Periodicity analysis of charging behavior of electric car drivers

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Periodicity analysis of charging behavior of electric car drivers: Latent class hazard models

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Key words: Hazard-based duration model, Inter-charging time, Latent segmentation

Abstract: The importance of public charging infrastructure has been recognised recently as it represents a key factor in the promotion of plug-in electric vehicles (PEV). Given that a large initial investment from the public sector is essential for its widespread adoption, many studies have focused on the issue how the charging infrastructure should be planned and located. Although it is of critical importance to understand PEV users’ charging behavior for improving public charging infrastructure, relatively few number of PEVs makes it difficult to analyze charging behavior of large sample of PEV users. This study uses a Dutch four-year comprehensive charging transaction dataset. Given that electric vehicle users likely exhibit heterogeneous charging behavior in terms of both charging frequency (time interval between successive charging events) and charging regularity (regular charging versus ad-hoc charging), this study applies a heterogeneous hazard-based duration model to examine how often PEV users charge their car at public charging stations and to distinguish the difference characteristics of random (erratic) users and regular (routine) users. The results show that 67 per cent of PEV users charge their car at irregular intervals, while 33 per cent charge regularly. It is also shown that regular users charge their PEV more often and are more likely to have a battery electric vehicle (BEV) compared to random users. Moreover, clear differences exist between the two groups in terms of vehicle and charging characteristics.
1. INTRODUCTION

Several governments have stimulated marketing campaigns and offered tax cuts to encourage people to adopt electric vehicles (EV) as an efficient and sustainable alternative to the internal combustion engine vehicle (ICEV). Although the absolute market size for electric vehicle is still insignificant and consumer purchasing behavior seems to stagnate until further improvement in technology and more competitive prices have become a reality (e.g., Rasouli and Timmermans, 2016), the market penetration of plug-in electric vehicle (PEV) raises issues about the availability of public charging infrastructure and its performance. Adequate availability of charging stations seems a sine qua non for the further acceptance and market penetration of electric cars.

The situation in the Netherlands can serve as an example. Tax reduction measures resulted in the selling of an increasing number of electric cars. Political parties have expressed the target of a substantially larger market share of electric cars by 2020. The Netherlands has been one of the leading countries with respect to the number of public charging stations (Appels, 2012). However, the absence of charging infrastructure and the restricted driving range of EVs are still major barriers to large adoption (Franke and Krems, 2013a). Consumers may hesitate buying an EV if not enough charging stations are readily available, whereas charging infrastructure providers are not willing to build new charging stations until there is a sufficient large developed EV market. This problem has been characterized in terms of the so-called chicken-and-egg allegory (Kitamura and Sperling, 1987; Nicholas et al., 2004; Kang and Recker, 2014).

To solve this problem, the commonly made assumption in EV charging station location-allocation analysis is that activity-travel patterns of EV users will not change when they switch from ICEV to EV. For example, Chen et al. (2013) optimized the location of charging stations based on the assumption that conventional gasoline vehicle parking demand is a strong proxy for EV charging demands. Similarly, Dong et al. (2014) used longitudinal GPS travel data collected from conventional gasoline vehicles to solve electric vehicle charger location problems in the greater Seattle metropolitan area. More recently, Shahraki et al. (2015) used the GPS trajectories of taxis to capture public charging demand, and located the public charging stations by maximizing the amount of vehicle-miles-traveled (VMT) being electrified. However, it has been shown that driving patterns of EV users are clearly different from those of ICEV users. The main reasons for this difference relate to limited range (Franke and Krems, 2013b), absence of charging infrastructure (Speidel and Bräunl, 2014), and refueling patterns (Kuby et al., 2013). Moreover, EV owners are not homogeneous, but rather differ in terms of their usage pattern of charging stations (Frank and Krems, 2013b). Since
charging an electric vehicle generally takes longer than refueling a gasoline vehicle, even with fast charging, users may adapt their charging decision based on the various constraints they face, such as their daily activity schedule and battery size.

Charging station location studies have also been based on the assumption that EV users maximize their utility by charging their EV as much as possible. Frank and Krems (2013c), however, found the presence of individual differences in charging behavior in terms of the utilization of limited energy resources. For example, some drivers (e.g., risk-takers) charge in an opportunistic way, while others (e.g., risk-avoiders) have a planned charging scheme with a preferred charging station at a relatively fixed interval. Thus, examining the usage pattern of public charging stations will give useful insights into how EV users cope with the space-time constraints, set by their daily activity schedule and the state of the battery.

Further empirical studies are therefore warranted to enhance our understanding of charging behavior in the context of daily activity-travel patterns to enhance our modeling efforts and improve the solutions offered to entice people to purchase more environmentally-friendly vehicles. Unfortunately, limited market penetration of EV makes it hard to observe real-world charging behavior (Zoepf et al., 2013). Although various attempts have been made in the past few years to examine the mobility pattern of EV drivers, as well as their charging behavior, most existing knowledge about charging behavior is based on a (very) small samples (Khan and Kockelman, 2012). Franke and Krems (2013b), for example, investigated the charging patterns of 79 drivers in a 6-month EV trial in Berlin and identified the underlying psychological factors related to the battery state. Speidel and Braunl (2014) examined the charging behavior of 11 vehicles and the usage patterns of 23 charging stations based on a 3 year Western Australian Electric Vehicle Trial. In the Victorian EV Trial, Khoo et al. (2014) conducted statistical analysis of the empirical relationships between vehicle/participant types and attributes of the charging events including charge duration, daily charging frequency, energy consumed, start charging hour, and time to next charging event. More recently, The Japan Automobile Research Institute (JARI) collected the probe data from a larger sample of 483 BEVs over two years from 2011 to 2013 (Sun et al., 2015). The probe installed in the vehicle provides rich information about charging behavior as well as vehicle information such as vehicle trajectory and state of charge (SOC). However, based on this data set it is hard to grasp the full picture of the usage of public charging infrastructure because the probes are only installed in BEVs. Additional research is therefore required. Still little is known about how often EV users charge their cars at public charging stations, how many of them charge randomly or regularly, and
which charging-related and vehicle characteristics motivate them to behave differently.

The aim of the study is to reduce this gap in our knowledge. Given that EV users exhibit heterogeneous charging behavior in terms of charging frequency and charging regularity (regular charging versus random charging), we applied a parametric hazard model of inter-charging times to examine the regularity and frequency of charging events at public charging stations. This study takes an in-depth look at the EV users’ inter-charging times to understand their charging patterns using four-year longitudinal charging transaction data. Our empirical results enable us to segment EV users into two groups in terms of charging regularity. We explore a new way of looking at longitudinal charging transaction data, segment EV users into two broad groups with respect to charging regularity, and show that regular users are clearly different from random users regarding several charging behavioral and vehicle variables.

The remainder of this paper is structured as follows. The following section reviews previous literature on inter-episode duration analysis. Section 3 describes the theoretical basis of the hazard-based duration models and their specification used to model inter-charging times. Section 4 describes the data used in this analysis. Then, the results of the model estimation are discussed. The final section summarizes the main conclusions, implications of this study and plans for future research.

2. LITERATURE REVIEW OF INTER-EPODSE DURATION ANALYSIS

Prior inter-episode duration analysis can be classified into two broad groups according to its purpose and the data used. The first group of inter-episode duration analyses uses shopping trip data to examine how marketing variables affect the consumers’ decision to go shopping. Kahn and Schmittlein (1989) found evidence of weekly cycles in shopping trips by observing inter-shopping times using IRI (Information Resources, Inc.) shopping trip data, and classified shopping trips into major and fill-in trips based on the amount of money spent on the corresponding shopping trip. In the context of examining trip regularity, they provided insightful results by classifying consumers into two segments: those who made more fill-in trips than regular trips (i.e., Quicks) and those who made more regular trips than quick trips (i.e., Regulars). This study, however, differentiates the two groups only by treating shopper’s trip regularity as an exogenous variable. By taking duration dependence and heterogeneity in purchase rates across consumers into account, as well as covariate effects for modeling inter-purchase times of
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ground coffee with scanner panel data, Gupta (1991) developed four stochastic models of inter-purchase timing and compared these models. Results indicated that the model with duration dependence and heterogeneity in purchase rates improved model fit. Kim and Park (1997) developed a parametric hazard model of inter-shopping times using IRI shopping trip data, which incorporated heterogeneity in shopping trip regularity as well as shopping rates. Based on the parameter estimates, they endogenously segmented shoppers into random and regular groups by taking into consideration the pattern of shopping trip intervals (i.e., inter-shopping times). They noted that the exponential and Erlang-2 distributions were suited for explaining the frequency distribution of inter-shopping times of random shoppers and regular shoppers, respectively. Heterogeneity in shopping trip frequency was taken into account by introducing a gamma distribution, while heterogeneity in shopping trip regularity was modeled with the mixture of the exponential and Erlang-2 distributions. This study provided a useful approach to distinguish between random shoppers and regular shoppers in terms of shopping regularity. In recent years, Kim (2013) compared the pattern of online purchase timing with the corresponding patterns in the offline market. The results support the hypothesis that shopping time regularity collapses in the online market.

Secondly, a growing body of research recently focused on examining multi-day or multi-week longitudinal activity diary data (Yang and Timmermans, 2015). Recognizing the limitations of the existing activity-based approach to travel demand modeling in that most studies have relied on cross-sectional data (Rasouli and Timmermans, 2014), previous research has stressed the necessity of a deeper insight into temporal patterns of daily activity and travel characteristics which vary across days or weeks (Axhausen et al., 2002; Bhat et al., 2005; Arentze and Timmermans, 2009). Previous researchers have applied inter-episode duration analysis for this problem. For example, Schönfelder and Axhausen (2001) used six-week travel diary data of 361 individuals from 162 households, located in the German cities of Halle/Saale and Karlsruhe, to analyze the rhythmic patterns of “daily shopping” and “active sports” activities. They estimated the Cox proportional hazard model and Weibull parametric hazard model for the inter-episode duration distribution, which allows not only to incorporate observed inter-episode durations for the probability of event occurrence, but also to treat duration-independent determinants such as socio-demographics or personal constraints. Bhat et al. (2004) used the same dataset to examine the regularity and frequency of shopping behavior. Moreover, they expanded the hazard-based formulation, which accommodates a non-parametric baseline hazard and unobserved heterogeneity across individuals in inter-shopping durations, and included a latent segmentation scheme to classify shoppers into regular
and erratic shoppers. In addition, Bhat et al. (2005) extended the previous analysis to five activity purposes, and found inherent weekly rhythms for participating in those activities. The results showed a stronger rhythmic pattern in the participation in the non-shopping activities (i.e., social, recreation, and personal business activities) than in the shopping activities (i.e., maintenance shopping and other shopping activities).

This paper deals with periodicity in charging behavior, which has been widely neglected, and segments EV users into two broad groups according to their charging regularity (i.e., random and regular group). Several hazard-based duration models will be formulated to examine inter-charging times of EV users using a Dutch four-year charging transaction data set. The model results provide information to private and public sector actors for the future development of charging infrastructure related to the understanding of the dynamic structure of space-time charging behavior. From a methodological standpoint, the estimated models can be considered an extension of Kim and Park’s work (1997).

### 3. MODEL STRUCTURE AND SPECIFICATION

This section describes the hazard-based duration model used to examine inter-charging times. Given the assumption that heterogeneity exists in charging frequency and charging regularity, a gamma mixing distribution and a mixture of the exponential and Erlang-2 distribution are used to examine charging frequency heterogeneity and heterogeneity in charging regularity, respectively. We endogenously divide EV owners into random and regular users using a latent segmentation approach. It is assumed that charging regularity is treated as a latent variable, which cannot be observed by researchers. In this study, the posterior membership probability of each user is obtained from the estimated parameters in order to segment EV users into two groups according their charging regularity.

Similar to previous studies, it is assumed that the exponential distribution is suitable to model inter-charging times of random users, while the Erlang-2 distribution is reasonable for regular users (Gupta, 1991). These properties can be easily illustrated by inspecting the hazard rate of these distributions. The probability density function \( f_t^E(x) \) and survival function \( s_t^E(x) \) of the exponential distribution are equal to

\[
f_t^E(x) = \lambda_t^E \exp(-\lambda_t^E x) \tag{1}
\]

and

\[
s_t^E(x) = \exp(-\lambda_t^E x) \tag{2}
\]
where $\lambda_i^E$ is the inter-charging hazard rate of user $i$.

The hazard function for exponential inter-charging times thus becomes $\lambda_i^E(x) = f_i^E(x)/s_i^E(x) = \lambda_i^E$, which is constant over time. Thus, this model represents random charging behavior of users.

Similarly, the probability density function $f_i^R(x)$ and survival function $s_i^R(x)$ of Erlang-2 can be written as

$$f_i^R(x) = (\lambda_i^E)^2 x \exp(-\lambda_i^E x)$$
$$s_i^R(x) = (1 + \lambda_i^E x) \exp(-\lambda_i^E x)$$

Thus, the hazard function of the Erlang-2 model is $\lambda_i^E(x) = \lambda_i^E(x) = (\lambda_i^E)^2 x / (1 + \lambda_i^E x)$. This equation shows that it is a monotonically increasing hazard over time and thus reflects duration dependence. Therefore, this model can be used to represent regular charging behavior.

Given that the charging transaction dataset is right-censored, the conditional likelihood function for random user $i$ becomes

$$L_i^E(x|\lambda_i^E) = \prod_{j=1}^{n(i)-1} f_i^E(x_{ij}) s_i^E(x_{in(i)})$$
$$= \prod_{j=1}^{n(i)-1} \lambda_i^E \exp(-\lambda_i^E x_{ij}) \exp(-\lambda_i^E x_{in(i)})$$

where $x_{ij}$ is the $j^{th}$ inter-charging time of user $i$, $n(i)$ is the last observation of user $i$ (i.e., censored inter-charging time). It is assumed that the hazard rate is constant here and identical for all users (i.e., $\lambda_i^E = \lambda^E$ for all $i$). However, it is not appropriate to assume that all EV users have the same charging rate. Therefore, heterogeneity in inter-charging rates across EV users can be incorporated by introducing a gamma distribution. With the gamma heterogeneity, the likelihood function of user $i$ can be rewritten as

$$L_i^E(x|\alpha, \gamma) = \int_0^\infty L_i^E(x|\lambda_i^E) g(\lambda_i^E|\alpha, \gamma) d\lambda_i^E$$
$$= \frac{\alpha^\gamma \prod_{j=1}^{n(i)-1} (\gamma+j)^{n(i)-1} x_j + x_{in(i)}^{n(i)-1+y}}{[\alpha + \gamma \sum_{j=1}^{n(i)-1} x_j + x_{in(i)}]^{n(i)-1+y}}$$

where $g(\lambda_i^E|\alpha, \gamma)$ is the density function of the gamma mixing distribution with scale parameter $\alpha$ and shape parameter $\gamma$. Then, the log-likelihood of the $N$ users in the sample becomes
As indicated, the Erlang-2 model is duration dependent, and therefore suitable for describing the charging behavior of regular users. This model is based on the assumption that the elapsed time since the last charging may affect the next charging time. Traditionally, the Erlang-2 distribution has been used by many marketing researchers to examine regular purchasing behavior (e.g., Jeuland et al., 1980; Gupta, 1991; Kim and Park, 1997). Thus, the inventory effect can be taken into consideration, which also exists in charging behavior related to the state of charge (SOC).

The conditional likelihood function of user $i$ given that he or she is regular user can be written as

$$P(T_i | X_i) = \frac{1}{\lambda_i} \exp \left( - \frac{T_i}{\lambda_i} \right)$$

$$L = \prod_{i=1}^{N} \frac{1}{\lambda_i} \exp \left( - \frac{T_i}{\lambda_i} \right)$$

(10)

We have expressed the likelihood function corresponding to random and regular users in equation (6) and equation (9), respectively. However, there is no information on the charging regularity as it is considered to be a latent variable, which cannot be observed. In this paper, the propensity to belong to
a segment (e.g., random user vs. regular user) is calculated using the posterior segment membership probability of user \( i \). The final unconditional likelihood function of user \( i \) can be obtained by integrating the two likelihood functions, conditional on the user being a random user or a regular user, weighted by \( \varphi \) and \( 1 - \varphi \).

\[
LL = \sum_{i=1}^{N} L_i(x|\varphi, \alpha, \gamma, \beta, \delta) \\
= \sum_{i=1}^{N} \log \left[ \varphi L_i^R(x|\alpha, \gamma) + (1 - \varphi)L_i^F(x|\beta, \delta) \right]
\] (11)

This log-likelihood can be maximized to estimate the following parameters: (a) scale parameter \( \alpha \) and shape parameter \( \gamma \) for the random user segment, (b) scale parameter \( \beta \) and shape parameter \( \delta \) for the regular user segment, and (c) weight \( \varphi \). The log-likelihood functions were maximized using \textit{optimx} in R statistical software (Nash and Varadhan, 2011; R core team, 2015). Once parameter values are obtained, each individual can be assigned to the segments. The posterior membership probability of user \( i \) being a random user can be calculated as \( \varphi L_i^R / L_i \), while the corresponding probability to be a regular user equals \( (1 - \varphi) L_i^F / L_i \). If EV users’ posterior membership probability of being in the exponential segment is greater than that of being in the Erlang-2 segment, he or she is seen as a random user, and vice versa for those in Erlang-2 segment.

4. CHARGING TRANSACTION DATA

The proposed approach is applied to the charging transaction panel data. The analysis of this data has the following challenges. First, the data contains not only ordinary charging transactions, but also charging transactions which can be seen testing. It is observed that some charging transactions occur too many times a day (e.g., dozens of times of charging a day), and are largely associated with specific individuals. We considered these data are not relevant for our purpose, and deleted 12 individuals who charged more than 20 times a day. Second, in order to obtain stable model results, very light users (i.e., users who do not charge at least five times) were also eliminated. Third, some inter-charging times were too large (e.g., 1263 days), which may occur for many reasons. Despite the E-laad data covers a significant number of charging stations in the Netherlands, there are charging stations that do not belong to the E-laad network. We assumed that all EV users in the data do not use a charging station outside the sample. It is also possible that users may be out of town for a long time. These extremely long inter-charging times, which are higher or equal to 30 days are considered as outliers, and were eliminated from the analysis. The upper bound was used here due to the small number of inter-
charging times exceeding this duration length (about 7% of the observations). Thus, the sample used in this study consists of the inter-charging times of 9,528 EV users. Table 1 shows the summary statistics of the data used. The number of inter-charging duration spells varies between 1 to 931 spells across individuals, with an average of 41.08 spells. The average inter-charging time of all individuals is 3.01 days.

Table 1. Summary of the charging transaction dataset

<table>
<thead>
<tr>
<th>Time span</th>
<th>8/20/2010 – 8/29/2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of users</td>
<td>9,528</td>
</tr>
<tr>
<td>Total number of inter-charging times</td>
<td>453,884</td>
</tr>
<tr>
<td>Number of inter-charging times per person</td>
<td>Min = 1, Max = 931, Mean = 41.08</td>
</tr>
<tr>
<td>Length of inter-charging time</td>
<td>Min = 1, Max = 29.49, Mean = 3.01</td>
</tr>
</tbody>
</table>

One way to capture the details of inter-charging times is to examine their frequency distribution. The left section of Figure 1 represents the frequency distribution of inter-charging times at an aggregate level, and resembles an exponential distribution. It may suggest that the EV users’ propensity to charge at time t is independent of the elapsed time since the last charging event. It seems that charging occurs randomly rather than regularly at first. However, the right section of the figure provides clear visual evidence of rhythmic patterns in charging activity.

Figure 1. Frequency distribution of inter-charging times and sample hazard

The sample hazard was calculated using the Kaplan-Meier method with an upper bound of 30 days. It is a reasonable inference that several peaks at weekly intervals are related to the charging patterns of regular users. Kahn and Schmittlein (1989) also noted that weekly patterns in shopping frequency were the by-product of individuals’ regular behavior. On the other hand, the high hazard at the first 6 days is monotonically decreasing indicating a negative duration dependence, which represents the inter-charging times of random
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users. In the next section, random users and regular users are separated out and compared.

5. EMPIRICAL RESULTS

Table 2 shows the estimation results for the different model specifications. First, the models with and without heterogeneity in charging frequency are compared. As we noted earlier, the charging rate \((\lambda)\) is assumed to be Gamma distributed across individuals to represent heterogeneity in charging frequency. It is clearly shown that the inclusion of heterogeneity improves model fit in all cases. Given that the magnitude of the shape parameter indicates the degree of heterogeneity in the sample, the low value of the shape parameter indicates that substantial heterogeneity exists among individuals.

Second, we assess the impact of including duration dependence in the model by comparing the exponential with Erlang-2 models and exponential/gamma with Erlang-2/gamma models. The model without duration dependence fits the data much better. In other words, the model with the memoryless property of the exponential distribution describes the charging behavior of the entire set of observations well, which implies that EV users tend to charge their cars more at random. Contrarily to the results of previous inter-purchase and inter-shopping time studies (Gupta, 1991; Bhat et al., 2004), these results suggest that charging behavior has a different underlying structure than shopping behavior in terms of regularity. In addition, as Gupta (1991) noted, the interpretation of the shape parameter provides useful insight in the understanding of the intra- and interpersonal variations in charging rates. When comparing exponential/gamma with Erlang-2/gamma models, the results show that the shape parameter for the latter is less than that of the former. This result has an intuitive interpretation based on the assumption that the total variance in EV users’ inter-charging times consists of within-individual variance (i.e., intrapersonal variability) and between-individual variance (i.e., interpersonal variability). As we noted earlier, the Erlang-2/gamma model assumes an Erlang-2 distribution for inter-charging times of individuals. This assumption implies that charging occurs more regularly than in the exponential model, which can be interpreted as the Erlang-2 model (or Erlang-2/gamma) having a smaller within-individual variance than the exponential model (or exponential/gamma). Thus, given the same amount of total variance in inter-charging times, an Erlang-2 model may represent larger between-individual variance than the exponential model. Therefore, in general, the shape parameter of Erlang-2 model is less than that of exponential model.
Thirdly, heterogeneity in charging regularity is taken into consideration by introducing a mixture of the exponential and Erlang-2 distribution into the model. It is shown that the inclusion of heterogeneity of charging regularity significantly improves model fit, as is evident from the lowest BIC (Bayesian Information Criterion) value. As we noticed in Section 3, the posterior membership probabilities of each individual being in the random users segment or in the regular users segment were calculated. The parameter estimates of $\phi$ indicate the proportion of the random users segment. The results suggest that about 67% of the entire sample of EV users is more likely to charge their car at random intervals, while 33% charges regularly.

Table 2. Model estimation results

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Erlang-2</th>
<th>Exponential /gamma</th>
<th>Erlang-2 /gamma</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>0.315</td>
<td>0.633</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Exponential parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shape ($\gamma$)</td>
<td>-</td>
<td>-</td>
<td>2.626</td>
<td>-</td>
<td>7.745</td>
</tr>
<tr>
<td>Scale ($\alpha$)</td>
<td>-</td>
<td>-</td>
<td>9.489</td>
<td>-</td>
<td>45.56</td>
</tr>
<tr>
<td>Erlang-2 parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shape ($\delta$)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2.477</td>
<td>7.211</td>
</tr>
<tr>
<td>Scale ($\beta$)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4.391</td>
<td>7.095</td>
</tr>
<tr>
<td>Size of Exponential ($\phi$)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.671</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-977,778</td>
<td>-1,032,236</td>
<td>-900,036</td>
<td>-864,511</td>
<td>-848,839</td>
</tr>
<tr>
<td>Total number of individuals</td>
<td>9,528</td>
<td>9,528</td>
<td>9,528</td>
<td>9,528</td>
<td>9,528</td>
</tr>
<tr>
<td>Total number of observations</td>
<td>453,884</td>
<td>453,884</td>
<td>453,884</td>
<td>453,884</td>
<td>453,884</td>
</tr>
<tr>
<td>BIC</td>
<td>1,955,569</td>
<td>2,064,485</td>
<td>1,800,098</td>
<td>1,729,048</td>
<td>1,697,743</td>
</tr>
</tbody>
</table>

Note: BIC = -2*log(maximum likelihood) + (number of estimated parameters)*log(number of observations). The model with the lowest BIC is preferred. For heterogeneity concerns, it is assumed that inter-charging time rates ($\lambda_i$) are to be distributed as gamma with a shape parameter and a scale parameter. (Mean = $\gamma/\alpha$, Variance=$\gamma/\alpha^2$)

To get a better understanding of the reasons why people behave differently in the context of charging regularity, we take a look at the charging-related and vehicle characteristics of each segment. Two sets of variables were considered: charging-related and vehicle characteristics (see Table 3 for descriptions of selected variables). Although demographic characteristics may also explain why heterogeneity in charging regularity arises, their effects could not be estimated because socio-demographic variables were not available due to confidentiality of the data. However, we have attempted to include any variables that were considered in other inter-episode duration studies. We considered six charging behavioral variables and two vehicle...
variables, as shown in Table 3. Charging behavioral characteristics included the average charging interval, charging duration, and charging frequency and the percentage of weekend charging. Moreover, we considered the charging station loyalty of each user, which can be calculated by \(\sum_{i=1}^{N} s_i^2\), where \(s_i\) is the frequency of visiting charging station \(i\) divided by the total number of \(N\) visited charging stations. Charging station loyalty can be used as a measure to identify whether regular users charge at a relatively fixed location than random user. Vehicle characteristics considered dummy variables for two EV types (BEV and PHEV).

Table 3. Description of variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging interval</td>
<td>Average charging interval in days</td>
</tr>
<tr>
<td>Charging duration</td>
<td>Average charging duration in hours (the elapsed hours between plug-in and plug-off time)</td>
</tr>
<tr>
<td>Number of charging</td>
<td>Average number of charging transaction</td>
</tr>
<tr>
<td>Weekend charging</td>
<td>Percentage of charging that occurred on Saturday and Sunday.</td>
</tr>
<tr>
<td>Charging station loyalty</td>
<td>Concentration ratio</td>
</tr>
</tbody>
</table>

**Vehicle characteristics**

<table>
<thead>
<tr>
<th>EV type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEV</td>
<td>1 if the user has a battery electric vehicle. 0 otherwise.</td>
</tr>
<tr>
<td>PHEV</td>
<td>1 if the user has a plug-in hybrid vehicle. 0 otherwise.</td>
</tr>
</tbody>
</table>

Based on the results of the mixed model, 6,273 EV owners are classified into the random users group while 3,255 are classified into the regular users group. Table 4 provides the mean values, the standard deviations of the selected variables for each segment, and the corresponding p-values for mean differences. All selected variables are statistically significant at the 5 per cent level. In terms of the vehicle characteristics, regular users are more represented by BEV owners. This result corresponds to our expectation that BEV owners are more likely to stick with charging infrastructure in that electricity is the sole source of energy for BEV even with limited driving range. For charging behavioral characteristics, on average, regular users charge at public (or semi-public) stations almost every 2 days while random users charge every 1 week. Also it is interesting to observe that regular users tend to charge longer time once they plug-in their EV, compared to random users. Weekend charging is more significant in the random user group, that is to say, regular users tend to charge more at weekdays. Moreover, regular users exhibit a stronger charging station loyalty than random users. This is an intuitive and reasonable result. In conclusion, the results indicate that regular users show distinct characteristics from random users for both charging behavioral and vehicle variables.
Table 4. Characteristic of random and regular users

<table>
<thead>
<tr>
<th>Variables</th>
<th>Random users (n=6273)</th>
<th>Regular users (n=3255)</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Charging behavioral characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charging interval</td>
<td>7.001 (2.949)</td>
<td>2.133 (1.055)</td>
<td>0.000</td>
</tr>
<tr>
<td>Charging duration</td>
<td>4.751 (12.558)</td>
<td>7.378 (5.404)</td>
<td>0.007</td>
</tr>
<tr>
<td>Weekend charging</td>
<td>0.298 (0.234)</td>
<td>0.222 (0.148)</td>
<td>0.000</td>
</tr>
<tr>
<td>Total number of charging</td>
<td>25.279 (29.169)</td>
<td>94.817 (117.547)</td>
<td>0.000</td>
</tr>
<tr>
<td>Charging station loyalty</td>
<td>0.218</td>
<td>0.621</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>Vehicle characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EV type</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BEV</td>
<td>0.201 (0.401)</td>
<td>0.221 (0.414)</td>
<td>0.035</td>
</tr>
<tr>
<td>PHEV</td>
<td>0.782 (0.414)</td>
<td>0.759 (0.428)</td>
<td>0.019</td>
</tr>
</tbody>
</table>

6. CONCLUSIONS

This study has examined EV users’ inter-charging times to understand their charging patterns with longitudinal charging transaction data covering more than 4 years. Given that EV users exhibit heterogeneous charging behavior in terms of charging frequency (time interval between successive charging events) and charging regularity (regular charging versus ad-hoc charging), this study applied a parametric hazard model to examine how often EV user charge their car, and to distinguish the distinct characteristics of random (erratic) users and regular (routine) users. The results show that 67 per cent of EV users charge their car at random, while 33 per cent of them charge regularly. It is shown that regular users charge their EV more often than random users and have a battery electric vehicle (BEV). Also, it is found that differences exist between the two user groups in terms of charging characteristics, such as charging interval, charging duration, loyalty to charging station and total number of charging episodes.

Our results can be associated with quantifiable information about the periodicity of everyday charging activity. Such information is directly relevant to energy providers and to better manage smart grids. It provides the input to decide on the optimal location patterns of charging stations. It would be of interest in future research to incorporate models of dynamic charging behavior into computational process models of activity-travel behavior or into scheduling tools to derive essential information concerning the temporal allocation of recurrent behavioral activity-travel patterns. Both researchers and practitioners can gain new insights to better understand the periodic and repetitive nature of charging at public charging station.

An interesting future research topic is to examine the effects of covariates on hazard rates. In this study, we endogenously segmented EV users into two groups by considering only the patterns of charging intervals. Given that
charging activity is chained with daily activity schedule and the state of charge (SOC), it would be a valuable to examine how those variables affect charging regularity and charging frequency.

ACKNOWLEDGEMENT

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7. REFERENCES

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