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Fast-charging station choice behavior among battery electric vehicle users

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A B S T R A C T

This study explores how battery electric vehicle users choose where to fast-charge their vehicles from a set of charging stations, as well as the distance by which they are generally willing to detour for fast-charging. The focus is on fast-charging events during trips that include just one fast-charge between origin and destination in Kanagawa Prefecture, Japan. Mixed logit models with and without a threshold effect for detour distance are applied to panel data extracted from a two-year field trial on battery electric vehicle usage in Japan. Findings from the mixed logit model with threshold show that private users are generally willing to detour up to about 1750 m on working days and 750 m on non-working days, while the distance is 500 m for commercial users on both working and non-working days. Users in general prefer to charge at stations requiring a shorter detour and use chargers located at gas stations, and are significantly affected by the remaining charge. Commercial users prefer to charge at stations encountered earlier along their paths, while only private users traveling on working days show such preference and they turn to prefer the stations encountered later when choosing a station in peak hours. Only private users traveling on working days show a strong preference for free charging. Commercial users tend to pay for charging at a station within 500 m detour distance. The fast charging station choice behavior is heterogeneous among users. These findings provide a basis for early planning of a public fast charging infrastructure.

Introduction

Electric vehicles (EVs) driven by electric motors instead of traditional internal combustion engines are attracting more and more attention because they offer the potential benefits of reducing fossil fuel dependency, improving urban air quality, and thus helping the transition to more sustainable and environment-friendly travel. Battery charging is one important aspect of EV operation, while an inadequate charging infrastructure is consistently cited as a major barrier to widespread EV adoption (Bapna et al., 2002; Romm, 2006; Melaina and Bremson, 2008; Johns et al., 2009).

With the current charging technologies, the usual method of charging an EV is to plug it into a 120 V or 240 V outlet, as standardized in SAE J1772 (2010). This type of charging is referred to as normal charging, and several hours are required to

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completely charge a fully depleted battery. This type of charging can be performed at home. An EV battery can also be recharged at 480 V or higher using CHAdeMO technology (CHAdeMO, 2010). This is known as fast charging (or quick or rapid charging), and achieves an 80% charge in 30 min. It is usually performed at a charging station. Although for most usage EVs can be normal-charged during long stationary periods, fast charging plays an important role in long-distance trips or when an unexpected emergency arises. An field trial of battery electric vehicles (BEVs) in Japan (Successful Applicant for the FY, 2012) showed that it is rare for a car to require fast charging every day, but seen over a period of a couple of weeks or months nearly all owners need to use fast charging. It has also been pointed out by Christensen et al. (2010) that a fast-charging infrastructure is the most important need if EVs are to come into widespread use. However, the EV market is immature and the fast-charging infrastructure is incomplete, creating a barrier to adoption as noted above. Thus, the construction of EV fast charging stations is essential if EVs are to come into widespread use.

The optimal location of fueling stations for alternative fuel vehicles (AFVs; vehicles that run on fuels other than traditional petroleum, including electricity, biodiesel, ethanol, hydrogen, and natural gas) has in recent years been the focus of many proposed approaches and models. These studies are generally based on assumptions about drivers' preferences for refueling location. For example, *p*-median model (Hakimi, 1964) and maximal covering location model (Church and Velle, 1974) assume that drivers prefer to refuel close to home, work, or other key trip anchors; Flow Capturing Location Model (FCLM, Hodgson, 1990) and Flow Refueling Location Model (FRLM, Kuby and Lim, 2005) assume that drivers prefer to refuel en-route from origin to destination. In addition, driver's willingness to deviate from the shortest path to access a refueling station has been incorporated into modeling, such as Deviation Flow Refueling Location Model (DFRLM, Kim and Kuby, 2012) and Deviation Flow Refueling Location Model - enhanced (DFRLM-E, Yildiz et al., 2015).

Unfortunately, empirical studies on the refueling preferences of AFV users, and even of petroleum-powered vehicle users, are rare. About the refueling location, Sperling and Kitamura (1986) surveyed the refueling behavior of gasoline and diesel vehicle drivers through interviews while they refueled at selected fuel stations in northern California, treating diesel vehicles as a proxy for AFVs. They found that 56% of diesel vehicle drivers stated that convenience to home, work or school is the primary reason for selecting a fuel station. In other work, Kitamura and Sperling (1987) found that the refueling stops of gasoline vehicle drivers are clustered at the beginning or end of a trip, and close to home or work locations in particular. Kelley and Kuby (2013) updated the Sperling and Kitamura studies by interviewing drivers of compressed natural gas (CNG) vehicles while they refueled at selected stations in southern California using the same type of survey methodology. They concluded that more CNG drivers prefer fuel stations requiring the least deviation from the path between origin and destination than stations closest to home. Kuby et al. (2013) came to the similar conclusion when they investigated the refueling behavior of CNG drivers in Los Angeles. While these studies provide a general descriptive analysis of where drivers are most likely to refuel their vehicles, they fall short of providing insight about the decision-making process that drivers use. Further, these studies demonstrate that the decision of where to refuel is related to many factors, including the driver's activity program, the quantity of fuel remaining in the tank, and the location and attributes of fuel stations (Sperling and Kitamura, 1986; Kitamura and Sperling, 1987). However, the tradeoff among these factors in making a refueling location choice is left unsolved. Pramono provided some insights about the decision-making process and the tradeoff among various factors in gas station choice using a two-stage fixed-effect conditional logit model applied to data obtained by interviewing gasoline vehicle drivers while they refueled at selected stations in Bandung, the capital of West Java Province, Indonesia. About the deviation for refueling, Lines et al. (2008) conducted surveys on hydrogen rental cars at the Orlando International Airport, finding that more than 80% of respondents expressed a willingness to detour more than one mile away in order to refuel, and 46% were willing to detour more than three miles. Kelley and Kuby (2013) and Kuby et al. (2013) found that there is a sharp decay beyond six minutes of deviation for CNG drivers and the willingness to deviate is relatively consistent across stations. Pramono found that the sampled drivers are most likely to refuel at gas stations within 1500 m detour distance. However, caution is needed in mapping these data to the charging behavior of EV drivers for two reasons: first, the fast-charging of an EV takes longer than traditional petroleum vehicle and other AFV refueling; second, EVs can be normal-charged at home or in other locations where they remain stationary for some hours, in addition to fast charging at public charging stations.

With growing usage of EVs around the world, studies of charging behavior are beginning. Jabeen et al. (2013) explored EV drivers' preference for charging at work, home or public charging stations through stated choice experiments in Western Australia. In fact, this study not only covers charging location choice, but also choice of charging method, normal charging or fast charging. Arslan et al. (2014) analyzed the degrees to which plug-in hybrid electric vehicle (PHEV) drivers deviated from their shortest paths to recharge under several deployment levels of fast charging stations, using simulated trips. They found that the deviation is higher when fast charging stations are sparse. However, to the authors' knowledge, there has been almost no empirical research into choice behavior for fast charging stations.

An understanding of fast charging station choice behavior is of paramount importance in knowing how EV users trade off the relevant factors to make fast charging decisions, and will provide the basis for developing an effective fast charging infrastructure to accelerate EV market growth, which is essential for promoting EVs as societal and environmental policies. The aim of this paper is to provide insight into the process by which BEV users choose fast charging stations by exploring how various factors influence choice behavior. This paper also explores the specific distance by which BEV users in the sample are generally willing to detour to reach a fast charging station, in light of the above-mentioned findings about the detour willingness for refueling.

The remainder of this paper is organized in the following manner. In Section 'Field trial and data profiles' that follows, a brief overview is provided of the field trial from which the dataset used in this study was derived. It also explains some characteristics of fast-charging behavior seen in the samples. Section 'Modeling process' presents the modeling process, including the generation of the choice set and the model specification. Results and a discussion of model estimation are presented in Section 'Results of model estimation'. Section 'Conclusions' wraps up the paper with some conclusions.

Field trial and data profiles

The dataset used in this study is derived from a recent BEV usage trial conducted in Japan. The Ministry of Economy, Trade and Industry (METI) launched its Project of Consigning Technology Development for Rational Use of Energy in 2011 (Successful Applicant for the FY, 2012). From February 2011 to January 2013, the Japan Automobile Research Institute (JARI) collected probe data from nearly 500 BEVs used by both commercial fleets and private households in 42 out of 47 prefectures across Japan. The probe installed in these BEVs provides the following information: clock time, location (longitude and latitude), vehicle state (driving, normal charging or fast charging), odometer reading, air-conditioner/heater on or off state and battery state of charge (SOC). More information is also provided about the region in which each vehicle is registered. However, this trial does not provide users' socio-economic and demographic information, as well as their attitudes and perceptions toward fast-charging infrastructure. Additional details on the trial can be found in our earlier paper (Sun et al., 2015).

As the description of the trial makes clear, the data includes repeated observations for each individual. What needs to be clarified is that this study assumes one vehicle is driven and charged by one individual during the trial, even though it may be driven and charged by more than one person in practice, since such information is not provided by the trial. Generally, repeated observations from an individual tend to be similar, which means that individuals tend to make choices according to the same principle from one observation to the next. However, there are differences in choices across individuals; for example, availability-sensitive drivers may opt to charge whenever there is an available fast-charging station because of uncertainty about subsequent alternatives along their paths, while price-sensitive drivers may bypass the fee-paying stations along their paths and charge at free stations. In addition, it might be argued that one individual's choices might vary over time, as a result of experience and other factors. Such similarities and differences are unobserved but, in principle, can be discovered, since an individual's choices reveal something about them. This means that fast-charging station choice behavior would better be estimated using panel data, which is regarded as offering advantages over a single cross-section or time series data in capturing the complexity of human behavior (Hsiao, 2007). And the efficiency of using panel data is also revealed by our earlier paper about the modeling of normal charge timing choice behavior among BEV users (Sun et al., 2015). For this reason, individuals for whom there is only one observation during this trial are excluded from the sample set used.

As of the end of this field trial, the charging infrastructure has been expanded into all 47 prefectures of Japan to encourage EV usage. The charging stations have a maximum of four chargers, each with or without normal chargers, but more than 98% have at least one fast charger. These fast chargers are generally located at workplaces, leisure places, car sales outlets, parking lots, convenience stores and gas stations. In addition, 79.2% of these stations are available to any EV users for free or by paying a fee, 10.2% are available to members only for free or by paying a fee, and the remaining 10.6% are not open to the public and are only available to users belonged to the constructors of the charging stations for free. However, the trial does not provide information about whether a user is a member or a constructor-belonged of a charging station. Considering an EV user who is a member or a constructor-belonged of a charging station, if the user charges at a member-only or ownership-only station, then membership or ownership can be assumed to be the main reason for the choice. On the other hand, if such a user chooses a different station, that choice is made for reasons other than simple membership or ownership. Based on this understanding and keeping in mind that the objective of this study is to explore how factors influence fast-charging station choice behavior, it is reasonable to focus only on fast-charging events at stations available to any EV users. In addition, the research objective also implies that fast-charging events at charging stations that are the only available choice should be excluded from the dataset used in this study, since the factor of no other choice undoubtedly makes other factors unnecessary.

The data provided by the field trial is the location of each BEV and whether it being driven, normal charged or fast charged every minute. However, fast-charging decisions are made while a BEV is moving through the road network along the path from an origin to a destination. Therefore, the necessary first step before analyzing fast-charging station choice behavior is map matching, which associates a sorted list of vehicle positions with the road network on a digital map. The unit of map matching and analysis is a trip with fast charging. Considering that the battery packs of BEVs covered by this field trial support maximum driving mileages of 120 km and 180 km on a single full charge under typical road conditions, as well as that range anxiety is usually felt by EV users (Sun et al., 2015), more than one fast charging may be conducted during a trip. On the other hand, the current fast-charging time is much longer than the traditional refueling time, and users may engage some activities while charging, such as having a tea or making a short-time shopping, which raise such question that whether a stay for fast-charging ends a trip or not. The distribution of duration between initiating a fast-charging and starting the next traveling is shown in Fig. 1, which indicates an increase in percentage of stays for fast-charging when the duration is longer than one hour. Thus this study defines a trip with fast charging as: (1) a contiguous sequence of vehicle locations with the same start-up time for driving, followed by a stay for fast charging with a duration longer than one hour (Fig. 2-(1)); (2) two or more contiguous sequences of vehicle locations with the same start-up time for driving connected by stays for

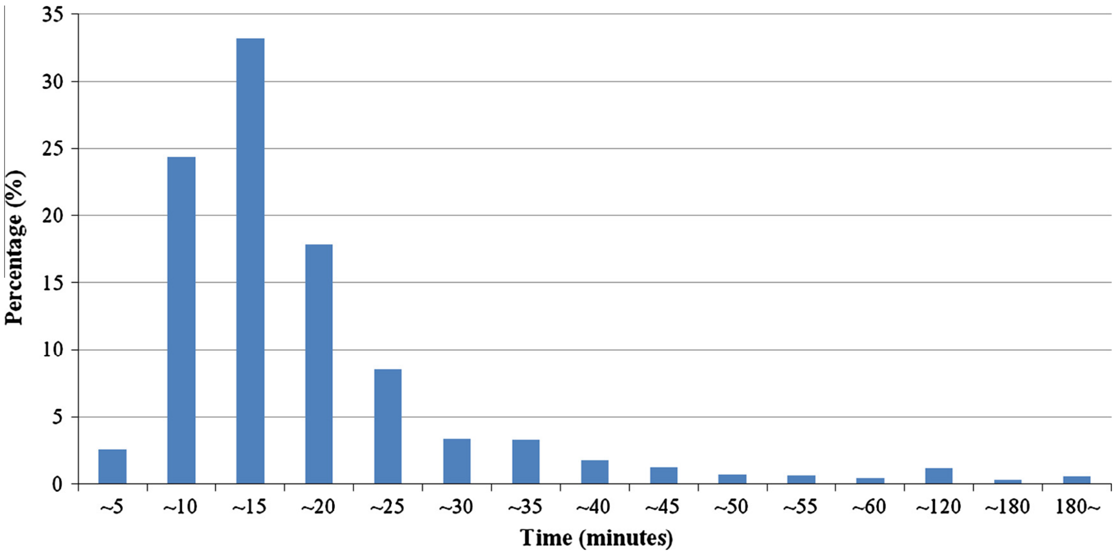

Fig. 1. Distribution of duration between initiating a fast-charging and starting the next traveling.

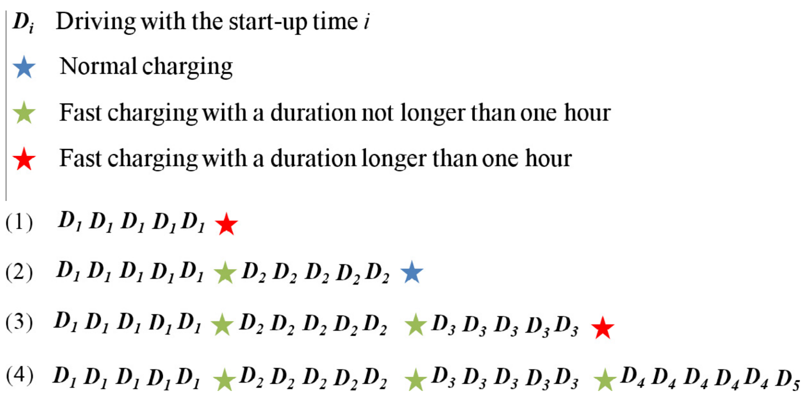

Fig. 2. Example diagram of a trip with fast charging.

fast-charging with a duration not longer than one hour, followed by a stay for normal charging (Fig. 2-(2)), or a stay for fast charging with a duration longer than one hour (Fig. 2-(3)), or a driving with a different start-up time (Fig. 2-(4)). And the origin and destination are denoted as the beginning and ending points of a trip with fast charging throughout this study. Given the good availability of digital maps for the prefecture and the sample size, the set of fast-charging events used for this study is further limited to those in Kanagawa Prefecture, where there are 2329 trips with fast charging made by 34 private vehicles and 518 trips with fast charging made by 12 commercial vehicles during the field trial.

Among trips with fast charging obtained according to the above definition, the trips with more than one fast charging do exist but the number is only 5% in Kanagawa Prefecture. The decision-making process for trips with one fast charge may be different from that for trips with more than one fast charge; for example, decisions about where to fast charge made during a particular trip may influence each other. Considering this situation and the available sample size, this study focuses only on trips where there is one fast-charging event between origin and destination.

In summary, this study focuses on fast-charging events that: (1) take place in Kanagawa Prefecture; (2) take place during trips that are successfully matched to the digital map; (3) take place at stations available to any BEV user; (4) permit a choice from more than one available station; (5) are by users who have more than one observation during the trial; and (6) are the only fast charging event between origin and destination. After data checking and cleaning, the final data set used in the study includes 24 private vehicles with 1513 fast-charging events and 8 commercial vehicles with 386 fast-charging events.

We now look at the characteristics of the data used in this study. Fig. 3 shows the distribution of observed SOC at the initiation of fast charging for commercial and private vehicles, respectively, on working and non-working days. Here "non-working days" includes both weekends and public holidays. This graph reveals that more commercial vehicles are fast charged at a higher SOC than private vehicles, and that a greater proportion of fast-charging events occur at higher SOC on non-working days. This makes it clear that charging behavior differs between commercial and private vehicles, as well as between working and non-working days.

The distribution of detour distance for commercial and private vehicles, respectively, on working and non-working days is shown in Fig. 4. The detour distance for individual n who charges at station j when traveling from origin O_{nt} to destination D_{nt} is:

$$detour_{njt} = d_{O_{nt}j} + d_{jD_{nt}} - d_{O_{nt}D_{nt}} \quad (1)$$

where $d_{O_{nt}j}$, $d_{jD_{nt}}$ and $d_{O_{nt}D_{nt}}$ are the shortest paths, respectively, between origin O_{nt} and station j, between station j and destination D_{nt}, and between origin O_{nt} and destination D_{nt}. This figure reveals that fast charging without detour is possible on only about 10% of trips. For trips with a detour for fast charging, about half have the minimum deviation from the shortest

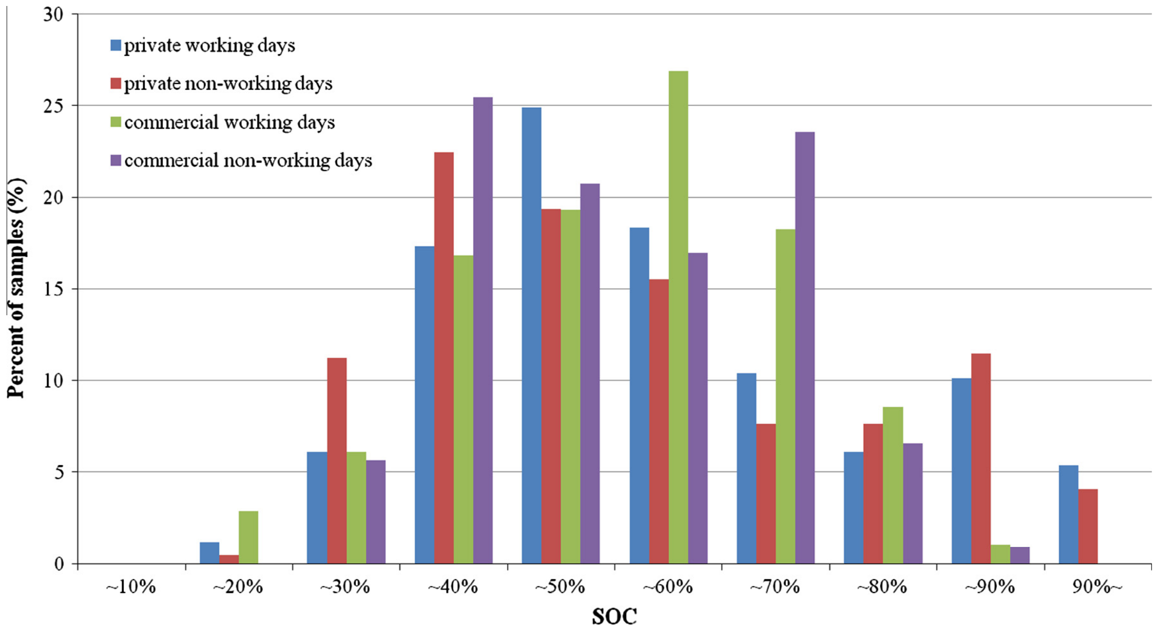

Fig. 3. Distribution of observed SOC at initiation of fast charging.

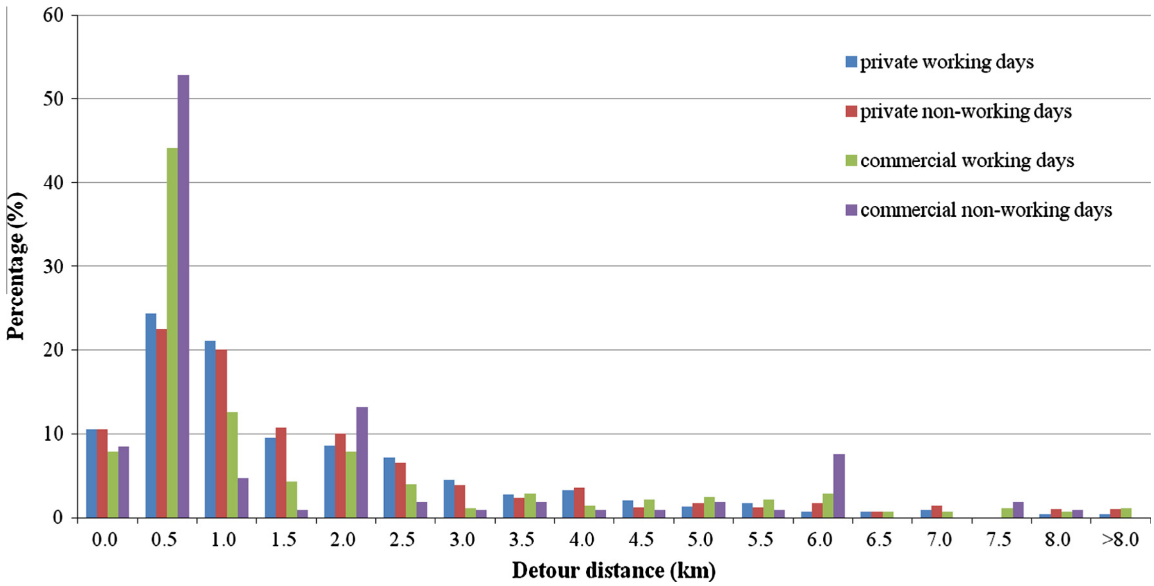

Fig. 4. Distribution of detour distance for fast charging.

path, 0.5 km or less, in the case of commercial vehicles, while the value is 1.0 km for private vehicles. In addition, greater detours for fast charging are more frequently seen on non-working days, but the difference between working days and non-working days is not as significant as that between private vehicles and commercial vehicles. However, it is still better to analyze fast-charging station choice behavior for private and commercial vehicles separately on working and non-working days, according to Figs. 3 and 4.

As previously mentioned, this study uses only fast-charging events occurring in Kanagawa Prefecture for reasons of map matching and sample size. Since the charging infrastructure is different in each Japanese prefecture and a different charging infrastructure can be expected to lead to different charging patterns, the charging characteristics displayed in Figs. 3 and 4 cannot be readily applied to other regions of Japan. Further, these charging characteristics cannot necessarily be regarded as an indication of the behavior of future BEV adopters in Kanagawa Prefecture, since the EV market is far from mature with an incomplete charging infrastructure, evolving battery technology and little utilization experience. It is for these very reasons that this study is carried out to explore how factors affect fast-charging station choice behavior. The ultimate aim is to provide a basis for developing an effective fast-charging infrastructure that accelerates EV market growth, and then promote EVs as societal and environmental policies.

Modeling process

The decision of where to charge can be described as a process by which BEV users choose one alternative from a set of alternatives while on their way to a destination. This section first discusses the generation of a choice set and then presents the methodology for modeling fast-charging station choice behavior.

Choice set

Generally, numerous charging stations are available to a BEV driver when the need to charge arises, but the level of remaining charge places some charging stations out of reach. Obviously, only accessible charging stations are considered, so the alternatives in the choice set must satisfy this spatial accessibility condition. Other studies related to spatial choice behavior usually consider simultaneously spatial accessibility and temporal accessibility in developing a choice set (Pramono; Arentze and Timmermans, 2005). However, in this trial there is no available information about trip purpose, time budget, traffic conditions and possible wait time due to the limited number of chargers at each charging station. For this reason, only spatial accessibility is adopted as a restriction in generating the choice set in this study. It is worth noting that the time at which the demand to charge arises is not available in the trial data and would be difficult to determine, so it is assumed that charging demand arises when a trip is started.

Among accessible stations, some may enable users to charge without detour from their intended routes, or with only a short detour; these stations can be reasonably taken as candidate alternatives in the choice set. However, there are accessible charging stations which are beyond a trip's origin or destination at a distance greater than the distance between the origin and the destination; whether these stations should be included in the choice set needs further discussion. The fast-charging events observed in Kanagawa Prefecture show that such stations are also chosen for charging, as revealed by Fig. 5. However, this does not mean it is reasonable to include all such accessible stations in the choice set, since a greater distance will place a station beyond consideration. In fact, private users on average tend to consider accessible stations that are an extra 1.8 km more than the distance between origin and destination, while the value is 2.8 km for commercial vehicles.$d_{O_{nt}j}$, $d_{jD_{nt}}$ and $d_{O_{nt}D_{nt}}$

In summary, this study adopts the following principles for generating the choice set, supplemented by the schematic diagram presented in Fig. 6. The alternatives in the choice set must satisfy:

(1) Accessibility: can be reached from the charging demand point (O_{nt}); the accessible set includes S_1, S_2, S_3, S_4, S_5 and S_6.
(2) Distance relations: $d_{O_{nt}S_j} \leqq d_{O_{nt}D_{nt}} + \varepsilon$ and $d_{S_jD_{nt}} \leqq d_{O_{nt}D_{nt}} + \varepsilon$, where $d_{O_{nt}S_j}$, $d_{S_jD_{nt}}$ and $d_{O_{nt}D_{nt}}$ are the shortest paths, respectively, between origin O_{nt} and station S_j, between station S_j and destination D_{nt}, and between origin O_{nt} and destination D_{nt}, where ε is 2.8 km for both private and commercial vehicles. The resulting choice set includes S_1, S_2, S_3, S_4 and S_5. This principle excludes from the set any fast-charging events where the station is more than distance ε further away than the distance between origin and destination; this accounts for 4.9% of the fast-charging events shown in Fig. 5 for private vehicles and 1.6% for commercial vehicles. These small proportions ensure the representativeness of the estimation results.

It should be noted that there is an assumption implied in generating choice set – that users have perfect information about the entire fast-charging infrastructure.

Methodology

This study adopts a mixed logit (ML) formulation to model fast-charging station choice behavior, since it is a powerful method for handing many sources of individual variability. The utility that individual n obtains from alternative j in choice situation t can be specified as:

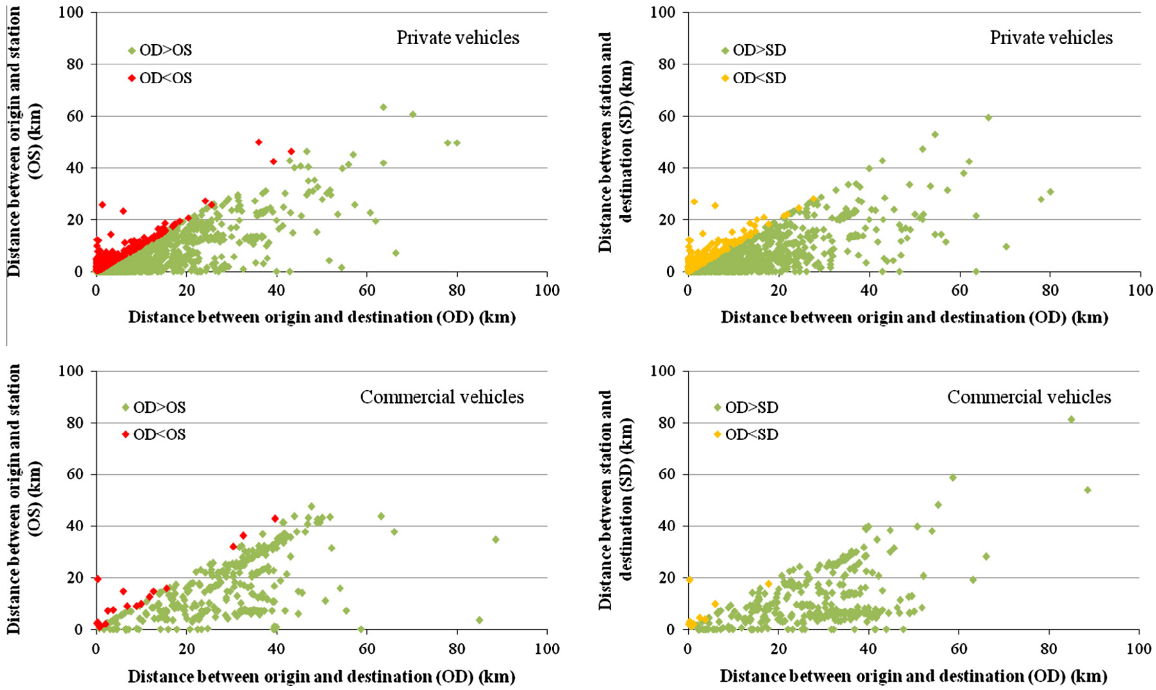

Fig. 5. Scatter diagrams of origin–destination distance against, respectively, origin-station distance and station-destination distance for private and commercial vehicles.

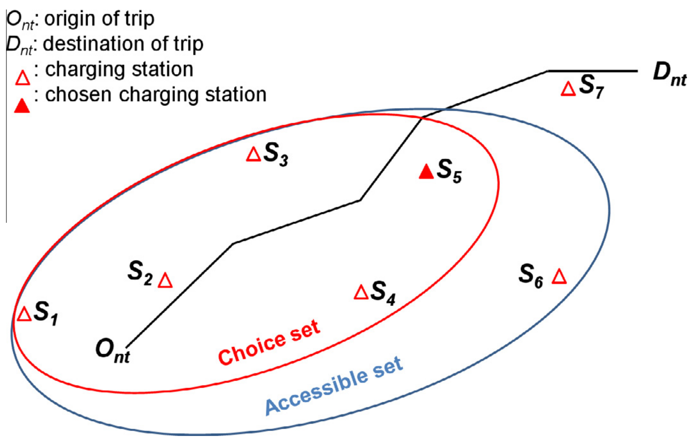

Fig. 6. Schematic diagram of choice set generation.

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \tag{2}$$

where X_{njt} is a vector of observed variables related to individual n and alternative j on choice situation t, β_n is a vector of coefficients of these variables for individual n, and ε_{njt} is a random term which is assumed to be an independently and identically distributed extreme value and varies over time, individuals, and alternatives.

The choice set for individual n in choice situation t is denoted by J_{nt}. Individual n chooses alternative i from J_{nt} if and only if $U_{nit} > U_{njt}\ \forall j \neq i$; here, U_{nit} and U_{njt} are obtained by individual n based on his/her own β_n, which is known to individual n but unobserved by the researcher. If the researcher were to observe β_n, then the choice probability would have the following form:

$$P_{nit}(\beta_n) = \frac{e^{\beta_n X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta_n X_{njt}}} \tag{3}$$

A detailed derivation of Formula (3) can be found in Train (Train, 2003). Since the researcher does not know β_n and therefore cannot condition on β_n, the unconditional choice probability must be the integral of $P_{nit}(\beta_n)$ over all possible values of β_n:

$$P_{nit} = \int \left(\frac{e^{\beta X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta X_{njt}}} \right) f(\beta) \mathrm{d}\beta \tag{4}$$

Thus the sample likelihood is:

$$L = \prod_{n=1}^{N} \int \prod_{t=1}^{T_n} \prod_{i=1}^{J_{nt}} \left\{ \frac{e^{\beta X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta X_{njt}}} \right\}^{d_{nit}} f(\beta) \mathrm{d}\beta \tag{5}$$

where $d_{nit} = 1$ if individual n chooses alternative i in choice situation t and zero otherwise. Usually, the distribution of β is specified freely by the researcher and then the parameters of that distribution are estimated. In most applications, $f(\beta)$ has been specified to be normal (Ben-Akiva and Bolduc, 1996) or log-normal (Revelt and Train, 1998), but other distributional assumptions also have been applied widely, such as truncated-normal and uniform (Revelt and Train, 2000), where, as pointed out by Train (Train, 2003), the appropriate choice depends on the research question. The parameters of the assumed distribution $f(\beta)$ can be estimated by maximizing the sample likelihood. However, there exists no analytical solution for the integral in (5). Therefore, in the literature, methods such as quadrature (Geweke, 1995) and simulation (Train, 2003) are proposed for its approximation.

This study assumes that β is identically and independently distributed over the individuals and follows a multivariate normal distribution with mean b and variance–covariance matrix W, $\beta \sim N(b,W)$, without correlations between independent variables. Simulation is used to estimate the parameters of the mixed logit model. The simulated sample likelihood is:

$$SL = \prod_{n=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} \prod_{i=1}^{J_{nt}} \left\{ \frac{e^{\beta_n^r X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta_n^r X_{njt}}} \right\}^{d_{nit}} \tag{6}$$

where R is the number of draws from the distribution of β, and β_n^r represents the rth draw for individual n. The standard approach to simulation-based estimation is to use random draws from the specified distribution; using this method, the accuracy of the results increases with the number of draws, but so does the estimation time. On the other hand, Halton sequences (Halton, 1960) have been used in several studies and they perform well with a small number of draws (Train, 2000; Bhat, 2001), so Halton sequences are adopted in this study.

The above-specified ML model is appropriate to accomplish one objective of this study, that of exploring how factors influence choice behavior for fast-charging stations. For the other objective, that of exploring the specific distance by which users in the sample are generally willing to detour for fast-charging, a ML model is also appropriate by just adding a threshold effect of detour distance to Formula (2):

$$U_{njt} = \alpha Z_{njt} + \beta_n X_{njt} + \varepsilon_{njt} \tag{7}$$

where Z_{njt} is a dummy variable related to individual n and alternative j in choice situation t representing whether the detour resulting from charging at alternative j is within the specific threshold value, α is the coefficient of this dummy variable fixed for all individuals,[3] and the other terms share the same meaning as that in Formula (2). This ML model with threshold effect is notated here as ML-T in order to differentiate it from the ML model in the discussion. The second objective of this study is explored by an iterative process of estimating ML-T with gradual changes in threshold value; the threshold value at which ML-T gives the closest model fitting is the distance by which users in the sample are generally willing to detour for fast charging.

It is obviously that ML-T can also be used to explore how factors influence fast-charging station choice behavior, so ML-T also offers an opportunity to explore choice behavior in a more effective way. The choice probability and model estimation of

[3] The threshold is not used in generating choice set. Actually, the choice sets used in each ML-T model (ML model with threshold effect for commercial and private vehicles, respectively, on working and non-working days) for different thresholds are the same in this study. However, there is an implication that users consider a charging station requiring a detour longer than the threshold as an alternative with certain probability, which is explained as follows:

Implicit choice set generation models (Cascetta and Popola, 2001; Martinez et al., 2009) have the probability expression for choosing alternative i as

$$P_{nit}(\beta_n) = \frac{\phi_{nit} e^{\beta_n X_{nit}}}{\sum_{j=1}^{J_{nt}} \phi_{njt} e^{\beta_n X_{njt}}} \tag{F-1}$$

where ϕ_{nit} is the probability that alternative i is included in the choice set, and the other terms share the same meaning as that in Formula (3). If we use the detour distance to affect this probability, $\phi_{nit} = 1$ if detour distance is within the threshold, and $\phi_{nit} = d$ $(0 \leqslant d < 1)$ if detour distance is longer than the threshold. The probability above can be rewritten as

$$P_{nit}(\beta_n) = \frac{e^{\beta_n X_{nit} + \ln(\phi_{nit})}}{\sum_{j=1}^{J_{nt}} e^{\beta_n X_{njt} + \ln(\phi_{njt})}} \tag{F-2}$$

Thus, compared with Formula (7), the parameter estimates on threshold can be interpreted as $\ln(\phi_{nit})$. If we use $Z'_{nit} = 1 - Z_{nit}$ as explanatory variable instead of Z_{nit} in Formula (7), we have $-\alpha$ as coefficient and adjust the constant term. And the probability of considering alternative i requiring a detour longer than the threshold as an alternative is: $\phi_{nit} = \exp(-\alpha)$.

ML-T can be obtained by simply adding αZ_{njt} to the exponential part in Formulas (3)–(6), so these formulas are not repeated here.

Next, we discuss the factors expected to affect users' choice of fast-charging stations.

Pramono's study revealed that two spatial effects influence users' choice behavior when selecting a gas station (Pramono). The first is a spatial structure effect, which derives from the fact that each alternative has a fixed position and faces a different degree of competition from the others, and the relative positive of each alternative will affect its likelihood of being chosen. The second is a spatial separation effect, which results from the fact that spatial separation between the individual's current location and the alternative has an impact on the individual's spatial cognition of the refueling infrastructure and, as a result, affects the choice. Given the similarity between choosing a refueling station for a gasoline vehicle and a BEV, in that the choice takes place while driving a route from origin to destination, this study adopts spatial dominance and detour distance, respectively, as representing the spatial structure effect and the spatial separation effect in modeling fast-charging station choice behavior.

The spatial dominance for alternative j with respect to individual n who is traveling from origin O_{nt} to alternative j is:

$$dom_{njt} = \sum_{i \in CS_{nt}} D_{nji} \tag{8}$$

where $D_{nji} = 1$ if alternative i is located along the shortest path between origin O_{nt} and alternative j, and zero otherwise; and CS_{nt} is the choice set for alternative n in choice situation t.

The detour distance between alternative j and the route of individual n who is traveling from origin O_{nt} to destination D_{nt} can be obtained using Formula (1).

In addition to these spatial effects, the non-spatial attributes of fast-charging stations can be expected to influence users' choice. This study adopts two indicators to explore the effect of non-spatial attributes based on the available information: an indicator for fast-charging stations available to any users for free and an indicator for fast chargers located at gas stations.

Waiting time due to the longer charging time compared with traditional petroleum vehicle and other AFV refueling time and limited number of chargers may affect users' choice, but unfortunately such data is not provided by this field trial. Since charging in peak hours might incur some waiting time, this study incorporates variables obtained by combining an indicator for charging in peak hours with the spatial variables of dominance and detour distance as well as with the non-spatial indicator for stations free to charge into the model in the hope of reflecting the effect of waiting time to some extent. Peak charging hours are taken to be 10:00–18:00 and 21:00–22:00, which are derived from observed charge timing in Kanagawa Prefecture.

Another important factor influencing fast-charging station choice is the remaining charge when fast charging begins, since this represents the urgency of charging. From this field trial we are able to obtain the SOC when fast charging is actually initiated at a charging station. For other stations in the choice set, however, the SOC when fast charging would begin if it were chosen is not directly provided. Therefore, we calculate the SOC for each alternative in the choice set to explore the effect of remaining charge. The remaining charge when an individual n reaches alternative j from origin O_{nt} is:

$$SOC_{njt} = SOC_{O_{nt}} - \frac{d_{O_{nt}j} \times eff_t}{cap_n} \times 100 \tag{9}$$

where $SOC_{O_{nt}}$ is the SOC at the origin O_{nt}; $d_{O_{nt}j}$ is the shortest path between origin O_{nt} and alternative j; eff_t is the average electric efficiency in choice situation t, which is calculated from the observed data and varies with usage of air-conditioner and heater as shown in Table 1; and cap_n is the battery capacity of vehicle n.

As previously mentioned, there is an indicator for alternatives where the detour distance is within the specific threshold value for the ML-T model. Additionally, the non-spatial attributes of fast-charging stations inside and outside the specific threshold value may have different attraction to users. So this study also incorporates a variable combining the indicator related to the specific threshold value with the non-spatial indicator for stations that are free to charge.

In summary, mixed logit models with and without a threshold effect of detour distance are used to model users' behavior in choosing a fast-charging station from a choice set. The spatial effects of dominance and detour distance, the non-spatial effects related to attributes of fast-charging stations, and the remaining *SOC* at initiation of fast charging, as well as certain combined effects, are incorporated into the models to explore their roles in determining charging station choice.

Table 1
Electrical efficiencies for different vehicle usage states.

Vehicle usage state	Electrical efficiency (Wh/km)
Heater (off) Air-conditioner (off)	109
Heater (off) Air-conditioner (on)	148
Heater (on) Air-conditioner (off)	186
Heater (on) Air-conditioner (on)	201

Results of model estimation

Given that two models are used in this study to explore the charging station choice behavior during trips with one fast-charging event between origin and destination, which is different for private and commercial users as well as between working and non-working days, eight sets of estimation results are presented in this section. Model estimation is conducted in the STATA software.

Since the number of parameters is different between ML and ML-T and the parameters are estimated by means of maximum likelihood estimation, we use Akaike's Information Criterion (AIC) Akaike, 1998 to choose the more effective model. Fig. 7 displays the AIC of ML model and ML-T models at different thresholds for private and commercial vehicles. It is clear that the introduction of the threshold effect of detour distance in the ML-T model improves the fitting for both private and commercial vehicles. Therefore, this study focuses on discussing fast-charging station choice behavior according to the estimation results of the ML-T model.

In Fig. 7, there are various local minima with similar AIC to the global minimum AIC, especially for private vehicles. So that, for the moment, one cannot be sure the results estimated at the optimum threshold at which the ML-T model achieves the closest fitting really represent the fast-charging station choice behavior of BEV users.

Comparisons of the estimation results of the ML-T models, respectively with the global minimum AIC and a local minimum AIC, reveal a very small difference, but the ML-T model with a local minimum AIC may yield a significant negative parameter estimate for the threshold variable. Since it can be expected that stations within the specific detour distance will be particularly attractive to BEV users, a statistically significant positive parameter estimate for the threshold variable seems largely reasonable. The t-statistics of the threshold parameter at different threshold values for both private and commercial vehicles are shown in Fig. 8, which, combined with Fig. 7, indicate that the threshold at which the ML-T model has the global minimum AIC also has the maximum significance in the model for private vehicles on working days and in the models for commercial vehicles on working and non-working days. In the model for private vehicles on non-working days, there are two threshold values with statistically significant positive parameter estimate and the threshold at which the ML-T model has the global minimum AIC has the second maximum significance.

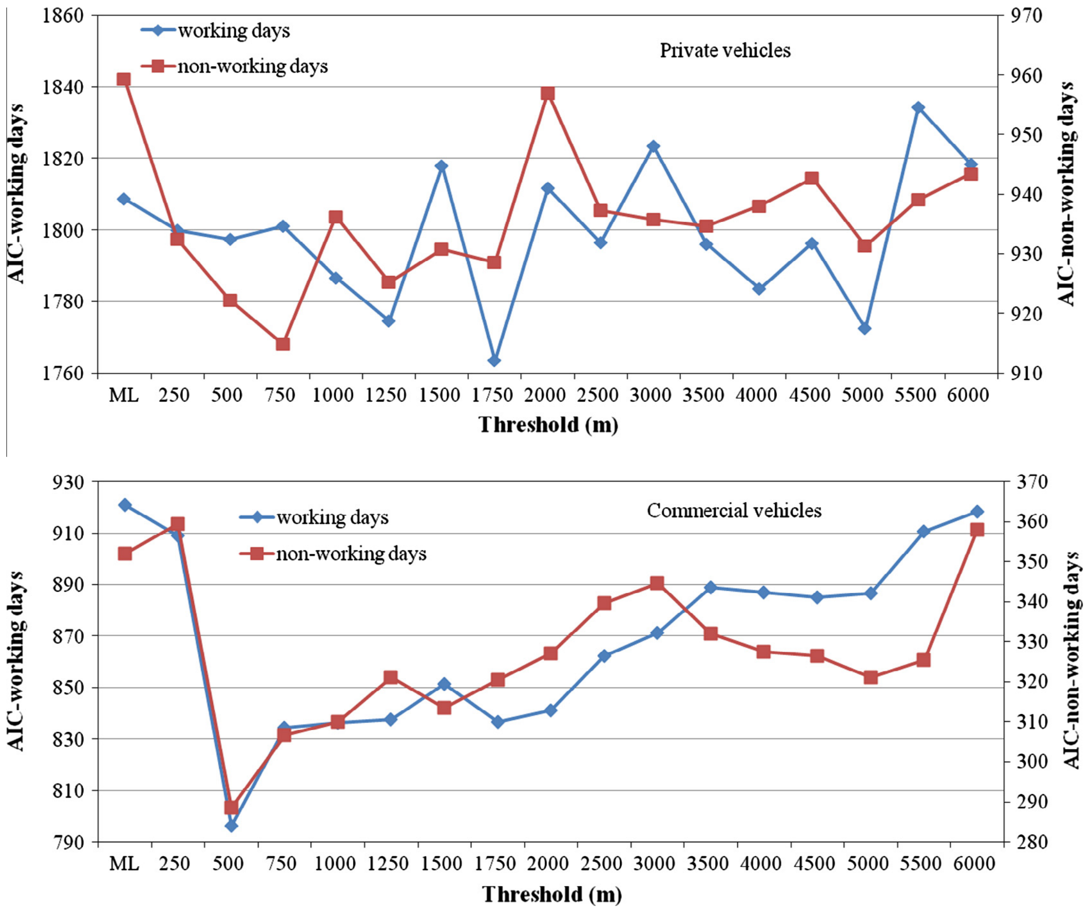

Fig. 7. AIC of ML model and ML-T models at different thresholds for private and commercial vehicles.

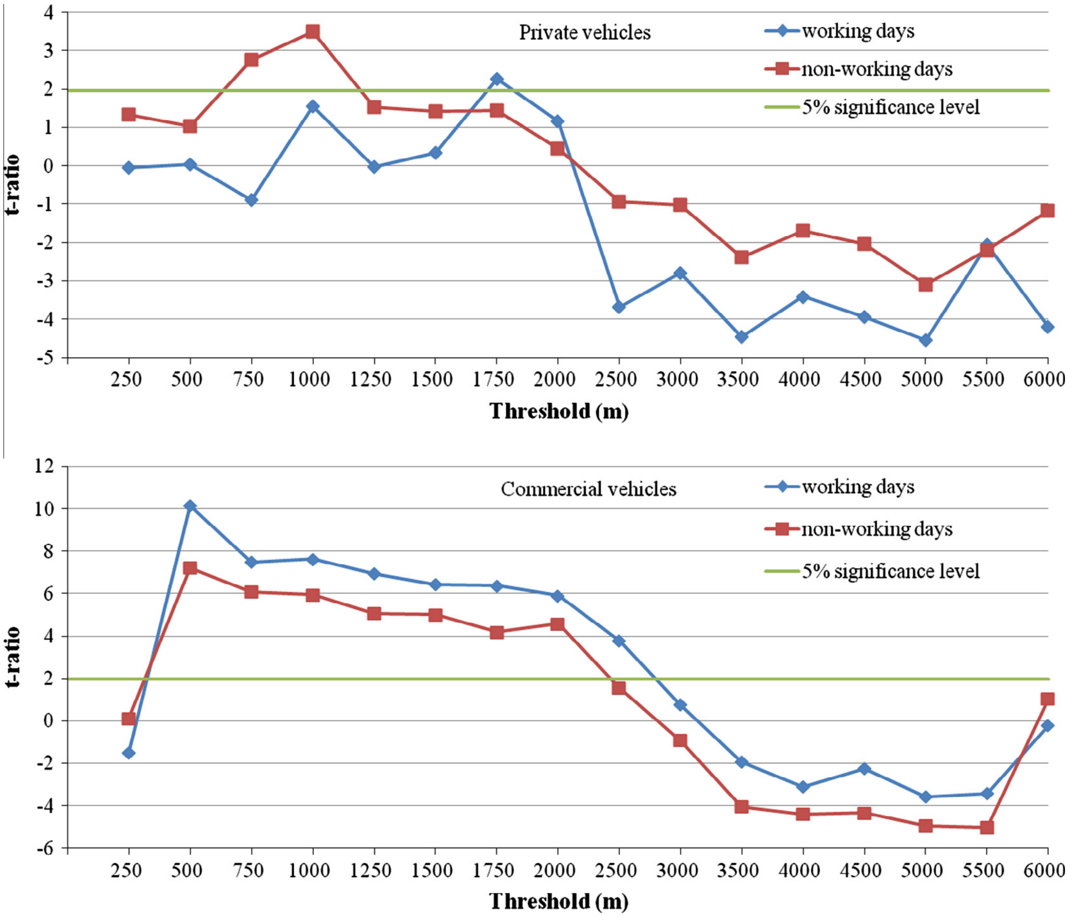

Fig. 8. t-statistic of threshold parameter at different thresholds for private and commercial vehicle.

All in all, there seems to be an indication that the results estimated at the optimum threshold at which the ML-T model achieves the closest fitting represent the fast-charging station choice behavior of BEV users in the sample to a large extent.

Table 2 presents the estimation results of the ML-T model for private and commercial vehicles, respectively, on working and non-working days, estimated at the optimum threshold at which the ML-T model achieves the closest fitting.

For private vehicles traveling on working days, users are generally willing to charge at stations that require a detour of 1750 m or less, and are less willing to charge at stations with a greater detour distance, as revealed by the significant negative effect of the detour variable. This preference is not significantly different when choosing a charging station in peak hours, as indicated by the non-significant effect of the variable of detour in peak hours. Further, they tend to charge at stations encountered earlier along their path from origin to destination, as revealed by the significant negative effect of the dominance variable. But they tend to charge at stations encountered later when they choose a station in peak hours, as indicated by the significant positive effect of the variable of dominance in peak hours. However, this does not mean they charge whenever they encounter an available fast-charging station earlier or later along their trips; in fact, they take the SOC into account when making charging decisions, as indicated by the significant negative effect of the SOC variable. In addition, these users prefer stations that are free to charge, and this preference is not significantly different when they choose a station in peak hours or from alternatives that require a detour of 1750 m or less, as revealed by the significant positive effect of the variable for stations free to charge, and the non-significant effects of the variables for stations free to charge in peak hours and stations free to charge within 1750 m' detour distance. Moreover, they prefer chargers located at gas stations. However, all the factors that significantly affect fast-charging station choice vary substantially among private users traveling on working days, as revealed by the statistically significant parameter estimates for the standard deviations of these random variables.

Users of private vehicles traveling on non-working days are generally willing to charge at stations that require a detour of up to 750 m. As on working days, they prefer to charge at stations with shorter detour distance and this preference is not significantly different when choosing a charging station in peak hours. Also they prefer to use chargers located at gas stations and take the SOC into account when making charging decisions. But the attribute of free to charge has no significant effect on their choice, neither choosing a station in peak hours or from alternatives within 750 m detour distance. And they do not show preference to charge at stations encountered earlier or later along their paths from origin to destination, neither

Table 2
Estimation results of ML model with threshold effect of detour distance.

Variable	Private vehicles				Commercial vehicles			
	Working days (Threshold = 1750 m)		Non-working days (Threshold = 750 m)		Working days (Threshold = 500 m)		Non-working days (Threshold = 500 m)	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Mean								
Threshold	0.490	0.217*	0.797	0.290**	2.837	0.279**	3.926	0.545**
Detour (km)	−0.800	0.070**	−0.650	0.101**	−0.661	0.113**	−0.511	0.122**
Dominance	−0.146	0.055**	0.043	0.040	−0.134	0.024**	−0.145	0.035**
Free	2.478	0.362**	0.681	0.517	0.698	0.531	−3.552	2.562
Gas-station	3.087	0.190**	2.760	0.292**	3.909	0.426**	3.007	0.692**
SOC (%)	−0.111	0.020**	−0.145	0.027**	−0.042	0.015**	−0.067	0.019**
Detour_peak (km)	0.023	0.071	0.001	0.113	0.168	0.128	0.048	0.482
Dominance_peak	0.077	0.029**	−0.036	0.046	0.058	0.035	0.047	0.066
Free_peak	0.311	0.300	0.625	0.554	1.659	0.535**	−1.130	1.622
Free_threshold	0.368	0.263	−0.078	0.419	−3.707	0.653**	−4.990	1.820**
Standard deviation								
Detour (km)	0.479	0.061**	0.096	0.050	0.117	0.094	0.473	0.812
Dominance	0.104	0.031**	0.096	0.031**	0.116	0.029**	0.065	0.152
Free	3.435	0.328**	2.314	0.383**	0.646	0.232**	2.992	1.454*
Gas-station	5.531	0.485**	1.889	0.275**	1.738	0.434**	0.212	0.806
SOC (%)	0.159	0.033**	0.256	0.048**	0.127	0.057*	0.777	0.720
Detour_peak (km)	0.234	0.083**	0.312	0.074**	0.004	0.094	0.481	1.051
Dominance_peak	0.065	0.029*	0.089	0.027**	0.095	0.053	0.131	0.065*
Free_peak	1.090	0.151**	2.512	0.770**	0.859	0.404*	3.564	1.622*
Free_threshold	2.540	0.286**	1.334	0.307**	0.488	0.423	0.995	1.409
LL(Bc)	−1077.019		−517.735		−414.143		−134.253	
LL(B)	−862.747		−438.441		−379.056		−125.305	

LL(Bc): log likelihood with constraint that all the standard deviations are equal to zero.
LL(B): log likelihood without constraint that all the standard deviations are equal to zero.
* Indicate significance at 5% level.
** Indicate significance at 1% level.

choosing a station in peak hours. Factors showing substantial variation in determining fast-charging station choice among private users traveling on non-working days include the indicator for chargers located at gas stations and SOC.

Next, we look at commercial vehicles traveling on working days. These users are generally willing to charge at stations that require a detour of up to 500 m. They prefer to charge at stations requiring a shorter detour or encountered earlier along their paths from origin to destination, and this preference is not significantly different when choosing a charging station in peak hours. Also they prefer to use chargers located at gas stations and take the SOC into account when making charging decisions. The free to charge attribute does not have a significant effect on choice, but it does have a significant positive effect when choosing a station in peak hours, while it has a significant negative effect when choosing a station from alternatives within 500 m detour distance. The factors showing substantial variation in determining fast-charging station choice among commercial users traveling on working days include dominance, the indicator for chargers located at gas stations, SOC and the indicator for stations free to charge in peak hours.

Lastly, users of commercial vehicles traveling on non-working days are also generally willing to charge at stations that require a detour of up to 500 m, and factors that significantly affect their choice are the same as those for commercial users traveling on working days, except that the interaction between free to charge and charging in peak hours has no significant effect. There are no factors showing substantial variation in determining fast-charging station choice among commercial users traveling on non-working days.

Comparing the estimation results in Table 2 shows that BEV users are willing to deviate from the shortest paths to reach a charging station, but the length of the detour is different for private and commercial users, respectively, on working and non-working days. Generally, private users are willing to detour by up to about 1750 m to charge their vehicles on working days and 750 m on non-working days, while the value is 500 m for commercial users on both working and non-working days. One possible reason for the shorter detour among private users on non-working days than on working days is that private users are less familiar with the charging stations along their trips on non-working days, so a greater detour may increases their anxiety of being stranded; this anxiety may encourage them to charge at stations requiring a smaller detour but where a fee must be paid. This is supported to some extent by the non-significant effect of the indicator for stations free to charge for private vehicles on non-working days. This argument implies that private users are price-sensitive and that their greater familiarity with stations along their trips on working days gives them the confidence to detour a greater distance to reach a free charging station. Another possible reason is that there is some degree of destination choice flexibility on non-working days, for example, a shopping destination which is near a charging station or whose route is dotted with charging stations.

The smaller detour among commercial users probably derives from the following three reasons: first, an anxiety (as noted above) resulting from less familiarity with stations along the trips; second, the nature of the service business, which requires punctuality, speed, and so on, leads commercial users to charge their vehicles at stations requiring a shorter detour; finally, commercial users may be less price-sensitive and are more willing to charge at stations requiring a smaller detour but where a fee must be paid, as indicated by the non-significant effects of the indicator for stations free to charge, as well as the significant negative effects of the combined indicator for stations free to charge and within 500 m detour distance, for commercial vehicles on both working and non-working days.

It is worth mentioning that although BEV users are willing to detour for fast charging, they actually want to avoid it, and this preference does not change significantly when choosing a station in peak hours. Moreover, the possible reason of familiarity with stations for different detours discussed above may also explain why BEV users all prefer to charge at gas stations.

Further, private users traveling on working days tend to charge at stations encountered earlier along their paths from origin to destination, but tend to charge at stations encountered later when choosing a station in peak hours, such change may be due to anticipated waiting time. On the other hand, commercial users tend to charge at stations encountered earlier along their paths on both working and non-working days, and this preference does not change significantly when they choose a station in peak hours. This may be due to the familiarity with stations and the nature of business, as mentioned previously, which might increase anxiety of commercial users that perhaps there would be no appropriate stations later in the trip, even for example stations requiring smaller detours. However, it should be noted that SOC also plays an important role in determining station choice for all BEV users, that is, the higher the SOC upon reaching a charging station, the lower the probability of charging at that station.

A final finding is that all or some of the factors that significantly affect fast-charging station choice vary substantially among users in three of the groups: private users traveling on working days, private users traveling on non-working days and commercial users traveling on working days. The less substantial variation among commercial users traveling on non-working days may result from the small sample size. However, a heterogeneity in choosing fast-charging stations is revealed among users in all four groups, as indicated by the likelihood ratio test; that is, the test statistic $-2[LL(Bc)\text{-}LL(B)]$ is significantly greater than the critical chi-square value with nine degrees of freedom in the four ML-T model estimates given in Table 2. Further, private users seem to be more heterogeneous than commercial users in choosing fast-charging stations, as revealed by the larger fluctuations of model fittings at different detour thresholds for private vehicles in Fig. 7.

In summary, choice behavior when choosing a fast-charging station differs between private and commercial users traveling on, respectively, working and non-working days. The distance by which they are generally prepared to detour for fast charging is different; the factors that significantly affect their choices are different; and the factors showing substantial variations in determining their choices are different. However, the results for all of these groups lead to broadly the same conclusions: that BEV users prefer to charge at stations requiring shorter detours and located at gas stations, and take the SOC into account when making charging decisions. In addition, the choice of fast-charging stations is heterogeneous among users in all four groups, though private users exhibit greater heterogeneity.

Conclusions

In this study, a mixed logit models with (ML-T) and without (ML) threshold effect are used to explore how various factors affect the choice of fast-charging stations made by users of battery electric vehicles (BEVs) and to explore the distance by which BEV users in the sample are generally willing to detour for fast charging. The data set used consists of trips that have one fast charge between origin and destination in Kanagawa Prefecture extracted from a BEV usage field trial in Japan. To the authors' knowledge, this is the first study applying a discrete choice model to the empirical analysis of fast-charging station choice behavior. The results should provide a basis for the early planning of a public fast-charging infrastructure, which can be expected to accelerate EV market growth and then promote EVs as societal and environmental policies.

The ML-T model is shown to fit better than the ML model, so ML-T estimation results are used to analyze fast-charging station choice behavior, leading to several discoveries. First, private users are generally willing to detour up to about 1750 m to charge their vehicles on working days and up to 750 m on non-working days, while the figure is 500 m for commercial users on both working and non-working days. Second, although BEV users are willing to deviate from the shortest path to reach a charging station, they prefer to charge at stations with a shorter detour. Third, commercial users show a preference to charge at a station encountered earlier along their paths from origin to destination, while only private users traveling on working days show such preference and they turn to prefer stations encountered later when choosing a station in peak hours. Fourth, the attribute of free to charge seems only to attract private users traveling on working days, and commercial users prefer to pay for charging at a station within 500 m detour distance. Fifth, all BEV users prefer chargers located at gas stations. Sixth, a higher SOC decreases the propensity to charge for all BEV users. Last, the choice of fast-charging stations is heterogeneous among users in all four groups: private and commercial users traveling on, respectively, working and non-working days. However, private users exhibit greater heterogeneity.

These results represent a glimpse into how BEV users choose a fast-charging station during trips that have one fast-charging event between the origin and the destination in Kanagawa prefecture. Caution must be exercised in extending the findings to other regions or to trips with more than one fast-charging event.

This study is limited in that some factors that might affect choice behavior are absent, including users' socio-economic and demographic attributes, users' attitudes and perceptions toward charging infrastructure, users' daily routine activities, and many others. Future studies including these factors may give further insights into users' charging behavior. In addition, given the long-noted variation of interpersonal and intrapersonal travel behavior in the transportation engineering literature, the relatively small sample of drivers that were eventually chosen (24 private vehicles and 8 commercial vehicles) may affect the consistency of results, which could be further verified by additional studies based on a large sample of drivers. It would be also interesting to apply the model proposed in this study to other areas with different fast-charging station densities to explore the relationship between charging patterns and development levels of charging infrastructure. The other key point is that this is a preliminary study on fast-charging station choice behavior based on trips, future study based on tours may presents a fuller picture of how users decide when and where to fast-charge their vehicles.

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