Empirical charging behavior of plug-in hybrid electric vehicles

Citation for the original published paper (version of record):
Mandev, A., Plötz, P., Sprei, F. et al (2022). Empirical charging behavior of plug-in hybrid electric vehicles. Applied Energy, 321. http://dx.doi.org/10.1016/j.apenergy.2022.119293

Applied Energy 321 (2022) 119293

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Empirical charging behavior of plug-in hybrid electric vehicles

Ahmet Mandev [a,*], Patrick Plötz [b], Frances Sprei [c], Gil Tal [d]

[a] Chalmers University of Technology, Department of Space, Earth and Environment, 412 96 Göteborg, Sweden
[b] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139 Karlsruhe, Germany
[c] Chalmers University of Technology, Department of Space, Earth and Environment, 412 96 Göteborg, Sweden
[d] Institute of Transportation Studies, University of California, Davis, 1590 Tilia Street, CA 95616, USA

HIGHLIGHTS

- We analyze over 10,000 PHEV with a total of 4.3 million driving days.
- We propose a new method to detect the frequency of individual charging behavior.
- Users avoid high share of nights without charging.
- Not charging overnight has a large effect on the share of electric driving.
- Intense drivers have high electric km per year with low shares of electric driving.

ARTICLE INFO

Keywords:
PHEV (plug-in hybrid electric vehicle)
Charging
User behavior

ABSTRACT

Plug-in hybrid electric vehicles (PHEV) offer greenhouse gas emission reduction in car usage if charged frequently and driven mainly on electricity. However, little is known about the actual charging behavior of PHEV owners. Here, we investigate the daily charging of 10,488 Chevrolet Volt PHEV driven on a total of 4.3 million total driving days in the US and Canada. We propose a new method to detect the frequency of individual charging behavior from the daily utility factor and daily distance travelled. Our results show that no charging overnight occurs typically on 3–7% of the driving days per user and additional charging happens on 20–26% of the driving days. We also analyze the relation between charging frequency and utility factor for different user groups and days. Our results show that the utility factor should not be used as the only measure of environmental performance of PHEVs.

1. Introduction

1.1. Motivation and background

Plug-in hybrid electric vehicles (PHEVs) can play an important role in reducing greenhouse gas emissions in the transport sector if charged frequently enough to cover a major share of their driving on electricity from low-carbon sources [1]. Empirical studies on PHEV charging behavior thus can provide several policy insights related to the decarbonization of the energy systems related to the transport sector. First, charging behavior and patterns can help understand the impact of charging on the electricity system, e.g., increased peak loads due to charging [2,3,4,5]. In addition, charging patterns are also of interest from an energy systems perspective, for example in helping integrate intermittent renewable energy sources [6,7,8,9]. Second, it adds to the understanding of the environmental performance of PHEVs —reducing CO_2 emissions and environmental pollutants— by giving an insight into how much driving is done on gasoline and electricity respectively [10,11,12,13,14,15]. Third, charging behavior provides input on how charging infrastructure policies should be developed [16,17]. Fourth, it adds to the understanding of the relationship between public charging infrastructure and users' charging behavior [18,19,20]. Fifth, it clarifies the relation between battery size and charging behavior and the relation between vehicle choice and driving needs [21,22,23,24].

Despite its policy relevance, there is still a lack of empirical studies in the literature that analyze the charging behavior and driving for large samples of PHEV users (see Section 1.2 on previous literature for an overview of existing studies). The goal of this paper is to fill this gap by

* Corresponding author.
E-mail addresses: mandev@chalmers.se (A. Mandev), patrick.ploetz@isi.fraunhofer.de (P. Plötz), frances.sprei@chalmers.se (F. Sprei), gtal@ucdavis.edu (G. Tal).

https://doi.org/10.1016/j.apenergy.2022.119293
Received 16 November 2021; Received in revised form 8 April 2022; Accepted 13 May 2022
Available online 1 June 2022

being, to the authors' best knowledge, the first study to quantify charging behavior through frequencies of overnight charging and additional charging and analyze this behavior with respect to different user groups and charging days. Moreover, we are the first to develop a method to identify charging frequencies based on daily driving distances on gasoline and electricity, which are easier to collect, compared to specific charging events. The paper also differs from previous research by using data containing a large number of users (10,488 users) with a long observation period, up to 8 years for some users, therefore providing a higher confidence level for our results. Our method is also relevant and can be used in studies for a variety of energy applications, from battery development to charging infrastructure and electricity systems, to integrating electric vehicles with intermittent renewable energy sources, such as vehicle-to-grid systems.

More specifically this paper aims to answer the following research question: What are typical frequencies for additional charging and no-overnight charging with respect to different user groups and charging days? To answer this question, we use an online database (voltstats.net) that collects real-world fuel economy data of Chevrolet Volt, a popular North American PHEV. We develop a method to estimate charging behavior from observed daily electric and conventional km travelled. We thereafter analyze frequencies of additional charging and of no overnight charging for different days and user groups. We also study the utility factor (UF), i.e., the share of electric driving, and the distribution of driving distances to understand its relation to charging behavior.

The outline of the paper is as follows. An overview of previous literature related to PHEV and charging is presented in Section 1.2. 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 summary and policy implications in Section 5.

1.2. Previous literature

There are two main approaches to PHEV charging in the literature. The first approach uses a range of methods and data but no actual PHEV charging or driving data. Data and methods used in this approach include household travel surveys, simulation and optimization models, online questionnaires, stated preference surveys or data from conventional vehicles applied to PHEVs or plug-in electric vehicles (PEVs) in general. Some studies focus solely on the impact of charging behavior on charging infrastructure. Dong and Lin [25] use a household travel survey in Austin, Texas, with recorded global positioning system (GPS) data for a single day, collected from 229 conventional vehicles. They analyze the impact of charger network coverage on PHEV energy consumption based on travel patterns. Xi et al. [20] develop a simulation-optimization model to determine the locations of charging points for electric vehicles and apply their model on a dataset from central-Ohio region with generated trip data based on a typical workday. Bi et al. [26] use an agent-based traffic simulation to analyze the impact of charging behavior on the performance of charging infrastructure in Singapore with the assumption that charging stations are placed at existing petrol stations and residential car parks. Pagani et al. [27] use an agent-based simulation to analyze the impact of individual charging behavior on charging infrastructure in a mid-sized city in Switzerland. Chakraborty et al. [28] and Chakraborty et al. [29] analyze the demand drivers for charging infrastructure by modelling the charging behavior of 3000 PEV drivers using survey data. Goebel and Plötz [30] compare machine learning methods and regression analysis to sample PHEV simulations using a full recharge overnight as assumption. They find machine learning methods to perform only slightly better than a simulation and their method does not directly estimate the user specific share of nights without charging or share of days with additional charging.

Other studies within this group focus on charging patterns, environmental impacts, share of electric driving and battery requirements rather than infrastructure. Axsen et al. [31] use survey data from 877 respondents in California and address the relationship between charging behavior and total greenhouse gas emissions. Tal et al. [22] and Tal et al. [23] use data from an online survey that includes extensive data on driving and charging behavior from more than 3500 plug-in electric vehicle owners in California to analyze how charging behavior impacts electric vehicle miles travelled. They conclude that higher range PHEV and battery electric vehicle (BEV) users charge more often compared to lower range PHEV and BEV owners which further increases their share of electric driving. Björnsson and Karlsson [32] use GPS logged data for 30 days or longer from 432 conventional vehicles in Sweden to analyze how individual driving and charging behavior impact battery requirements for PHEVs. Philipsen et al. [33] conducted qualitative interviews and a large-scale questionnaire with 1021 respondents in Germany to identify conventional refueling behavior and charging behavior and then make a comparison between the two regarding conditions, frequencies and critical filling levels. They conclude that the perceived critical filling level is identical for fuel tanks and batteries, but in terms of behavioral patterns conventional vehicle users often run on empty and then refill tank completely while electric vehicle users charge in a timely manner. Tal et al. [34] provide a snapshot of charging behavior of PEV users in California based on self-reported data. Chakraborty et al. [35] analyze the 30-day charging behavior of 5418 PHEV users in California and investigate why some PHEV users do not charge their vehicles. They find that several factors play a role in the decision making of plugging in or not, such as high home electricity prices, low electric driving range and low potential cost savings from charging. Ashkrof et al. [36] use data from a stated preference survey with 505 BEV drivers in the Netherlands to explore charging preferences and drivers' route choices for BEVs. Zhou et al. [24] conduct an online stated preference survey with 132 respondents to study charging decision making of BEV users and then analyze the data using a latent class model. They apply their model to a case study in Beijing and conclude that to satisfy travel demand for 90% of drivers, a 354 km (220 US miles) battery range is needed for taxis, and a 482 km (300 US miles) battery range is needed for private vehicle owners.

The second approach in the literature uses empirical PHEV or PEV charging or driving data. Some of these studies use data collected from charging stations. Gnann et al. [16] analyze the charging behavior in Norway and Sweden by using empirical fast charging data from charging points. They conclude that if battery size and charging power keep increasing, the ratio of PEVs and fast chargers can be similar to conventional vehicles and refueling stations. Morrissey et al. [17] analyze the charging behavior in Ireland and Northern Ireland by using data from 711 charging points with mixed fast and standard chargers, of which 43 are household charging points. They find that majority of PEV users charge at home during peak demand times and incentivization may be necessary to encourage charging at other times. They also find that fast chargers have a much higher usage frequency compared to standard charging points.

Some of the studies within this second group use data collected directly from the vehicles. Ligterink et al. [12] analyze the charging behavior of more than 10% of the Dutch plug-in fleet using the charging data from plug-in vehicles collected through lease companies in the Netherlands. Davies and Kurani [13] use data from 25 converted Toyota Prius with recorded driving and charging data and explore the effects of assumptions regarding PHEV charging and driving behavior on the estimated emission impacts of PHEVs. Nicholas et al. [14] analyze the charging behavior of 72 PEV households in California with recorded driving and charging behavior from onboard loggers for a full year. Srinivasa Raghavan and Tal [37] and Raghavan and Tal [38] use multi-year longitudinal data from 153 PHEVs in California, ranging from 18 to 85 km (11 to 53 US miles) in all-electric-range and analyze their driving and charging patterns. They conclude that enhanced charging infrastructure can improve the observed UF of short-range PHEVs, and increasing the frequency of home charging can improve the observed UF of long-range PHEVs. Fieltsch et al. [39] use recorded charging, driving and energy data from 160 commercial BEVs in Hamburg, Germany to analyze the charging behavior of BEVs in commercial transport. Their analysis focuses on temporal charging behavior and the initial and final state of charge. They conclude that longer charging events tend to occur after operating hours and that the BEVs in their dataset are predominantly fully charged since most charging events start at a high initial state of charge. Most recently, Plötz et al. [40] compare the actual mean real world UF as a function of all-electric range of 1385 PHEV in Germany to the simulated mean UF of a large fleet of conventional vehicles. Using different scenarios for the share of days with charging, they conclude that the typical charging frequency of privately owned PHEV in Germany is about 75% of the days [40,41]. Tal et al. [42] examines vehicle usage in PEV households in California using a combination of vehicle logs supported with surveys and interviews with users.

Different types of data have advantages and disadvantages. A short observation period may be easier to obtain and thus facilitates a higher resolution or more information on individual users; however, the results can be difficult to generalize and apply to different circumstances due to limitations of spatial and geographical scopes. Longer observation periods are more cumbersome to collect and usually result in lower resolution due to higher data collection costs and can provide a better understanding of general trends. Similarly, non-empirical PHEV data collected through surveys, test cycles and simulation/optimization models can be less costly than installing monitors on actual PHEVs, therefore easier to obtain, however could be limited by assumptions and might not directly correspond to actual real-life usage. Empirical data on the other hand gives the advantage of shining a light on real-life usage, however installing monitors on vehicles comes at a cost, and thus there is usually a trade of between collecting short-period data with high resolution and small sample size, and collecting long-period data with low resolution and large sample size. The advantage of our dataset is the large sample size and long observation period; however, this comes at the cost of low resolution such as limited information on individual users, daily data instead of per second and individual charging events not being recorded.

In summary, existing studies on PHEV charging are often based on conventional vehicles only or have either a limited PHEV sample or a short observation period. Here, we fill this gap in the literature with an analysis of a large sample and long observation period for one PHEV model in North America.

2. Data and methods

2.1. Data

The data for our analysis is retrieved from voltsats.net, an online database with automatically collected (from an additional device) real-world fuel consumption data from 10,488 registered Chevrolet Volts in the United States and Canada. Every user profile on the website contains cumulative daily data on the electric and gasoline mileage including daily fuel consumption on gallons of gasoline per day. The data was processed, cleaned and cumulative mileage values were converted to daily driven km. Data cleaning comprised the exclusion of values with daily vehicle kilometers travelled (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 set of user specific performance data from April 2011 to January 2020, with 4.3 million driving days. After data cleaning, the average number of days observed per vehicle is 479 days with a median of 355, and maximum of 2751 days; and average number of driving days per vehicle is 410 with a median of 303 and maximum of 2500 days. Only users with at least 28 driving days were included in the analysis.

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 observed UF per user is obtained by dividing all electric km by total km driven during the observation period.

2.2. Methods

2.2.1. Identification of charging

Our data does not provide us directly with the charging behavior of the users and thus this has to be computed. Departing from the common assumption in drive cycles and simulations that the PHEVs are charged once during a 24 h cycle (referred to as overnight charging in the present paper), we develop a method to identify how real-life data deviates from this assumption through additional charging events and nights with no charging. We calibrate and demonstrate our method through a real-world dataset which included detailed charging and driving data for the same type of vehicle (Chevrolet Volt). We then analyze the frequency of additional charging and of no overnight charging using descriptive and inductive statistical methods. The frequency of additional charging is defined as the share of days with an additional charging 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. A charging event here refers to the driver plugging in the vehicle to the grid and charging the battery.

For the first step in our analysis, we compute a calculated UF and an observed UF for each day and user. See Eqs. (1) and (2) respectively where AER stands for all-electric range.

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

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

The calculation implicitly assumes a full charge once per day. This assumption is based on common practices in literature and analysis of empirical data on frequency of charging in literature [43,44]. To calculate the frequency of additional charging event and no overnight charging we look at the ratio of observed UF to calculated UF ($\mathrm{UF_{obs}}/\mathrm{UF_{cal}}$). Intuitively, if the observed UF is much higher than the calculated UF, the vehicle must have had at least one additional charge during the day. We identify two thresholds to compare the ratio of $\mathrm{UF_{obs}}/\mathrm{UF_{cal}}$, X and Y. We assume an additional charging event occurs if the observed UF for a vehicle for that given day is at least X times higher than the calculated UF. Similarly, we assume the vehicle is not charged overnight if the ratio between observed UF and calculated UF is smaller than Y

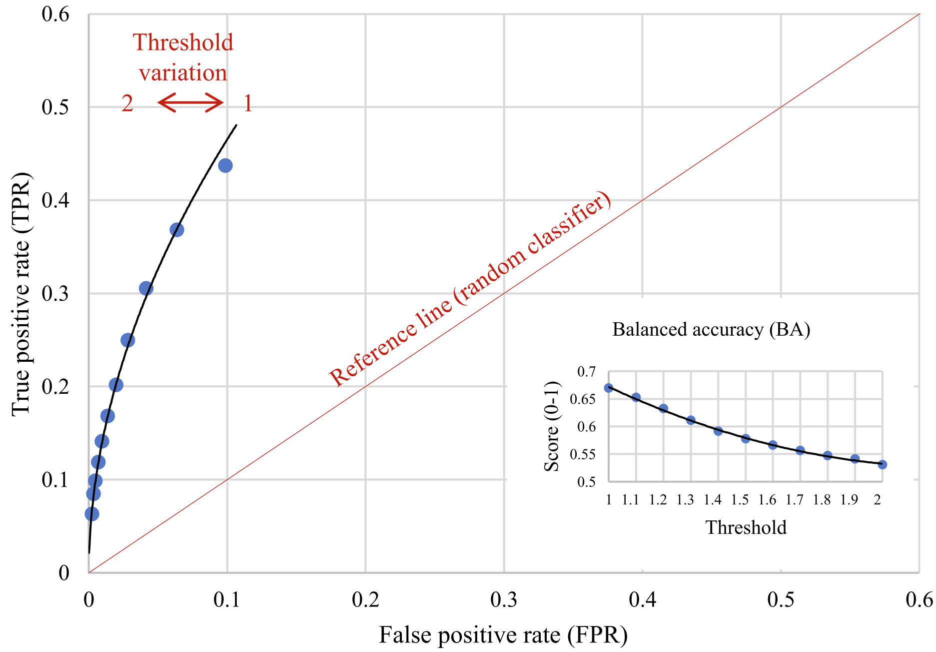

Fig. 1. ROC curve for the threshold of additional charging, varied from 1 to 2 with 0.1 increments. Evaluation metric of balanced accuracy is given inset.

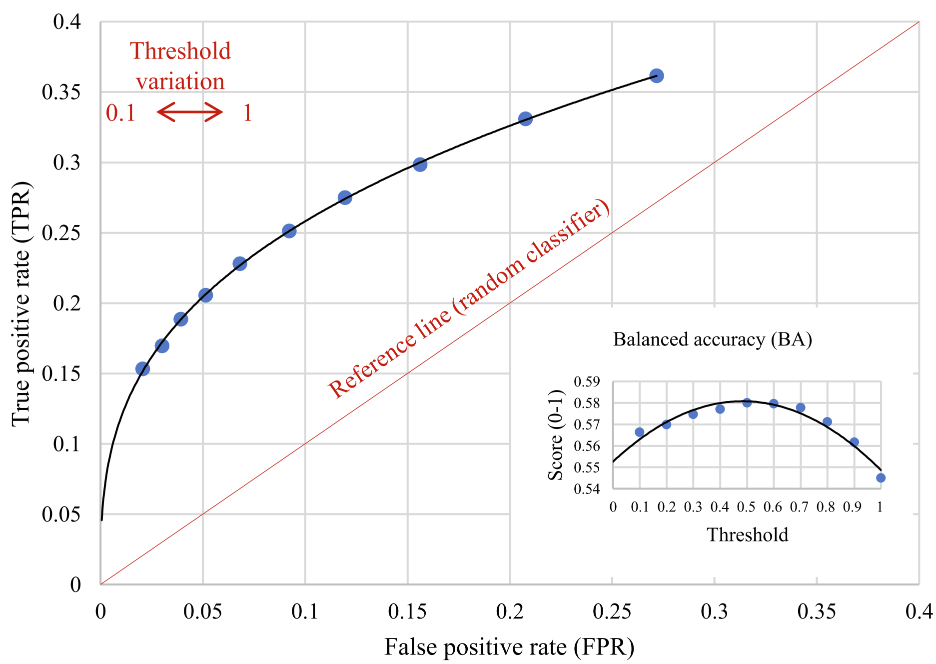

Fig. 2. ROC curve for the threshold of no overnight charging, varied from 0.1 to 1 with 0.1 increments. Evaluation metric of balanced accuracy is given inset.

times. These assumptions are summarized in Eqs. (3) and (4) below.

$$\text{additional charging} = \begin{cases} \text{true}, & \text{if } \dfrac{UF_{obs}}{UF_{cal}} > X \\ \text{false}, & \text{otherwise} \end{cases} \tag{3}$$

$$\text{No overnight charging} = \begin{cases} \text{true}, & \text{if } \dfrac{UF_{obs}}{UF_{cal}} < Y \\ \text{false}, & \text{otherwise} \end{cases} \tag{4}$$

In order to estimate the two thresholds (X and Y), we use a real-world charging data for the Chevrolet Volt. The data comes from the Advanced Plug in Electric Vehicle Travel and Charging Behavior Project, initiated by the Plug-in Hybrid & Electric Vehicle Center at University of California, Davis. In this study, we only use part of the dataset that includes detailed charging and driving data on Chevrolet Volt. We only use this data for calibration and demonstration of our method, the main results of the present work will use the much larger Chevrolet Volt data set without individual charging information.

Data was collected from summer 2015 to spring 2019 and includes 84 Chevrolet Volts. Monitors were placed on these 84 vehicles and their driving and charging data were recorded for the duration of a year. Model years of the vehicles vary from 2012 to 2017. See [45] for details on data collection and parameters. The driving and charging data were processed to clear discrepancies where the driving and charging data did not overlap timewise. (Start and end times for the collection of driving

Table 1
True positive rate (TPR), true negative rate (TNR) and accuracy of additional charging and no overnight charging occurrences when the threshold choices are 1 and 0.5 respectively.

	True positive rate (TPR)	True negative rate (TNR)	Accuracy
Additional charging	44%	90%	80%
No overnight charging	23%	93%	76%

Note: False positive rate (FPR) is 1-TNR and false negative rate (FNR) is 1-TPR. The share of real positives within total cases is 20% for additional charging and 24% for no overnight charging.

and charging data do not always match for a given vehicle.) There are in total 19,679 days that contain driving and charging data for the 84 vehicles, on average 234 days per vehicle.

For a given day, we utilize the driving data for these 84 Chevrolet Volts, and through varying X and Y in Eqs. (3) and (4), we estimate the occurrence of additional charging and no overnight charging. Then we compare these estimations with the real-world charging data of the same vehicles to see how well our model performs. In Figs. 1 and 2, we provide the receiver operating characteristic (ROC) curves for additional charging and no overnight charging, which illustrates the performance of our model when the threshold is varied. The ROC curve shows the true positive rate (TPR), known as the probability of detection or sensitivity, as a function of the false positive rate (FPR), i.e., the probability of false alarm. For graphical interpretation, the point on the ROC curve that is closest to the (0,1) point on the coordinate (100% TPR and 0% FPR), also known as the perfect classification point, gives the best performance for the varied threshold. Aside from graphical interpretation, we also provide the balanced accuracy scores to evaluate the performance of the threshold levels. Balanced accuracy, the arithmetic mean of TPR and true negative rate (TNR), is one of the most common metrics used to evaluate how good a varied threshold is on a ROC curve [46].

In Fig. 1, the ROC curve for additional charging is given. The threshold (X in Eq. (3)) is varied between 1 and 2, with 0.1 increments and fitted with a power trendline. In the top-left corner of Fig. 1, we provide the direction of the threshold variation. We observe that as the threshold gets closer to 1, the estimates get more accurate (closer to the perfect classification point). We limited the variation of threshold between 1 and 2, because thresholds above 2 provide visibly worse estimates (very low TPR and FPR) and thresholds below 1 provide extremely high FPR (the FPR instantly jumps from approx. 20% when the threshold is 1 to above 70% when the threshold is 0.99). The inset in Fig. 1 is the evaluation metric of balanced accuracy for additional charging, with a score of 0 to 1 for varied thresholds (higher is better), fitted with a polynomial trendline. Thus, both the ROC and balanced accuracy scores indicate a threshold of 1 as best estimate for our method of additional PHEV charging detection.

Fig. 2 plots the ROC curve for no overnight charging. The threshold (Y in Eq. (4)) is varied between 0.1 and 1, with 0.1 increments and fitted with a power trendline. The direction of the threshold variation is provided in the top-left corner of Fig. 2. We limited the threshold variation between 0.1 and 1, because any threshold above 1 provides extremely high FPR (the FPR instantly jumps from around 20% when the threshold is 1 to above 70% when the threshold is 1.01). We observe that the closest point to the perfect classification point is around $Y = 0.5$. The balanced accuracy scores of the thresholds are shown in the inset, fitted with a polynomial trendline. The balanced accuracy scores and the ROC curve indicate 0.5 as best estimate for the Y parameter of no charging during the day.

For the rest of our analysis, we use a threshold of 1 for additional charging and 0.5 for no overnight charging. Other evaluation metrics for the ROC curve are discussed in Section 3.4.

With a threshold choice of 1 for additional charging, TPR is 44%, TNR is 90% and overall accuracy is 80% (see Table 1). This shows that our method is better at identifying days where additional charging did not happen (TNR) compared to the days where additional charging did happen (TPR). Given any random driving day, our method can identify that day as a day with additional charging or not with 80% accuracy. On the other hand, with a threshold of 0.5 for no overnight charging, TPR is 23%, TNR is 93% and overall accuracy is 76%. Given any random driving day, our method can identify that day as a day with overnight charging or not with 76% accuracy.

Our method to detect additional charging and no overnight charging is rather conservative, e.g., if a vehicle drives less than the AER on a given day and still charges that day, this charging event will not be captured. Thus, some additional charging will be missed, however, this additional charging will not contribute to increased UF and thus the environmental performance of the PHEV. In addition, we perform a sensitivity analysis and vary the thresholds used in Eqs. (3) and (4) for the ratio of UF_{obs}/UF_{cal} and this is addressed in section 3.4.

The dataset does not contain the model year of the vehicle. To address this, we use the date of the first logged trip for the vehicles as the model year. Although each user id contains a year, this is not the model year of the vehicle but more likely the year of registration to the website. Based on our assumption, the following all-electric ranges (AER) are used: 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, to see the effect of our model year assumption on our results (see section 3.4).

2.2.2. Analysis of users

In our analysis regarding the frequency of additional charging and no overnight charging among users, we first aggregated each user over observed days. The following metrics were calculated based on the entire observation period for each user: daily eVKT, daily calculated eVKT, daily gVKT, daily VKT, total eVKT, total calculated eVKT, total gVKT, total VKT, annual VKT, frequency of additional charging and the frequency of no overnight charging. The daily calculated eVKT is computed by multiplying the daily calculated UF given in Eq. (1) with the daily VKT, meaning that if daily VKT is larger than AER, then daily calculated eVKT equals AER, otherwise daily calculated eVKT equals daily VKT. The frequency of additional charging is given by the number of days where additional charging occurs — as defined in Eq. (3) — divided by the total number of driving days per user during the entire observation period. Similarly, the frequency of no overnight charging is given by the number of days where no overnight charging occurs — as defined in Eq. (4) — divided by the total number of driving days per user during the entire observation period.

Thereafter the aggregated observed UF was calculated for each user, which is given by $total\ eVKT/total\ VKT$. Note that the aggregated observed UF here is different from the mean of daily observed UF given in Eq. (2) which is used in estimating the occurrence of additional charging events. UF values shown in Fig. 5 and Tables A1 and A2 reflect the aggregated observed UF. (Note that our usage of UF throughout the text always refers to the observed aggregated UF, if not specified as

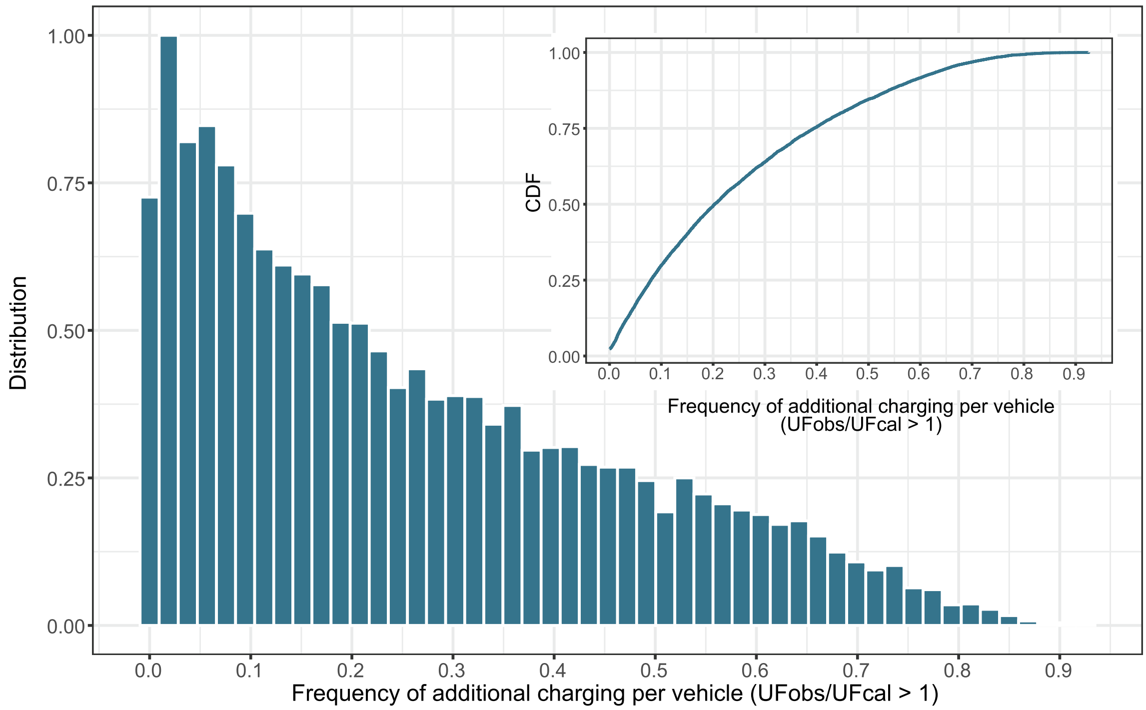

Fig. 3. Distribution of additional charging frequency, normalized so maximum is 1. CDF given inset.

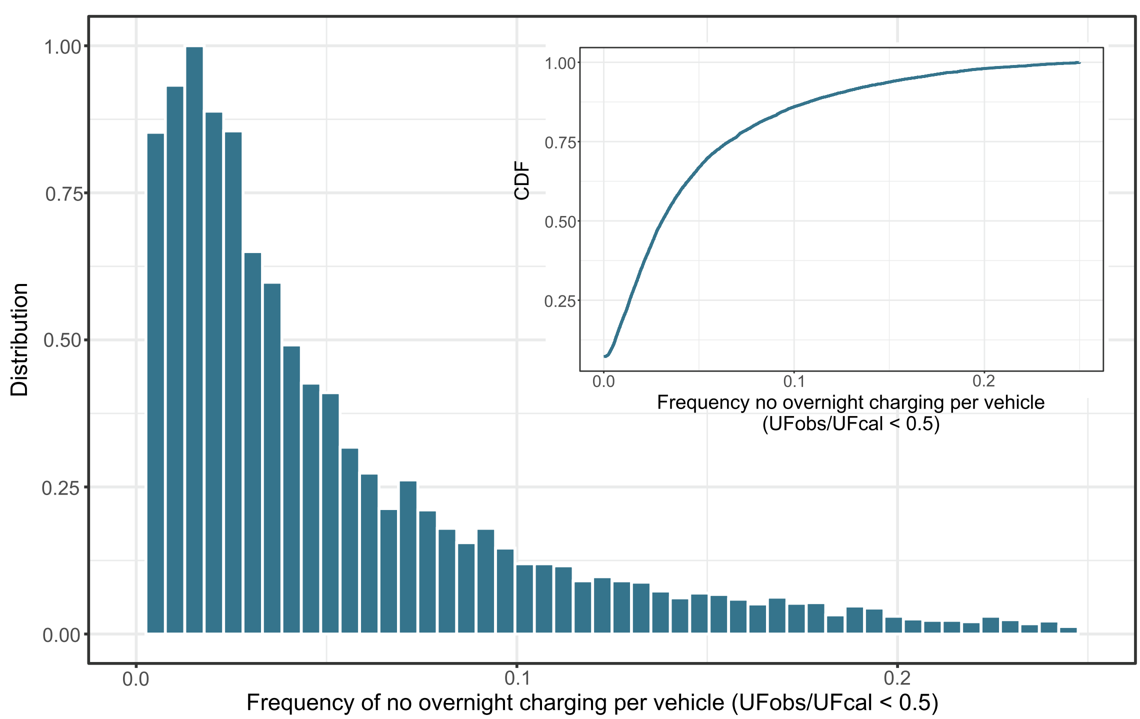

Fig. 4. Distribution of frequency of no overnight charging, normalized so maximum is 1. CDF given inset.

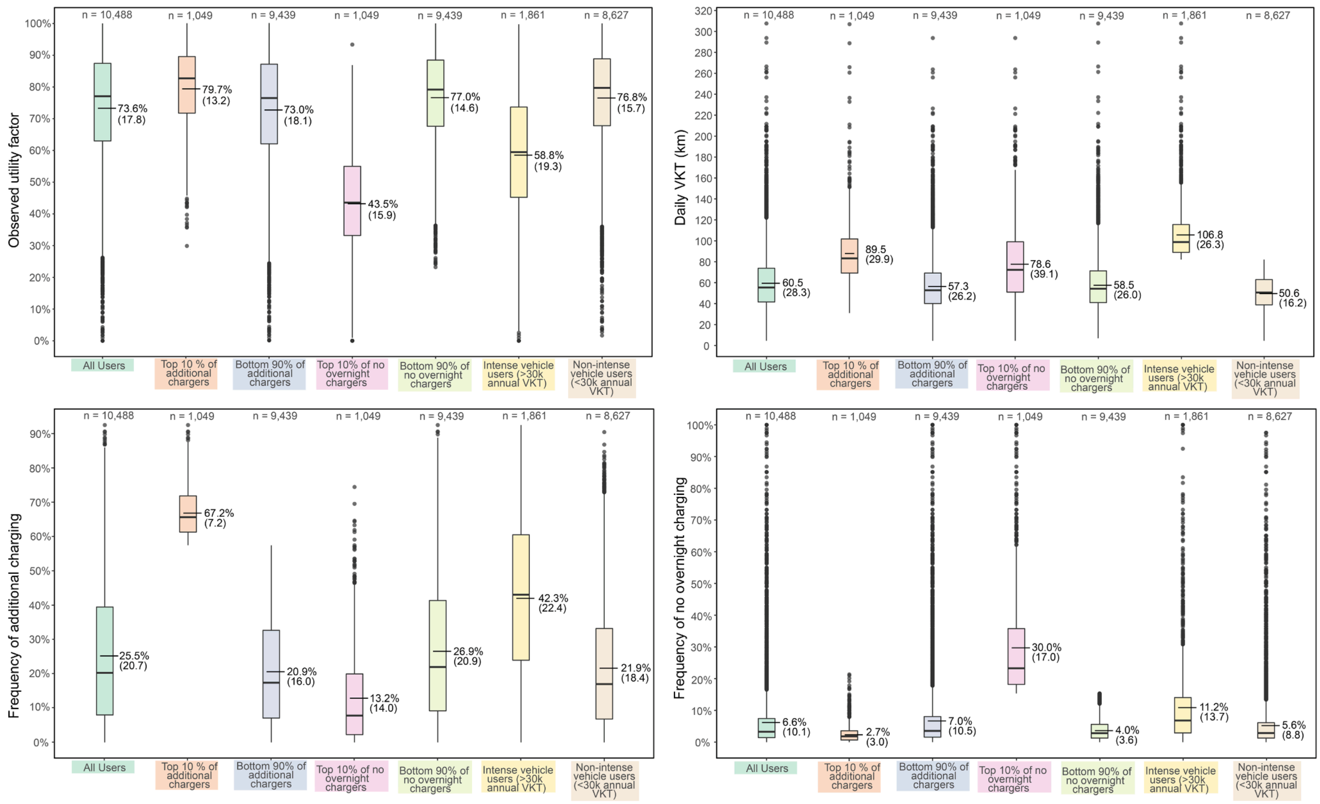

Fig. 5. Distribution of observed utility factor (UF), daily VKT, frequency of additional charging and frequency of no overnight charging in different user groups. Means are indicated and the standard deviation is given in parentheses.

Table 2
Means of frequency of additional charging, no overnight charging, and daily VKT of weekdays, weekends and observed holidays.

	Mean frequency of additional charging	Mean frequency of no overnight charging	Mean daily VKT
All driving days (N = 4,301,842)	**25.5%**	**6.6%**	**60.5**
Monday-Thursday	28.5%	5.6%	64.3
Friday-Sunday	20.9%	8.0%	56.8
Difference	*7.6%******	*2.5%******	*7.5*
Monday	27.5%	5.4%	62.2
Tuesday	29.0%	5.4%	63.8
Wednesday	28.9%	5.5%	64.6
Thursday	28.6%	6.0%	65.8
Friday	22.1%	8.4%	59.9
Saturday	17.6%	9.2%	50.1
Sunday	22.1%	6.8%	57.7
New Year's Eve	9.8%	10.9%	39.6
New Year's Day	15.1%	7.8%	48.8
Easter Sunday	21.9%	6.7%	60.7
Memorial Day	25.2%	5.6%	60.9
Independence Day	23.3%	6.9%	54.5
Labor Day	24.6%	5.5%	60.5
Thanksgiving	15.2%	11.2%	47.5
Christmas Eve	12.6%	12.6%	40.6
Christmas Day	12.7%	10.7%	45.8

Note: Observation period is from April 2011 to January 2020. Difference indicates the absolute difference between the means of two subgroups. Frequency of no overnight charging on a specific day reflects the night before, e.g. mean frequency of no overnight charging on Tuesday (5.4%) reflects the night connecting Monday to Tuesday.
Sign. Codes: '***': $p < 0.001$; '**': $p < 0.01$; '*': $p < 0.05$.

'daily' or 'calculated'.) Similarly, the aggregated calculated UF was computed for each user, which is given by $total\ \ calculated\ eVKT/total\ \ VKT$. Using the total eVKT and total VKT for the long-term UF calculation, we avoid the potential bias in UF calculation discussed by Lin and Greene [47].

To better understand the difference in driving and charging behavior among users, we look more specifically at certain user groups. The studied groups are top 10% and bottom 90% of additional chargers — top referring to more frequent and bottom to less frequent —, top 10% and bottom 90% of no overnight chargers, intense vehicle users (users with more than 30,000 km annual VKT) and non-intense vehicle users. Motivation for choosing these specific groups is provided in section 3.4 under the sensitivity analysis.

2.2.3. Analysis of days

In our analysis regarding the characterization of charging days, a given day of the week (Monday to Sunday) or an observed holiday (New Year's Eve, New Year's Day, Easter Sunday, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas eve and Christmas Day) was aggregated for each user and we calculated the frequency of additional charging and the frequency of no overnight charging for a given day. Below the generic equation of the mean frequency of either additional charging or no overnight charging for a specific day is given.

$$\overline{y_{ij}} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk} \tag{5}$$

$$y_{ijk} = \frac{Number\ \ of\ \ days\ \ j\ \ with\ \ i}{total\ \ number\ \ of\ \ driving\ \ days\ \ that\ \ fall\ \ on\ \ j}\ \ \text{for user } k \tag{6}$$

$y\ refers\ to\ the\ frequency\ of\ i\ on\ day\ j\ for\ user\ k$

$i = \{additional\ charging,\ no\ overnight\ charging\}$

Table 3
Comparison of mean daily VKT statistics for different user groups.

	Daily VKT (km)						N (users in the sample)
	Median	Mean	SD	Std. error	CV	Gini	
Top 10% of additional chargers	83.90	89.55	29.89	0.92	0.33	0.17	1049
Bottom 90% of additional chargers	52.81	57.32	26.18	0.27	0.46	0.24	9439
Difference	*31.10****	*32.23****	*3.71*	*0.65*	*0.12****	*0.07****	–
Top 10% of no overnight chargers	72.27	78.60	39.15	1.21	0.50	0.27	1049
Bottom 90% of no overnight chargers	54.20	58.53	26.04	0.27	0.44	0.24	9439
Difference	*18.07****	*20.07****	*13.11*	*0.94*	*0.05****	*0.03****	–
Users above 30k annual VKT	98.80	106.75	26.32	0.61	0.25	0.12	1861
Users below 30k annual VKT	50.55	50.57	16.20	0.17	0.32	0.18	8627
Difference	*48.25****	*56.18****	*10.12*	*0.44*	*0.07****	*0.06****	–

Note: Difference indicates the absolute difference between the means of two subgroups.
Sign. Codes: '***': $p < 0.001$; '**': $p < 0.01$; '*': $p < 0.05$.

Table 4
Share of days with long-distance driving within driving days and annual VKT among different user groups.

	Mean share of days where				N (users in the sample)
	Daily VKT > 100 km		Daily VKT > 200 km		
	Driving days	Annual VKT	Driving days	Annual VKT	
All users	19.7%	41.3%	4.3%	15.9%	10,488
Top 10% of additional chargers	41.8%	60.3%	6.7%	15.0%	1049
Bottom 90% of additional chargers	17.3%	39.2%	4.0%	16.0%	9439
Top 10% of no overnight chargers	31.4%	58.9%	9.5%	28.0%	1049
Bottom 90% of no overnight chargers	18.4%	39.3%	3.7%	14.6%	9439
Users above 30 k annual VKT	48.3%	73.5%	12.3%	29.8%	1861
Users below 30 k annual VKT	13.6%	34.4%	2.5%	12.9%	8627

$$j = \{monday,\ \ldots,\ sunday,\ new\ year's\ eve,\ \ldots,\ christmas\ day\}$$

$$k = \{1,\ \ldots,\ 10,488\}$$

$$n = 10,488$$

Similarly, the daily VKT for each user on our days of interest was calculated and the means were aggregated over users to calculate the overall mean daily VKT for that specific day of interest.

3. Results

3.1. Frequency of charging

In this section, we analyze frequency of additional charging and no overnight charging. Distributions of these charging frequencies are shown in Figs. 3 and 4 and detailed summary statistics of daily driving, UF, annual VKT and charging behavior for different user groups are given in Table A1 in the appendix. We also analyze charging behavior for different days of the week and observed holidays. We use a two-sample *t*-test to check for any statistically significant difference between average charging frequencies on Monday to Thursday and Friday to Sunday.

Fig. 3 and Fig. 4 show the normalized distributions of driving days with additional charging and no overnight charging frequency among all users, respectively. From Fig. 3, we observe that the average share of days with additional charging is typically 20–26% and most commonly less than 40% of the days with a mean of 25.5% and a median of 20.3%.

The typical share of days without overnight charging, shown in Fig. 4, is 3–7% and almost always below 25% of the days with a mean of 6.6% and a median of 3.3%. Accordingly, the observed Chevrolet Volts are commonly charged overnight, and users avoid high shares of nights without charging. This implies that the PHEV in our sample are, on average, almost daily charged. Detailed summary statistics are given in Table A1 in the appendix.

Looking at the different days of the week, we find a difference in both driving behavior and charging frequency between weekdays and weekends. Table 2 provides a comparison of weekdays, weekends and observed holidays in terms of frequency of additional charging, no overnight charging and daily VKT. Users charge additionally on average more frequently on Monday to Thursday with an average frequency of 28.5%, while the average for Friday to Sunday is 20.9%, meaning additional charging is more common on working days. They also have nights without charging less frequently on the nights before weekends, with an average frequency of 8.0% compared to 5.6% on Monday to Thursday, meaning that not charging overnight is more common on weekends. A two-sample *t*-test shows that there is a statistically significant difference between Monday to Thursday and Friday to Saturday in charging frequencies both additionally and overnight.

There is also a difference in daily driving distances. On average, the vehicles are driven less on weekends with Saturday having the lowest average VKT of 50.1 km.

Given the large number of users and long average observation time, our sample allowed us to investigate specific days such as holidays. Generally, we observe that the vehicles are charged less during these days and that the driving distances are shorter (it's possible that longer driving distances occur on the days around the holidays). New Year's Eve sees the lowest frequency of additional charging, with only 9.8% of users charging on New Year's Eve on average, this is followed by Christmas Eve, Christmas Day, New Year's Day, and Thanksgiving. These five days also have the lowest mean daily VKT among holidays, ranging from 39.6 km on New Year's Eve to 48.8 km on New Year's Day, and the highest mean frequency of no overnight charging, ranging from 7.8% the night before New Year's Day, to 12.6% the night before Christmas Eve. On the other hand, Easter Sunday, Memorial Day, Independence Day, and Labor Day are comparable to a weekend with mean frequency of additional charging between 21.9% and 25.2%, and no overnight charging between 5.5% and 6.9%.

Table 5
Comparison of mean and median of frequency of additional charging and no overnight charging among all users under different threshold conditions.

	Frequency of additional charging (all users)		Frequency of no overnight charging (all users)	
	Mean	Median	Mean	Median
Base model (additional charging occurrence threshold: 1.0, no overnight charging occurrence threshold: 0.5)	25.5%	20.3%	6.6%	3.3%
Additional charging occurrence threshold: 1.3	12.6%	6.8%	Same as base model	
Additional charging occurrence threshold: 1.5	7.9%	3.1%	Same as base model	
No overnight charging occurrence threshold: 0.3	Same as base model		4.4%	1.9%
No overnight charging occurrence threshold: 0.7	Same as base model		10.5%	6.1%

3.2. Charging frequency in different user groups

In this section, we analyze charging frequency, daily VKT and observed utility factor for different user groups (top 10% and bottom 90% of additional chargers, top 10% and bottom 90% of no overnight chargers, intense vehicle users and non-intense vehicle users). We provide a box plot distribution in Fig. 5 for a visual representation of the differences in user groups. A further comparison is given in Table A2 in the appendix. We use a rank-sum test to compare the medians and two sample *t*-test to compare the means to check if the UF, frequency of additional charging and no overnight charging in different groups statistically significantly differ from each other.

Fig. 5 summarizes the observed utility factor, daily VKT, frequency of additional charging and frequency of no overnight charging for all users and all subgroups (top 10% and bottom 90% of additional chargers, top 10% and bottom 90% of no overnight chargers, intense vehicle users and non-intense vehicle users). Top 10% of additional chargers have a mean frequency of additional charging of 67.2%, whereas the bottom 90% is at 20.9%. There are on average 410 driving days recorded per user and the observed average UF for all users is 73.6%. Detailed summary statistics for all user groups are given in Table A1 in the appendix.

We find that not charging overnight has a larger effect on the utility factor than more frequent additional charging. The change in UF from not charging overnight is typically larger than charging additionally. The top 10% of no overnight chargers have an average UF of 43.5% compared to the average UF of 73.6% for all users and the average UF of 77% for the bottom 90% of no overnight chargers. In comparison the top 10% of additional chargers have a UF of 79.7% compared to the average UF of 73.0% for the bottom 90% of additional chargers. The top 10% of no overnight chargers seem to charge less in general since their average frequency of additional charging is also lower (13.2%) compared to all users (25.5%).

The intense vehicle users (users above 30,000 km annual VKT) have an average frequency of additional charging of 42.3% compared to average of the whole sample of 25.5% and 21.9% for the non-intensive users. However, their average UF is lower (58.8% compared to 73.6% for all users) meaning their increased additional charging behavior falls short of matching their increased total VKT. It should also be noted that they also have a higher frequency of no overnight charging.

A further comparison of UF, frequency of additional charging, and no overnight charging is given in Table A2 in the appendix. To check if the UF, frequency of additional charging and no overnight charging of the two groups significantly differ, we used a rank-sum test to compare the medians and two sample *t*-test to compare the means. The difference in UF between the top 10% additional chargers and the bottom 90% is statistically significant both for the mean UF and median UF at the 0.1% level. The same holds for the difference in mean of no overnight charging for these groups.

When analyzing the differences between the top 10% of no overnight chargers and the bottom 90% for the various frequencies we also find that these are statistically significant at the 0.1% level.

The results of the statistical tests we performed regarding the difference in daily VKT and UF, between (1) the top 10% of most frequent additional chargers 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 charging behavior of these user groups.

3.3. Daily and annual VKT within different user groups

In this section, we analyze daily and annual VKT within different user groups. We provide mean daily VKT statistics for different user groups in Table 3. We check if the difference between two user groups is statistically significant by using a rank-sum test for the medians, a two-sample *t*-test for the means, Levene's test for the variances (not shown in the Table 3), and bootstrap hypothesis testing for the CV and the Gini coefficients. We also analyze the share of days with long-distance driving within driving days and annual VKT among different users, shown in Table 4.

The UF is determined by the charging frequency and driving distance. We therefore take a closer look at overall values of VKT and the distribution of daily VKT in the observed groups. Mean annual VKT for all users is 22,113 km; mean daily eVKT and mean daily VKT are 42.2 km and 60.5 km, respectively (see Table A1 in the appendix). We observe that top 10% of most frequent additional chargers have a higher average daily VKT, daily eVKT, 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 daily eVKT, but a higher daily VKT which results in a lower UF compared to the bottom 90%.

A comparison of summary statistics for the daily VKT for different user groups is given in Table 3. 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 group. Table 3 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: rank-sum test for the median, two-sample *t*-test for the mean, Levene's test for the variance (not shown in the table), and bootstrap hypothesis testing for the CV and the Gini coefficient. For all test statistics, and for both the comparison of additional charging and no overnight charging, the differences are statistically significant at the 0.1% level.

For additional charging, we observe that the top 10% of most frequent chargers 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 within the group. This shows that users who often don't charge overnight, do not do it because they drive less, instead they drive more on average, thus they have a potential to electrify more kilometers but choose not to do so.

As expected, intense vehicle users (users above 30,000 km annual VKT) have a higher average daily VKT of 106.8 km with a larger standard deviation, compared to the average daily VKT of 50.6 km of non-intense vehicle users (see Table 3). 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 1861 individuals in our sample, making up 17.7% 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. The statistically significant difference in daily VKT between intense vehicle users and the rest of the users indicates that there is an existing distinct difference in driving behavior between the two groups. Intense vehicle users on average have a daily eVKT of 60.7 km compared to the 38.2 km of non-intense vehicle users, as can be seen in Table A1 in the appendix. Thus, even if their UF is lower than the average they electrify more kilometers than the average user and are an important group to target when it comes to charging availability and behavior.

Within the total 4.3 million driving days in our dataset, the share of days where the daily VKT is larger than the AER is 36%. This shows that more than one third of the time users drive beyond the AER, which makes the impact of long-distance driving worth looking into. Table 4 shows the share of days with long-distance driving, i.e., days with daily VKT over 100 km or 200 km, within driving days and annual VKT among different user groups. We observe that daily VKT larger than 100 km happens on 19.7% of the driving days for all users, but accounts for 41.3% of the annual VKT. This indicates that long distance driving, although occurring only once in five days on average, accounts for close to half of the annual VKT. A threshold of 200 km for long distance driving highlights this impact even more and we observe that days with daily VKT larger than 200 km make up 4.3% of the driving days but 15.9% of the annual VKT on average. The vehicles in our sample appear to drive a lot, but please note the average annual driving distance in our sample is comparable to the US national average (22,113 km annual driving distance for our sample compared to 21,700 km US average) [48].

For intense vehicle users and top 10% of the most frequent additional chargers, daily long-distance driving of 100 km occurs almost every second driving day and accounts for nearly three quarters (60% to 75%) of the annual VKT. Long distance driving can be a limiting factor for the effect of additional charging on achievable electric driving share; we observe this especially for intense vehicle users who have a higher frequency of additional charging on average but lower UF. This is supported with the findings of Plötz et al. [11] where they conclude that tendency for long distance trips results in a lower PHEV fuel economy and thus a lower electric driving share.

3.4. Sensitivity analysis

In this section, we test how different model parameter assumptions change our results. We test different threshold choices for additional charging and no overnight charging. Our base model uses thresholds based on the metric of balanced accuracy scores; however, we also compute other metrics that are common evaluation metrics for ROC curves: basic accuracy, F1-score, Matthews correlation coefficient (MCC) and Fowlkes-Mallows index (FM). We explain how our choice of thresholds in our base model are robust and were suggested by the majority of these evaluation metrics. We also show that even with slightly different threshold choices, all of the statistical tests performed remain significant at the same significance level, thus the overall interpretation of our results does not change. We test a single model year assumption for all vehicles instead of a multiple model year assumption in our base model. For different groups of users, we use the distinction between top 10% and bottom 90% (regards to frequency of charging) which is arbitrary. In this section, we also perform a k-means clustering analysis to check for the presence of highly varying charging behavior in users, which supports our choice of distinguishing very frequent chargers from the rest.

We tested different model parameters to check how our assumptions affect the results. The results are shown in Table A2 in the appendix. In our base model, we use multiple model years for the vehicles and a threshold of $UF_{obs}/UF_{cal} > 1$ for the occurrence of additional charging and $UF_{obs}/UF_{cal} < 0.5$ for the occurrence of no overnight charging. For the occurrence of additional charging, we tested a continuous threshold between 1 and 1.5 with increments of 0.01 to observe the rate of decrease in mean frequency of additional charging. We observe that the decrease in the mean frequency of additional charging gets increasingly smaller, from 0.6% at 1 to 0.3% at 1.3 and 0.2% at 1.5 at every 0.01 increment in the threshold. As expected for the higher thresholds 1.3 and 1.5, the average share of additional charging is lower than our base model and in the range of 7–13% for 1.3 and 3–8% for 1.5 with respect to the mean and median values.

For the occurrence of no overnight charging, we also tested a continuous threshold between 0.3 and 0.7 with increments of 0.01 to observe the rate of increase in mean frequency of no overnight charging. We find that the increase in mean frequency of no overnight charging gets increasingly larger, from 0.1% at 0.3 to 0.25% at 0.7 at every 0.01 increment in the threshold. In this case the higher threshold (0.7) resulted in an average share of days without overnight charging in the range of 6–11% and the lower threshold of 0.3 decreases the average share of days without overnight charging to the range of 2–4%. The changes in frequency of additional charging and no overnight charging based on different thresholds are summarized in Table 5. More detailed results are shown in Table A2 in the appendix. We observe that the estimated range for the charging frequencies are more robust for days with no overnight charging against parameter variations than for the days with additional charging.

We also observe that the mean daily VKT and mean UF show very little difference among different user groups and all the tests remain significant at the same significance level as in our base model when changing the threshold levels.

True positive rates (TPR) that we show in Figs. 1 and 2 and explain in Section 2.2.1. is not a measure of accuracy on its own and does not tell if the model is good at predicting occurrences. A good model balances TPR and TNR by taking into account the real class ratio (actual positives to actual negatives) and the four confusion matrix categories (true positives, true negatives, false positives and false negatives) [49,50]. For overall model predictability, we need to take into account the class ratio and pick a threshold that performs well overall. We use balanced accuracy scores for a precise interpretation of the best threshold in ROC curves. In addition, we also computed the following evaluation metrics: basic accuracy, F1-score, Matthews correlation coefficient (MCC) and Fowlkes-Mallows index (FM). For additional charging, all evaluation metrics with the exception of basic accuracy indicate that a threshold of 1 will give the best performance, same as the balanced accuracy metric, whereas basic accuracy suggests a threshold of 1.2 for best performance. For no overnight charging, FM index indicates a threshold of 0.5 for the best performance, same as the balanced accuracy metric; whereas F1-score indicates a slightly higher threshold and, MCC and basic accuracy indicates a slightly lower threshold than 0.5 for best performance, yet a threshold of 0.5 comes in a close second in F1-score, MCC and basic accuracy. These metrics slightly differ in how they evaluate a threshold level; for a detailed read on ROC curves and how these evaluation metrics differ, see [51,52]. We conclude that the choice of 1 for the threshold of additional charging (X in Eq. (3)) is robust since it is indicated as the threshold to give the best performance from a majority of the evaluation metrics; and the choice of 0.5 for the choice of no overnight charging (Y in Eq. (4)) is also robust since it is either indicated as the threshold to give the best performance or comes in a close second in all of the evaluation metrics.

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, average share of additional charging is in the range of 27–31%, which is higher compared to our base model (20–26%); and average share of days without overnight charging is in the range of 3–6%, which is similar to our base model (3–7%). All statistical differences between different user groups remain significant at the same significance level.

Testing different model parameters shifts the frequencies for additional and no overnight charging to the upper and lower ranges of our base model, which does not affect our results qualitatively. In all cases, share of days with additional charging is close to or less than 10% and users avoid high share of nights without charging. Our calculation of UF_{cal} uses the all-electric range of the vehicle based on U.S. Environmental Protection Agency (EPA) labels which is based on a certain efficiency; however, it should be noted that real world range is also affected by driving style and weather conditions, for which we don't have data on to incorporate into our calculations. Yet, our thresholds estimates are estimated and tested based on real world driving conditions. In addition, difference in charging behavior between our studied groups are statistically significant in all cases.

In our analysis of charging by different groups of users, we use the distinction between top 10% and bottom 90% which is arbitrary. However, we also performed a k-means clustering analysis to check for the presence of highly varying charging behavior in users. We used the following two variables as the basis for our clustering: (1) mean frequency of additional charging and mean frequency of no overnight charging. To determine the optimal number of clusters, we used the traditional elbow method, the silhouette method and the gap statistic [53,54]; of which the first two suggested four and the latter seven clusters. Testing with different number of clusters produces similar cases where there is an extreme cluster with high additional charging compared to the rest of the group and an extreme cluster with high no overnight charging compared to the rest of the group. Thus, the cluster analysis supports our approach to distinguish a group of very frequent additional chargers and a group of very frequent no overnight chargers. Accordingly, our distinction between top 10% and bottom 90% for both additional charging and no overnight charging are confirmed by the cluster analysis.

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 and specific group of users that may create some biases and thus the results may not be generalizable to other PHEVs with different electric range or other characteristics. Chakraborty et al. [28] e.g., show that the all-electric range influences charging behavior. Because voltstats.net users enter fuel consumption data on a voluntary basis, there is a risk of self-selection bias in the data for consumers who are particularly concerned about fuel economy. It can be assumed, that mainly those PHEV users who are sensitive to their fuel economy register on these platforms. Furthermore, all users can 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. However, the average annual VKT of our sample is close to the US average, indicating not too strong deviation from other vehicle with respect to total distance travelled. Furthermore, access to charging infrastructure might change over time and influence charging behavior. PHEV charging behavior in the literature, as given in section 1.2., spans from early 2010s to 2021. However, charging infrastructure and charging station density has changed significantly within this time frame, and the availability of choices can have an impact on PHEV charging behavior. This makes it difficult to use early studies for comparison. 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.

Our own study also spans a long time period, from 2011 to 2020, which implies that our results give an overall picture of PHEV charging behavior in this period. However, we do not delve into how developments in charging infrastructure change this behavior over time, since this requires higher resolution data (e.g. GPS data) with more information on individual users, which were not available to us, thus falling outside of the scope of our paper. A shorter observation period with a large sample, high resolution data and detailed information on individual users could be more useful to analyze how developments in charging infrastructure impacted the most recent PHEV charging behavior. However, this type of empirical, real-life data is difficult to obtain and has high collection costs, and therefore not widely available and more importantly could not be generalized to larger populations due to geographical limitations and different states of charging infrastructure.

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 [55]. Lee et al. [55] 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 [56]. 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. As Plötz et al. [41] show utility factors of PHEV differ between countries and if they are private or company vehicles. In their sample the US & Canada has the highest compliance compared to the driving cycle. This thus limits the transferability of our results regarding the frequency of charging to other regions and countries.

Furthermore, we assume that the year of the first entry in the database corresponds to the model year, which would be incorrect for resold vehicles. However, our general results are stable against dropping this assumption and assuming the all-electric range for all vehicles.

Our method implicitly assumes a full charge once a day. Yet, in practice some users might not fully charge the battery to 100% or have a partial charge one day and second full charge, e.g., for free at work, the following day. Our method is not able to detect such cases. However, as PHEV batteries and charged within a few hours and vehicles are typically standing many hours at the most common locations such as home or work, the share of these cases is likely limited. Furthermore, our conclusions are on a more aggregated level about the overall share of no charging and charging twice per day that this uncertainty in the method will not qualitatively affect our conclusions. Our method might also wrongly assign certain charging events, for instance if the daily VKT is very small and the vehicle on that day is used on electric mode only; however, these cases account for less than 1% of the dataset and do not impact our overall results. Thus, despite its limitations, our method is far easier to use for large samples than comprehensive technical in-vehicle measurement or surveys.

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 charging of those driving shorter daily distances. This means our results are rather conservative, i.e., actual additional charging or no overnight charging should occur slightly more frequently than indicated by our results. Yet, 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. [55] find that PHEV owners with longer commute distances tend to seek out additional charging opportunities. From an environmental perspective, it is beneficial if those that charge more often are also the long-distance drivers because then more kilometers will be electrified.

Future studies could collect larger samples of PHEV users to study empirical charging behavior in different PHEV populations and user groups. Furthermore, more emphasis could be given on reasons for not charging to improve policies that aim to increase the electric driving share of PHEV and thus their environmental benefit.

5. Summary and policy implications

In this paper, we used empirical data of 10,488 Chevrolet Volt PHEV and analyzed the frequency of additional charging and of no overnight charging in general, for specific days, and for specific user groups. Our results indicate that the average share of driving days with additional charging is typically in the range of 20–26% of the driving days, and the typical share of days without overnight charging is 3–7% of the driving days, indicating users avoid high shares of night without charging. This implies that the PHEV in our sample are, on average, charged roughly once per 24 h. Additional charging is more common on working days and no overnight charging is more common on weekends and holidays.

The most frequent chargers drive more km per day but still have a higher electric driving share than the average user. Yet, not charging at all per 24 h has a larger effect on the utility factor for longed-ranged PHEV as in our sample than more frequent additional charging, i.e., the change in UF from not charging overnight is typically larger than charging additionally. Looking at daily driving distances alone, intense vehicle users with high annual VKT show a higher additional charging frequency but not enough to compensate for their longer driving distances. However, in absolute terms the intense vehicle users drive more km on electricity per year (e.g., 60% *30,000 km = 18,000 km compared to 80% * 15,000 km = 12,000 km). This implies that even for intense vehicle users driving a PHEV might be more advantageous from a fuel consumption perspective compared to a modern diesel, especially if it is charged daily.

Our findings have a number of policy implications. First, PHEVs are charged during most nights, but no overnight charging is a common yet infrequent behavior. This implies that any future policy making should take into account the increased load on the electricity system during nighttime and thus the possibility to even the load curve. This can be a preparation for increased load from pure EVs that are also expected to be charged on a regular basis during the night [57]. Given the larger battery capacity of pure EVs it is possible that they will have a higher impact on the design of the electricity system [58] especially since PHEVs most probably only will be an interim solution.

The possibility to charge overnight has a bigger effect than additional charging during the day, thus, to support the advantages of PHEVs, policies should prioritize easy access to home charging, e.g., through support for installation of charging in multi-dwelling buildings, above public and workplace charging infrastructure. Second, the UF should not be used as the only measure of environmental performance of PHEVs since users with below average UF can drive above average km on electricity per year. Third, the effect of additional charging is limited with respect to achievable electric driving share as even intense chargers with long-ranged PHEV such as analyzed here can hardly achieve more than 90% of electric driving. The main reason is that long-distance driving has a noteworthy impact. Fourth, to incentivize a high share of electric driving in the long-term, purchase or tax incentives for private as well as company car users could also be coupled to reaching a sufficiently high electric driving share. For example, the tax benefit of PHEVs could depend on reaching a significant share of the test-cycle UF even in real life driving. Charging frequency can further be increased through pushing for performance-based policies that credit the OEM based on road performance of their vehicles and thus pushing for more involvement from OEMs in charging behavior, which could result in OEMs taking active roles in making it easier to charge and install or subsidize chargers.

CRediT authorship contribution statement

Ahmet Mandev: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Patrick Plötz:** Conceptualization, Methodology, Data curation, Writing – review & editing. **Frances Sprei:** Conceptualization, Methodology, Writing – review & editing. **Gil Tal:** Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

AM and FS acknowledge the funding of Swedish Electromobility Centre for this publication. PP acknowledges that this publication was written in the framework of the Profilregion Mobilitätssysteme Karlsruhe, which is funded by the Ministry of Economic Affairs, Labour and Housing in Baden-Württemberg and as a national High Performance Center by the Fraunhofer-Gesellschaft.

Appendix

See the Table A1 and A2.

Table A1
Summary statistics of daily driving, UF, annual VKT and charging behavior for different user groups.

	Min	0.25-quantile	Median	Mean	0.75-quantile	Max
All users (N = 10,488)						
Number of driving days	29	138.75	303	410.17	581	2500
Daily eVKT	0.0	30.6	40.6	42.2	51.9	149.1
Daily VKT	4.5	41.6	55.4	60.5	73.8	307.6
UF	0.0%	63.0%	77.1%	73.6%	87.4%	100.0%
Annual VKT	1654	15,189	20,246	22,113	26,944	112,342
Frequency of additional charging	0.0%	8.0%	20.3%	25.5%	39.5%	92.5%
Frequency of no overnight charging	0.0%	1.4%	3.3%	6.6%	7.5%	100.0%
Top 10% of additional chargers (N = 1049)						
Number of driving days	29	117	263	403.97	582	2280
Daily eVKT	28.6	57.6	65.9	68.8	77.6	149.1
Daily VKT	31.7	69.8	83.9	89.5	102.5	307.6
UF	29.8%	71.7%	82.6%	79.7%	89.5%	100.0%
Annual VKT	11,563	25,502	30,646	32,708	37,425	112,342
Frequency of additional charging	57.5%	61.3%	65.7%	67.2%	71.9%	92.5%
Frequency of no overnight charging	0.0%	0.7%	1.8%	2.7%	3.6%	21.3%
Bottom 90% of additional chargers (N = 9439)						
Number of driving days	29	141	307	410.86	580.50	2500
Daily eVKT	0.0	29.3	38.8	39.3	48.3	103.8

(*continued on next page*)

Table A1 (*continued*)

	Min	0.25-quantile	Median	Mean	0.75-quantile	Max
Daily VKT	4.5	40.1	52.8	57.3	69.2	293.7
UF	0.0%	61.9%	76.4%	73.0%	87.0%	100.0%
Annual VKT	1654	14,645	19,287	20,935	25,271	107,274
Frequency of additional charging	0.0%	7.1%	17.4%	20.9%	32.7%	57.5%
Frequency of no overnight charging	0.0%	1.6%	3.5%	7.0%	8.1%	100.0%
Top 10% of no overnight chargers (N = 1049)						
Number of driving days	29	114	250	323.57	469	1649
Daily eVKT	0.0	21.0	30.9	31.5	41.1	91.5
Daily VKT	4.5	51.0	72.3	78.6	99.1	293.7
UF	0.0%	33.2%	43.6%	43.5%	55.0%	93.3%
Annual VKT	1654	18,617	26,397	28,710	36,206	107,274
Frequency of additional charging	0.0%	2.2%	7.8%	13.2%	19.9%	74.5%
Frequency of no overnight charging	15.3%	18.2%	23.3%	30.0%	35.8%	100.0%
Bottom 90% of no overnight chargers (N = 9439)						
Number of driving days	29	141	311	419.79	596	2500
Daily eVKT	5.6	31.9	41.6	43.4	53.0	149.1
Daily VKT	7.0	41.0	54.2	58.5	71.3	307.6
UF	23.2%	67.6%	79.2%	77.0%	88.5%	100.0%
Annual VKT	2553	14,969	19,796	21,380	26,025	112,342
Frequency of additional charging	0.0%	9.2%	22.0%	26.9%	41.4%	92.5%
Frequency of no overnight charging	0.0%	1.3%	2.8%	4.0%	5.6%	15.3%
Users above 30 k annual VKT (N = 1861)						
Number of driving days	29	115	279	378.08	544	2405
Daily eVKT	0.0	48.1	60.1	60.7	73.3	149.1
Daily VKT	82.1	89.0	98.8	106.8	115.6	307.6
UF	0.0%	45.2%	59.4%	58.8%	73.7%	99.8%
Annual VKT	30,004	32,510	36,085	38,992	42,219	112,342
Frequency of additional charging	0.0%	23.9%	43.0%	42.3%	60.5%	92.5%
Frequency of no overnight charging	0.0%	2.9%	6.8%	11.2%	14.1%	100.0%
Users below 30 k annual VKT (N = 8627)						
Number of driving days	29	143	309	417.09	590	2500
Daily eVKT	0.4	28.7	37.9	38.2	47.3	79.3
Daily VKT	4.5	38.8	50.5	50.6	62.9	82.1
UF	1.7%	67.8%	79.7%	76.8%	88.9%	100.0%
Annual VKT	1654	14,175	18,462	18,471	22,990	29,985
Frequency of additional charging	0.0%	6.8%	17.0%	21.9%	33.2%	90.5%
Frequency of no overnight charging	0.0%	1.3%	2.9%	5.6%	6.1%	97.5%

Note: UF refers to the observed aggregated UF.

Table A2
Comparison of means of daily VKT, UF, frequency of additional charging, and no overnight charging in different user groups under different assumptions.

		Mean Daily VKT	Utility Factor (UF)		Frequency of additional charging		Frequency of no overnight charging		N (users in the sample)
			Mean	Median	Mean	Median	Mean	Median	
Base model	All users	60.5	73.6%	77.1%	25.5%	20.3%	6.6%	3.3%	10,488
	Top 10% of additional chargers	89.5	79.7%	82.6%	67.2%	65.7%	2.7%	1.8%	1049
	Bottom 90% of additional chargers	57.3	73.0%	76.4%	20.9%	17.4%	7.0%	3.5%	9439
	Difference	*32.2*	*6.7%* ***	*6.2%* ***	*46.3%*	*48.3%*	*4.3%* ***	*1.7%* ***	–
	Top 10% of no overnight chargers	78.6	43.5%	43.6%	13.2%	7.8%	30.0%	23.3%	1049
	Bottom 90% of no overnight chargers	58.5	77.0%	79.2%	26.9%	22.0%	4.0%	2.8%	9439
	Difference	*20.1*	*33.4%* ***	*35.6%* ***	*13.7%* ***	*14.2%* ***	*26.1%*	*20.5%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	42.3%	43.0%	11.2%	6.8%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	21.9%	17.0%	5.6%	2.9%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*20.4%* ***	*26.1%* ***	*5.7%* ***	*3.9%* ***	–

(*continued on next page*)

Table A2 (*continued*)

		Mean Daily VKT	Utility Factor (UF)		Frequency of additional charging		Frequency of no overnight charging		N (users in the sample)
			Mean	Median	Mean	Median	Mean	Median	
Higher additional charging occurrence threshold (UFobs/UFcal > 1.3)	All users	60.5	73.6%	77.1%	12.6%	6.8%	6.6%	3.3%	10,488
	Top 10% of additional chargers	91.9	79.5%	82.1%	49.2%	47.5%	2.9%	2.0%	1049
	Bottom 90% of additional chargers	57.1	73.0%	76.4%	8.6%	5.6%	7.0%	3.5%	9439
	Difference	*34.8*	*6.5%* ***	*5.7%* ***	*40.6%*	*42.0%*	*4.0%* ***	*1.5%* ***	–
	Top 10% of no overnight chargers	78.6	43.5%	43.6%	5.3%	1.8%	30.0%	23.3%	1049
	Bottom 90% of no overnight chargers	58.5	77.0%	79.2%	13.4%	7.6%	4.0%	2.8%	9439
	Difference	*20.1*	*33.4%* ***	*35.6%* ***	*8.1%* ***	*5.8%* ***	*26.1%*	*20.5%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	25.6%	20.7%	11.2%	6.8%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	9.8%	5.5%	5.6%	2.9%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*15.7%* ***	*15.3%* ***	*5.7%* ***	*3.9%* ***	–
	All users	60.5	73.6%	77.1%	7.9%	3.1%	6.6%	3.3%	10,488
Higher additional charging occurrence threshold (UFobs/UFcal > 1.5)	Top 10% of additional chargers	92.1	78.5%	81.2%	38.2%	35.2%	3.3%	2.2%	1049
	Bottom 90% of additional chargers	57.0	73.1%	76.5%	4.6%	2.4%	6.9%	3.5%	9439
	Difference	*35.0*	*5.4%* ***	*4.7%* ***	*33.7%*	*32.8%*	*3.6%* ***	*1.3%* ***	–
	Top 10% of no overnight chargers	78.6	43.5%	43.6%	3.0%	0.5%	30.0%	23.3%	1049
	Bottom 90% of no overnight chargers	58.5	77.0%	79.2%	8.5%	3.6%	4.0%	2.8%	9439
	Difference	*20.1*	*33.4%* ***	*35.6%* ***	*5.4%* ***	*3.1%* ***	*26.1%*	*20.5%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	18.2%	11.6%	11.2%	6.8%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	5.7%	2.4%	5.6%	2.9%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*12.4%* ***	*9.2%* ***	*5.7%* ***	*3.9%* ***	–
	All users	60.5	73.6%	77.1%	25.5%	20.3%	4.4%	1.9%	10,488
Lower no overnight charging occurrence threshold (UFobs/UFcal < 0.3)	Top 10% of additional chargers	89.5	79.7%	82.6%	67.2%	65.7%	1.8%	1.1%	1049
	Bottom 90% of additional chargers	57.3	73.0%	76.4%	20.9%	17.4%	4.7%	2.0%	9439
	Difference	*32.2*	*6.7%* ***	*6.2%* ***	*46.3%*	*48.3%*	*2.9%* ***	*0.9%* ***	–
	Top 10% of no overnight chargers	76.7	44.2%	43.9%	14.5%	8.5%	23.2%	16.8%	1049
	Bottom 90% of no overnight chargers	58.8	76.9%	79.2%	26.8%	21.7%	2.3%	1.6%	9439
	Difference	*17.9*	*32.7%* ***	*35.3%* ***	*12.3%* ***	*13.2%* ***	*20.9%*	*15.2%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	42.3%	43.0%	7.6%	3.8%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	21.9%	17.0%	3.7%	1.6%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*20.4%* ***	*26.1%* ***	*3.8%* ***	*2.2%* ***	–
	All users	60.5	73.6%	77.1%	25.5%	20.3%	10.5%	6.1%	10,488
		89.5	79.7%	82.6%	67.2%	65.7%	4.3%	3.2%	1049

(*continued on next page*)

Table A2 (*continued*)

		Mean Daily VKT	Utility Factor (UF)		Frequency of additional charging		Frequency of no overnight charging		N (users in the sample)
			Mean	Median	Mean	Median	Mean	Median	
Higher no overnight charging occurrence threshold (UFobs/UFcal < 0.7)	Top 10% of additional chargers								
	Bottom 90% of additional chargers	57.3	73.0%	76.4%	20.9%	17.4%	11.1%	6.6%	9439
	Difference	*32.2*	*6.7%* ***	*6.2%* ***	*46.3%*	*48.3%*	*6.8%* ***	*3.3%* ***	–
	Top 10% of no overnight chargers	80.9	43.8%	44.4%	11.7%	7.6%	41.5%	35.9%	1049
	Bottom 90% of no overnight chargers	58.3	76.9%	79.2%	27.1%	22.2%	7.0%	5.3%	9439
	Difference	*22.6*	*33.1%* ***	*34.8%* ***	*15.4%* ***	*14.7%* ***	*34.5%*	*30.6%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	42.3%	43.0%	17.8%	11.9%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	21.9%	17.0%	8.9%	5.4%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*20.4%* ***	*26.1%* ***	*8.9%* ***	*6.6%* ***	–
	All users	60.5	73.6%	77.1%	31.0%	27.1%	6.0%	3.0%	10,488
Single model year	Top 10% of additional chargers	95.0	79.9%	82.7%	70.1%	68.5%	2.7%	1.8%	1049
	Bottom 90% of additional chargers	56.7	72.9%	76.4%	26.7%	24.1%	6.4%	3.2%	9439
	Difference	*38.3*	*7.0%* ***	*6.3%* ***	*43.4%*	*44.4%*	*3.6%* ***	*1.4%* ***	–
	Top 10% of no overnight chargers	76.1	44.3%	44.3%	20.9%	17.6%	27.7%	21.2%	1049
	Bottom 90% of no overnight chargers	58.8	76.9%	79.2%	32.2%	28.4%	3.6%	2.6%	9439
	Difference	*17.3*	*32.5%* ***	*34.9%* ***	*11.3%* ***	*10.8%* ***	*24.1%*	*18.5%*	–
	Users above 30 k annual VKT	106.8	58.8%	59.4%	51.5%	54.2%	9.8%	5.9%	1861
	Users below 30 k annual VKT	50.6	76.8%	79.7%	26.6%	22.9%	5.2%	2.7%	8627
	Difference	*56.2*	*18.0%* ***	*20.2%* ***	*24.9%* ***	*31.3%* ***	*4.7%* ***	*3.2%* ***	–

References

[1] Poullikkas A. Sustainable options for electric vehicle technologies. Renew Sustain Energy Rev 2015;41:1277–87.
[2] Weiller C. Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States. Energy Policy 2011;39:3766–78.
[3] Hartmann N, Özdemir ED. Impact of different utilization scenarios of electric vehicles on the German grid in 2030. J Power Sources 2011;196:2311–8.
[4] Göransson L, Karlsson S, Johnsson F. Integration of plug-in hybrid electric vehicles in a regional wind-thermal power system. Energy Policy 2010;38:5482–92.
[5] Guille C, Gross G. A conceptual framework for the vehicle-to-grid (V2G) implementation. Energy Policy 2009;37:4379–90.
[6] Li C, Zhang L, Ou Z, Wang Q, Zhou D, Ma J. Robust model of electric vehicle charging station location considering renewable energy and storage equipment. Energy 2022;238:121713.
[7] Park S-W, Cho K-S, Hoefter G, Son S-Y. Electric vehicle charging management using location-based incentives for reducing renewable energy curtailment considering the distribution system. Appl Energy 2022;305:117680.
[8] Kikusato H, Fujimoto Y, Hanada S, Isogawa D, Yoshizawa S, Ohashi H, et al. Electric Vehicle Charging Management Using Auction Mechanism for Reducing PV Curtailment in Distribution Systems. IEEE Trans Sustainable Energy 2020;11:1394–403.
[9] Szinai JK, Sheppard CJR, Abhyankar N, Gopal AR. Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management. Energy Policy 2020;136:111051.
[10] Plötz P, Funke S, Jochem P. Empirical Fuel Consumption and CO2 Emissions of Plug-In Hybrid Electric Vehicles: Fuel Consumption of Plug-In Hybrid Electric Vehicles. J Ind Ecol 2017;22.
[11] Plötz P, Funke SÁ, Jochem P. The impact of daily and annual driving on fuel economy and CO2 emissions of plug-in hybrid electric vehicles. Transport Res Part A: Policy Pract 2018;118:331–40.
[12] Ligterink NE, Smokers RTM, Bolech M. Fuel-electricity mix and efficiency in Dutch plug-in and range-extender vehicles on the road. 2013 World Electric Vehicle Symposium and Exhibition (EVS27), 17-20 Nov. 2013; 2013. p. 1–4.
[13] Davies J, Kurani KS. Moving from assumption to observation: Implications for energy and emissions impacts of plug-in hybrid electric vehicles. Energy Policy 2013;62:550–60.
[14] Nicholas MA, Tal G, Turrentine TS. Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report; 2017.
[15] Plötz P, Funke SA, Jochem P, Wietschel M. CO2 Mitigation Potential of Plug-in Hybrid Electric Vehicles larger than expected. Sci Rep 2017;7:16493.
[16] Gnann T, Funke S, Jakobsson N, Plötz P, Sprei F, Bennehag A. Fast charging infrastructure for electric vehicles: Today's situation and future needs. Transport Res Part D: Transport Environ 2018;62:314–29.
[17] Morrissey P, Weldon P, O'Mahony M. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy 2016;89:257–70.
[18] Jochem P, Brendel C, Reuter-Oppermann M, Fichtner W, Nickel S. Optimizing the allocation of fast charging infrastructure along the German autobahn. J Bus Econ 2016;86:513–35.
[19] Rahman I, Vasant PM, Singh BSM, Abdullah-Al-Wadud M, Adnan N. Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures. Renew Sustain Energy Rev 2016;58:1039–47.
[20] Xi X, Sioshansi R, Marano V. Simulation–optimization model for location of a public electric vehicle charging infrastructure. Transport Res Part D: Transport Environ 2013;22:60–9.
[21] Jenn A, Lee JH, Hardman S, Tal G. An in-depth examination of electric vehicle incentives: Consumer heterogeneity and changing response over time. Transport Res Part A: Policy Pract 2020;132:97–109.
[22] Tal G, Nicholas MA, Davies J, Woodjack J. Charging Behavior Impacts on Electric Vehicle Miles Traveled: Who is Not Plugging In? Transp Res Rec 2014;2454:53–60.
[23] Tal G, Nicholas MA, Davies J, Woodjack J. Charging behavior impacts on electric VMT: Evidence from a 2013 California drivers survey. Transportation Research Board Annual Meeting. Washington, DC. Citeseer; 2014b.
[24] Zhou Y, Wen R, Wang H, Cai H. Optimal battery electric vehicles range: A study considering heterogeneous travel patterns, charging behaviors, and access to charging infrastructure. Energy 2020;197:116945.

[25] Dong J, Lin Z. Within-day recharge of plug-in hybrid electric vehicles: Energy impact of public charging infrastructure. Transport Res Part D: Transport Environ 2012;17:405–12.
[26] Bi R, Xiao J, Viswanathan V, Knoll A. Influence of charging behaviour given charging infrastructure specification: A case study of Singapore. J Comput Sci 2017;20:118–28.
[27] Pagani M, Korosec W, Chokani N, Abhari RS. User behaviour and electric vehicle charging infrastructure: An agent-based model assessment. Appl Energy 2019;254:113680.
[28] Chakraborty D, Bunch DS, Lee JH, Tal G. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transport Res Part D: Transport Environ 2019;76:255–72.
[29] Chakraborty D, Bunch DS, Lee JH, Tal G. What Factors Drive Commuters' Demand for Electric Vehicle Charging Infrastructure? UC Office of the President: University of California Institute of Transportation Studies; 2020.
[30] Goebel D, Plötz P. Machine learning estimates of plug-in hybrid electric vehicle utility factors. Transport Res Part D: Transport Environ 2019;72:36–46.
[31] Axsen J, Kurani KS, McCarthy R, Yang C. Plug-in hybrid vehicle GHG impacts in California: Integrating consumer-informed recharge profiles with an electricity-dispatch model. Energy Policy 2011;39(3):1617–29.
[32] Björnsson L-H, Karlsson S. Plug-in hybrid electric vehicles: How individual movement patterns affect battery requirements, the potential to replace conventional fuels, and economic viability. Appl Energy 2015;143:336–47.
[33] Philipsen R, Brell T, Brost W, Eickels T, Ziefle M. Running on empty – Users' charging behavior of electric vehicles versus traditional refueling. Transport Res Part F: Traffic Psychol Behav 2018;59:475–92.
[34] Tal G, Lee JH, Nicholas MA. Observed Charging Rates in California. UC Davis: Plug-In Hybrid & Electric Vehicle Research Center; 2018.
[35] Chakraborty D, Hardman S, Tal G. Why do some consumers not charge their plug-in hybrid vehicles? Evidence from Californian plug-in hybrid owners. Environ Res Lett 2020;15:084031.
[36] Ashkrof P, Homem De Almeida Correia G, Van Arem B. Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands. Transport Res Part D: Transport Environ 2020;78:102206.
[37] Srinivasa Raghavan S, Tal G. Influence of User Preferences on the Revealed Utility Factor of Plug-In Hybrid Electric Vehicles. World Electric Vehicle J 2020;11.
[38] Raghavan SS, Tal G. Plug-in hybrid electric vehicle observed utility factor: Why the observed electrification performance differ from expectations. Int J Sustain Transport 2020:1–46.
[39] Fieltsch P, Flämig H, Rosenberger K. Analysis of charging behavior when using battery electric vehicles in commercial transport. Transp Res Proc 2020;46:181–8.
[40] Plötz P, Moll C, Bieker G, Mock P, Li Y. Real-world usage of plug-in hybrid electric vehicles - fuel consumption, electric driving, and CO2 emissions. *ICCT White paper*; 2020.
[41] Plötz P, Moll C, Bieker G, Mock P. From lab-to-road: real-world fuel consumption and CO2 emissions of plug-in hybrid electric vehicles. Environ Res Lett 2021;16:054078.
[42] Tal G, Karanam VC, Favetti MP, Sutton KM, Ogunmayin JM, Raghavan SS, et al. Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior. UC Davis, Plug-in Hybrid & Electric Vehicle Research Center; 2021.
[43] Committee H-E. Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data. SAE International; 2010.
[44] Mandev A, Sprei F, Tal G. Electrification of vehicle miles travelled within the household context. *Transportation Research Board 99th Annual Meeting.* Washington DC, USA; 2020.
[45] Tal G, Raghavan SS, Karanam VC, Favetti MP, Sutton KM, Ogunmayin JM et al. Advanced Plug-in Electric Vehicle Travel and Charging Behavior Final Report. UC Davis, Plug-in Hybrid & Electric Vehicle Research Center; 2020.
[46] Carrillo H, Brodersen KH, Castellanos JA. Probabilistic performance evaluation for multiclass classification using the posterior balanced accuracy. In: ROBOT2013: First Iberian Robotics Conference. Springer; 2014. p. 347–61.
[47] Lin Z, Greene DL. Significance of daily VMT variation over time and among drivers on assessment of PHEV energy impact. Proceedings of the 90th Annual Meeting of the Transportation Research Board, Washington, DC, USA; 2011. p. 23–7.
[48] FHWA. *Average Annual Miles per Driver by Age Group* [Online]; 2020. Available: https://www.fhwa.dot.gov/ohim/onh00/bar8.htm [accessed June 21, 2020].
[49] Chicco D. Ten quick tips for machine learning in computational biology. BioData Mining 2017;10:35.
[50] Chicco D, Jurman G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC Genomics 2020;21:6.
[51] Fawcett T. An introduction to ROC analysis. Pattern Recogn Lett 2006;27:861–74.
[52] Tharwat A. Classification assessment methods. Appl Comput Inform 2021;17:168–92.
[53] Tibshirani R, Walther G, Hastie T. Estimating the number of clusters in a data set via the gap statistic. J Roy Statist Soc: Ser B (Statist Methodol) 2001;63:411–23.
[54] Kaufman L, Rousseeuw PJ. Finding groups in data: an introduction to cluster analysis. John Wiley & Sons; 2009.
[55] Lee JH, Chakraborty D, Hardman SJ, Tal G. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. Transport Res Part D: Transport Environ 2020;79:102249.
[56] Funke SÁ, Sprei F, Gnann T, Plötz P. How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. Transport Res Part D: Transport Environ 2019;77:224–42.
[57] Hardman S, Jenn A, Tal G, Axsen J, Beard G, Daina N, et al. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transport Res Part D: Transport Environ 2018;62:508–23.
[58] Taljegard M, Walter V, Göransson L, Odenberger M, Johnsson F. Impact of electric vehicles on the cost-competitiveness of generation and storage technologies in the electricity system. Environ Res Lett 2019;14:124087.