Charging Behavior of Battery Electric Vehicle Users in Japan

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Doctoral Dissertation

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by

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Abstract

Electric vehicles are expected to reduce fossil fuel dependency, improve urban air quality, and thus help the transition to more sustainable and environment-friendly travel. These effects are dependent greatly on how an electric vehicle is used. However, researches have shown that it is challenging for users to utilize batteries and charging infrastructure in an optimal way. Therefore, this study aims to explore how factors influence the way people currently charge their vehicles by using battery electric vehicle usage data extracted from a two-year field trial in Japan, with the hope of encouraging users to make effective use of battery and charging infrastructure. In addition, researches have shown that electric vehicle recharging in the evening or during off-peak hours has less of an impact on the electricity grid. However, users tend to recharge electric vehicles randomly at their convenience without considering the state of the electricity grid. Therefore, this study also aims to explore how factors influence choice behavior related to recharge timing by using the same data, with the hope of encouraging users to charge during off-peak hours by adopting suitable measures.

A stochastic frontier model is first used to explore how factors including charging infrastructure and battery technology associate the way people currently use batteries, as well as to explore whether good use of battery capacity can be encouraged, with the remaining charge when mid-trip fast charging begins is treated as a dependent variable. The estimation results obtained using four models, for commercial and private vehicles, respectively, on working and non-working days, show that remaining charge is associated with number of charging stations, familiarity with charging stations, usage of air-conditioning or heater, battery capacity, number of trips, Vehicle Miles of Travel, speed, and the type of business. However, the associated factors are not similar for the four models. In general, battery electric vehicles with high-capacity batteries are initiated at higher remaining charge. The

estimation results also show that there are great opportunities to encourage more effective battery usage. It appears that the stochastic frontier modeling method is an effective way to model the remaining charge at which mid-trip fast-charging should be initiated, since it incorporates trip and vehicle characteristics into the estimation process to some extent.

Then this thesis 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, and the former shows a better model fitting. Findings from the mixed logit model with threshold show that private users are generally willing to detour up to about 1750m on working days and 750m on non-working days, while the distance is 500m 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 meters' 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.

Lastly, this thesis examines choice behavior in respect of the time at which battery electric vehicle users charge their vehicles. The focus is on normal charging conducted at home after the last trip of the day, and the alternatives presented are no charging, charging immediately after arrival, nighttime charging, and charging at other times. A mixed logit

model with unobserved heterogeneity is applied separately for commercial and private vehicles, and estimation results suggest that state of charge, interval in days before the next travel day, and vehicle-kilometers to be traveled on the next travel day are the main predictors for whether a user charges the vehicle or not, that the experience of fast charging negatively affects normal charging, and that users tend to charge during the nighttime in the latter half of the trial. On the other hand, the probability of normal charging after the last trip of a working day is increased for commercial vehicles, while is decreased for private vehicles. Commercial vehicles tend not to be charged when they arrival during the nighttime, while private vehicles tend to be charged immediately. Further, the correlations of nighttime charging with charging immediately and charging at other times reveal that it may be possible to encourage charging during off-peak hours to lessen the load on the electricity grid. This finding is supported by the high variance for the alternative of nighttime charging.

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Chapter 1

Introduction

1.1 Background

Electric vehicles (EVs) are attracting more and more attention because they are expected to help the transition to more sustainable and environment-friendly travel, for their potential to improve urban air quality levels (Hawkins et al., 2013), and reduce fossil fuel dependency (Lopes et al., 2009). However, despite the impressive environmental, economic and societal benefits that EVs may deliver, there are several major problems that stand in the way of promoting their greater use, and the limited range between charges is typically perceived as one of them (Dimitropoulos et al., 2011).

To make consumers more comfortable buying and using EVs, part of great efforts is being made to improve the storage capacity of batteries, with the expectation of dealing with the range problem by increasing range on a single full charge. However, researches have shown that it is a big challenge for users to utilize batteries optimally, they typically initiate recharging at higher remaining electricity (Franke et al., 2012; Franke and Krems, 2013a), which is mainly because the limited range compared to that of conventional vehicles heightens the fear of running out of power. Since the economic and environmental benefits of EVs are dependent greatly on the battery capacity (Shiau et al., 2009; Neubauer et al., 2012), the additional battery requirement resulted from the inefficient range utilization certainly has an adverse impact on the benefits that EVs may deliver. Therefore, it would be beneficial to understand the charging behavior related to battery usage to guide more effective utilization of EV battery.

Another part of efforts is being made to deploy a public charging infrastructure to solve the range problem by providing convenient recharging opportunities, which has been shown to be an effective way to address the anxiety caused by limited range (Neubauer and Wood, 2014). However, the charging infrastructure seems to have been underutilized. Observation of EV usage at Tokyo Electric Power Company (TEPCO) has indicated that though the remaining charge at the end of a journey decreases with the implementation of additional charging stations, these stations are infrequently utilized (Electrification Coalition, 2009). TEPCO's experience raises questions such as how much charging infrastructure is sufficient, what kind of charging infrastructure layout is effective, which show the importance of understanding charging behavior related to charging station usage to develop an effective charging infrastructure.

One inevitable concern which comes with EVs' popularization is the impact of recharging on the electricity grid, since it might add a significant load, which possibly requiring changes to the existing infrastructure. Previous researches demonstrate that the effect of EV recharging on the electricity grid depends crucially on the timing of recharging (Hadley, 2006; Shao et al., 2009; Axsen and Kurani, 2010; Elgowainy et al., 2012). Generally speaking, recharging initiated during off-peak hours has less impact on peak loads than that during peak hours. However, users tend to recharge EVs randomly at their convenience without considering the state of the electricity grid, thus it is important to understand charging behavior related to charge timing choice to encourage users to charge at appropriate timing.

Currently, the EV market is far from mature with evolving battery technology, an incomplete charging infrastructure and a small number of EVs on the roads. But several national and local governments around the world are promoting the introduction and mass market adoption of EVs. Therefore, it is necessary to explore charging behavior, related to battery usage, charging infrastructure usage, and charge timing choice, to provide a basis for guiding effective battery utilization, developing an effective charging infrastructure, and encouraging more appropriate charge timing, which can be expected to accelerate EV market growth and promote EVs as societal and environmental policies.

1.2 Electric vehicles

1.2.1 Types of electric vehicles

Electric vehicles are all kinds of vehicles that are powered entirely or partially by electricity. Currently, there are four types of EVs: battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs) and fuel-cell electric vehicles (FCEVs). While each has its advantages and disadvantages, all save on fuel and reduce greenhouse gas emissions.

BEVs run entirely on electricity via batteries that are recharged by plugging into electricity grid. BEVs have no internal combustion engine, so they do not directly consume any fossil fuel and do not produce any pollution from the vehicles themselves. Moreover, because BEVs use electricity instead of fossil fuel, consumers can save more money by using a BEV than they would with a conventional vehicle. But the initial purchase price of BEVs is significantly higher than the similar conventional vehicles. Also the BEVs on the market today generally go around 120 to 180km on a single full charge, which is very limited compared with 500km or more between refuelings for most conventional vehicles. The higher purchase cost and limited range are two major barriers for their acceptance. However, there is strong government support for the development and sale of BEVs for their excellent fuel-saving and environmental benefits, including incentives to developers for improving battery technology and to consumers for their purchase. Thus it is likely that BEV ranges will be extended even further and the purchase cost will be lowered in the future, making BEVs become attractive alternatives for many consumers.

PHEVs run partially on electricity via batteries that are recharged by plugging into the electricity grid. The PHEVs on the market generally support a range of 10 to 35km in electric-only mode. They are also equipped with an internal combustion engine that can be used to replace the electric motor when the battery is depleted and more power is required, which gives PHEVs a significantly increased range compared to BEVs. What’s more, the initial purchase cost of PHEVs is comparable to the similar conventional vehicles. The usage of electricity would save more money for consumers than they would with a conventional vehicle, and the savings can be comparable to BEVs if the distance traveled before recharging always less than the vehicle's range in electric-only mode. Also, using electricity makes PHEVs achieve good environmental benefit. But the fuel savings and environmental benefit are not so significant if consumers always take long distance trips using gas mode. PHEVs currently have advantages over BEVs because the initial purchase cost is acceptable for consumers and the internal combustion engine makes consumers comfortable with driving range. However, once purchase cost of BEVs resembles the conventional vehicles and their driving ranges are extended, consumers may prefer BEVs for their increased fuel savings and lessened environmental impact.

HEVs combine both an electric motor and a gasoline engine. Though these vehicles have a battery, they cannot be plugged into electricity grid to be recharged. Instead their batteries are recharged by converting kinetic energy into electricity using regenerative breaking, such energy is normally wasted in the conventional vehicles. The electric motor works simultaneously with the gasoline engine to power the vehicle, which dramatically increase fuel economy and reduce gasoline use. HEVs have an advantage in initial purchase cost, but the environmental benefit is very limited.

FCEVs use only an electric motor like BEVs, but the energy is stored in a quite different way. FCEVs store hydrogen gas in a tank, the fuel cell in FCEVs combines hydrogen with oxygen to produce electricity, which then powers the electric motor just like a BEV. And like BEVs, there is no pollution from the vehicles themselves – the only byproduct is water. Unlike BEVs, however, there is no need to plug FCEVs into electricity grid, because their fuel cells are recharged by refilling with hydrogen gas. Though FCEVs are considered as the best EVs for their water-only emissions, they are still in development phases, and there are many challenges in extracting hydrogen from renewable resources and delivering hydrogen to fuel stations.

The BEVs and PHEVs are the most common EVs offering impressive environmental, economic and societal benefits on the current market. They are collectively referred to as “plug-in electric vehicle” (PEV), which is defined as any vehicle that can be recharged from an external source of electricity (Sandalow, 2009). And the issues of charging behavior discussed above are raised related to them.

1.2.2 Types of battery charging

The introduction of EVs shows that battery charging is one important aspect of PEV operation. A convenient infrastructure for charging may bolster the market acceptance of PEVs.

Charging PEVs requires plugging in to electric vehicle supply equipment (EVSE). EVSE for PEVs is classified by the rate at which the batteries are charged. And charging times vary depending on the type of EVSE, as well as the type of battery, how much energy it holds, and how depleted the battery is.

Currently there are three types of EVSE: Level 1, 2 and 3. Level 1 EVSE provides charging through a standard alternating current (AC) 120 Volt (V) household outlet. This is the most convenient home-based charging method, but it is also the slowest one. Charging times vary greatly from vehicle to vehicle depending on the battery type, but generally take around 10-20 hours for a fully depleted battery to be fully recharged.

Level 2 EVSE offers charging through 240V AC outlet, and is therefore a bit faster than Level 1, but requires installation of dedicated equipment. Level 2 EVSE is usually located in public places, such as the workplaces, parking lots, shopping centers, restaurants, and so on. It can also be located at home, which typically means an additional investment is required for PEV owners. Level 2 charging times are variable and depend upon the vehicle as well as the equipment. Generally speaking, Level 2 charging takes around 4-8 hours for a full charge.

Level 3 charging typically operates at 480V or higher voltage. Due to the much higher voltage, Level 3 EVSE requires installation of dedicated equipment, and is normally located in public places, operating like a filling station. The higher voltage also offers Level 3 as the fastest and most powerful type of charging available, which typically provides an 80% charge in 30 minutes.

Level 1 and Level 2 are often collectively referred to as normal charging, which takes several hours to fully recharge a PEV; while level 3 is known as fast charging (also known as quick or rapid charging), which reduces the charging time from hours to minutes, making an effective complement to normal charging.

For a PEV recharging, the battery charger is one of the key auxiliaries, which replenishes energy for a PEV like a gasoline pump refills a gas tank. The battery chargers can be classified into two types: on-board and off-board. An on-board charger means the charger is in the PEV, and the battery can be recharged anywhere there is an electric outlet. While an off-board charger means the charger is at a fixed location, and the battery can be recharged only there is an available charger. Typically, an on-board charger is limited in the power output because of size, weight, and cost constraints dictated by the vehicle design, while an off-board charger is less constrained by size and weight. Both Level 1 and Level 2 charging are on-board, supplying AC power to the vehicle's charger, which then converts the energy to direct current (DC) for storage in the battery. However, Level 3 charging is off-board, with the DC output directly to the vehicle's battery pack bypasses PEV on-board chargers, thus Level 3 charging is also called DC fast charging.

Level 1 and Level 2 have been standardized in SAE J1772 (Electric Vehicle and Hybrid Electric Vehicle Conductive Charge Coupler, 2010), but have slight national differences given the differences in utility voltages among countries, for example, in Japan, Level 1 and 2 charge at 100V and 200V respectively. Most vehicles and charging equipment support the standard of SAE J1772, which provides an excellent compatibility for Level 1 and Level 2 charging. However, Level 3 has not been standardized, and there are currently three major fast-charging standards in the world: CHAdeMO, the SAE J1772 Combined Coupler Standard (called CCS or "Combo"), and Tesla. All these three standards use different connectors and software, leading to compatibility problem. But CHAdeMO is the most common fast charging technology by far, as it is used by the Nissan Leaf – the most popular EV on the market.

The characteristics of each type charging are summarized in Table 1.1.

Table 1.1 Characteristics of battery charging

Charging Level	Type	Power supply	Charger location	Charging time (24kWh battery)	Typical use	Standard
Level 1	Normal	120V AC	On-board	16 hours	Home	SAE J1772
Level 2	Normal	240V AC	On-board	8 hours	Home or public places	SAE J1772
Level 3	Fast	480V DC	Off-board	30 minutes	Public places	CHAdeMO/CCS/ Tesla

1.3 Related researches

Exploring on refueling behavior with alternative fuel vehicles (AFVs, vehicles that run on fuels other than traditional petroleum, including electricity, biodiesel, ethanol, hydrogen, and natural gas) started about several decades ago. Since there were few AFVs on the road, however, such studies usually entail analyzing the refueling behavior of traditional-fuel-vehicle drivers (e.g. Dingemans et al., 1986; Kitamura and Sperling, 1987). With the promotion of AFV Projects around the world, refueling behavior is beginning to be explored based on real-life AFV usage data (e.g. Kuby et al., 2013; Kelley and Kuby, 2013), and so is the charging behavior of EV users (e.g. Smart and Schey, 2012; Robinson et al., 2012; Franke et al., 2012; Franke and Krems, 2013a; Franke and Krems, 2013b; Zoepf et al., 2013; Jabeen et al., 2013).

Generally, previous researches on EV charging behavior can be classified into three groups according to their research contents. The first one usually presents the statistical characteristics of charging behaviors observed in an EV project, such as the number of daily charging, the remaining electric when charging begins, the location of charging (home, work, public charging stations, and others), and so on. The studies of Smart and Schey (2012), Robinson et al. (2012) belong to this group. The second group focuses on the EV range utilization from psychological perspective. The representative studies are Franke et al. (2012), Franke and Krems (2013a), Franke and Krems (2013b). By investigating the psychological dynamics of user-range interaction, these studies identified the variables that influence the actual usable range for EV users. And the third group aims to model the behavior of charging choice, such as whether charge or not at the end of a trip, where to charge (home, work, or public charging stations), and so on. The studies of Zoepf et al. (2013) and Jabeen et al. (2013) belong to the third group.

Previous studies have revealed that familiarity or experience greatly influences refueling behavior (Dingemans et al., 1986; Kitamura and Sperling, 1987; Franke et al., 2012), and refueling choice is the result of a learning process (Dingemans et al., 1986; Franke et al., 2012). Currently, the EV market is at developing stage with the charging infrastructure becomes more spatial diffusion, technical progress is made with batteries, and drivers gain more experience. Therefore, just presenting the statistical characteristics of charging behaviors and exploring the variables that influence the charging behaviors are not enough to provide informed strategies for promoting the development of EV market, as well as constructive advices for directing the construction of infrastructure for EVs. Rather, it is necessary to explore how various factors influence charging behaviors based on real-life EV usage data, which is rarely involved in previous studies.

1.4 Objective of this thesis

In light of the above discussion about the related researches on charging behavior as well as the charging issues mentioned in the background, basing on the two-year field trial on BEV usage in Japan, this thesis aims to explore: 1) how various factors influence charging behavior related to battery usage; 2) how various factors influence charging behavior related to charging infrastructure usage; 3) how various factors influence charging behavior related to charge timing choice.

1.5 Organization of the thesis

This thesis is composed of six chapters, and the remainder is organized in the following manner.

Chapter 2 introduces the field trial on BEV usage in Japan. The BEVs participating in the field trial and the development of charging infrastructure in Japan are firstly introduced. Then the statistical characteristics of observed driving and charging behaviors are presented, including the trip distance, the number of daily trips, the remaining electricity when charging begins, the charge timing, and so on.

Chapter 3 examines the charging behavior related to battery usage. The focus is on the mid-trip fast charging, taking place after leaving the origin and before arriving at the destination. A stochastic frontier model is used to explore factors that influence the remaining charge when mid-trip fast charging begins, as well as to explore whether good use of battery capacity can be encouraged. The effects of various factors on the remaining charge when mid-trip fast charging begins are discussed based on the estimation results. And the average inefficiency in battery usage is also discussed by comparing the actual remaining charge with the predicted required charge.

Chapter 4 examines the charging behavior related to charging infrastructure usage. The focus is on fast-charging events during trips that include just one fast-charge between origin and destination in Kanagawa Prefecture. Mixed logit models with and without a threshold effect for detour distance are applied to explore how BEV 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 estimation results are discussed to show the effects of various factors on the choice of fast charging stations. And the generally willing detour distance is obtained by comparing the model fittings of models with different thresholds.

Chapter 5 examines the charging behavior related to charge timing choice. The focus is on normal charging after the last trip of the day, and the alternatives presented are no charging, charging immediately after arrival, nighttime charging, and charging at other times. A mixed logit model with unobserved heterogeneity is applied to explore choice behavior in respect of the time at which BEV users charge their vehicles. The effects of various factors on the choice of normal charge timing are discussed based on the estimation results.

Chapter 6 provides the conclusions and future directions followed by this thesis.

Chapter 2

Field trial and data profiles

This chapter introduces the field trial on BEV usage conducted in Japan. Firstly, the BEVs participating in the field trial and the development of charging infrastructure in Japan are introduced. Following this, the statistical characteristics of observed driving and charging behaviors are presented, including the trip distance, the number of daily trips, the remaining electricity when charging begins, the charging locations, the charging timing, and so on. Finally, a summary is presented to wraps up this chapter.

2.1 Background

The Ministry of Economy, Trade and Industry (METI) launched its Project of Consigning Technology Development for Rational Use of Energy in 2011 (Successful Applicant, 2012). From February 2011 to January 2013, the Japan Automobile Research Institute (JARI) collected data from nearly 500 BEVs used by both commercial fleets and private households in 42 out of 47 prefectures across Japan. Throughout this thesis, vehicles owned by fleets are referred to as "commercial vehicles", which include both business vehicles and government vehicles, while vehicles owned by households are referred to as "private vehicles".

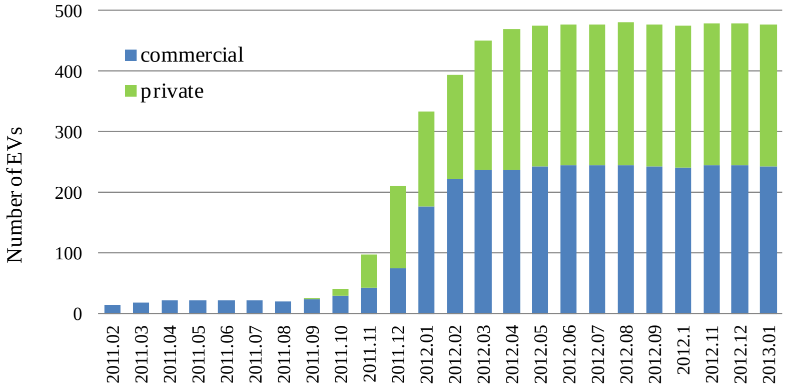


Figure 2.1 Number of BEVs participating in the field trial

Figure 2.1 shows these BEVs participating in the field trial. It is worth noting, from Figure 2.1, that although the total trial period was 24 months, the sampling of private vehicles began in October 2011, and not every vehicle in each group participated in the trial at the same time. Most vehicles, however, were observed over the final 12 months of the trial.

As of the end of this field trial, the charging infrastructure has been expanded into all 47 prefectures of Japan to encourage BEV usage. The charging station density for each prefecture is shown in Figure 2.2, which indicates that the density of charging stations varies greatly from region to region in Japan.

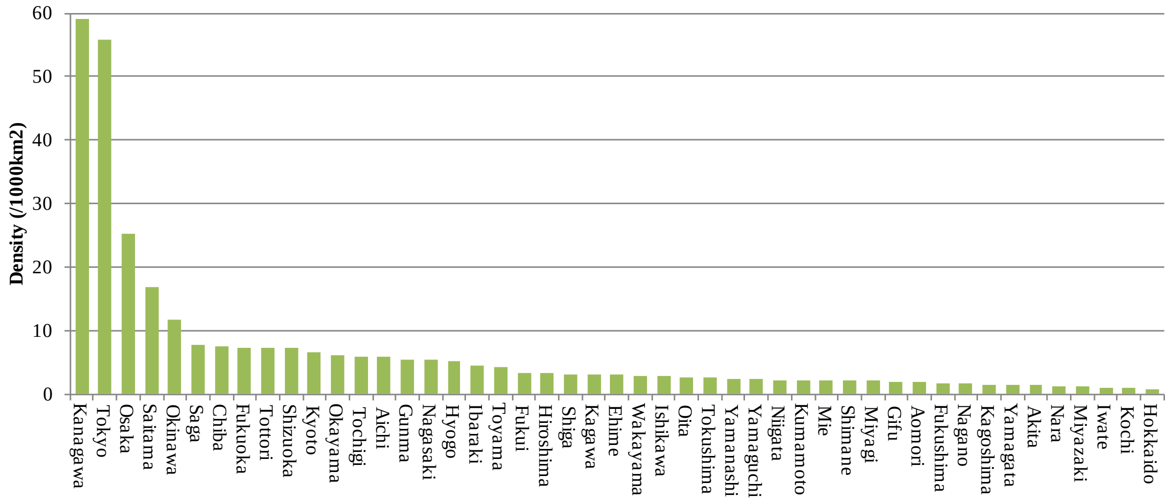


Figure 2.2 Charging station density for each prefecture

2.2 Vehicles and charging infrastructure

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. The normal charger operates at 100V or 200V, and the fast charger operates at 480V using CHAdeMO technology (CHAdeMO, 2010). 79.2% of these stations are available to any BEV 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. The fast chargers are generally located at workplaces, leisure places, car sales outlets, parking lots, expressway service areas, convenience stores and gas stations, as shown in Figure 2.3.

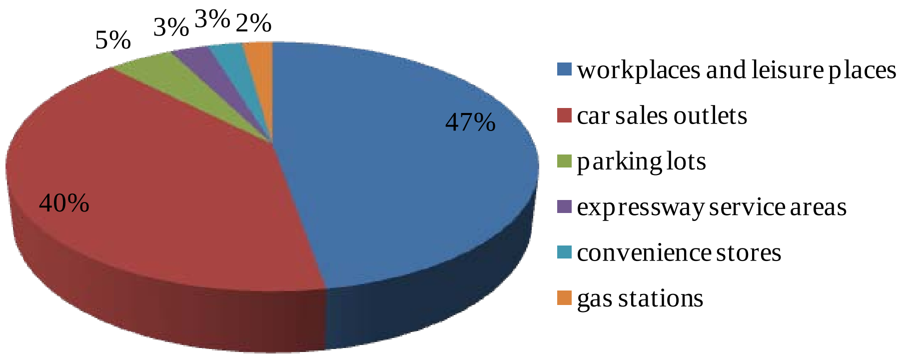


Figure 2.3 Locations of fast charging infrastructure

The type of BEVs participating in the field trial is not disclosed for privacy reasons, but the battery packs used in these vehicles can support maximum driving mileages of 120km and 180km on a single full charge under typical road conditions. All of the vehicles trialed can both be normal-charged and fast-charged using the public charging infrastructure, except for charging at home.

2.3 Observed driving and charging behaviors

The probe installed in these BEVs provides the following information: clock time, vehicle 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 and the type of business in the case of commercial vehicles. However, this trial does not provide users' socio-economic and demographic information, as well as their attitudes and perceptions toward charging infrastructure. The following sections will present the statistical characteristics of driving and charging behaviors of nearly 500 BEVs observed in two years.

2.3.1 Driving behaviors

The analyzing unit of driving behavior is typically a trip. Considering that the battery packs of BEVs covered by this field trial support maximum driving mileages of 120km and 180km on a single full charge under typical road conditions, as well as that range anxiety is usually felt by BEV users (Sun et al., 2015a), more than one fast charging may be conducted during a long 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 Figure 2.4, which indicates an increase in percentage of stays for fast-charging when the duration is longer than one hour.

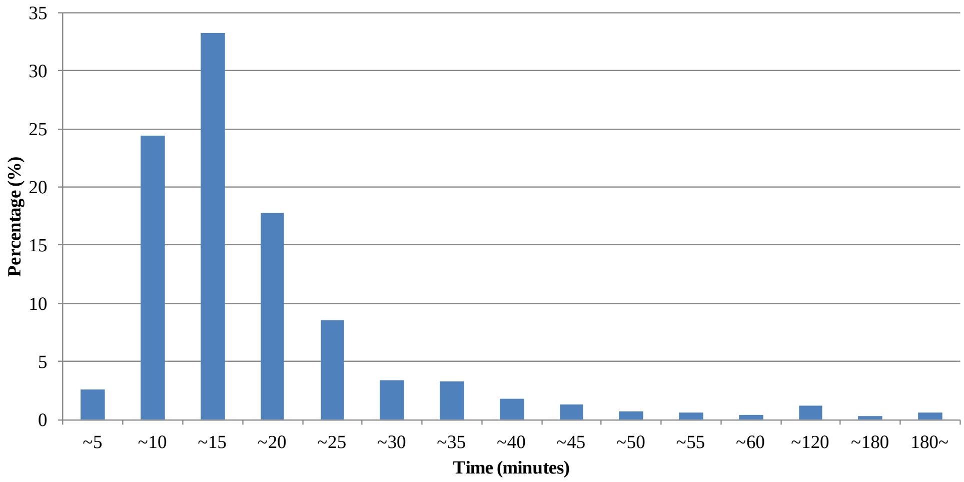


Figure 2.4 Distribution of duration between initiating a fast-charging and starting the next traveling

Thus this study defines a trip as:

(1) a contiguous sequence of vehicle locations with the same start-up time for driving,

followed by a driving with a different start-up time (Figure 2.5-(1)), or a stay for normal charging (Figure 2.5-(2)), or a stay for fast charging whose duration time is more than one hour (Figure 2.5-(3)), or nothing (Figure 2.5-(4));

(2) two or more contiguous sequences of vehicle locations with the same start-up time for driving connected by stays for fast-charging whose duration time is not more than one hour, followed by a driving with a different start-up time (Figure 2.5-(5)), or a stay for normal charging (Figure 2.5-(6)), or a stay for fast charging whose duration time is more than one hour (Figure 2.5-(7)), or nothing (Figure 2.5-(8)).

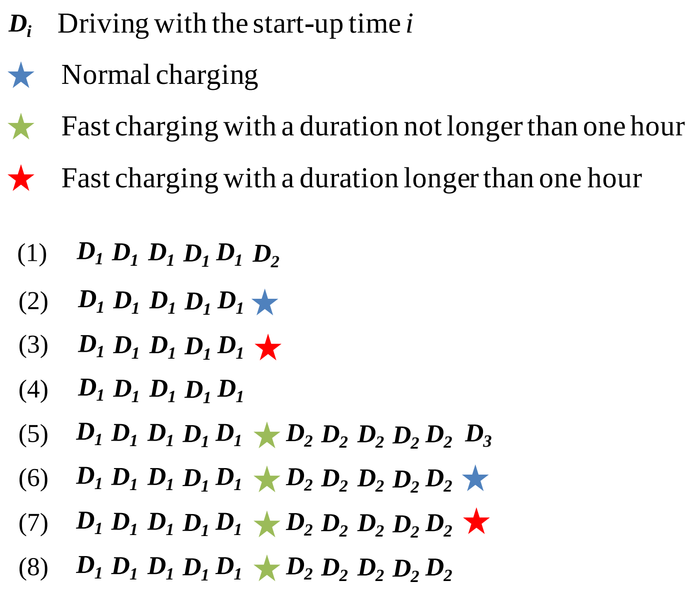


Figure 2.5 Example diagram of a trip

Based on the above definition, there are 578,287 trips observed during this two-year field trial, 49.4% of these trips are completed by commercial vehicles and the other 50.6% are completed by private vehicles. The statistical characteristics of trips are calculated and depicted in Table 2.1. It is worth noting that the daily statistics are obtained by only including days with trips. Table 2.1 shows that all the BEVs participating in this field trial were driven 5.7 times per travel day on average, but the value is larger for commercial vehicles. In addition, BEVs were driven on average about 5.2 km/12.2 minutes per trip, but the trip completed by private vehicles is longer. What's more, BEVs were driven on average about 24.6 km/68.9 minutes per travel day, and both commercial and private vehicles have the similar daily travel distance, however, the daily travel time is longer for commercial vehicles.

Table 2.1 Statistical characteristics of driving behaviors

Item	Mean			Median			Standard deviation		
	All	Commercial	Private	All	Commercial	Private	All	Commercial	Private
Number of daily trips*	5.7	7.0	4.7	4	5	4	5.0	6.5	3.0
Trip length (km)	5.2	4.5	5.9	3	3	3	6.7	5.6	7.5
Trip duration (minute)	12.2	11.2	13.3	7	6	8	18.0	18.4	17.4
Daily sums of trip length* (km)	24.6	24.5	24.7	19	19	18	22.9	20.8	24.4
Daily sums of trip duration* (minute)	68.9	78.4	61.8	53	63	46	62.7	67.9	57.5

* including days with trips

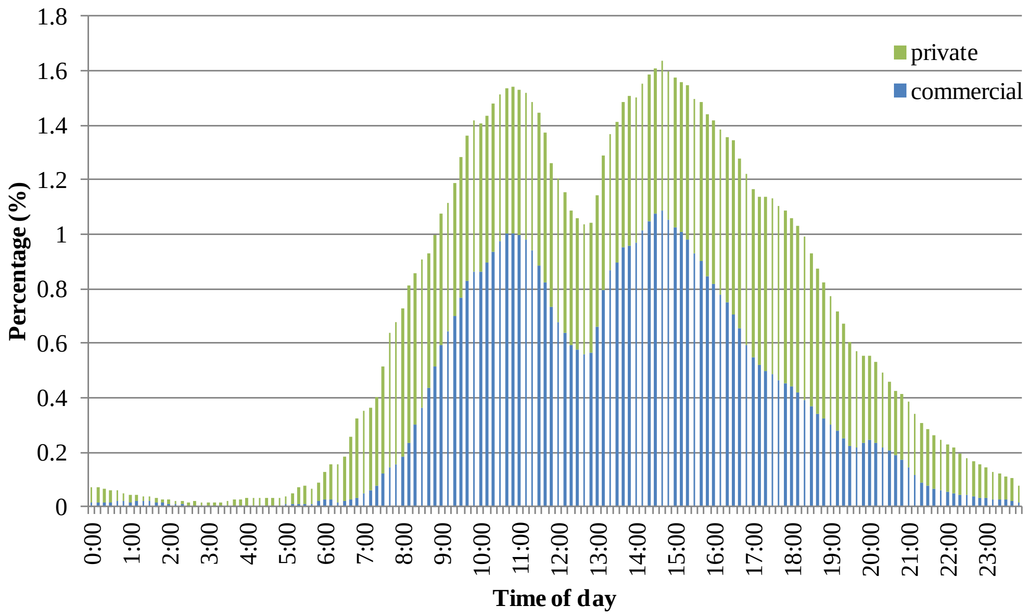


Figure 2.6 Distribution of driving along time of day

The results indicate that BEVs were usually used for short trips, but there are differences between commercial and private vehicles in their usage. Generally speaking, commercial vehicles were used for shorter trips with a higher use frequency than private vehicles. But there is almost no difference in the average distance driven per travel day between commercial and private vehicles. The inconsistency between daily travel distance and daily travel time for commercial and private vehicles could be because of their travel periods and the traffic condition. And this possible explanation can be supported by Figure 2.6, which shows the distribution of driving along time of day. The larger percentage of driving commercial vehicles in the high traffic periods may results in the longer travel time of commercial vehicles for the similar travel distance.

To examine the driving behavior in more detail, the following will presents the distributions of number of daily trips, trip length, trip duration, daily sums of trip length and daily sums of trip duration.

The distribution of the number of daily trips for commercial and private vehicles is shown in Figure 2.7, which indicates that the highest frequency of daily trips is two times per day for both commercial and private vehicles, and that the higher frequency is more common among commercial vehicles.

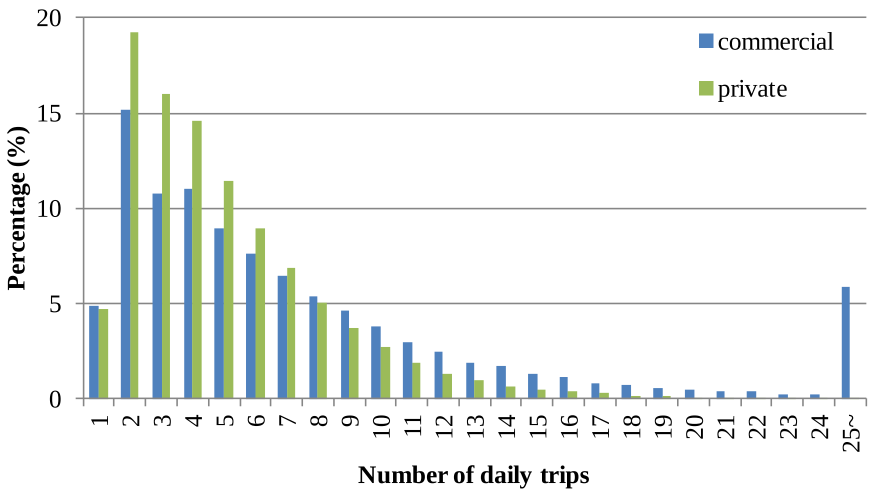


Figure 2.7 Distribution of number of daily trips

The distribution of the trip length for commercial and private vehicles is shown in Figure 2.8, which indicates that most of the trips are shorter than 30 km for both commercial and private vehicles; that the very short trips less than 1 km are more common among commercial vehicles; and that the private vehicles were generally used for longer trips than commercial vehicles.

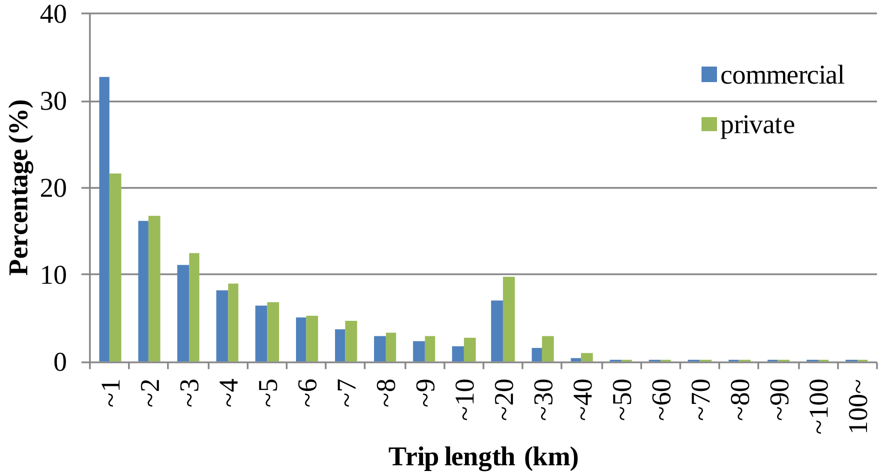


Figure 2.8 Distribution of trip length

The distribution of the trip duration for commercial and private vehicles is depicted in Figure 2.9, which shows the similar trend as the distribution of trip length in Figure 2.8 for both commercial and private vehicles.

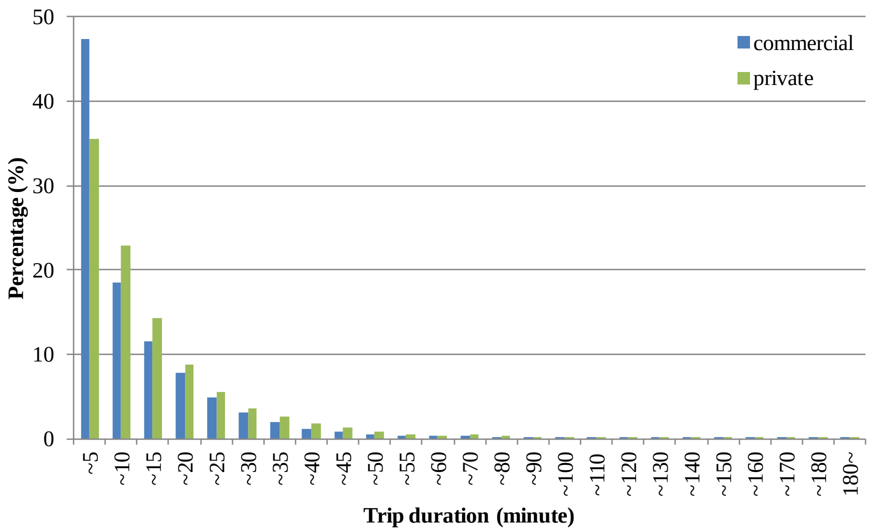


Figure 2.9 Distribution of trip duration

The distribution of the daily sums of trip length for commercial and private vehicles is shown in Figure 2.10, which indicates that most of the daily travel distance is less than 100 km for both commercial and private vehicles. It seems that any fully charged BEV participating in the field trial can satisfies the daily travel demand.

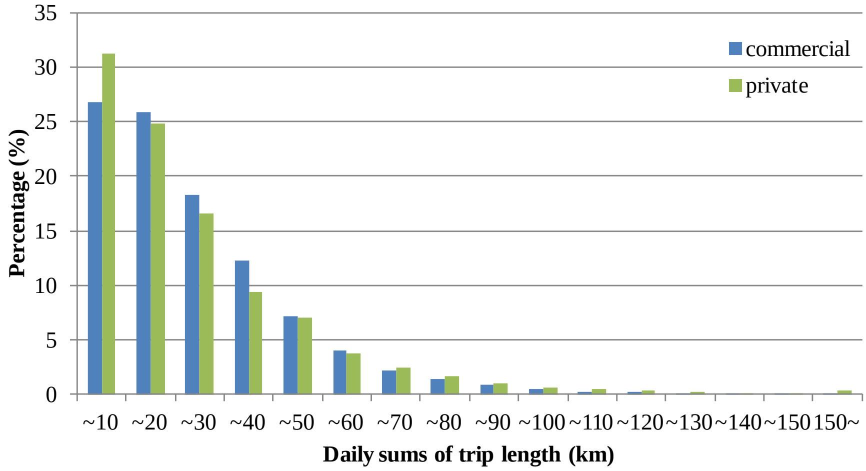


Figure 2.10 Distribution of daily sums of trip length

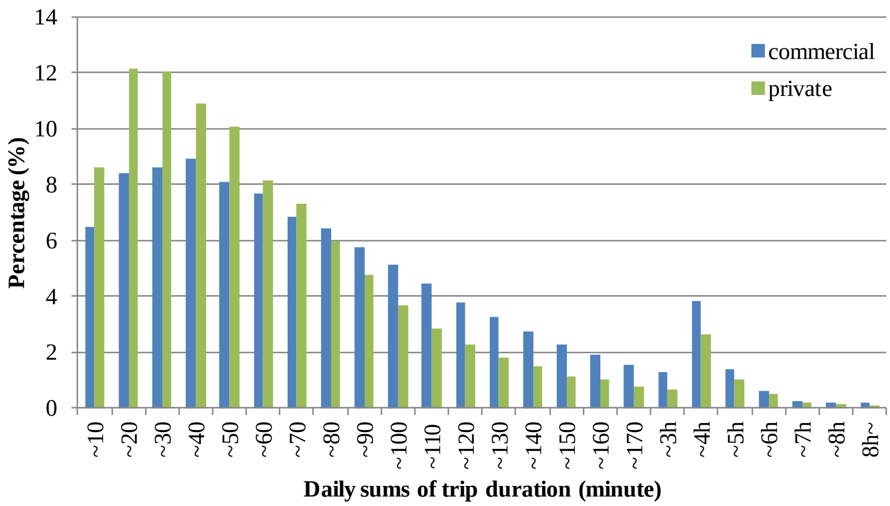


Figure 2.11 Distribution of daily sums of trip duration

The distribution of the daily sums of trip duration for commercial and private vehicles is shown in Figure 2.11, which indicates that almost half of the daily travel time is less than one hour for both commercial and private vehicles; and that the longer travel time per day is more common among commercial vehicles.

2.3.2 Charging behaviors

During this two-year field trial, there are 104,632 charging events conducted by all the BEVs, and normal charging accounts for 90.6% while fast charging accounts for 9.4%. Considering the differences between normal charging and fast charging mentioned in Section 1.2.2, the characteristics of observed charging behavior will be presented for normal charging and fast charging respectively.

Table 2.2 Statistical characteristics of charging behaviors

Item	Mean			Median			Standard deviation		
	All	Commercial	Private	All	Commercial	Private	All	Commercial	Private
Number of normal charging per day*	0.77	1.04	0.60	1	1	0	0.89	1.05	0.74
Number of fast charging per day*	0.36	0.40	0.35	0	0	0	0.77	0.87	0.74
Normal charging time per day* (hour)	1.75	2.09	1.54	1.27	1.88	0	2.08	2.00	2.10
Fast charging time per day* (minute)	8.32	4.32	9.46	0	0	0	57.16	9.91	64.55
SOC at the start of normal charging (%)	62.26	67.75	54.80	64	71	54	21.80	20.39	21.42
SOC at the start of fast charging (%)	54.55	56.74	53.72	51.5	56.5	49.5	22.21	22.71	21.96
SOC at the end of normal charging (%)	94.86	94.88	94.82	100	100	100	12.94	12.84	13.07
SOC at the end of fast charging (%)	83.98	85.43	83.43	83.5	83.5	83.5	10.45	9.18	10.84

* including days with trips, with or without charging

The normal charging performed to commercial vehicles accounts for 57.5% of the total 94,832 normal charging and the other 42.5% are performed to private vehicles, while the fast charging performed to commercial and private vehicles accounts for 27.5% and 72.5% respectively of the total 9800 fast charging. Table 2.2 gives the statistical characteristics of observed charging behavior. It is worth noting that the daily statistics are obtained by including days with trips, with or without charging. Table 2.2 shows that all the BEVs participating in this field trial were normal-charged 0.77 times and fast-charged 0.36 times per travel day on average, and these values are both larger for commercial vehicles. In addition, BEVs were normal-charged about 1.75 hours and fast-charged 8.32 minutes per travel day on average, but the daily normal charging time is longer while the daily fast charging time is shorter for commercial vehicles. What's more, the SOC at which normal charging begins is 62.26% and the SOC at which fast charging begins is 54.55% on average, and these values are both larger for commercial vehicles. However, the SOC at which normal charging ends is 94.86%, which is similar between commercial and private vehicles, but the SOC at which fast charging ends is 83.98%, which is larger for commercial vehicles.

The results indicate that BEVs were recharged more frequently by normal charging than by fast charging, especially the commercial vehicles which were normal-charged at least once a travel day on average. In addition, normal charging typically began at a higher SOC than fast charging, but private vehicles were generally recharged at a relatively stable level of SOC for both normal charging and fast charging. On the other hand, normal charging typically ended at a higher SOC nearly 100% than fast charging, and there were not much difference between commercial and private vehicles.

Like analyzing driving behaviors, the distributions of number of charging per day, charging time per day, SOC at the start of charging and SOC at the end of charging for normal and fast charging respectively will be presented below to examine the charging behavior in more detail.

The distribution of the number of normal charging per day for commercial and private vehicles is shown in Figure 2.12, which indicates that private vehicles were not normal-charged in a much larger percentage of their travel days than commercial vehicles; and that for the days with normal charging, the highest frequency of normal charging is once a day for both commercial and private vehicles, but sometimes commercial and private vehicles were normal-charged multiple times during a travel day.

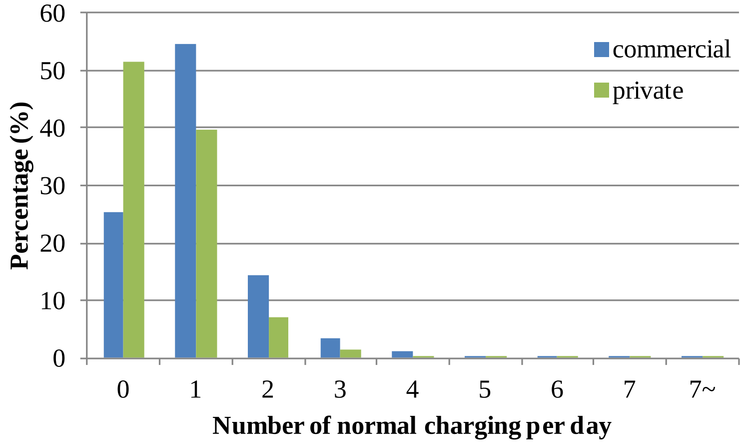


Figure 2.12 Distribution of number of normal charging per day

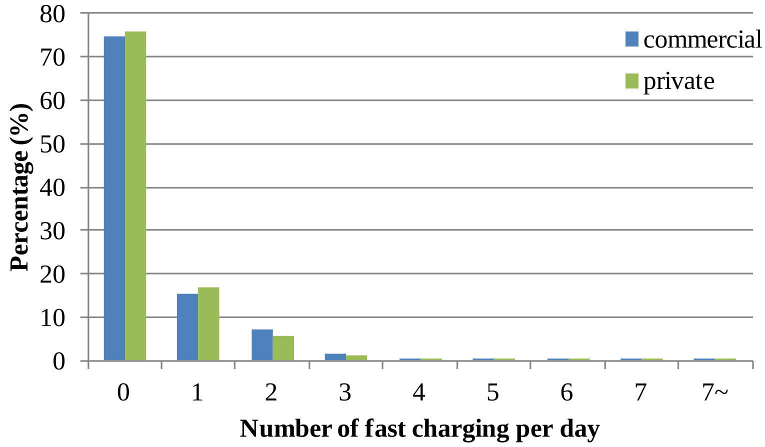


Figure 2.13 Distribution of number of fast charging per day

The distribution of the number of fast charging per day for commercial and private vehicles is shown in Figure 2.13, which indicates that BEVs were not fast-charged in a much large percentage of their travel days for both commercial and private vehicles, and the percentage without fast charging is larger than the percentage without normal charging shown in Figure 2.12 for both commercial and private vehicles; and that for the days with fast charging, the highest frequency of fast charging is once a day for both commercial and private vehicles, but sometimes commercial and private vehicles were fast-charged multiple times during a travel day.

The distribution of the normal charging time per day for commercial and private vehicles is depicted in Figure 2.14, which shows the same percentage of travel days without normal charging as that shown in Figure 2.12 for both commercial and private vehicles; and that for travel days with normal charging, the percentage with shorter daily normal charging time is higher for commercial vehicles.

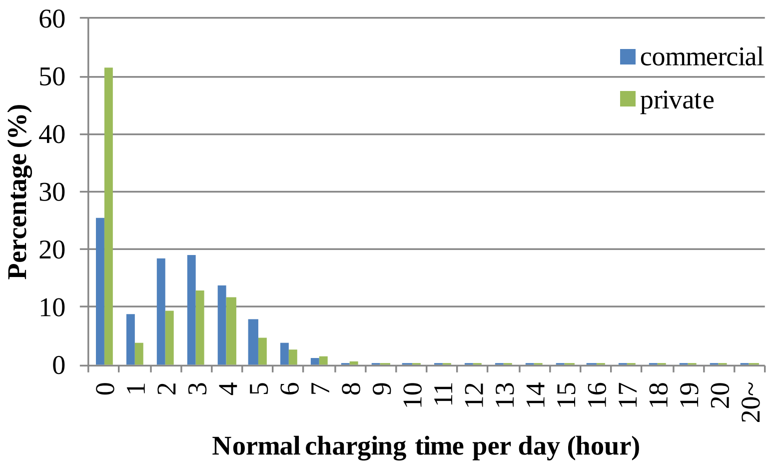


Figure 2.14 Distribution of normal charging time per day

The distribution of the fast charging time per day for commercial and private vehicles is depicted in Figure 2.15, which shows the same percentage of travel days without fast charging as that shown in Figure 2.13 for both commercial and private vehicles; and that for travel days with fast charging, the percentage with shorter daily fast charging time is a little higher for commercial vehicles.

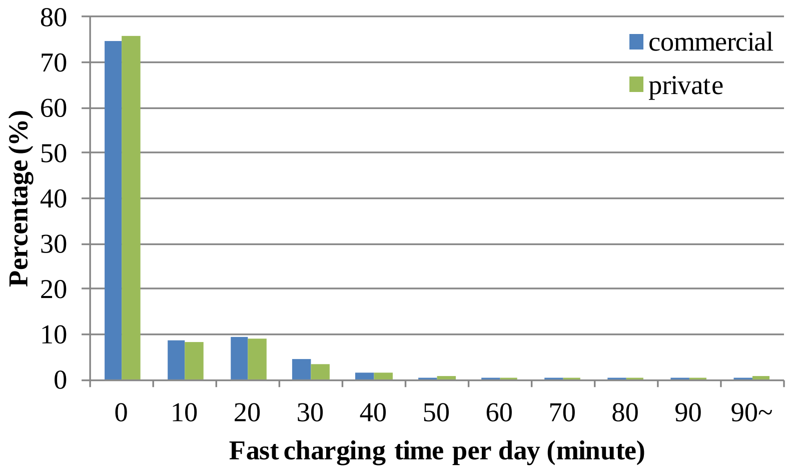


Figure 2.15 Distribution of fast charging time per day

The distribution of the SOC at the start of normal charging for commercial and private vehicles is depicted in Figure 2.16, which shows that very few BEVs were started to be normal-charged when they are about to run out of power; and that commercial vehicles were generally started to be normal-charged at a higher SOC than private vehicles. The higher SOC when normal charging begins possible because BEV users tend to normal-charge their vehicles at their convenience in advance for the next trip.

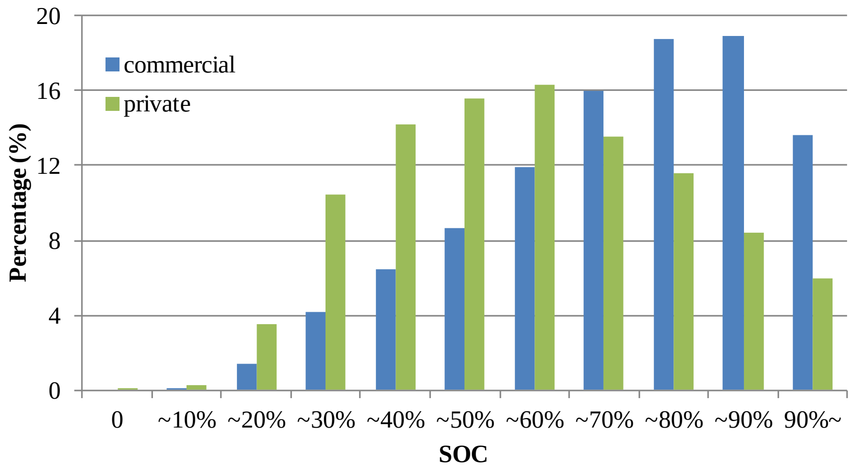


Figure 2.16 Distribution of SOC at the start of normal charging

The distribution of the SOC at the start of fast charging for commercial and private vehicles is depicted in Figure 2.17, which shows that very few BEVs were started to be fast-charged when they are about to run out of power; and that though the SOC at the start of fast charging is higher for commercial vehicles on average, the comparison of fast charging behavior between commercial and private vehicles is more complex than that of normal charging behavior: fast charging initiated at a particularly low SOC of less than 20% is more common among commercial vehicles, while fast charging initiated at a particularly high SOC of more than 80% is more common among private vehicles. The higher SOC when fast charging begins possible because BEV users tend to fast-charge their vehicles when there is an available fast charging station in advance for the next trip. The complicated difference in SOC at the start of fast charging between commercial and private vehicles might be resulted from the layout of fast charging stations.

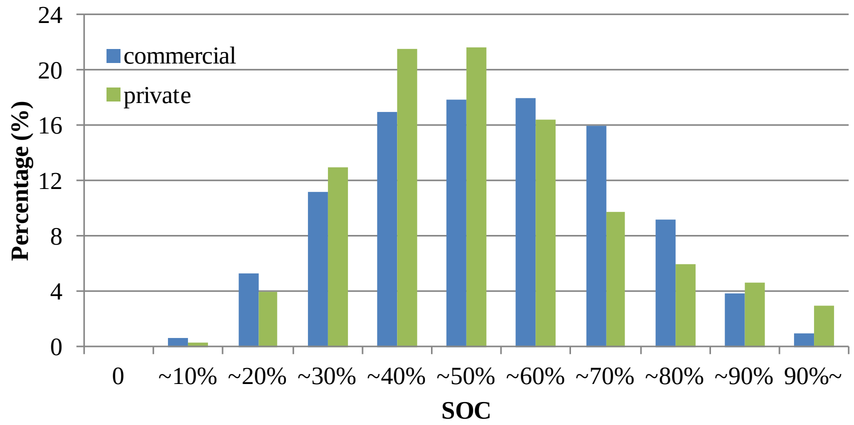


Figure 2.17 Distribution of SOC at the start of fast charging

Another possible explanation for the higher SOC when normal charging or fast charging begins is that BEV users in their early participation of this trial have less experience of driving BEVs, and they are worried about to be stranded with the limited range between rechargings of BEVs compared with range between refuelings of traditional petroleum vehicles. Therefore, BEV users can be expected to begin to charge their vehicles at lower SOC according to their needs with more experience being gained. To examine this learning effect, the statistical characteristics of SOC when normal charging and fast charging begins are presented for, respectively, the earlier and the latter period of this trial (the observations are divided into two equal stages for each individual according to the sample date).

As shown in Table 2.3, the SOC at which normal charging begins in the earlier period of this trial is smaller on average than that in the latter period, so is the SOC at which fast charging begins, which are the cases for both commercial and private vehicles.

Table 2.3 Statistical characteristics of SOC at the start of charging at different stages (%)

	Mean			Median			Standard deviation		
	All	Commercial	Private	All	Commercial	Private	All	Commercial	Private
Normal charging									
The earlier	59.95	63.92	54.55	61.5	66.5	53.5	21.43	20.74	21.16
The latter	64.57	71.58	55.05	67.0	75.5	54.0	21.92	19.29	21.68
Fast charging									
The earlier	50.97	54.50	49.62	47.5	54.5	46.0	21.70	23.12	20.98
The latter	58.16	59.00	57.84	55.0	58.0	54.0	22.14	22.07	22.16

The distribution of the SOC at the start of normal charging for commercial and private vehicles, respectively, in the earlier and the latter period of this trial is depicted in Figure 2.18, which shows an obvious increase in percentage of normal charging initiated at higher SOC in the latter period among commercial vehicles.

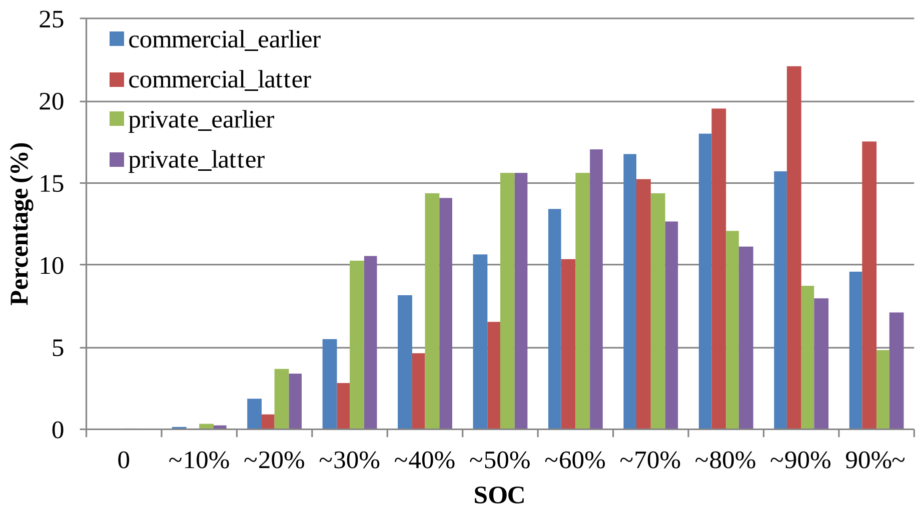


Figure 2.18 Distribution of SOC at the start of normal charging in different stages

The distribution of the SOC at the start of fast charging for commercial and private vehicles, respectively, in the earlier and the latter period of this trial is depicted in Figure 2.19, which shows that the percentage of fast charging initiated at SOC smaller than 40% decreased obviously in the latter period for both commercial and private vehicles, while the percentage of fast charging initiated at SOC larger than 50% increased.

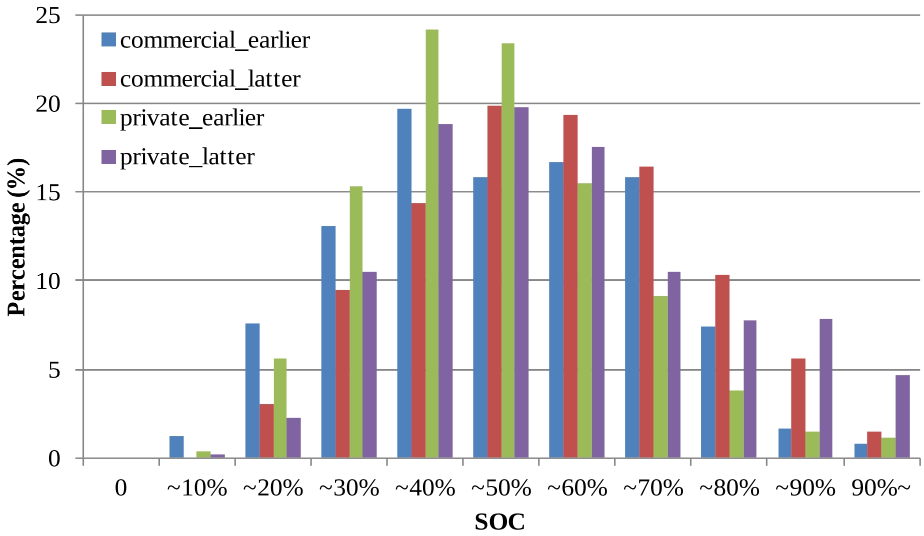


Figure 2.19 Distribution of SOC at the start of fast charging in different stages

The larger SOC at which charging begins in the latter period of this trial is inconsistent with our expectation, and the reason needs further discussion.

Now let's get on to the other aspects of charging behavior. The distribution of the SOC at the end of normal charging for commercial and private vehicles is depicted in Figure 2.20, which shows that most of the normal charging ends at a level of SOC higher than 90% for both commercial and private vehicles; and that more than half of normal charging performed to private vehicles ends with fully charged battery pack.

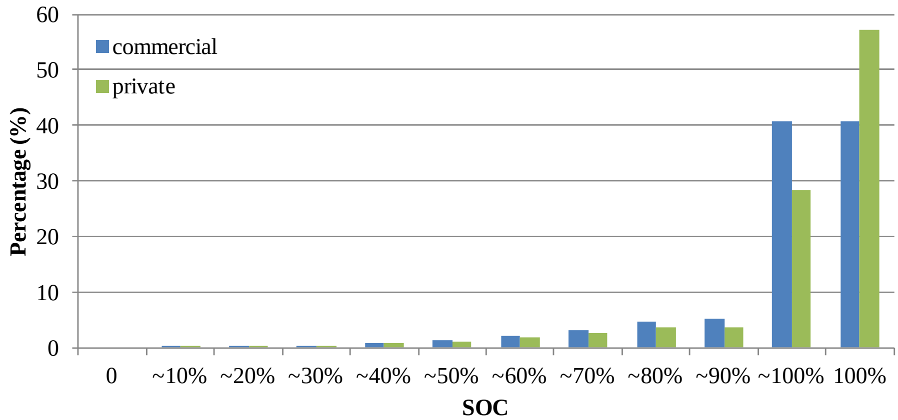


Figure 2.20 Distribution of SOC at the end of normal charging

The distribution of the SOC at the end of fast charging for commercial and private vehicles is depicted in Figure 2.21, which shows that most of the fast charging ends at a level of SOC higher than 70% for both commercial and private vehicles; and that nearly half of the fast charging ends at 80%~90% for both commercial and private vehicles.

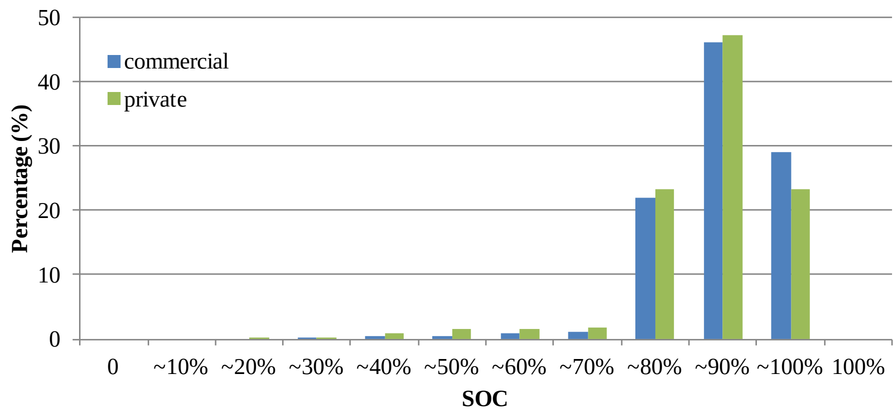


Figure 2.21 Distribution of SOC at the end of fast charging

Charge timing is an important aspect of EVs as mentioned in the Background, so the next will presents the characteristics of observed charge timing.

The distribution of normal charging along time of day for commercial and private vehicles is depicted in Figure 2.22, which shows that normal charging occurred during nighttime is more common among private vehicles, and the home-based characteristic of normal charging definitely is a reason.

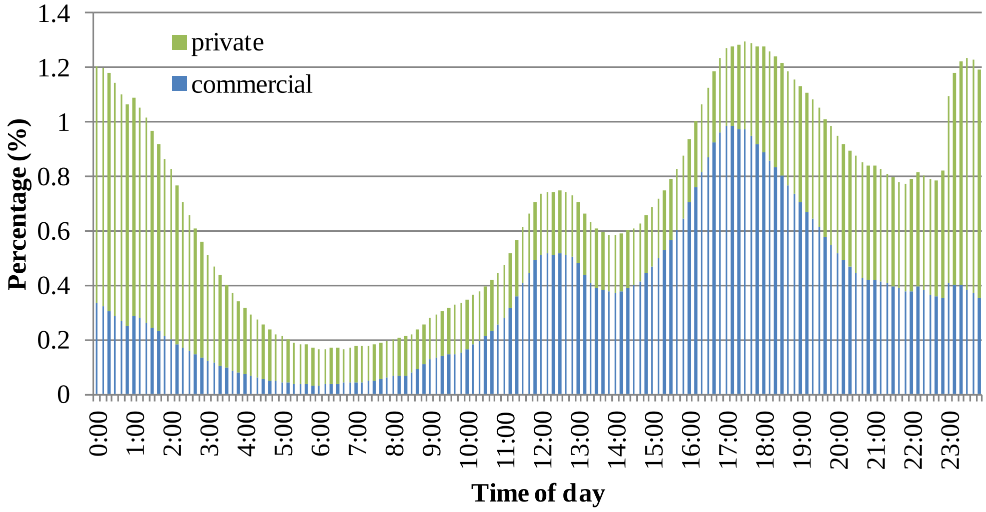


Figure 2.22 Distribution of normal charging along time of day

The distribution of fast charging along time of day for commercial and private vehicles is depicted in Figure 2.23, which shows that fast charging performed to both commercial and private vehicles typically occurred during periods with higher traffic, as shown in Figure 2.6, and the reason may be that fast charging must be completed through dedicated equipment normally located in public places.

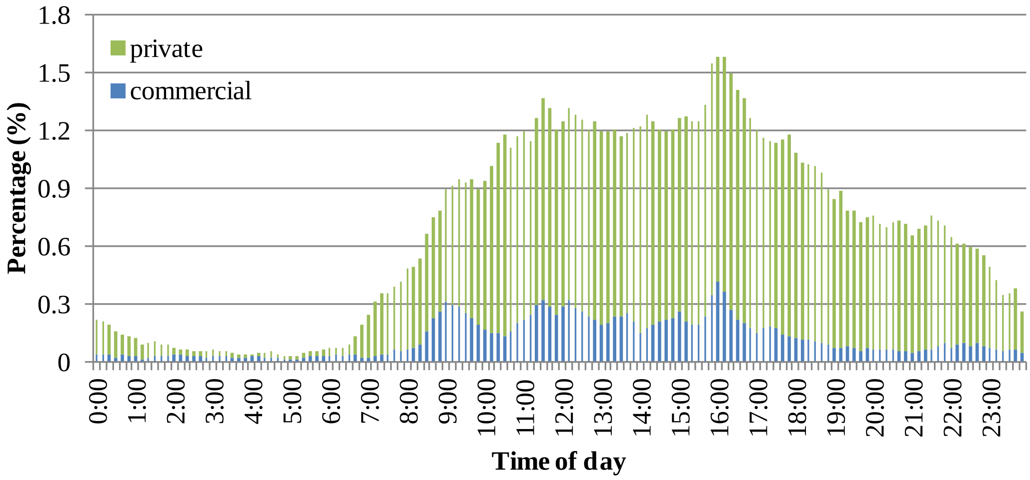


Figure 2.23 Distribution of fast charging along time of day

2.4 Summary

This chapter assessed the driving and charging behavior observed from nearly 500 BEVs in a two-year field trial on BEV usage in Japan. On average, BEVs were driven 5.7 trips per day, 5.2 km per trip and 24.6 km per day. However, differences in charging behavior exist between commercial and private vehicles, which are that commercial vehicles were used for shorter trips with a higher use frequency than private vehicles, but the daily travel distance is similar between commercial and private vehicles. For the charging behavior, BEVs were normal-charged 0.77 times and fast-charged 0.36 times per travel day on average. Differences also exist between commercial and private vehicles with respect to normal charging as well as fast charging. Typically, normal charging began at a higher SOC than fast charging, but private vehicles were generally recharged at a relatively stable level of SOC for both normal charging and fast charging. What's more, the SOC at which charging begins is larger on average in the latter period of this trial for both normal and fast charging, which are the cases among both commercial and private vehicles. On the other hand, normal charging typically ended at a higher SOC nearly 100% than fast charging, and there were not much difference between commercial and private vehicles. What's more, normal charging occurred during nighttime is more common among private vehicles, but fast charging performed to both commercial and private vehicles typically occurred during periods with higher traffic.

It is important to point out that the characteristics of driving and charging behavior displayed in this Chapter are only indicative of BEV adopters in Japan, and they may not necessarily be generalized outside of Japan.

Chapter 3

Stochastic frontier analysis of excess access to mid-trip battery electric vehicle fast charging

This chapter examines the charging behavior related to battery usage. By analyzing the research background, this study focuses on the mid-trip fast charging events taking place after leaving the origin and before arriving at the destination. Then, some characteristics of mid-trip fast charging behavior seen in the samples used in this study are explained. And a stochastic frontier model is described and used to explore factors that influence the remaining charge when mid-trip fast charging begins, as well as to explore whether good use of battery capacity can be encouraged. The effects of various factors on the remaining charge when mid-trip fast charging begins are discussed based on the estimation results. In addition, the average inefficiency in battery usage is also discussed by comparing the actual remaining charge with the predicted required charge. Finally, some conclusions are presented to wraps up this chapter.

3.1 Introduction

To deal with the range problem typically perceived by consumers as a barrier in their buying and using EVs, great efforts are currently being made to deploy a charging infrastructure and improve the storage capacity of batteries. These efforts deal with the range problem on two fronts: by providing convenient recharging opportunities and by increasing range on a single full charge. However, observation of EV usage at Tokyo Electric Power Company (TEPCO) has indicated that the remaining charge at the end of a journey decreases with the implementation of additional charging stations, even though these stations are infrequently utilized (Electrification Coalition, 2009), which suggests that drivers are recharging just to give themselves a larger margin of error to prevent running out of charge without a station nearby. This raises questions such as how much charging infrastructure and what battery capacity is sufficient, whether charging stations and battery capacity are being effectively used and, more importantly, how to encourage users to make effective use of charging stations and battery capacity. TEPCO's experience may suggest that charging behavior, especially the SOC at which drivers begin to charge their EVs, may provide some answers to these questions.

Previous studies have revealed that refueling behavior is greatly influenced by users' familiarity with refueling station locations (Dingemans et al., 1986; Kitamura and Sperling, 1987; Plummer et al., 1998), and refueling choice is the result of a learning process (Dingemans et al., 1986). Currently, however, the EV market is far from mature. There is an incomplete charging infrastructure, battery technology is evolving, and there is only a small number of EVs on the roads, so drivers' present charging behavior is likely to change over time as the infrastructure becomes more spatial diffusion, technical progress is made with batteries, and drivers gain more experience. Therefore, it is important to explore how charging behavior is influenced by the charging infrastructure and battery capacity based on real-life EV usage data, which is rarely involved in previous studies.

Currently EVs can be recharged by normal charging and fast charging, as introduced in Section 1.2.2. Normal charging usually receives special attention because it is most frequent, but although most charging can be done while stationary, fast charging plays an important role in long-distance trips or when an unexpected emergency arises. The BEV field trial in Japan (Successful Applicant, 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 cars need to use fast charging. The widespread availability of fast chargers but with limited numbers in Japan, characteristic revealed by the introduction of charging infrastructure in Section 2.2, probably results from the understanding that fast charging is needed by most vehicles but only very rarely. In addition, Christensen et al. (2010) pointed out that a fast-charging infrastructure is the most important need if EVs are to come into widespread use.

This chapter investigates fast-charging behavior in consideration of charging infrastructure and battery capacity. The layout of fast chargers in Japan, depicted in Figure 2.3, may generate three types of fast-charging events: beginning-of-trip, mid-trip and end-of-trip. Beginning-of-trip and end-of-trip fast-charging occurs respectively at the origin and destination of trips, while mid-trip fast-charging takes place after leaving the origin and before arriving at the destination. Although the focus is on fast charging, it is mid-trip fast-charging events that are of interest rather than beginning-of-trip and end-of-trip events. Because we think mid-trip fast-charging represents the intended demand for fast charging, while beginning-of-trip and end-of-trip fast-charging does not seem to represent intended demand for fast charging. For instance, some BEV drivers typically plug in their vehicles for fast charging prior to departing from or when parked at a charging location regardless of the vehicle's SOC and their upcoming driving plans. This type of fast-charging event does not happen during trips. Actually, the beginning-of-trip and end-of-trip fast-charging account for 11.2% of all the fast charging events observed during the field trial.

Personality trait has been shown to affect EV range utilization (Franke and Krems, 2013a), which may results in a complicated pattern of SOC at the initiation of fast charging. For example, a risk-averse driver will probably choose to fast charge at a higher remaining charge in order to avoid the risk of running out of charge; in an extreme case, such a driver may charge whenever there is a fast-charging station available. Such excessive "just-in-case" behavior would require a high density of charging stations that would be unnecessarily wasteful. On the other hand, the most adventurous driver will charge only on the realization that the remaining charge cannot support the rest of the trip. Planning for this behavior would, inversely, require a lower density of fast-charging stations leading to greater risk of stranding and might discourage some customers from buying an EV. This means it is better to estimate charging behavior on an individual level.

Thus, this chapter aims at developing a methodology for effectively representing the relationship between remaining charge when mid-trip fast charging is initiated and the charging infrastructure, taking into account the charge capacity of the vehicle. A stochastic frontier model is used for the analysis, using real-life BEV usage data collected in Japan, and each individual's remaining charge at fast-charging initiation is taken to be a function of the characteristics of charging stations, BEV's charge capacity, travel patterns, and the familiarity with charging infrastructure.

3.2 Data profiles

As mentioned previously, only mid-trip fast-charging events were under consideration. After selecting the required fast-charging events and bypassing individuals for whom there is only a single mid-trip fast-charging event, the final dataset used in the study included 40 commercial vehicles with 1794 fast-charging events and 114 private vehicles with 4702 fast-charging events.

We now look at the characteristics of the data used in this study. Figure 3.1 shows the distribution of SOC when mid-trip fast charging begins for commercial and private vehicles, respectively, on working and non-working days. Here "non-working days" include both weekends and holidays. From this graph, it can be shown that nearly half of fast-charging events occur at an SOC of 30-50% in the case of private vehicles, while the proportion is 40-70% for commercial vehicles. On the other hand, very few vehicles start fast charging when they are about to run out of power (less than 10% charge, in fact, the smallest SOC when mid-trip fast charging begins is 5.5%). Further, a greater proportion of commercial vehicle fast-charging events occur at a higher SOC on non-working days, while the distributions are similar for private vehicles both on working and 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.

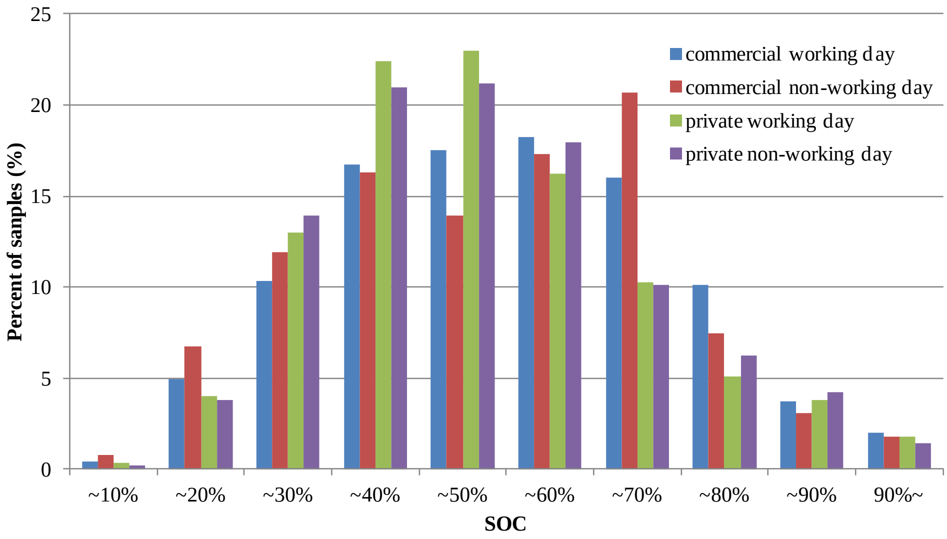


Figure 3.1 Distribution of SOC at initiation of mid-trip fast charging

The purpose of this study is to explore how factors including charging infrastructure and battery capacity affect charging behavior for different users by analyzing the behavior of commercial and private users who participated in this trial. The ultimate aim is to assess the possibility of encouraging more effective charging behavior. It is important to point out that the results of this study are only indicative of early BEV adopters, given the limited number and spatial distribution of charging stations. Also the results may not necessarily be generalized outside of Japan.

3.3 The stochastic frontier model

Generally speaking, a BEV will be stranded without charge if there are no charging stations within the range provided by the remaining charge. Here we assume that at every possible location on the road network one can estimate the nearest charging station. Then, given the battery capacity, there is a critical value of SOC for that “location & battery capacity” combination that would be the minimum required charge to prevent being stranded. While the actual remaining charge when fast charging begins is almost always available from the trial data, the minimum required charge is not observable. A modeling approach, therefore, is adopted in this study to estimate the minimum required charge based on the inequality,

$$RE_0 \leq RE_1 \tag{3.1}$$

Where RE_0 is the minimum required charge and RE_1 is the actual remaining charge when a fast-charging event begins. For this inequality, we can state

$$RE_1 = RE_0 + u \tag{3.2}$$

where u is a non-negative random variable representing the inefficiency inherent in fast charging. It is this inefficiency that demands more infrastructure and bigger batteries than absolutely necessary.

As noted earlier, it is better to carry out estimations at the individual level rather than as an average. Additionally, as noted in the description of the samples above, the BEV usage data used in this study consists of an unbalanced panel of data representing 154 vehicles for the months from February 2011 to January 2013. One possible model that can be applied to this relationship is the true random effects stochastic frontier model (Greene, 2005), whose general form can be presented as

$$y_{it} = \alpha + w_i + \beta' x_{it} + \varepsilon_{it} = \alpha + w_i + \beta' x_{it} + v_{it} + u_{it} \tag{3.3}$$

Where i denotes the vehicle, t denotes the trial period of the vehicle, the observed dependent variable y_{it} is the remaining charge of vehicle i during period t when a fast-charging event begins and obviously y_{it} is RE_1 defined previously, w_i is the random vehicle specific effect, β is a vector of coefficients, x_{it} is a vector of explanatory variables, and v_{it} and u_{it} are the symmetric and one-sided random error terms, which represent the statistical noise and inefficiency, respectively. The random variables w_i and v_{it} are typically assumed to be normally distributed, while a half-normal or truncated-normal distribution is often used for u_{it}.

$$w_i \sim N[0, \sigma_w^2] \tag{3.4}$$

$$v_{it} \sim N[0, \sigma_v^2] \tag{3.5}$$

$$u_{it} = |U_{it}|, U_{it} \sim N[0, \sigma_u^2] \tag{3.6}$$

$\alpha + w_i + \beta' x_{it} + v_{it}$ is the optimal, frontier goal which, in this study, is RE_0 defined previously and can be viewed as the minimum required charge at the initiation of fast charging. The observed remaining charge will not be less than $\alpha + w_i + \beta' x_{it} + v_{it}$, since u_{it} is non-negative, to satisfy inequality (3.1).

At first sight, this appears to be a model with a three-part disturbance, which would surely be inestimable. But as Greene (2005) pointed out, it is in fact a model with a traditional random effect, but with a compound error ε_{it} having the asymmetric distribution given by (3.7) below.

$$f(\varepsilon_{it}) = \frac{\Phi(-\varepsilon_{it}\lambda/\sigma)}{\Phi(0)}\frac{1}{\sigma}\phi(\frac{\varepsilon_{it}}{\sigma}) \tag{3.7}$$

where $\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$.

The parameters of the model are estimable by maximum likelihood based on simulation or quadrature, since there is no closed form for this density.

Although the stochastic frontier model was originally proposed independently by Aigner et al. (1977) and Meeusen and van den Broeck (1977) for estimating the effects of technical inefficiency in production, recent applications have also been found in many other fields. These include agriculture (Baten et al., 2009; Ali and Samad, 2013), finance (Wang, 2003; Neffati et al., 2011), public utility (Hattori, 2002; Vishwakarma and Kulshrestha, 2010), and transportation (Pendyala et al., 2002; Cullinane et al., 2002; Holmgren, 2013). In these applications, the observed outcomes below the frontier level (for the production frontier model) or above the frontier level (for the cost frontier model) lead to inefficiency, so the observed outcomes are modeled as deviating from the frontier level in a particular direction according to the model type. Thus a stochastic cost frontier model seems appropriate for this study when seen in terms of these application contexts.

Considering that the same SOC means different electricity for different EVs and it is difficult to convert electricity to supportable range, the dependent variable of this study is defined as the remaining charge in kWh when a mid-trip fast-charging event begins. The focus is then on the independent variables.

First is the factors related to charging stations, inspired by TEPCO's experience (Electrification Coalition, 2009). The number of charging stations varies greatly from region to region in Japan (see Figure 2.2). In order to accurately describe the relationship between charging behavior and charging stations, further, to evaluate and instruct the construction of charging infrastructure, the charging stations are divided into three groups: Tokyo & Kanagawa (stations/1000km^2 > 55), Osaka & Saitama (15 < stations/1000km^2 < 55), and other prefectures; the first two groups are expressed with dummy variables, while specific value is used for the third group. These cut-offs are fixed based on the similarities and differences of charging station densities among prefectures as well as the sample size for each group. For the value of the third group, four types are examined: number of charging stations per 1000 square kilometers in prefecture where BEV is registered (number of charging stations 1), number of charging stations per 1000 square kilometers in prefecture where the charging station used in the trip is located (number of charging stations 2), number of charging stations within a 30km radius of home/company location (number of charging stations 3), and number of charging stations within a 30km radius of the charging station used in the trip (number of charging stations 4). It's worth noting that all the four definitions don't apply to BEVs in Tokyo, Kanagawa, Osaka and Saitama. It can be expected that the remaining charge could be decreased with increasing number of charging stations, as shown by the TEPCO's experience (Electrification Coalition, 2009).

In addition, familiarity with charging stations has been revealed that it may affect users' charging decision (Dingemans et al., 1986; Kitamura and Sperling, 1987; Plummer et al., 1998). So this study includes familiarity as one independent variable and defines it as the perception of whole charging station network. Familiarity is calculated based on the following two principles: the more fast-charging stations one uses, the more familiarity with charging infrastructure; the smaller fluctuation of SOC at which fast charging is initiated, the more familiarity with charging infrastructure. The remaining charge can be expected to be decreased when users get more familiar with charging stations.

The results of electricity consumption obtained from this trial show that it is around 109Wh/km when air-conditioning and heater are both turned off, while around 186Wh/km when they are both turned on. Therefore, it can be expected that the usage of air-conditioning or heater will decreases the remaining charge when the available charging stations are sparse, or increases the remaining charge when users want to give themselves a larger margin of error to prevent running out of charge in case of using air-conditioning or heater during the next tour.

Limited range of EVs has long been criticized as a major barrier in their promotion, but more range is not necessarily better if it is not used efficiently. So battery capacity is also treated as one independent variable, and expressed as a dummy variable by considering there are two types of battery capacities in this trial.

The stations during this trial provide different price for fast-charging, 43.0% are free for all users, 6.8% must be paid for all users, and 50.2% are only free for their members. As revealed by the previous studies (Kitamura and Sperling, 1987; Plummer et al., 1998), price for fast-charging may affect the remaining charge, for example, some users charge their EVs at a high remaining charge at a special charging station because it is for free. However, the trial does not provide information about whether a user is a member of a charging station or not. So this study includes variables of free and paid to indicate respectively stations that are free for all users and are paid for all users.

Besides, about 89.4% of these stations are available to any BEV users, while 10.6% can only be used by their constructors. What’s more, 83.1% of stations are exclusively for members who belong to electricity companies. Therefore, the variable of electricity is included to explore the charging behavior of electricity users.

Previous research also shows that refueling choice is the result of a learning process (Dingemans et al., 1986). So an indicator for the latter half of this trial is included to explore whether any difference exists between the earlier and the latter period of this trial (the observations are divided into two equal stages for each individual according to the sample date).

Lastly, travel patterns have been shown to be related to refueling behavior (Kitamura and Sperling, 1987), and so does the speed because it affects the electricity consumption of EVs (Yao et al., 2013). So this study includes explanatory variables of number of trips, Vehicle Miles of Travel (VMT), and speed to analyze fast-charging behavior. Here "number of trips" and "VMT" is respectively the number of trips and VMT on the day it was charged, and "speed" is the average speed between the origin or the last fast-charging location and the current fast-charging location or home/company location.

The explanatory variables used in the analysis for commercial and private vehicles as well as the statistical characteristics of the selected mid-trip fast charging events are described in Tables 3.1.

The formulation adopted in this study defines the observed remaining charge when a mid-trip fast-charging event begins as y_{it}; and the number of charging stations, familiarity with charging infrastructure, usage of air-conditioning or heater, battery capacity, price for recharging, electricity vehicles, and travel patterns as x_{it}. But given what we know, the remaining charge is also influenced greatly by driver characteristics in addition to the factors included in x_{it}, such as the attitudes toward risk exemplified above. Thus, some error is inevitable because of the fact that the observed charging behavior is governed by individual characteristics. However, it is reasonable to assume that $\alpha + w_i + \beta' x_{it} + v_{it}$ is a useful measure for the minimum required charge at initiation of fast charging, and that it can be used to encourage more rational charging behavior by alleviating anxiety among risk-averse drivers and providing warnings to the most adventurous drivers.

Table 3.1 Definitions and statistical characteristics of independent variables

Variable	Definition	Descriptive statistic*			
		Commercial vehicles		Private vehicles	
		Working day	Non-working day	Working day	Non-working day
Number of charging stations 1	Number of charging stations per 1000 square kilometers in prefecture where EV is registered, except for Tokyo, Kanagawa, Osaka and Saitama	n.a.	n.a.	2.5	n.a.
Number of charging stations 2	Number of charging stations per 1000 square kilometers in prefecture where the charging station used in the trip is located, except for Tokyo, Kanagawa, Osaka and Saitama	n.a.	n.a.	n.a.	2.7
Number of charging stations 3	Number of charging stations within a 30km radius of home/company location**, except for Tokyo, Kanagawa, Osaka and Saitama	n.a.	6.3	n.a.	n.a.
Number of charging stations 4	Number of charging stations within a 30km radius of the charging station used in the trip, except for Tokyo, Kanagawa, Osaka and Saitama	5.3	n.a.	n.a.	n.a.
Tokyo & Kanagawa	1 if EV or the charging station used in the trip belongs to Tokyo or Kanagawa; 0 otherwise	58.6%	51.9%	51.8%	45.0%
Osaka & Saitama	1 if EV or the charging station used in the trip belongs to Osaka or Saitama; 0 otherwise	13.0%	16.0%	6.7%	8.7%
Familiarity	Indicator of perception of whole charging station network	1.1	0.7	1.1	1.0
Air-conditioning or heater	1 if air-conditioning or heater is on; 0 otherwise	49.8%	41.6%	42.6%	44.3%
High-capacity battery	1 if EV has high-capacity battery; 0 otherwise	14.7%	14.7%	15.7%	20.7%
Number of trips	Number of trips per day	6.9	6.2	6.9	5.5
VMT (km)	Vehicle Miles Traveled per day	73.9	88.9	70.8	83.3
Speed (0,20]	1 if speed of EVs travelling not more than 20km/h; 0 otherwise	45.4%	34.9%	38.8%	37.0%
Speed (40~)	1 if speed of EVs travelling faster than 40km/h; 0 otherwise	14.8%	19.1%	10.9%	17.1%
Free	1 if fast-charging is free for all users; 0 otherwise	17.2%	21.4%	22.6%	26.5%
Paid	1 if fast-charging is paid for all users; 0 otherwise	n.a.	n.a.	13.1%	10.3%
Latter half	1 if observation belongs to the latter half of this trial; 0 otherwise	49.3%	49.6%	49.4%	48.6%
Electricity	1 if EV belongs to electricity company; 0 otherwise	9.1%	n.a.	n.a.	n.a.

* *mean for continuous variables and % for dummy variable. If there is no % symbol, then the value is the mean.*

** *since the data set didn't include users' personal information, home location is determined by the frequency of normal charging, for each vehicle, the location with highest frequency is regarded as the user's home location. This result is almost the same with the location determined by highest first departure frequency of the day.*

n.a. indicates variables not included in the model. For the variables of number of charging stations, they are resulted from optimum choosing based on the goodness-of-fit of their models, while for the other variables, they are resulted from few samples.

3.4 Results of model estimation

Mid-trip fast-charging characteristics are, as has been noted, different for commercial and private users as well as between working and non-working days, so the estimation results of four groups are presented in this section: commercial vehicles on working days, commercial vehicles on non-working days, private vehicles on working days and private vehicles on non-working days.

Table 3.2 presents the estimation results obtained with the true random effects stochastic frontier model for the four groups. And the likelihood at convergence of the random effects regression model for each group is also included for comparison for the following three considerations: the simple regression analysis is another parametric approach to assess efficiency; there is reason to believe that differences across BEV users have some influence on the remaining charge; the simple regression model is a special case of the stochastic frontier model, the essential difference between them is that the stochastic frontier model distinguishes the effects of statistical noise from those of inefficiency while the simple regression model does not.

In fact, before results presented here, we examined four types of number of charging stations for each model, and so did the non-linear form with quadratic term and linear form for number of charging stations. And finally, linear form with specific definition of number of charging stations is chosen for each model based on the goodness-of-fit.

The comparison of the true random effects stochastic frontier model and the random effects regression model is conducted by doing the likelihood ratio test. The test statistic *-2[log likelihood for regression model-log likelihood for stochastic frontier model]* is 43.8, 13.1, 94.7 and 49.0, for commercial and private vehicles, respectively, on working and non-working days, all of them are greater than the critical chi-square value with one degree of freedom. So it is clear that the stochastic frontier analysis is more effective than the simple

Table 3.2 Estimation Results for mid-trip fast charging

Variable	Commercial vehicles				Private vehicles			
	Working days		Non-working days		Working days		Non-working days	
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
Constant (E[α])	2.851**	0.415	-0.069	2.788	3.842**	0.134	3.822**	0.177
Number of charging stations 1	n.a.	n.a.	n.a.	n.a.	-0.033*	0.016	n.a.	n.a.
Number of charging stations 2	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-0.080**	0.020
Number of charging stations 3	n.a.	n.a.	0.216	0.141	n.a.	n.a.	n.a.	n.a.
Number of charging stations 4	0.013	0.015	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Tokyo & Kanagawa	0.016	0.292	2.247	2.901	0.350**	0.123	-0.192	0.144
Osaka & Saitama	1.553**	0.348	-0.046	2.794	-0.302	0.154	0.128	0.183
Familiarity	-0.028	0.168	0.780	0.975	-0.408**	0.044	-0.137*	0.060
Air-conditioning or heater	0.014	0.114	0.254	0.384	-0.078*	0.038	0.106	0.077
High-capacity battery	1.670**	0.196	0.688	0.363	1.602**	0.075	1.692**	0.105
Number of trips	0.032	0.017	0.025	0.060	-0.030**	0.007	0.004	0.012
VMT	-0.006**	0.002	-0.0003	0.004	-0.000	0.0005	-0.001	0.001
Speed (0,20]#	-0.076	0.170	0.300	0.886	0.002	0.082	0.219*	0.103
Speed (40~)#	-0.002	0.206	0.544	0.617	-0.291**	0.110	0.033	0.134
Free	0.187	0.163	0.016	0.275	-0.099	0.055	0.055	0.088
Paid	n.a.	n.a.	n.a.	n.a.	-0.198	0.101	-0.197	0.173
Latter half	0.283*	0.123	0.331	0.393	0.129**	0.041	-0.161*	0.073
Electricity##	1.602**	0.204	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Log likelihood (regression model)	-2820.216		-744.109		-5698.322		-3115.346	
Log likelihood (stochastic frontier model)	-2798.333		-737.563		-5650.956		-3090.860	
Std(u), Std(v), Std(w)	2.444,0.971,1.408		2.034,1.060,3.135		1.966,0.903,1.116		2.013,1.010,1.458	
Observations	1407		387		3085		1617	
Unbalanced panels	39		11		95		90	

 # referenced group is speed (20, 40]

referenced group is other commercial units except electricity

***, * significance at 1%, 5% level*

n.a. indicates variables not included in the model. For the variables of number of charging stations, they are resulted from optimum choosing based on the goodness-of-fit of their models, while for the other variables, they are resulted from few samples.

regression analysis in modeling the mid-trip fast charging behavior for commercial and private vehicles, respectively, on working and non-working days. Therefore, this study focuses on discussing mid-trip fast charging behavior according to the estimation results of the true random effects stochastic frontier model.

For commercial vehicles on working days, number of charging stations 4 is better to explain their mid-trip fast charging behavior. However, it doesn’t show significant association with the remaining charge. Apparently increasing charging stations doesn’t effectively decrease the remaining charge. And the remaining charge can't seem to be significantly decreased even when the charging station density larger than 55 stations/1000km^2, as shown by the insignificant effect of Tokyo & Kanagawa. The effect of Osaka & Saitama shows that the remaining charge significantly increases with charging station density increases to $15 <$ stations/1000km^2 < 55. These results are contrary to TEPCO’s experience (Electrification Coalition, 2009).

The significant positive correlation between high-capacity battery and remaining charge means that remaining charge increases with the battery capacity – which seems not the original intention of developing battery technology. VMT per day correlates negatively with remaining charge, which is consistent with previous studies (Kitamura and Sperling, 1987; Yao et al., 2013) that travel patterns do have correlations with charging behavior. The significant positive correlation of latter half on remaining charge shows the obvious difference of charging behavior between the earlier and the latter period of this trial, however, the increasing remaining charge in the latter period seems not to be desired. The results also show that EV users from electricity companies start fast charging with about 1.6kWh more additional remaining charge than other users, which is accordance with the statistical result that the average SOC at mid-trip fast charging for the electricity users is 61.3%, while the overall average is 50.4%. In addition, inconsistent with our expectation, variables of familiarity, air-conditioning or heater, number of trips, speed and free of charge don’t have significant correlations with remaining charge.

Then, for commercial vehicles on non-working days, number of charging stations 3 is chosen to explain their mid-trip fast charging behavior. However, none of the explanatory variables show any significant association with remaining charge, which may result from the few samples.

Now the results of private vehicles on working days are discussed. In this model, number of charging stations 1 is used to explain the mid-trip fast charging behavior. The results show that number of charging stations has a significant negative correlation with remaining charge, which is consistent with TEPCO's experience (Electrification Coalition, 2009). While the dummy variables of Tokyo & Kanagawa has a significant positive correlation with remaining charge, which is contrary to TEPCO's experience (Electrification Coalition, 2009). The variables of familiarity and air-conditioning or heater have significant negative correlations with remaining charge as hypothesized. In addition, the significant correlations of high-capacity battery and latter half are similar with their correlations in the model for commercial vehicles on working days, and so does the insignificant effect of free of charge. Also the dummy variable of paid charging doesn't show significant effect on the remaining charge. However, the correlations of travel patterns are opposite to their correlations in the model for commercial vehicles on working days, and number of trips has a significant negative correlation with remaining charge, while VMT doesn't show significant correlation. What's more, the dummy variable of speed faster than 40km/h has a significant negative correlation with the remaining charge, while the variable of speed not more than 20km/h doesn't show significant correlation.

Lastly is the model for private vehicles on non-working days, which chooses number of charging stations 2 to explain the mid-trip fast charging behavior. The results show that number of charging stations has a significant negative correlation with remaining charge, which is consistent with TEPCO's experience (Electrification Coalition, 2009). While the dummy variables of Tokyo & Kanagawa and Osaka & Saitama don't have significant associations with remaining charge. These results possibly reveal that increasing charging infrastructure helps to decrease remaining charge, but more charging infrastructure is not necessarily better, there must be an optimal number of charging stations to encourage the effective use of both battery capacity and charging infrastructure, which is expected in the development of charging infrastructure. The significant negative correlation of familiarity is similar with its correlation in the model for private vehicles on working days. The variable of high-capacity battery, again, has a significant positive correlation with remaining charge. The dummy variable indicating speed not more than 20km/h has a significant positive correlation with the remaining charge, while the variable indicating speed faster than 40km/h doesn't show significant correlation. The significant negative correlation of latter half on remaining charge shows a desired development trend of charging behavior, that is the remaining charge when mid-trip fast charging begins decreases with the increasing BEV usage experience. Other variables — air-conditioning or heater, number of trips, VMT, free and paid — don't show any significant association with remaining charge.

Excluding the model for commercial vehicles on non-working days in which none of the explanatory variables is significantly correlated with remaining charge, the chosen definitions of number of charging stations are different for the other three models. This difference is probably due to the BEVs' usage patterns: commercial vehicles are usually used for widely distributed businesses, so a conception of charging station defined relative to charging locations is better to explain the charging behavior; private vehicles in general be used for daily travel (especially commuter travel), so a conception of charging station defined relative to home locations is better to explain the charging behavior.

In summary, the factors that are significantly correlated with the remaining charge are not similar for commercial and private vehicles, respectively, on working and non-working days. But generally speaking, BEVs with high-capacity batteries are initiated at higher remaining charge. Inconsistent with the previous studies, the free of charge and paid charging don’t show any significant association with remaining charge.

3.5 Discussion

This section discusses the possible explanations for certain charging patterns and the possibility of encouraging more efficient charging behavior among users.

Since none of the explanatory variables is significantly correlated with remaining charge for commercial vehicles on non-working days, the discussion about possible explanations for charging patterns will focus on the other three models: commercial vehicles on working days, private vehicles on working days and private vehicles on non-working days.

Related studies have shown that the more range anxiety felt by an EV user, the more likely he/she will apply coping strategies, such as charging EV (Franke and Krems, 2013a; Franke and Krems, 2013b; Franke et al., 2012). Here “range anxiety” is defined as the fear of running out of power before the destination or a suitable charging station is reached when driving an EV (Nilsson, 2011). It affects user’s behavior in this way: an EV user continuously checks the difference between available range and intended range, then the difference is compared with the preferred range buffer, it is the compared result that determines whether user feel anxiety or not, and if so, some coping strategies (e.g. charging EV) will be applied (Franke and Krems, 2013b). Thus, it can be stated that range anxiety is one possible explanation for more remaining charge when mid-trip fast-charging begins.

Comparing the effects of the continuous variable of number of charging stations in the three models, it seems commercial users unaffected by the increasing charging infrastructure, while private users tend to charge their BEVs at lower level of remaining charge with increasing charging infrastructure. According to the previous discussion, therefore, it possibly reveals that increasing charging infrastructure helps to alleviate range anxiety felt by private users, while it has no effect on commercial users, which may result from the nature of the business, which requires punctuality, speed, and so on. The suggested explanation between remaining charge and the number of charging stations for commercial users seems to apply to the positive effect of electricity users, since electricity users can access to more charging stations that are exclusive for them. The significant positive effects of dummy variable of Osaka & Saitama in the model for commercial vehicles on working days and dummy variable of Tokyo & Kanagawa in the model for private vehicles on working days reveals that more charging infrastructure may causes more remaining charge when mid-trip fast charging begins. The above discussions seem to show that increasing charging infrastructure to a certain extent may helps to alleviate range anxiety felt by BEV users, but the charging infrastructure is not the more the better.

The insignificant effect of familiarity in the model for commercial vehicles but significant negative effects in the models for private vehicles may reveal that commercial users are more anxious about the limited range, which may be caused by the nature of business discussed above.

The variable of air-conditioning or heater only significantly correlates with private vehicles on working days, which may result from the driving and charging experience developed in daily travel. Other insignificant correlations may reveal that users don’t care about the extra electricity consumption by using air-conditioning or heater, and just charge if a certain remaining charge is reached. These possible explanations may reveal that the range anxiety is less among private users on working days to some extent.

The significant negative effect of number of trips in the model for private vehicles on working days but insignificant effects in other models may be due to the less range anxiety felt by private users resulted from the more familiarity with charging infrastructure on working days: more trips offer private users the opportunity to charge at a convenient charging station by considering all trips. However, the significant negative effect of VMT in the model for commercial vehicles on working days but insignificant effects in other models may be due to the more range anxiety caused by the nature of business, which offers limited time to stop and charge during the trip and thus decreases the remaining charge, especially for the long trips.

The speed has significant effect only for private vehicles. The significant negative effect of the variable indicating speed faster than 40km/h in the model for private vehicles on working days may be due to the less range anxiety felt by private users resulted from the more familiarity with charging infrastructure on working days, which alleviates the fear of running out of power without an available charging station caused by the faster rate of electricity consumption. The significant positive effect of the variable indicating speed not more than 20km/h in the model for private vehicles on non-working days may be due to the more diversified activities for private users on non-working days, for example, private users may charge their vehicles at a shopping center with fast charging infrastructure while they make a short-time shopping during a trip. The example may also reveals that private users are a bit more anxious on non-working days and they charge when there is a convenient charging station without considering too much about the remaining charge, which may be caused by the less familiarity with charging infrastructure when traveling in non-commuting area on non-working days.

Lastly, the significant positive effects of latter half in the models for commercial and private vehicles on working days as well as the significant negative effect in the model for private vehicles on non-working days may result from the experienced range anxiety during BEV use, as pointed out in the previous research (Franke and Krems, 2013c). Possible explanations may be that the longer charging time has influenced the punctuality, so commercial users tend to charge their BEVs at their convenience without considering too much about the remaining charge; the adventure in charging caused by the less range anxiety on working days has led to private users be stranded, so they tend to charge their BEVs at a higher level of remaining charge; the more range anxiety on non-working days always gives private users a higher level of remaining charge when mid-trip fast charting begins, so they tend to charge their BEVs at a lower level of remaining charge.

Above all, range anxiety is one possible explanation for more remaining charge when mid-trip fast charging begins, which is mainly caused by the sparse charging stations, less familiarity with charging stations, and the nature of business (which requires punctuality, speed, and so on).

Next the possibility of encouraging more efficient charging behavior among users is discussed. The approach is to compare the predicted required charge with the actually observed values at which fast charging is initiated. Here the comparison covers the four cases of commercial vehicles on working days, commercial vehicles on non-working days, private vehicles on working days and private vehicles on non-working days.

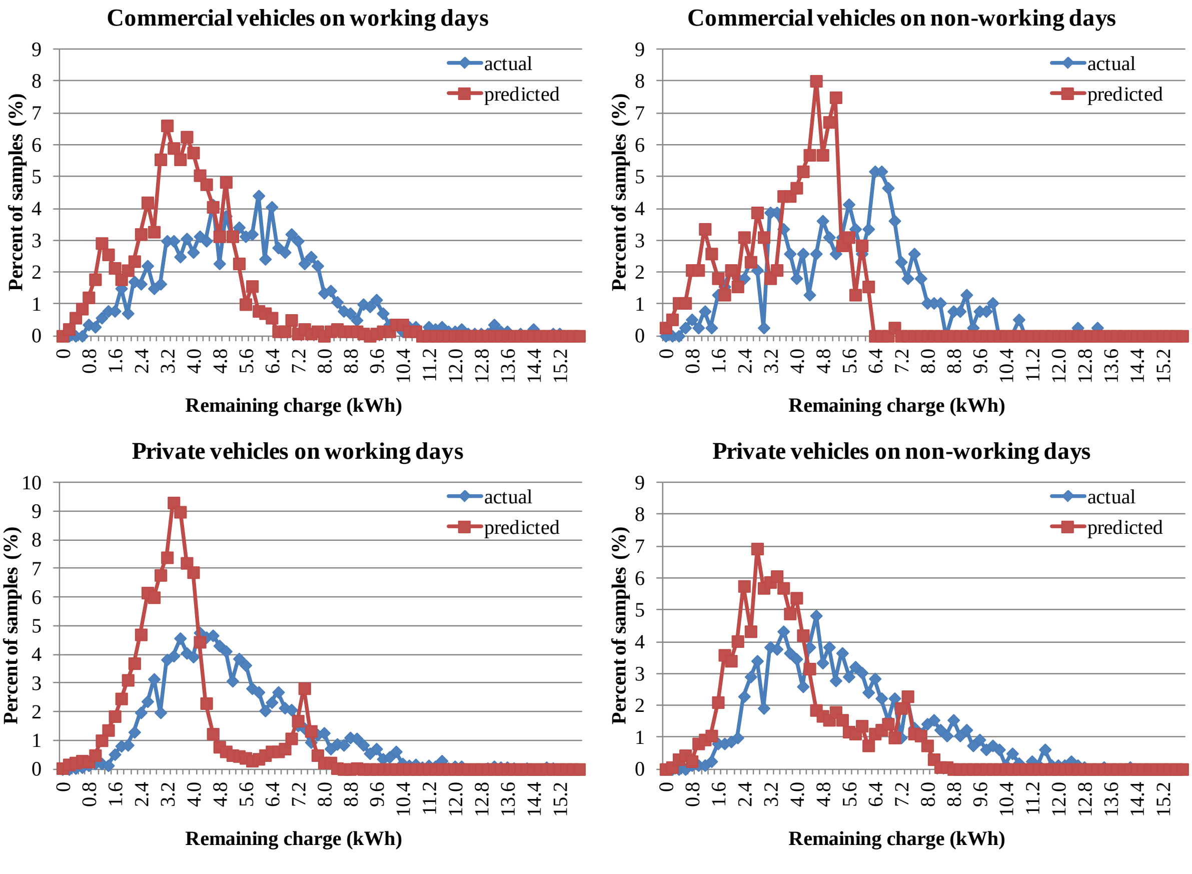


Figure 3.2 Distribution of minimum required and actual remaining charge

Figure 3.2 shows the distributions of predicted required charge and actual remaining charge at the initiation of mid-trip fast charging for the four models. There are clear differences between the two distributions in each case, with actual charging generally being initiated at a higher level of remaining charge than the predicted required charge. It is worth noting that these differences come from the inefficiency in mid-trip fast charging, and thus they point to ample opportunity to encourage improvements in current charging behavior. However, the degree of possible improvement varies with the situation. The average inefficiency, defined as the additional electricity demand in actual behavior as compared with the predicted required charge, can be evaluated by the expected value of u_{it}

$$E[u_{it}] = \left(\frac{2}{\pi}\right)^{1/2} \widehat{\sigma_u} \tag{3.8}$$

where $\widehat{\sigma_u}$ is the estimate of σ_u. The average inefficiency is respectively 1.95kWh, 1.62kWh, 1.57kWh, and 1.61kWh for the four situations, which equates to driving about 22.0km, 18.3km, 17.7km, and 18.1km (according to electricity consumption figures provided by the Ministry of Land, Infrastructure, Transport and Tourism, MLIT). The estimated inefficiencies seem to be reasonable since the regular behavior for private vehicles on working days is more difficult to be improved, which possibly results from the range anxiety according to the discussions of the estimation results. Therefore, it can be expected that the estimations are obtained by considering the influence factors mentioned above to some degree. What’s more, the average predicted required charge for the four cases is respectively 3.75kWh, 3.85kWh, 3.70kWh and 3.89kWh, likely indicate that the stable behavior after alleviating inefficiency is similar among both commercial and private users. The possible measures can be applied to alleviate inefficiency include increasing charging stations and increasing familiarity with charging stations, as revealed by the estimation results of number of charging stations and familiarity, which is consistent with the previous findings (Mirchandani et al., 2014;

CABLED, 2011).

Overall, the results seem to show that range anxiety is a probable reason for current inefficient charging behavior of BEV users, and there are great opportunities to encourage greater rationality in charging behavior.

3.6 Summary

In this study, the stochastic frontier modeling methodology is used to explore how factors including charging infrastructure and battery capacity affect the mid-trip fast-charging behavior of BEV drivers. The results are then used to estimate the possibility of encouraging more effective use of battery capacity and the charging infrastructure. Estimation results are presented for four cases (commercial vehicles on working days, commercial vehicles on non-working days, private vehicles on working days and private vehicles on non-working days) based on mid-trip fast-charging data extracted from a BEV usage trial conducted in Japan.

The comparison of the estimation results with the true random effects stochastic frontier model and the random effects regression model indicates that the stochastic frontier modeling methodology is more effective in analyzing the battery usage behavior. The estimation results obtained with the true random effects stochastic frontier model show that the remaining charge at the initiation of fast charging during a trip associates with number of charging stations, familiarity with charging stations, usage of air-conditioning or heater, battery capacity, number of trips, VMT, speed, and the type of business. All the factors correlated with charging behavior of commercial and private vehicles, respectively, on working and non-working days in different way, which possibly result from range anxiety felt by users. The range anxiety arises mainly from the sparse charging stations and unfamiliarity with charging infrastructure, which seems can be alleviated by increasing charging stations and providing detail infrastructure information for BEV users. The positive correlation between high-capacity battery and remaining charge shows that higher capacity battery is not necessarily better. And the unexpected positive correlation between remaining charge and the latter half of this trial may indicates that it would be a long time to form reasonable behavior in using battery capacity and charging infrastructure.

Comparison of actual and predicted values for the four models indicated that there is considerable opportunity to encourage improvements in charging behavior. It appears that the stochastic frontier modeling method is an effective way to model the required charge at which mid-trip fast charging could be initiated as it takes into account trip and vehicle characteristics to some extent in the process of estimation.

Lastly, since the remaining charge when mid-trip fast-charging begins is affected by user perceptions, which may change with increasing experience, further research should focus on evaluating these perceptions to explore the process by which charging behavior is learned, thereby accurately representing the required charge needed by the mass consumer market.

Chapter 4

Fast-charging station choice behavior among battery electric vehicle users

This chapter examines the charging behavior related to charging infrastructure usage. The focus is on fast-charging events during trips that include just one fast-charge between origin and destination in Kanagawa Prefecture, Japan. The characteristics of fast-charging behavior seen in the samples used in this study are then described. Mixed logit models with and without a threshold effect for detour distance are applied to explore how BEV 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 generation of the choice set is also described in the modeling process. The estimation results are discussed to show the effects of various factors on the choice of fast charging stations. And the generally willing detour distance is obtained by comparing the model fittings of models with different thresholds. Finally, some conclusions are presented to wraps up this chapter.

4.1 Introduction

The introduction of EVs in Section 1.2 shows that 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, EVs can be recharged by normal charging and fast charging, as introduced in Section 1.2.2. 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. The field trial of BEV usage in

Japan introduced in Chapter 2 shows 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 AFVs 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 (2013) 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 (2013) found that the sampled drivers are most likely to refuel at gas stations within 1500 meters' 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 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 EV 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.

4.2 Data profiles

As the description of the field trial in Chapter 2 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 study on the modeling of normal charge timing choice behavior among BEV users (Sun et al., 2015b). For this reason, individuals for whom there is only one observation during this trial are excluded from the sample set used.

What do we know about fast charging stations introduced in Section 2.2 is that 79.2% of these stations are available to any BEV 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 BEV 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. Based on the definition of a trip in Section 2.3.1, 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 whose duration time is more than one hour; (2) two or more contiguous sequences of vehicle locations with the same start-up time for driving connected by stays for fast-charging whose duration time is not more than one hour, followed by a stay for normal charging, or a stay for fast charging whose duration time is more than one hour, or a driving with a different start-up time. 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.

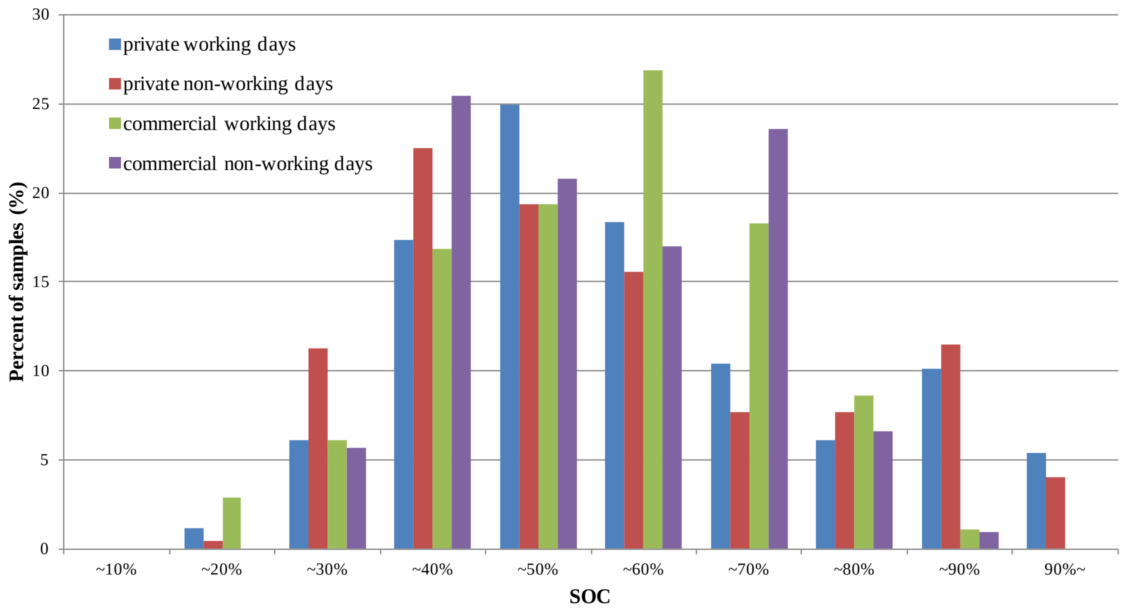


Figure 4.1 Distribution of observed SOC at initiation of fast charging during trips that include just one fast-charge between origin and destination in Kanagawa Prefecture

We now look at the characteristics of the data used in this study. Figure 4.1 shows the distribution of observed SOC at the initiation of fast charging during trips that include just one fast-charge between origin and destination in Kanagawa Prefecture, for commercial and private vehicles, respectively, on working and non-working days. 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.

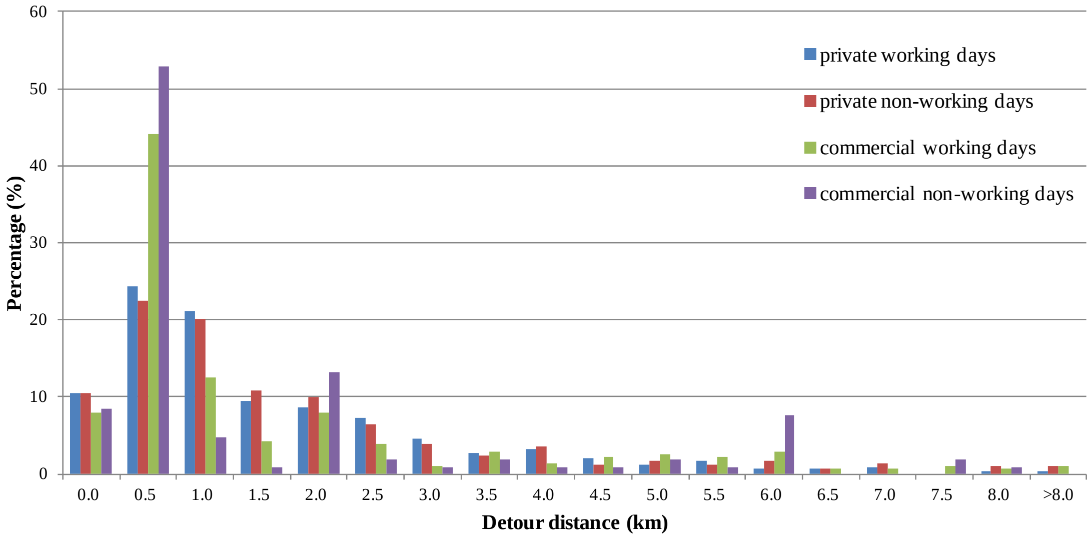


Figure 4.2 Distribution of detour distance for fast charging during trips that include just one fast-charge fast-charge between origin and destination in Kanagawa Prefecture

The distribution of detour distance for commercial and private vehicles, respectively, on working and non-working days is shown in Figure 4.2. The detour distance for individual n who charges at station j when traveling from origin O_{nt} to destination D_{nt} is:

$$detour_{njt} = d_{O_{nt}j} + d_{jD_{nt}} - d_{O_{nt}D_{nt}} \tag{4.1}$$

where d_{Ontj}, d_{jDnt} and d_{OntDnt} 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 path, 0.5km or less, in the case of commercial vehicles, while the value is 1.0km 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 Figure 4.1 and Figure 4.2.

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 Figure 4.1 and Figure 4.2 cannot be readily applied to other regions of Japan. Further, these charging characteristics can not 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.

4.3 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.

4.3.1 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, 2013; 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.

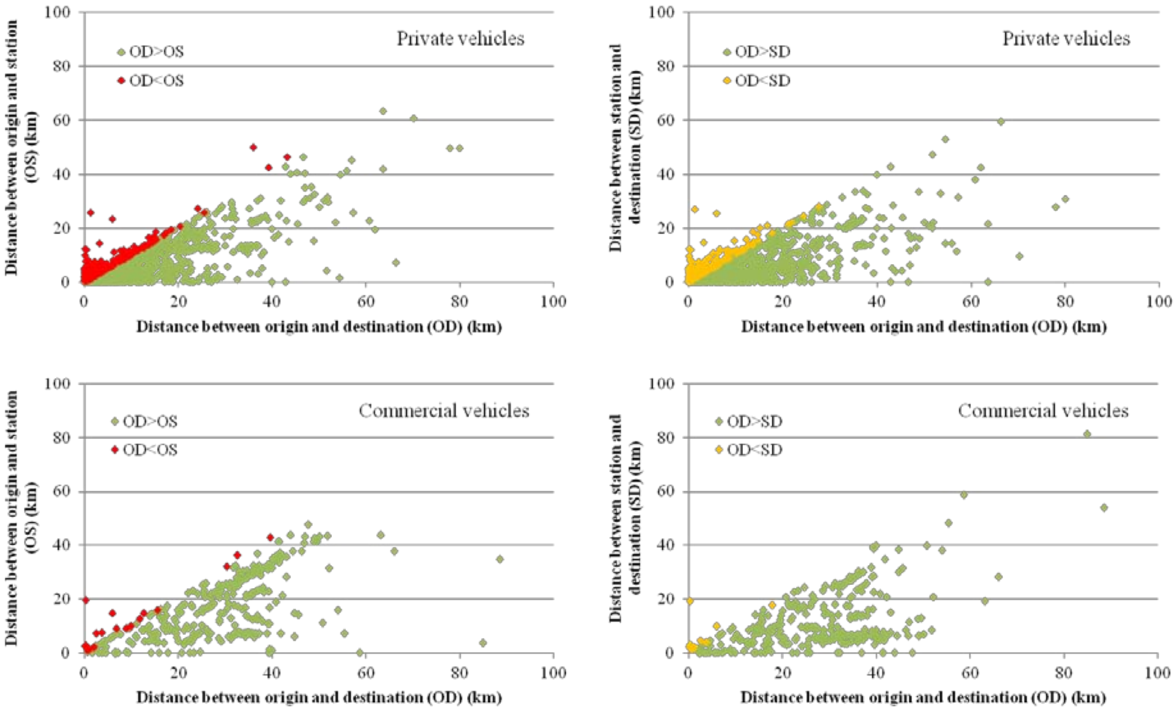


Figure 4.3 Scatter diagrams of origin-destination distance against, respectively, origin-station distance and station-destination distance in Kanagawa Prefecture

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 Figure 4.3. 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 1.8km more than the distance between origin and destination, while the value is 2.8km for commercial vehicles.

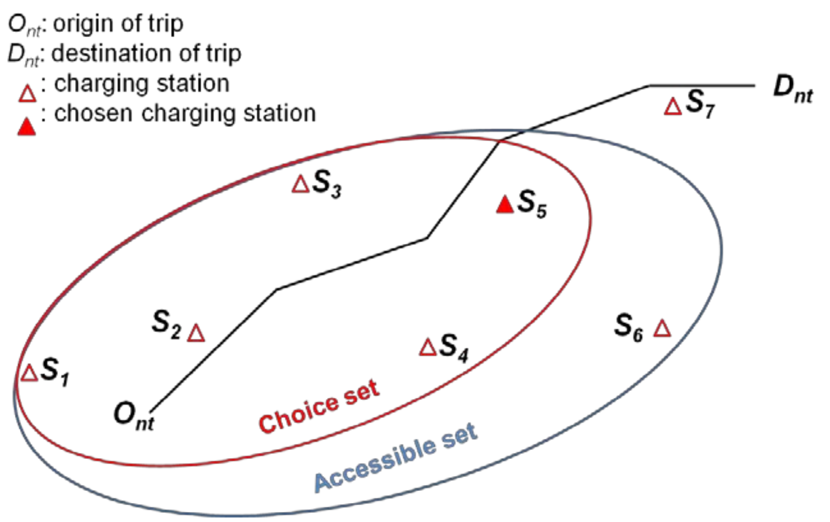


Figure 4.4 Schematic diagram of choice set generation

In summary, this study adopts the following principles for generating the choice set, supplemented by the schematic diagram presented in Figure 4.4. 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: $d_{OntSj} \leqq d_{OntDnt}+\varepsilon$ and $d_{SjDnt} \leqq d_{OntDnt}+\varepsilon$, where d_{OntSj}, d_{SjDnt} and d_{OntDnt} 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 2.8km 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 Figure 4.3 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.

4.3.2 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:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \tag{4.2}$$

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:

$$P_{nit}(\beta_n) = \frac{e^{\beta_n X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta_n X_{njt}}} \tag{4.3}$$

A detailed derivation of Formula (4.3) 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:

$$P_{nit} = \int \left(\frac{e^{\beta X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta X_{njt}}}\right) \mathrm{f}(\beta)\,\mathrm{d}\beta \tag{4.4}$$

Thus the sample likelihood is:

$$L = \prod_{n=1}^{N} \int \prod_{t=1}^{T_n} \prod_{i=1}^{J_{nt}} \left\{ \frac{e^{\beta X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta X_{njt}}} \right\}^{d_{nit}} f(\beta)\,\mathrm{d}\beta \tag{4.5}$$

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 (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 (4.5). Therefore, in the literature, methods such as quadrature (Geweke, 1996) 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:

$$SL = \prod_{n=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} \prod_{i=1}^{J_{nt}} \left\{ \frac{e^{\beta_n^r X_{nit}}}{\sum_{j=1}^{J_{nt}} e^{\beta_n^r X_{njt}}} \right\}^{d_{nit}} \tag{4.6}$$

where R is the number of draws from the distribution of β, and $\beta_n^{\,r}$ 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 (4.2):

$$U_{njt} = \alpha Z_{njt} + \beta_n X_{njt} + \varepsilon_{njt} \tag{4.7}$$

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, and the other terms share the same meaning as that in Formula (4.2). 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 ML-T can be obtained by simply adding αZ_{njt} to the exponential part in Formulas (4.3)-(4.6), 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, 2013). 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:

$$dom_{njt} = \sum_{i \in CS_{nt}} D_{nji} \tag{4.8}$$

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 (4.1).

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:

$$\mathrm{SOC}_{njt} = SOC_{O_{nt}} - \frac{d_{O_{nt}j} \times eff_t}{cap_n} \times 100 \tag{4.9}$$

where SOC_{Ont} is the SOC at the origin O_{nt}; d_{Ontj} 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 4.1; and cap_n is the battery capacity of vehicle n.

Table 4.1 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

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.

4.4 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. Figure 4.5 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.

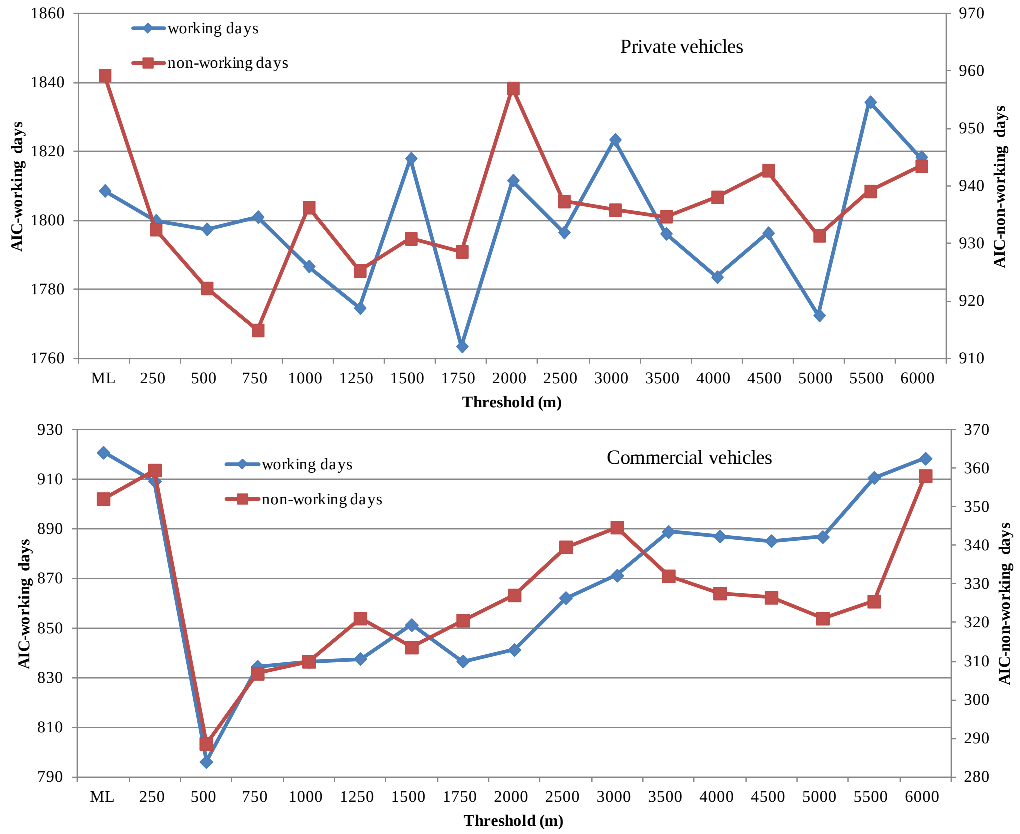


Figure 4.5 AIC of ML model and ML-T models at different thresholds

In Figure 4.5, there are various local minima with similar AIC to the global minimum AIC, especially for private vehicles. So that, for the moment, one can not be sure the results estimated at the optimum threshold at which the ML-T model achieves the closest fitting really represent fast-charging station choice behavior of BEV users.

The comparisons of the estimation results of the ML-T models with the global minimum AIC and with a local minima AIC show that the ML-T model with a local minima AIC may gives a significant negative parameter estimate for the threshold variable; that there is only a small difference in the estimation results that the evidence showing a variable has an effect on the fast-charging station choice becomes weak for some variables in the ML-T model with a local minima AIC. Since it can be expected that stations within the specific distance by which BEV users are generally willing to detour to charge may have additional attraction for users, a statistically significant positive parameter estimate for the threshold variable seems largely reasonable. The t-statistic of threshold parameter at different threshold values for both private and commercial vehicles are shown in Figure 4.6, which, combined with Figure 4.5, indicates 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 the models for commercial vehicles on working and non-working days. In the model for private vehicles on non-working days, the threshold at which the ML-T model has the global minimum AIC has the second maximum significance of the two statistically significant positive parameter estimates.

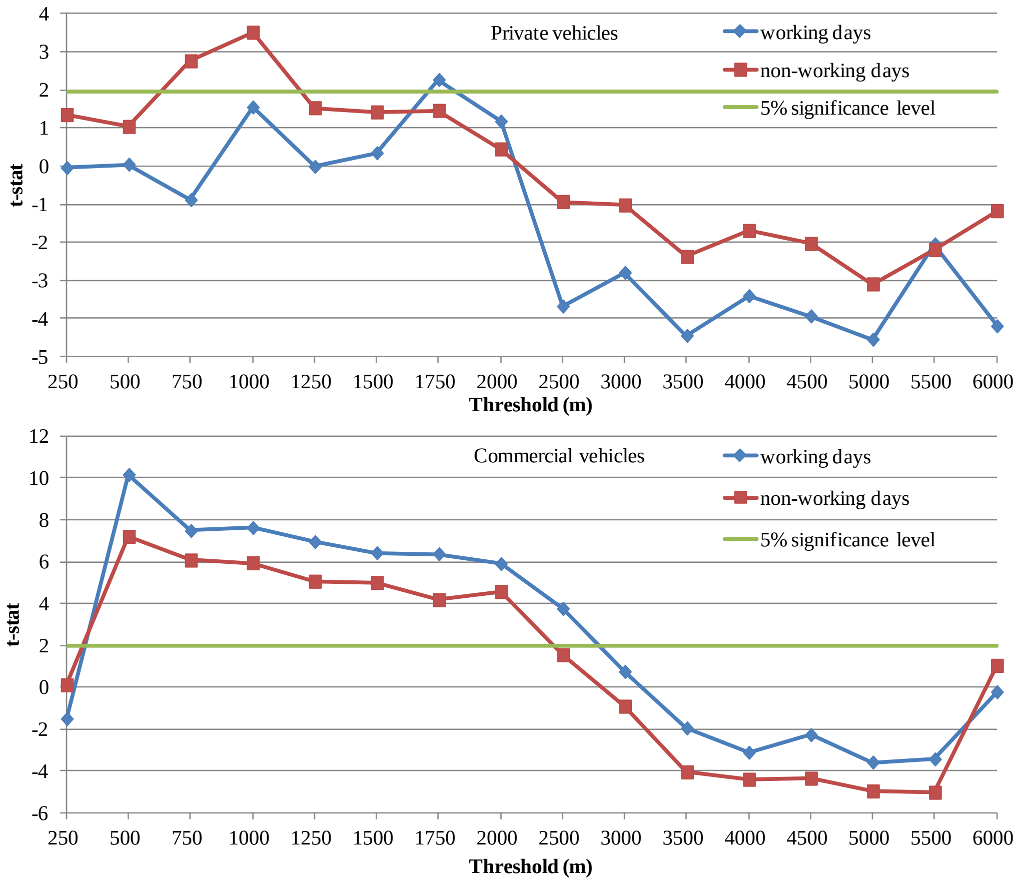


Figure 4.6 t-statistic of threshold parameter at different thresholds

Above 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 fast-charging station choice behavior of BEV users in the sample to a large extent.

Table 4.2 presents the estimation results of the ML-T model for private and commercial users, respectively, on working and non-working days, estimated at the optimum threshold at which the ML-T model achieves the closest fitting.

Table 4.2 Estimation results of ML model with threshold effect of detour distance

Variable	Private vehicles				Commercial vehicles			
	Working days (Threshold=1750m)		Non-working days (Threshold=750m)		Working days (Threshold=500m)		Non-working days (Threshold=500m)	
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	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	

*, ** *indicate significance at 5% and 1% levels, respectively*
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

For private vehicles traveling on working days, users are generally willing to charge at stations that require a detour of 1750 meters 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 meters 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 meters' 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 meters. 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 meters' detour distance. And they do not show preference to charge at stations encountered earlier or later along their paths from origin to destination, neither 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 meters. 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 meters' 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 meters, 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 4.2 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 1750m to charge their vehicles on working days and 750m on non-working days, while the value is 500m 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 meters' 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 — unobserved taste variation — 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)-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 4.2. 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 Figure 4.5.

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 or 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.

4.5 Summary

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 1750m to charge their vehicles on working days and up to 750m on non-working days, while the figure is 500m 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 meters' 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.

Chapter 5

Charge timing choice behavior of battery electric vehicle users

This chapter examines the charging behavior related to charge timing choice. The research background is firstly introduced, which states the focus of this study: normal charging after the last trip of the day. Then, the characteristics of the normal-charging behavior seen in the samples used in this study are described, and the alternatives are presented that no charging, charging immediately after arrival, nighttime charging, and charging at other times. A mixed logit model with unobserved heterogeneity is applied to explore choice behavior in respect of the time at which BEV users charge their vehicles. The effects of various factors on the choice of normal charge timing are discussed based on the estimation results. Finally, some conclusions are presented to wraps up this chapter.

5.1 Introduction

It is generally known that EVs may deliver impressive environmental, economic and societal benefits. A recent area of research relates to the costs and benefits to the environment, economy, and society of EVs. A number of authors have already discussed this question (e.g. van Vliet et al., 2011; Campanari et al., 2009; Eaves and Eaves, 2004; Delucchi and Lipman, 2001; Funk and Rabl, 1999). However, the impact of EVs on the electricity grid has become a growing concern in recent years, since they will add a significant load as they become more popular, possibly requiring changes to the existing infrastructure.

Previous research demonstrates that the effect of EV recharging on the electricity grid depends crucially on the timing of charging as well as the type of charging. Hadley (2006) pointed out that nighttime recharging had less impact on peak loads than charging during the early evening. Similarly, discussion by Axsen and Kurani (2010) shows that shifting recharging to off-peak hours could eliminate the threat to California utilities caused by the additional electricity demand. The significant effect of early evening (or peak period) recharging is mainly a result of it coinciding with the peak in household electricity consumption. Staggered EV recharging therefore seems necessary. Here ‘recharging’ refers to level 1 charging.

Shao et al. (2009) compared the peak loads resulting from two charging scenarios: all assumed vehicles are charged at level 1 at 6 p.m. and all are charged at level 2 at 6 p.m. They concluded that the first case increases the transformers to 68%/52% of their limits in winter/summer while the second overloads transformers to 103%/98%. The increased peak load of level 2 charging is due to the higher voltage requirement. Further, Shao et al. (2009) examined what happened if level 1 and level 2 charging were shifted to off-peak hours, finding that the peak load was then 58%/52% for level 1 charging and 93%/86% for level 2 charging. Similar results are obtained by Elgowainy et al. (2012), who compared the impacts on grids of recharging conducted at different timing and different level using the U.S. National Household Travel Survey.

The above discussion makes clear that appropriate timing of EV recharging is crucial to the impact of EVs on the electricity grid. However, users tend to recharge EVs randomly at their convenience without considering peak or off-peak hours. In order to maintain the reliability of the electricity grid once EVs are integrated into the economy, many studies suggest that recharging must be controlled and coordinated (Clement et al., 2009). As a result, smart charging with vehicle-to-grid (V2G) technology has begun to be widely discussed as a way to regulate recharging (Venayagamoorthy et al., 2009; Acha et al., 2010). Although this topic is not the focus of the present study, more details and related research can be found in Green II et al. (2011). Rather, the focus of this work is to explore what and how factors influence choice behavior related to recharge timing, and whether it is possible to encourage users to charge during off-peak hours by adopting suitable measures.

To the authors' knowledge, there has been almost no research on the choice behavior of recharge timing. Zoepf et al. (2013) used a mixed logit model to estimate the binary choice as to whether a PHEV was charged or not at the end of a trip. They suggested that the probability of charging overnight at home is going to be relatively high. Jabeen et al. (2013) explored EV drivers' preferences for charging at work, home or public charging stations through stated choice experiments, using a multinomial logit model and a mixed logit model, with indicators for time of day (morning, lunchtime and night hours) as explanatory variables. Both estimation results showed that drivers preferred to charge their EVs during the night hours. However, neither of these studies is really about the choice of recharge timing, with recharge timing as the dependent variable.

For EVs owned by households (hereafter referred to as private EVs), a typical daily trip may be from home to work, maybe to lunch, back home, and possibly for shopping or social. Considering that several hours are needed for normal charging, EVs might possibly be normal-charged at home, at an employer's parking lot if chargers are provided, or at a restaurant/store parking lot if enough time is spent there and if chargers are provided. For EVs owned by commercial fleets (hereafter referred to as commercial EVs), on the other hand, a typical day may start at the company premises with a trip to another business, then maybe on to a second business, then back to the company premises, and such a trip could be repeated several times. The possible locations for normal charging are the company premises, a parking lot if the dwell time is long enough and if chargers are provided. However, both private and commercial EVs can be fast-charged at any point during a trip as long as fast chargers are available, because of the short time requirement of fast charging.

This study will focus only on behavior related to normal charging after the last trip of the day, and on charging at home for private EVs and at the company premises for commercial EVs. The reasons for this choice are as follows. Firstly, EVs can be normal-charged at home or at the company premises without concerns about the availability of chargers. Secondly, after the last trip of the day, there is plenty of time to make a decision about when to begin normal charging – during peak hours or off-peak hours or randomly – and this decision significantly affects the power load as mentioned above.

In general, this study aims at exploring what and how factors influence the choice behavior for normal charging after the last trip of the day, in the hope that it may be possible to encourage recharging with appropriate timing, such as during off-peak hours. The analysis uses a mixed logit model with unobserved heterogeneity based on real-life BEV usage data collected in Japan.

5.2 Data profiles

As previously mentioned, this study uses only one choice situation – that of normal charging after the last trip of the day. After data checking and cleaning, the final data set used in the study included 249 commercial vehicles with 51,333 observations and 234 private vehicles with 66,933 observations. Table 5.1 compares the charging events used in this study and that in the field trial and shows that the normal-charging events used in this study represent a large proportion of the total charging events, which further reveals the importance of studying charge timing choice behavior for normal charging.

Table 5.1 Comparison of charging events in this study and field trial

Charging Events	Commercial Vehicles		Private Vehicles		Total		
	Normal Charging	Fast Charging	Normal Charging	Fast Charging	Normal Charging	Fast Charging	Total
This Study	34801	n.a.	26164	n.a.	60965	n.a.	60965
Field Trial	52575	2637	66784	6948	119359	9585	128944
Percentage (%)	66.2	n.a.	39.2	n.a.	51.1	n.a.	47.3

n.a. *indicates variables not included in the analysis*

One characteristic of EVs is that charging takes a long time, even for the fast charging, so an effective behavior is to end a travel day by doing a normal charging ready for the next travel day. However, this trial in Japan shows that only 67.8% of arrival events for commercial vehicles and 39.1% for private vehicles are charged in this way. The necessity of analyzing choice behavior regarding whether perform normal charging or not at the end of a travel day (and before the next trip) is thus clear. And the difference between commercial and private vehicles reveals that it is better to analyze commercial and private vehicles separately.

Among users who perform normal charging at the end of a travel day, there are two different behaviors: charging immediately after arriving at home or the company premises, and charging time later. By examining the delay time between arriving at the end of the travel day and starting normal charging separately for commercial and private vehicles, in about 80% of sampled normal-charging events, normal charging starts within 30 minutes for commercial vehicles, while the figure is 45% for private vehicles. Again this indicates the importance of analyzing normal charging behavior for commercial and private vehicles separately. This “delay time” so far is referred to as the lag between arrival time and when normal charging begins. However, this is a slightly incorrect definition for several reasons: users may need some time to prepare for charging; users may have some customary behavior immediately after arriving (and before charging), such as checking the mail or playing with the children; and the common occurrence of sampling errors. So we redefine “delay time” such that the lag is counted as a delay if it is greater than 30 minutes, otherwise we will say that users begin charging immediately upon arrival.

Even with this definition of “delay time”, 20% of sampled normal-charging events for commercial vehicles and 55% for private vehicles begin after a certain delay. The reason for this delay before beginning to charge a BEV is worthy of attention – particularly given that normal charging initiated in off-peak hours has less impact on the electricity grid. We first attempt to discover a pattern by drawing the distributions of arrivals and the start of normal-charging events through the day, and then the distribution of delay events against the time at which normal charging starts. The results are shown in Figure 5.1.

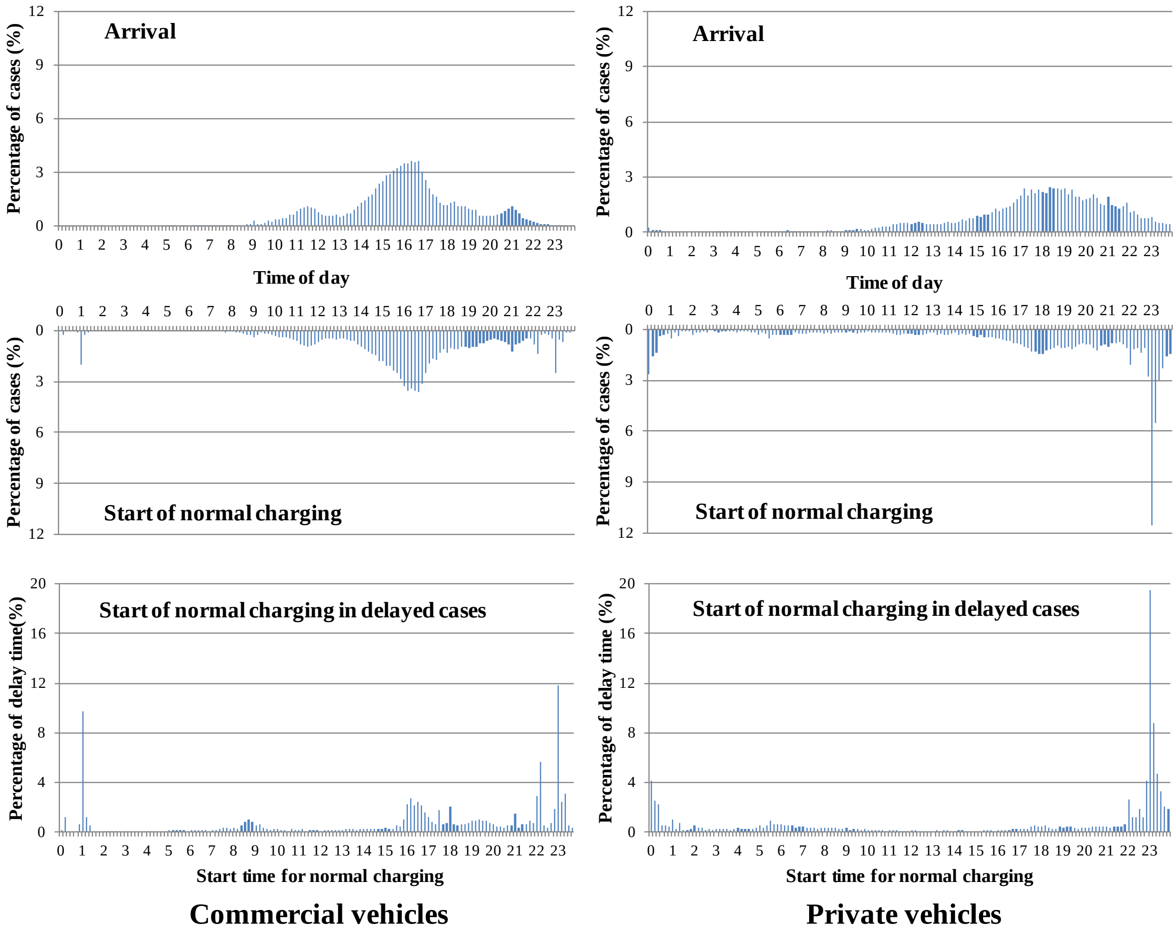
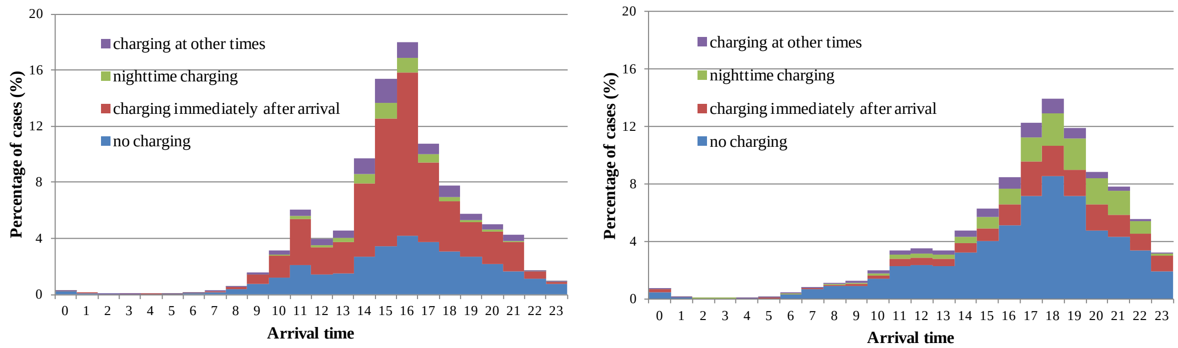


Figure 5.1 Distributions of arrivals, start of normal charging, and start of delayed normal charging after arrival of the last trip of the day

Figure 5.1 reveals that there is a greater spread of delay in the case of private vehicles than for commercial vehicles. Further, it seems that most users who delay charging are waiting until 23:00 to begin charging, for both commercial and private vehicles. This might be caused by electricity pricing, since one low-price electricity tariff begins at 23:00 and ends at 7:00 in Japan. However, there are some differences in delay behavior between commercial and private users. For commercial vehicles, there is a small rise in delayed charging events between 16:00 and 17:00; this may just be because users leave work at this time and leave their BEVs on charge. Similarly, delayed charging events that start between 8:00 and 9:00 are possibly caused by users arriving at work. There are two other charging peaks around 22:00 and 1:00 for commercial vehicles, which may need further explanation except for a possible link with electricity pricing (since there are several different electricity tariffs in Japan). For private vehicles, there is a peak in delayed charging events between 22:00 and 0:00, which is possibly linked with electricity pricing.

Given that a large proportion of delayed charging events start around 23:00 and the time period from 23:00 to 7:00 corresponds with off-peak hours and with a lower electricity tariff for some users (though not all, because of the various electricity tariffs), we divide delay behavior for normal charging into two categories: nighttime charging (from 23:00 to 7:00) and charging at other times.

Based on the above discussion, therefore, there are four choices of normal charging behavior after the last trip of the day: no charging, charging immediately after arrival, nighttime charging, and charging at other times. Figure 5.2 shows the distributions of choice behavior among these four possibilities for normal charging with arrival time, separately for commercial and private vehicles. To summarize, there is a difference of normal charging after the last trip of the day between commercial and private vehicles, with most commercial vehicles being charged at the end of the travel day while most private vehicles are not; most normal-charging events are initiated immediately after arrival at home or company premises, but a larger percentage of charging events take place at nighttime in the case of private vehicles.



Commercial vehicles **Private vehicles**

Figure 5.2 Distributions of choice behavior for normal charging after arrival of the last trip of the day

The assumption that BEV users are faced with the above-mentioned four choices after the last trip of the day does have some limitations. It does not include other charging opportunities during off-peak or low-price hours, which exist since the arrival time of the end-of-day trip varies in a wide range and there are several different electricity tariffs in Japan. Also it does not include such charging behavior that the normal-charging start time is determined by the departure time of the next travel day and duration time of fully charged. However, the assumed four choices are appropriate for this study since the purpose of this study is to explore what and how factors influence choice behavior related to recharge timing, and whether it is possible to encourage users to charge during off-peak hours by adopting suitable measures. It is important to point out that the results of this study are only indicative of early BEV adopters, given the few BEVs on the road. And the results may not necessarily be generalized outside of Japan.

5.3 Methodology

The decision whether to charge after the last trip of the day seems appropriately modeled as a multinomial discrete choice problem in which BEV users choose one alternative from the set of alternatives: no charging, charging immediately after arrival (at home or company premises), nighttime charging and charging at other times. As the introduction to the field trial in Chapter 2 makes clear, the data includes repeated observations for each individual and this warrants further consideration. 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 user information is not provided by the field trial in Japan. Generally, repeated observations from an individual tend to be similar, which means that individuals tend to make the same choices from one observation to the next. However, there are differences in preference for alternatives within and across individuals; for example, some users who are price-sensitive like to charge their BEVs at night for the lower price, while others who are less price-sensitive tend to charge at any time after the last trip of the day. In addition, it might be argued that one individual's choices will 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 normal charging choices would better be estimated using panel data, with appropriate specifications of similarity and difference within one individual's choices as well as differences among individuals. These specifications are modeled through an individual-specific and alternative-specific as well as time-invariant error component in this study, by assuming that differences over time within an individual's choices have an important component that is individual-specific and time-invariant and that affects the charging choice after the last trip of the day.

The utility that individual n obtains from alternative j in choice situation t can be specified as:

$$U_{njt} = \beta_j X_{njt} + \alpha_{nj} + \varepsilon_{njt} \tag{5.1}$$

where X_{njt} is a vector of observed variables related to alternative j which varies between individuals and over time, β_j is a vector of coefficients of these variables for alternative j, α_{nj} is an unobserved individual effect related to alternative j which is time invariant and represents the individual's preference, and ε_{njt} is a random term which is assumed to be independently and identically distributed and to vary over time, individuals, and alternatives. $\beta_j X_{njt}$ is the deterministic portion of utility, while the term α_{nj} is an error component, along with ε_{njt}, defining the stochastic portion of utility.

Individual n chooses alternative i from the set of alternatives J in choice situation t 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 α_n, which is known to individual n but unobserved by the researcher. If the researcher were to observe α_n, then the choice probability has the following form:

$$P_{nit}(\alpha_n) = \frac{e^{\beta_i X_{nit} + \alpha_{ni}}}{\sum_{j=1}^{J} e^{\beta_j X_{njt} + \alpha_{nj}}} \tag{5.2}$$

A detailed derivation of Formula (5.2) can be found in Train (2003). Since the researcher does not know α_n and therefore cannot condition on α_n, the unconditional choice probability must be the integral of $P_{nit}(\alpha_n)$ over all possible values of α_n:

$$P_{nit} = \int \left(\frac{e^{\beta_i X_{nit} + \alpha_i}}{\sum_{j=1}^{J} e^{\beta_j X_{njt} + \alpha_j}} \right) \mathrm{f}(\alpha)\, \mathrm{d}\,\alpha \tag{5.3}$$

Thus the sample likelihood is:

$$L = \prod_{n=1}^{N} \int \prod_{t=1}^{T} \prod_{i=1}^{J} \left\{ \frac{e^{\beta_i X_{nit} + \alpha_i}}{\sum_{j=1}^{J} e^{\beta_j X_{njt} + \alpha_j}} \right\}^{d_{nit}} \mathrm{f}(\alpha)\, \mathrm{d}\,\alpha \tag{5.4}$$

where d_{nit}=1 if individual n chooses alternative i at time t and zero otherwise. Usually, the distribution of α is specified freely by the researcher and then the parameters of that distribution are estimated. In most applications, $f(\alpha)$ 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 (2003), the appropriate choice depends on the research question. The parameters of the assumed distribution $f(\alpha)$ can be estimated by maximizing the sample likelihood. However, there exists no analytical solution for the integral in (5.4). Therefore, in the literature, methods such as quadrature (Geweke, 1996) and simulation (Train, 2003) are proposed to approximate the integral.

This study assumes that α is identically and independently distributed over the individuals and follows a multivariate normal distribution with mean b and variance-covariance matrix W, $\alpha \sim N(b,W)$, and uses simulation to estimate the parameters of the multinomial logit model with unobserved heterogeneity. The simulated sample likelihood is:

$$SL = \prod_{n=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{i=1}^{J} \left\{ \frac{e^{\beta_i X_{nit} + \alpha_{ni}^r}}{\sum_{j=1}^{J} e^{\beta_j X_{njt} + \alpha_{nj}^r}} \right\}^{d_{nit}} \tag{5.5}$$

where R is the number of draws from the distribution of α, and α_{ni}^r represents the rth draw for individual n and alternative i. 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.

Although α is specified as independent over individuals, there are possibly correlations between alternatives within one individual, since individuals might view one alternative as closer to a certain other one than others. For example, charging immediately after arrival can be expected to be seen as more similar to charging at other times or nighttime charging than to the alternative of no charging. Therefore, this study assumes that there are correlations between alternatives. Correlated draws can be created through transformations of independent draws, such as with the Cholesky transformation (Train, 2003).

For model identification, the coefficient vector and the unobserved heterogeneity of one choice are both normalized to zero. Therefore, each draw contains three values (ε_1, ε_2, ε_3), which follow a standard normal distribution. And α can be calculated using the Cholesky factor, L:

$$\alpha = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} = L\varepsilon = \begin{pmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} \tag{5.6}$$

where, L is defined as a lower-triangular matrix such that $LL' = W$. It is worth noting that it does not matter which alternative is normalized to zero, but the estimations of all other choices do have to be interpreted relative to whichever one is normalized to zero. In this study, the alternative of no charging is chosen as the one to be normalized to zero in order to interpret the results much more intuitively.

The dependent variable, which is known with certainty, is the choice from no charging, charging immediately after arrival (at home or company premises), nighttime charging, and charging at other times. The focus is then on the independent variables.

(1) The SOC after the last trip of the day, which visually represents the need for charging. It can be expected that the higher SOC the higher probability of no charging.

(2) The number of interval days before the next travel day, because generally users can be expected not to charge their BEVs if they do not plan to use it again for a couple of days.

(3) The vehicle-kilometers of travel (VKT) on next travel day, which reflects the electricity demand. It can be expected that the longer planned travel distance the higher probability of normal charging.

(4) The experience of fast charging, measured as the total number of fast charging events before the last trip of the current travel day. If the experienced fast charging is convenient, then the urgency of normal charging can be expected to be reduced, otherwise will be increased.

(5) A working day indicator for the current travel day and the next travel day, since it can be expected that the behavior pattern would be different for working days and non-working days.

(6) An indicator for nighttime return to home/company premises (from 23:00 to 7:00), which relates to charge timing.

(7) An indicator for the latter half of this trial. Since previous research shows that refueling choice is the result of a learning process (Dingemans, 1986), this indicator is included to explore whether any difference exists between the earlier and the latter period of this trial (the observations are divided into two equal stages for each individual according to the sample date).

Table 5.2 Statistical characteristics of independent variables

Variable	Commercial vehicles					Private vehicles				
	Total (n=51333)	No charging (n=16532)	Charging immediately (n=27591)	Nighttime charging (n=2588)	Other times (n=4622)	Total (n=66933)	No charging (n=40769)	Charging immediately (n=11616)	Nighttime charging (n=9769)	Other times (n=4779)
SOC (%)	69.3 (*19.7*)	74.1 (*18.2*)	67.9 (*19.7*)	65.8 (*20.5*)	63.1 (*20.6*)	63.2 (*20.4*)	70.5 (*17.1*)	54.2 (*20.8*)	49.4 (*19.2*)	50.7 (*19.1*)
Interval days before next travel day	1.9 (*2.7*)	1.9 (*3.2*)	1.9 (*2.6*)	1.8 (*1.7*)	1.7 (*1.7*)	1.3 (*1.4*)	1.3 (*1.7*)	1.3 (*1.0*)	1.2 (*0.8*)	1.3 (*0.9*)
VKT on next travel day (km)	24.5 (*20.5*)	21.1 (*21.7*)	26.2 (*19.6*)	30.0 (*22.1*)	23.6 (*19.1*)	24.6 (*24.1*)	19.7 (*19.6*)	31.1 (*26.4*)	34.6 (*30.0*)	29.2 (*27.8*)
Experience of fast charging	10.9 (*43.8*)	21.6 (*64.6*)	5.1 (*25.6*)	8.8 (*39.1*)	7.9 (*31.1*)	25.8 (*62.8*)	28.5 (*67.6*)	20.3 (*52.6*)	23.8 (*57.4*)	20.7 (*51.6*)
Working day (current travel day) (%)	88.8	82.0	92.5	95.1	87.6	70.8	71.3	69.9	71.0	67.9
Working day (next travel day) (%)	88.9	82.6	92.3	94.7	87.9	70.9	71.2	71.0	70.4	68.4
Nighttime (arrival at home /company premises) (%)	1.3	3.2	0.4	0.5	0.4	4.7	4.9	7.4	1.6	2.5
Latter half of trial (%)	49.9	49.0	49.9	59.4	47.4	49.9	49.7	49.1	52.6	48.7
Electricity company (%)	46.1	23.2	58.8	83.1	31.8	n.a.	n.a.	n.a.	n.a.	n.a.

Value in () indicates the standard deviation, while outside is the mean value
n.a. indicates variables not included in the analysis

(8) An indicator for BEVs operated by the electricity company, since it can be expected that electricity workers are better aware of the distribution of peaks and troughs in electricity grid demand.

There is an assumption implied in the above discussion that individuals can correctly predict their next travel plans in the definitions of interval days, VKT, and the working day indicator. The statistical characteristics of the independent variables for both commercial and private vehicles as well as for each choice are described in Table 5.2.

In summary, this study uses a multinomial logit model with unobserved heterogeneity based on panel data to model users' behavior in choosing a mode of normal charging after the last trip of the day. In fact, it is an application of a mixed logit model, the derivation and estimation of which can be found in Train (2003) in greater detail.

5.4 Results of model estimation

Choice behavior for normal charging after the last trip of the day is, as has already been noted, different for commercial and private users. So the estimation results of two groups are presented in this section, respectively, for commercial vehicles and private vehicles.

Table 5.3 presents the estimation results of mixed logit model with unobserved heterogeneity (ML) for commercial and private vehicles, the likelihood at convergence of multinomial logit model (MNL) is also presented for comparison. All of these results should be interpreted relative to the alternative of no charging, since this is specified as the baseline. It is clear from the AICs in Table 5.3 that mixed logit model with unobserved heterogeneity is more effective than multinomial logit model in analyzing the charge timing choice behavior. Therefore, this study focuses on discussing charge timing choice behavior after arrival of the last trip of the day according to the estimation results of the mixed logit model with unobserved heterogeneity.

Table 5.3 Estimation results for normal charge timing choice after the last trip of the day[#]

Variable	Alternative	Commercial vehicles		Private vehicles	
		Coef.	Std. error	Coef.	Std. error
SOC	Charging immediately	-0.066**	0.001	-0.104**	0.001
	Nighttime charging	-0.059**	0.002	-0.100**	0.001
	Charging at other times	-0.059**	0.001	-0.096**	0.001
Interval days before next travel day	Charging immediately	-0.042**	0.005	-0.058**	0.017
	Nighttime charging	-0.086**	0.020	-0.195**	0.023
	Charging at other times	-0.059**	0.010	-0.008	0.013
VKT on next travel day	Charging immediately	0.015**	0.001	0.025**	0.001
	Nighttime charging	0.018**	0.001	0.028**	0.001
	Charging at other times	0.009**	0.001	0.024**	0.001
Experience of fast charging	Charging immediately	-0.002**	0.0004	-0.001**	0.0003
	Nighttime charging	-0.003**	0.001	-0.0003	0.0003
	Charging at other times	-0.002**	0.001	-0.001**	0.0004
Working day (current travel day)	Charging immediately	0.166**	0.045	-0.174**	0.034
	Nighttime charging	0.321**	0.121	-0.092*	0.036
	Charging at other times	0.090	0.061	-0.203**	0.040
Working day (next travel day)	Charging immediately	0.008	0.045	0.076*	0.034
	Nighttime charging	0.052	0.119	0.009	0.036
	Charging at other times	0.032	0.062	-0.040	0.039
Nighttime (arrival at home/company premises)	Charging immediately	-0.817**	0.127	0.504**	0.068
	Nighttime charging	-0.433	0.343	-1.434**	0.105
	Charging at other times	-1.293**	0.254	-0.916**	0.110
Latter half of trial	Charging immediately	0.108**	0.029	0.104**	0.031
	Nighttime charging	1.121**	0.070	0.289**	0.033
	Charging at other times	-0.0002	0.041	0.104**	0.037
Electricity company	Charging immediately	1.750**	0.049	n.a.	n.a.
	Nighttime charging	2.735**	0.092	n.a.	n.a.
	Charging at other times	-0.309**	0.063	n.a.	n.a.
Alternative specific constant (i.e. Mean)	Charging immediately	3.751**	0.084	4.497**	0.080
	Nighttime charging	-1.489**	0.192	3.053**	0.088
	Charging at other times	3.239**	0.107	3.477**	0.084
Variance	Charging immediately	4.503**	0.100	8.200**	0.168
	Nighttime charging	7.843**	0.314	7.333**	0.168
	Charging at other times	6.697**	0.188	3.588**	0.106
Covariance	Charging immediately & Nighttime charging	0.279**	0.098	2.798**	0.087
	Charging immediately & Charging at other times	2.698**	0.118	4.330**	0.095
	Nighttime charging & Charging at other times	1.934**	0.134	2.435**	0.065
Log likelihood (MNL)		-48489.578		-62803.558	
Log likelihood (ML)	LL (Bc)	-30708.327		-40994.861	
	LL (B)	-30503.235		-39873.729	
AIC (MNL)		97033.156		125655.116	
AIC (ML)		61078.47		79813.458	

 # Reference group is: no charging
n.a. indicates variables not included in the analysis
**, ** indicate significance at 5%, and 1% level, respectively*
LL(Bc): log likelihood without correlated coefficients for ML
LL (B): log likelihood with correlated coefficients for ML

For commercial vehicles, firstly we consider the variable of indicator for BEVs operated by electricity company, which has significant positive effects on the choices of charging immediately and nighttime charging as well as significant negative effect on the choice of charging at other times. The low utility of charging at other times indicates that electricity workers prefer to charge at some points after their last trip of the day, rather than randomly. And the high utility of the nighttime charging indicates that they prefer to delay charging until nighttime. The reason for this pattern may be that electricity workers know the exact distribution of peaks and troughs in the electricity grid and choose to charge during off-peak hours to regulate the peak-trough differential. This might also be used to explain the charging peak at 1:00 for commercial vehicles in Figure 5.1, maybe something like smart charging is used to initiate such nighttime charging.

Next, we see that, compared to no-charging, the probabilities of charging immediately, nighttime charging and charging at other times are lower when SOC is higher, which is consistent with our expectation, since a higher SOC means greater available range and thus smaller charge demand.

Then let’s examine the effect of interval days before the next travel day. The results show that there are significant negative effects on the choices of charging immediately, nighttime charging and charging at other times, which may reveal again that normal charging is a demand-based behavior.

Looking at VKT on the next travel day, the significant positive effects on the choices of charging immediately, nighttime charging and charging at other times reveal that a longer planned travel distance increases the probability of normal charging. This effect is similar to that of SOC and interval days before next travel day, and reveals again that normal charging is a demand-based behavior.

The total number of fast charging events before the last trip of the current travel day has significant negative effects on the choices of charging immediately, nighttime charging and charging at other times, which seems to reveal that fast charging reduces the demand for normal charging. One possible reason is the convenience provided by the much shorter charging time of fast charging as compared with normal charging, which attracts commercial users to take fast charging.

The working day indicator for this current travel day has significant positive effects on the choices of charging immediately and nighttime charging. One possible reason is the nature of the service business, which requires punctuality, speed, and so on, and commercial users charge their BEVs ready for the upcoming travel demand. However, the insignificant effect on the choice of charging at other times reveals that commercial users prefer to charge at some points after their last trip of the day, rather than randomly, even though they are anxious about the upcoming electricity demand. The nature of the service business can also be used to explain the insignificant effects of working day indicator for the next travel day on the choices of normal charging.

Table 5.3 shows that commercial users tend not to charge when they arrive during the nighttime, which may because it is too late to begin charging, or all of the chargers are in use by other vehicles if the number of chargers is less than the number of vehicles.

Lastly, the indicator for the latter half of the trial data has significant positive effects on the choices of charging immediately and nighttime charging. These results can be seen as the development of consistent charging behavior with experience. Therefore, it can be said that commercial users tend to charge during the nighttime, which is expected because off-peak tariffs generally operate at night and charging events initiated during off-peak hours will reduce the impact on the electricity grid.

Now the results of private vehicles are discussed. First we see that, the significant negative effects of SOC on the choices of charging immediately, nighttime charging and charging at other times are similar with the effects in the model for commercial vehicles, which can be explained by the demand of normal charging as discussed for commercial vehicles.

Then, the results show that the interval days before the next travel day has significant negative effects on the choices of charging immediately and nighttime charging. These results may also reveal that normal charging is a demand-based behavior.

The VKT on the next travel day has significant positive effects on the choices of charging immediately, nighttime charging and charging at other times, which reveals again that normal charging is a demand-based behavior.

The total number of fast charging events before the last trip of the current travel day has significant negative effects on the choices of charging immediately and charging at other times. This reveals that fast charging reduces the demand for normal charging for the possible reason discussed for commercial vehicles. However, this variable doesn't have significant negative effect on the choice of nighttime charging, which may reveals that private users are price-sensitive, with the low price in off-peak hours attracts them to charge their BEVs.

The effects of the working day indicator for this current travel day on the choices of charging immediately, nighttime charging and charging at other times are all significantly negative, which is opposite to commercial vehicles. This reveals that private users tend not to charge after the last trip of a working day, which may be because private users can charge their BEVs in their companies. The significant positive effect of the working day indicator for the next travel day on the choice of charging immediately shows that private users tend to charge immediately after arrival if the next travel day is a working day, which may reveals that private users also worry about the upcoming travel demand.

Unlike commercial users, private users prefer to charge immediately rather than wait for other times or no charge when they come home during the nighttime, which may reflects the effect of electricity price to some extent.

Lastly, the effects of the indicator for the latter half of the trial data on the choices of charging immediately, nighttime charging and charging at other times are all positive. These results reveal that private users tend to charge during the nighttime, which is expected for the benefit of electricity grid as discussed for the commercial vehicles.

In summary, the effects of all factors on the choice probability of each alternative are somewhat different for commercial and private vehicles. The effects of working day indicator for this current travel day on the choices of charging immediately, nighttime charging and charging at other times are positive for commercial vehicles but negative for private vehicles. The effect of nighttime indicator for arriving on the choice of charging immediately is negative for commercial vehicles but positive for private vehicles. However, the results come to broadly the same conclusions that SOC, interval days before the next travel day, and VKT on the next travel day are the main predictors for whether a user charges the vehicle or not, that the experience of fast charging reduces the demand for normal charging after the last trip of the day, and that there is a trend to charge during the nighttime.

Next, we see the estimation results of individual effect related to alternatives in the mixed logit model with unobserved heterogeneity. The variance of each random coefficient is statistically significant for both commercial and private vehicles, indicating that there are substantial variations across individuals in their choices of normal charging after the last trip of the day. Specifically, the variance for nighttime charging is larger, which could have two underlying causes: (i) users are somewhat price-sensitive and like to charge during low-price hours; (ii) there are various electricity tariffs in Japan and thus several different periods of low-tariff hours. On the other hand, the variance for charging immediately after arrival is the smallest for commercial vehicles but the largest for private vehicles, which can be expected because this alternative reveals arrival distribution that is affected by certain relatively stable factors for commercial vehicles (e.g. working hours) while relatively flexible factors for private vehicles (e.g. working, shopping and socializing). In addition, the variance of charging at other times for private vehicles is smaller than that for commercial vehicles[1],

[1] The coefficient estimates can be compared because the scale parameters of the two models are the same.

which may because private users are more price-sensitive and they tend not to charge their BEVs randomly.

The significance of the correlation between alternatives can be tested using the likelihood ratio test. The test statistic *-2[LL(Bc)-LL(B)]* is 410.2 and 2242.3, respectively, for commercial and private vehicles, both of which are greater than the critical chi-square value with three degrees of freedom. This implies rejection of the null hypothesis that there are no correlations between alternatives. For both commercial and private vehicles, charging immediately and charging at other times correlate positively with nighttime charging, implying that users who prefer to charge immediately or at other times tend to be attracted by nighttime charging. It can be expected that more users will initiate normal charging during the nighttime after the last trip of the day if the utility of nighttime-charging option is increased with some measures. This is exciting because BEV users are price-sensitive, especially private users as discussed previously, and reducing electricity price at nighttime is one possible measure to increase the attractiveness of nighttime charging. Therefore, it could be concluded that it’s possible to encourage users, not only those who tend to charge immediately but also those who tend to charge at other times, to charge at during off-peak periods by offering price reductions or other measures.

5.5 Summary

In this study, a mixed logit model with unobserved heterogeneity is used to explore how factors affect users’ choices in relation to the normal charging of a BEV after the last trip of the day (where the choices are no charging, charging immediately after arrival at home or company premises, nighttime charging, and charging at other times). To the authors’ knowledge, this is the first study that directly examines this timing choice behavior for the charging of EVs by users. The results are used to consider the possibility of encouraging normal charging at an appropriate time. Estimation results are separately presented for two models, one for commercial vehicles and one for private vehicles, as well as for the last three alternatives (with the first alternative adopted as the baseline), based on normal charging events after the last trip of the day extracted from a BEV usage field trial in Japan.

The comparison of the estimation results with mixed logit model with unobserved heterogeneity and multinomial logit model indicates that the mixed logit model with unobserved heterogeneity is more effective in analyzing the charge timing choice behavior. The estimation results with mixed logit model with unobserved heterogeneity show that SOC, interval days before the next travel day, and VKT on the next travel day are the main predictors for whether a user charges the BEV or not, that the experience of fast charging decreases the probability of normal charging. These hold for both commercial and private vehicles. However, the probability of normal charging after the last trip of a working day is increased for commercial users, while is decreased for private users. In addition, commercial users tend not to charge their BEVs when they arrival during the nighttime, while private users tend to charge immediately. In this study, the nighttime charging choice can be seen as a kind of desired behavior, since these are usually off-peak hours for the electricity grid with lower tariffs, so factors that positively influence the choice might be used to encourage appropriate timing of normal charging. In the case of commercial vehicles, BEVs operated by electricity company have high utilities when they are charged during the nighttime, which may indicate that electricity workers are better aware of the distribution of peaks and troughs in electricity grid demand and they choose to charge during off-peak hours to balance the differential. Although drivers with other business types might not know the details of electricity demand or not care about it, measures can still be implemented to encourage normal charging during off-peak hours, such as providing detailed information about electric loading and electricity prices at different times of the day, and the technology and facilities of smart charging may be expected. Similar measures might be effective for private users according to the analysis of estimation results for private vehicles. In fact, users gradually form such desired charging behavior as revealed by the effects of the “latter half” indicator of the trial on choice of charge timing.

The possibility of encouraging normal charging with an appropriate timing can be further supported by the significant positive correlations of nighttime charging with charging immediately and charging at other times for both commercial and private vehicles. In addition, the great variation across individuals in nighttime charging may further indicate that encouraging BEV users to charge off-peak by adjusting the price is possible, since the variation may result from two characteristics: first, that users are somewhat price-sensitive and tend to charge during low-price hours; second, that there are various electricity contracts in Japan and thus several different low-price tariffs with different hours.

A final observation is that users’ family and personal attributes can be expected to affect their choice behavior, including factors such as income, age, and so on. However, such information is unfortunately not included in this field trial data. Future studies of charge timing choice should take these factors into account.

Chapter 6

Conclusions

Battery charging is one important aspect of EV operation. However, it is a big challenge for users to charge their vehicles optimally: they typically initiate charging at higher remaining electricity; the charging infrastructure seems to have been underutilized. On the other hand, the EV market is currently far from mature with battery technology is being evolved, charging infrastructure is being developed and users are gaining experience in charging EVs. Therefore, it is necessary to explore how various factors influence charging behaviors related to battery usage and charging infrastructure usage based on real-life EV usage data to provide a basis for guiding efficient battery utilization and developing an effective charging infrastructure.

In addition, the impact of battery charging on the electricity grid should not be ignored, since it will add a significant load as EVs become more popular, possibly requiring changes to the existing infrastructure. Considering that recharging during off-peak hours has less of an impact on the electricity grid, and that users tend to recharge EVs randomly at their convenience without considering the state of the electricity grid, it is necessary to explore how various factors influence charging behaviors related to charge timing choice to provide a basis for encouraging more appropriate charge timing.

Exploring on charging behavior is rarely involved in previous studies, since there were few EVs on the road. This thesis uses the dataset derived from a recent two-year field trial on BEV usage in Japan to determine factors that significantly influence charging behavior related to battery usage, charging infrastructure usage, and charge timing choice.

This final chapter summarizes the major findings, and then presents practical implications for guiding effective battery utilization, developing an effective charging infrastructure, and encouraging more appropriate charge timing based on the findings of this study, the limitations of the current study and suggestions for the future research are also included in this chapter.

6.1 Major findings

6.1.1 Charging behavior related to battery usage

By applying the true random effects stochastic frontier model to panel data about mid-trip fast-charging events taking place after leaving the origin and before arriving at the destination, the battery usage behavior of BEV drivers is examined.

The comparison of the estimation results with the true random effects stochastic frontier model and the random effects regression model indicates that the stochastic frontier modeling methodology is more effective in analyzing the battery usage behavior. The estimation results obtained with the true random effects stochastic frontier model for commercial and private vehicles, respectively, on working and non-working days show that only private users tend to charge their BEVs at lower level of remaining charge with increasing charging infrastructure, but both commercial and private users traveling on working days in areas with higher density of charging stations tend to initiate mid-trip fast charging at a higher level of remaining charge; that private users tend to charge at lower level of remaining charge with increasing familiarity with fast charging infrastructure, however, the familiarity does not have significant effect on the remaining charge when mid-trip fast charging begins for commercial users; that the usage of air-conditioning or heater only has significant negative effect on private users traveling on working days; that users driving BEVs with high-capacity battery tend to charge at higher level of remaining charge; that private users traveling on working days tend to charge at lower level of remaining charge with increasing number of daily trips; that commercial users traveling on working days tend to charge at lower level of remaining charge with increasing daily travel distance; that the speed only has significant effect for private vehicles, the variable indicating speed faster than 40km/h has a significant negative correlation with the remaining charge in the model for private vehicles on working days and the variable indicating speed not more than 20km/h has a significant positive correlation in the model for private vehicles on non-working days; that commercial users and private users traveling on working days tend to charge at higher level of remaining charge during the latter half of the trial, while private users traveling on non-working days tend to charge at lower level; that electricity users tend to charge at higher level of remaining charge.

Above all, the factors that significantly correlated with battery usage behavior of commercial and private vehicles, respectively, on working and non-working days and the way in which they affect the battery usage behavior are not similar. According to the related research, range anxiety felt by BEV users is one possible explanation for more remaining charge when mid-trip fast-charging begins.

Lastly, comparison of actual and predicted remaining charge for commercial and private vehicles, respectively, on working and non-working days indicates that there is considerable opportunity to encourage improvements in battery usage behavior.

6.1.2 Charging behavior related to charging infrastructure usage

By applying mixed logit models with (ML-T) and without (ML) threshold effect to panel data about fast-charging events during trips that include just one fast-charging between origin and destination in Kanagawa Prefecture, Japan, the choice behavior of fast-charging stations made by BEV users is examined.

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 1750m to charge their vehicles on working days and up to 750m on non-working days, while the figure is 500m 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 meters' 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.

6.1.3 Charging behavior related to charge timing choice

By applying a mixed logit model with unobserved heterogeneity to panel data about normal charging after the last trip of the day, the choice behavior in respect of the time at which BEV users charge their vehicles is examined.

The comparison of the estimation results with mixed logit model with unobserved heterogeneity and multinomial logit model indicates that the mixed logit model with unobserved heterogeneity is more effective in analyzing the charge timing choice behavior. The estimation results with mixed logit model with unobserved heterogeneity show that SOC, interval days before the next travel day, and VKT on the next travel day are the main predictors for whether a user charges the BEV or not; that the experience of fast charging decreases the probability of normal charging, which hold for both commercial and private vehicles; that the probability of normal charging after the last trip of a working day is increased for commercial users, while is decreased for private users; that commercial users tend not to charge their BEVs when they arrival during the nighttime, while private users tend to charge immediately; that BEVs operated by electricity company have high utilities when they are charged during the nighttime; that BEV users tend to charge during nighttime in the latter half of the trial.

In this study, the nighttime charging choice can be seen as a kind of desired behavior, since these are usually off-peak hours for the electricity grid with lower tariffs, so factors that positively influence the nighttime charging choice might be used to encourage appropriate timing of normal charging.

The possibility of encouraging normal charging with an appropriate timing can be further supported by the significant positive correlations of nighttime charging with charging immediately and charging at other times for both commercial and private vehicles.

6.2 Practical implications

The above mentioned findings provide a basis for guiding effective battery utilization, developing an effective charging infrastructure, and encouraging more appropriate charge timing.

Firstly, for BEV users, in order to help them use battery and charging infrastructure in an optimal way, it is better to provide them with information about the distribution of charging infrastructure as well as information about electricity consumption rates under different conditions, such as using air-conditioning or heater, driving with different speeds. Since the familiarity with charging infrastructure and electricity consumption rates helps to alleviate the anxiety of running out of power before a suitable charging station is reached, providing such information can be expected to help BEV users arrange the charging activities according to the actual needs. On the other hand, in order to encourage BEV users to normal-charge their vehicles during off-peak hours, it is better to provide them with the detailed information about electric loading and electricity prices at different times of the day.

Secondly, for the charging infrastructure constructors, in order to develop an effective charging infrastructure, the following considerations should be taken into account: 1) although increasing charging infrastructure helps to decrease remaining electricity when fast charging begins, more charging infrastructure is not necessarily better, there is an optimal number of charging stations to encourage the effective use of both battery capacity and charging infrastructure; considering both the commercial and private users, the current research reveals that the number of charging stations per 1000 square kilometers should not be more than 55, and the optimal number of charging stations per 1000 square kilometers is between 15 and 55; 2) 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, so it is better to locate charging stations to ensure the detour resulting from charging at a station within users' willingness to detour; considering both the commercial and private users, the current research reveals that the willingness to detour is not more than 1750 meters; 3) since BEV users prefer chargers located at gas stations, it is better to install more chargers at gas stations if other technologies allow.

Lastly, there are some implications for the BEV manufacturers. The positive correlation between high-capacity battery and remaining electricity when fast charging begins indicates that higher capacity battery is not necessarily better, so an appropriate battery size designed according to the travel demand is good for both BEV manufactures and BEV users, since larger capacity battery needs more advanced battery technology and makes BEVs more expensive; Although this study has not identified the most appropriate battery size, the current research shows that BEVs with a higher capacity battery, 5.5kWh more than the lower capacity battery, are generally initiated to fast charging at a higher level of remaining electricity for an extra 1.6kWh. In addition, more information about the state of battery during driving should be provided by the manufacturers in more precise and more intuitive way.

6.3 Limitations and future research direction

This thesis is a preliminary study on charging behavior, and there are some limitations, which point out the direction for future research.

Firstly, some factors that might affect charging behavior are absent, including users' socio-economic and demographic attributes, users' attitudes and perceptions toward charging infrastructure, users' daily routine activities, the charging cost and other attributes of charging stations, and many others. Future studies including these factors may give further insights into users' charging behavior. A stated preference (SP) survey seems to be necessary, however, attention should be paid to the combination of SP data and the observed data if the two surveys are not conducted at the same time or not performed to the same participant.

Secondly, since fast charging infrastructure is being developed, further studies exploring the relationship between charging patterns and development levels of charging infrastructure, by applying the models to areas with different fast-charging station densities, would be helpful to provide advices for planning a public fast charging infrastructure.

Thirdly, 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 in the study about fast charging station choice (24 private vehicles and 8 commercial vehicles) and the study about mid-trip fast charging for commercial vehicles (33 on working days and 10 on non-working days) may affect the consistency of results, which could be further verified by additional studies based on a large sample of drivers.

Finally, it would be interesting to integrate the studies of this thesis to develop a charging navigation system, proving information in real time to guide an effective charging behavior, such as where is the best place to charge EVs, when is the best timing to charge EVs, and so on. It would be also interesting to compare the charging behavior examined in this study with that in other countries or regions.

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