT	7.0	40.9	54.2	58.6	71.2	309.6
UF	24.1%	67.9%	79.5%	77.2%	88.7%	100.0%
Annual VKT	2,553	14,950	19,804	21,391	26,001	113,072
Frequency of over-day recharging	0.0%	0.8%	3.8%	8.8%	10.9%	86.1%
Frequency of no overnight charging	0.0%	1.2%	2.8%	3.8%	5.4%	14.9%
Users above 30,000 km annual VKT (N=2,640)						
Number of driving days	29	110	264	344.89	464	2,169
Daily eVKT	0.0	48.7	60.4	61.3	74.0	149.1
Daily VKT	82.1	89.3	99.2	106.8	115.6	309.6
UF	0.0%	45.6%	59.9%	59.3%	74.1%	98.6%
Annual VKT	30,004	32,602	36,218	39,015	42,228	113,072
Frequency of over-day recharging	0.0%	3.6%	12.6%	19.0%	30.0%	86.1%
Frequency of no overnight charging	0.0%	2.9%	6.5%	10.8%	13.5%	100.0%
Users below 30k annual VKT (N=7,347)						
Number of driving days	29	137	284	385.99	531	2,342
Daily eVKT	0.4	28.9	38.1	38.4	47.4	80.0
Daily VKT	4.5	38.8	50.6	50.6	63.1	82.1
UF	2.0%	68.0%	79.9%	77.1%	89.0%	100.0%
Annual VKT	1,654	14,159	18,468	18,481	23,059	29,978
Frequency of over-day recharging	0.0%	0.4%	2.6%	5.9%	7.5%	76.9%
Frequency of no overnight charging	0.0%	1.2%	2.8%	5.4%	5.9%	98.4%

Figure 1 and Figure 2 below show the normalized distributions of over-day recharging and no overnight charging among users, respectively. From Figure 1 we observe that the average share of days with additional recharging during daytime is low, mostly less than 10 % of the days with mean and median of 8 and 3 %, respectively. Yet, some users show additional recharging on at least every third day. The typical share of days without overnight charging (Figure 2) is 3 – 6 % of the days, with very few users above 25% of the days. Accordingly, the Chevrolet Volt are commonly recharged overnight, and users avoid high shares of nights without recharging.

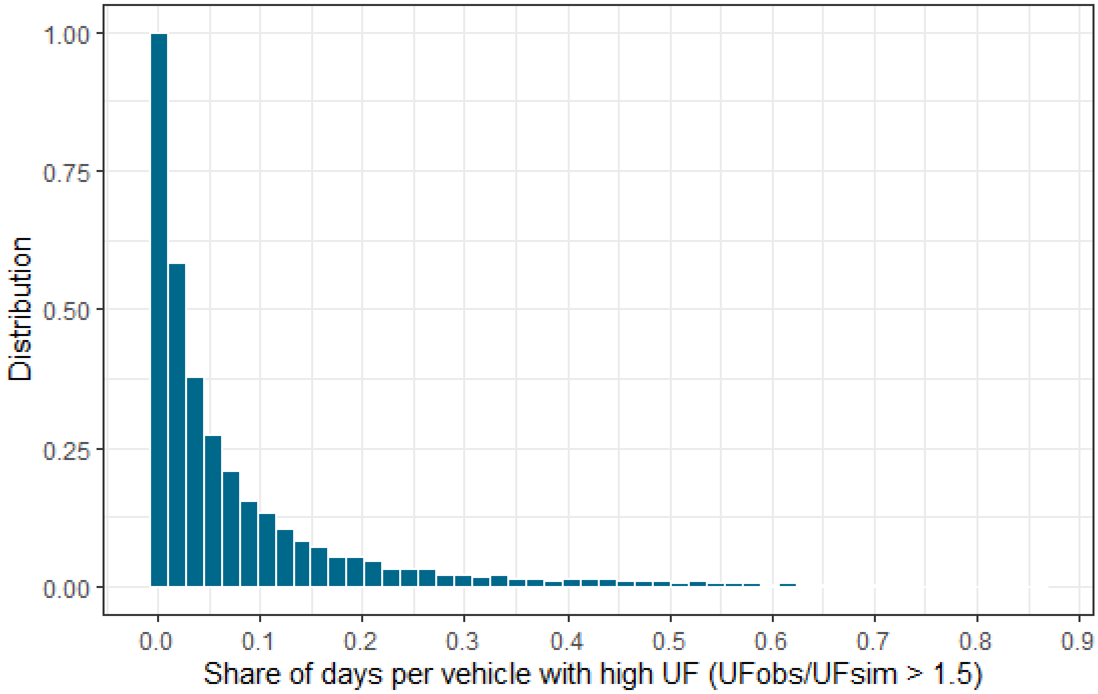

Figure 1: Distribution of over-day recharging frequency, normalized so maximum is 1.

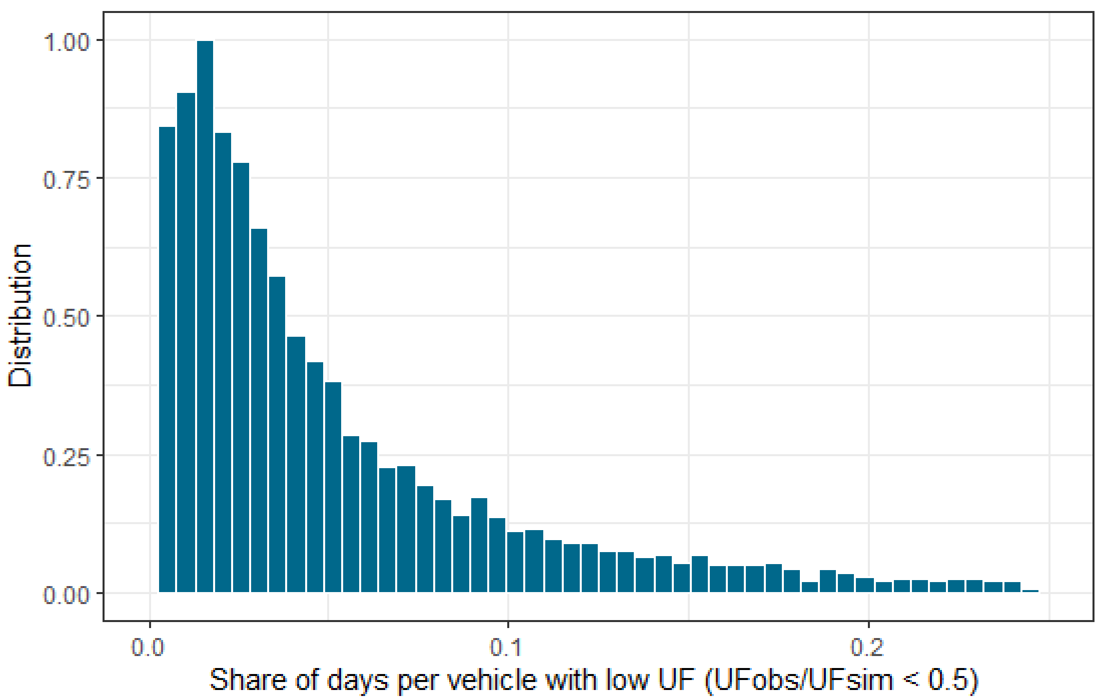

Figure 2: Distribution of frequency of no overnight charging, normalized so maximum is 1.

3.2 Characterization of Most Frequent Recharging Users

A comparison of summary statistics for the daily VKT for different user groups is given in Table 2. We calculate the median, mean, standard deviation (SD), standard error (SE = $SD/\sqrt{N}$), coefficient of variance (CV = SD / mean), and Gini coefficient for each user. Table 2 shows the mean of these values within the specific groups. We used the following statistical tests to check if the difference between two groups is statistically significant: two-sample t-test for the mean, Levene's test for the variance, and bootstrap hypothesis testing for the CV and the Gini coefficient. For all test statistics, and for both the comparison of over-day charging and no overnight charging, the differences are statistically significant at the 0.1 % level.

For over-day recharging, we observe that the top 10 % of most frequent rechargers have a higher mean daily VKT with a slightly larger standard deviation. CV and the Gini coefficient are both smaller for the top 10 % compared to the bottom 90 % indicating less dispersion within the group.

For no overnight charging, we observe that top 10 % of most frequent no overnight chargers have on average a higher daily VKT with a larger standard deviation. Coefficient of variation and the Gini coefficient are both higher for the top 10 % compared to the bottom 90 % indicating more dispersion withing the group.

In Table 3, a comparison of means of daily VKT, UF, frequency of over-day recharging, and no overnight charging in different groups is given. To check if the UFs of the two groups significantly differ, we used the rank-sum test to compare the median and t-test to compare the means. We observe that the UFs of the top 10 % most frequent over-day rechargers and top 10 % most frequent no overnight chargers differ significantly from their 90 % counter parts at the 0.1 % level.

Table 2: Comparison of mean daily VKT statistics for different user groups

	Daily VKT (km)						N (sample size)
	Median	Mean	SD	Std. error	CV	Gini	
Top 10% of Over-day Rechargers	86.20	92.39	30.18	0.95	0.33	0.17	999
Bottom 90% of Over-day Rechargers	52.75	56.94	25.63	0.27	0.45	0.24	8,988
Difference	*33.45****	*35.44****	*4.55*	*0.68*	*0.12****	*0.07****	
Top 10% of No Overnight Chargers	71.30	77.79	38.48	1.22	0.49	0.27	999
Bottom 90% of No Overnight Chargers	54.22	58.57	26.12	0.28	0.45	0.24	8,988
Difference	*17.08****	*19.22****	*12.36*	*0.94*	*0.05****	*0.03****	
Users above 30,000 km annual VKT	99.16	106.82	26.26	0.63	0.25	0.12	2,640
Users below 30,000 km annual VKT	50.56	50.60	16.18	0.18	0.32	0.18	7,347
Difference	*48.60****	*56.22****	*10.08*	*0.45*	*0.07****	*0.06****	

Sign. Codes: '***': $p < 0.001$; '**': $p < 0.01$; '*': $p < 0.05$

Table 3: Comparison of means of daily VKT, UF, frequency of additional over-day recharging, and no overnight charging in different user groups

	Mean Daily VKT	Mean UF	Median UF	Mean Frequency of over-day recharging	Mean Frequency of no overnight charging	N (users in the sample)
All Users	60.5	73.9%	77.4%	8.2%	6.3%	9987
Top 10 % over-day rechargers	92.4	78.8%	81.7%	39.0%	3.2%	999
Bottom 90 % over-day rechargers	56.9	73.4%	76.7%	4.8%	6.7%	8,988
Difference	*35.4*	*5.4%****	*5.0%****	*34.2%*	*3.4%*	-
Top 10 % no overnight chargers	77.8	44.3%	44.7%	3.1%	28.9%	999
Bottom 90 % no overnight chargers	58.6	77.2%	79.5%	8.8%	3.8%	8,988
Difference	*19.2*	*33.0%****	*34.8%****	*5.7%*	*25.1%*	-
Users above 30,000 km annual VKT	106.8	59.3%	59.9%	19.0%	10.8%	2,640
Users below 30,000 km annual VKT	50.6	77.1%	79.9%	5.9%	5.4%	7,347
Difference	*56.2*	*17.8%****	*20.0%****	*13.0%*	*5.4%*	-

Sign. Codes: '***': $p < 0.001$; '**': $p < 0.01$; '*': $p < 0.05$

The results of the statistical tests we performed regarding the difference in daily VKT and UF, between (1) the top 10 % of most frequent over-day rechargers and their respective bottom 90 % and (2) top 10 % of most frequent no overnight chargers and their respective bottom 90%, indicates an apparent, statistically significant difference in the recharging behavior of these user groups.

3.3 Recharging Behavior of Intense Vehicle Users

As seen in Table 2, intense vehicle users (users above 30,000 km annual VKT) have a higher average daily VKT with a larger standard deviation. The coefficient of variation and Gini coefficient are slightly lower for intense vehicle users indicating less dispersion within the group. Intense vehicle users total at 2,640 individuals in our sample, making up 26.4 % of all users in the dataset. The differences regarding daily VKT for the median, mean, coefficient of variation and Gini coefficient are all statistically significant at the 0.1 % level.

Intense vehicle users have an average UF of 59.3 %, much lower than the UF of 77.1 % for the rest of the group as seen in Table 3. The mean and median UF of the two groups are statistically significantly different from each other at the 0.1 % level.

The statistically significant difference in daily VKT and UF between intense vehicle users and the rest of the users indicates that intense vehicle users have a distinct recharging behavior.

3.4 Sensitivity Analysis

We tested different model parameters to check how our assumptions affect the results. In our base model, we use multiple model years for the vehicles and a threshold of 1.5 for UF_{obs}/UF_{sim} for over-day recharging and 0.5 for UF_{obs}/UF_{sim} for no overnight charging.

We tested a threshold for over-day recharging for UF_{obs}/UF_{sim} of 1.7, which is an even more conservative assumption, keeping all the other assumptions the same. If over-day recharging threshold is increased to 1.7, we observe a lower frequency of over-day charging. With this new assumption, top 10 % of the most frequent over-day charging users are slightly different. However, the mean daily VKT and mean UF show very little difference to the base model. All test parameters that were significant in our base model are still significant without any change of significance level. If the threshold for no overnight charging for UF_{obs}/UF_{sim} is lowered to 0.3 from 0.5, keeping all other assumptions the same, we also observed that the mean daily VKT and mean UF show very little difference and the all tests remain significant at the same significance level as in our base model. We also tested a single model year assumption where all vehicles have an AER of 61 km (38 US miles) instead of a multiple model year assumption. Under a single model year assumption, all statistical differences remains significant at the same significance level.

4 Discussion

Our results are based on analysis of a large data set, however there are some drawbacks. First, our data only covers one PHEV model. Chakraborty et al. [6] show that the AER influences charging behavior. The Chevrolet Volt may also attract a certain type of user and thus bias the results. All users can also be considered as early adopters, especially those from the first years of data collection. It is not sure that the early majority users will have the same behavior. Furthermore, access to charging infrastructure might change over time and influence charging behavior. In addition, the users are most likely almost all private vehicle owners and our results are not directly transferable to company cars or fleet vehicles.

Second, while the data are rich when it comes to number of users and observation time, they are sparse when it comes to additional information about the users and the actual charging behavior. Factors that might affect charging behavior are access to workplace charging, dwelling type, commute distance and number of vehicles in the household [7]. Lee et al. [7] also find that gender and age influence the preference for home vs non-home charging. Similarly, all drivers are from North America (Canada and the US) with a high availability of home charging in garages comparable to Europe [8]. Accordingly, the same vehicles might be charged and used differently in other parts of the world with less home charging, such as China or Japan.

Our calculation method has a certain bias for users with long driving distances, i.e., there is a risk we do not capture the additional recharging of those driving shorter daily distances. Still, our analysis of long-distance drivers shows that there is a heterogeneity in this group and thus our results are not only a function of long-distance driving. Lee et al. [7] find that PHEV owners with longer commute distance tend to seek out additional charging opportunities. From an environmental perspective it is beneficial if those that recharge more often are also the long-distance drivers because then more kilometers will be electrified.

5 Conclusions

In this paper, we used an empirical dataset of 9,987 Chevrolet Volt users and analyzed the frequency of over-day recharging and the frequency of no overnight charging. Our results indicate that the average share of days with additional recharging during daytime is low, less often 3 – 8 % of the days, and the typical share of days without overnight charging is 3 – 6 % of the days. We tested if (1) the top 10 % most frequent over-day rechargers, (2) the top 10 % most frequent no overnight chargers, and (3) intense vehicle users have statistically different recharging behavior compared to the rest of the group. There are statistically significant differences in daily VKT and UF between these groups. Our results add to the very limited literature on recharging behavior of distinct user groups.

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