Research on Factors That Influence the Fast Charging Behavior of Private Battery Electric Vehicles

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Abstract: Due to the limited power cell performance of battery electric vehicles (BEVs), BEV drivers endure a short cruising range and a long charging time. Additionally, uneven charging facilities and unreasonable charging arrangements result in partial queuing and partial idling of charging stations. To solve these problems, it is critical to understand BEV charging behavior and its influential factors. Considering the urgency of BEV charging, BEV drivers tend to choose fast charging when BEV is in driving state. This study investigates fast charging behavior by utilizing private BEV connected data collected from Beijing. First, 130 private BEVs with travel rules were screened out. Using seven months of BEV data, a total of 15,752 trajectories were identified, among which 2161 have fast charging behavior. According to the relationship between fast charging behavior and some influential factors, including battery modeling, driving behavior, weather and environment, and even user habit, were empirically investigated. Moreover, the battery state of charge at the start time, time-origin, travel time duration, driving distance, driving speed, wind power, temperature, and last-fast-status are determined as significant influencing factors. Lastly, a prediction model based on the significant factors is proposed to estimate whether there is fast charging in a day trajectory. The proposed model achieves the best accuracy over compared models, i.e., univariate linear regression (ULR) with several factors and multivariate linear regression (MLR) model. The study is expected to help better understand fast charging behavior and further contribute to the future improvement of fast charging efficiency.

Keywords: battery electric vehicles; fast charging behavior; influential factors; significant analysis; prediction model

1. Introduction

In recent years, the number of motor vehicles worldwide exceeded 1 billion. The massive amount of motor vehicle possession has increased people’s concerns over petroleum dependence, energy security, and environmental quality of cities [1,2]. Due to zero carbon-based emissions and high energy-efficiency, battery electric vehicles (BEVs) have substantial potential for fleet applications [3]. Based on these considerations, many countries carried out the national policies to support and promote the BEVs, and the number of BEVs has increased rapidly [4].

Now, in China, the number of electric vehicles reached 2.81 million, and Beijing alone has 171,000. It is noted that BEV’s cruising range confined by the battery capacity has long been a problem for drivers [5]. The power battery performance of BEV has attracted more and more attention from researchers, policy-makers, consumers, and industry. So, battery performance has been greatly improved. For example, a BYD Qin of its 2014 version can run up to 120 miles under actual traffic conditions, and a BYD e5 can run up to 400 miles with a full charge. The worry of batteries running out
of power during driving is referred to as “range anxiety” in the literature [6], which inevitably affects the travel choices of BEV drivers such as charging decision-making and charging stations choice.

At present, there are two types of electric power supply methods for BEVs: charging and battery replacement [7,8]. The charging methods mainly include slow charging, fast charging, and wireless charging modes. Each charging mode has different charging times. Slow energy supply pattern lasts longer, which is about 5 to 8 hours, or even up to 10 hours for certain types of batteries [9]. The charging period lasts from about 15 minutes to 2 hours. Slow charging is more suitable for fixed places where people stay for a long time, such as residential areas at night or office areas during working hours [10]. At the same time, due to the low SOC at the start of the journey, or too far to the destination, it is often possible to charge during the journey. In this case, considering the urgency of charging, fast charging is usually required. Compared with fixed slow charging [11], this study tends to analyze random fast charging behavior.

However, due to the limited performance of power batteries, BEVs take a long time to charge [12]. In addition, the uneven distribution of charging facilities leads to the phenomenon of some charging queuing and some idle [13]. This severely limits the charging of BEVs and further affects the promotion and application of electric vehicles. Therefore, it is necessary to study the fast charging behavior of BEVs and its influencing factors. Most researches at home and abroad focus on the impact of BEV charging behavior on the power grid [14], and there is less analysis of the charging behavior itself. In the study of factors affecting charging behavior, most studies only consider the influence of single or several factors on charging behavior and cannot comprehensively analyze the impact of each factor on charging behavior.

This paper will use the historical data of Beijing’s electric private BEVs to extract and analyze the trajectory data and fast charging behavior information of each vehicle every day. This research will comprehensively consider various potential factors that affect the fast charging behavior of BEVs and predict the fast charging behavior of BEVs based on the day trajectory. The results of this research will guide users to make reasonable charging arrangements, avoid charging queues, and improve travel and charging efficiency.

The rest of the paper is organized as follows. Section 3 provides a brief description of data preparation, followed by the exploration of influential factors that significantly affect the fast charging behaviors in Section 4. Section 5 introduces a logistic regression model for fast charging behavior prediction and presents the comparison results of the proposed prediction models. At the end, we conclude this paper with a few perspectives for future research.

2. Literature Review

Recently, there are many literatures of the charging behavior of electric vehicles. Gennaro, Paaffumi, Scholz and Martini [15] collected gasoline vehicle driving information to simulate the charging behavior of EVs. Ashtari, Bibeau, Shahidinejad and Molinski [16] analyzed the path selection of EVs using the fuel vehicle data based on the Logit model. Nicholas et al. [17] investigated the fast charging behavior of the electric vehicles. The simulation results showed that between 8.5% and 3.4% of tours would require some public charging under different range and charging assumptions while accounting for 46% and 30% of vehicle miles traveled (VMT), respectively. Darabi and Ferdowski [18] used the U.S. national travel survey to estimate the charge demand curve of EVs.

However, the charging behavior of EVs is much more complicated than the refueling behavior of motor vehicles. On the one hand, the capacity of EV batteries is still small, making the travel distance relatively limited so that EVs may require multiple charges during one trip. On the other hand, EVs may have different charging modes, such as slow charging and fast charging. Each charging mode has different charging times, costs, and battery life losses [19,20]. Shun et al. [21] used the Monte Carlo method to simulate the complete trip and calculate the spatial-temporal distributions of charging demands. These simulation results could not reflect realistic behaviors, that is because various factors could influence the charging behaviors of EVs.
To overcome these limitations, the actual data was employed. Motoaki and Shirk [22] analyze real-world field data to examine direct current fast charger usage in the United States. Quiros-Tortós et al. [23] investigated the charging behavior of 221 real residential EV users spread across the U.K. The results showed that approximately 70% of the EVs were connected once a day, irrespective of weekday and weekend. Moon, Park, Jeong and Lee J [24] found that the users usually chose to charge at night. If the users chose to charge during the peak hours, the behaviors were usually fast charging behaviors. Franke and Krems [25] examined the psychological dynamics underlying the charging behavior of EV users. The results showed that the users charged their EVs three times per week, and they typically had a large surplus of energy remaining upon recharging. Steen et al. [26] considered that the charge state of battery, the duration of parking and the type of parking were significant factors in each parking event.

Moreover, some influencing factors of charging behavior were analyzed and verified. Yi and Bauer [27] conducted a sensitivity analysis of the environmental factors of EVs. The results showed that environmental factors affect the power and power transmission of the EV battery. The analysis of Yang et al. [28] showed that the initial charge state, charging time, distance from the starting point, and the charging station significantly affected the charging options of EV users. Wang et al. [29] analyzed the relationship between temperatures and charging behavior using the statistical methods. Hu, Dong and Lin [30] analyzed the influence of psychological factors such as personality and risk preference on BEV charging behavior.

Smuts et al. [31] analyzed the relationship between the environmental factors and the remaining driving range of the EVs. Younes et al. [32] investigated some factors that have an essential impact on charging behaviors, such as the route type, the driving style, and the ambient temperature. Liu et al. [33] estimated the remaining driving range by precisely predicting the remaining discharge energy of the applied battery system. Vaz et al. [34] predicted the driving range based on optimal trip parameters before the trip, enabling the users. Wang, Liu, and Yamamoto [35] proposed an estimation model by considering both the dynamic characteristics from sparse GPS observations and the unique attributes of EVs. Bi et al. [36] established the nonlinear estimation models for the remaining driving range under different temperature conditions based on the data-driven method.

Due to the uncertainty and difference of electric vehicle users’ demands and behaviors [37], large-scale electric vehicle charging always has uncertain characteristics such as randomness, intermittence, and volatility in time and space, which will bring significant influence to the power system planning and operation [38, 39]. Studies have been done in recent years. Alizadeh et al. [40] proposed a stochastic model based on queue theory for BEV and plug-in hybrid electric vehicle charging demand. Arias et al. [41] presented a time-spatial EV charging-power demand forecast model at fast-charging stations located in urban areas. Based on the data of electric vehicles in China, Cai et al. [42] analyzed the impact of large-scale access of electric vehicles on the grid and the environment.

In conclusion, although many researchers have explored the factors that influence the fast charging behavior of private BEVs, this issue still deserves to be further discussed. Most of these studies try to identify the influential factors based on the simulation method because of lacking data. Extensive research focuses on the energy consumption, remaining driving range, or charging demand of large-scale BEVs. As the technology improves, massive amounts of BEVs data could be collected. Therefore, this study tries to explore the relationship between the fast charging behaviors and the affecting factors.

3. Data Preparation

In this section, we first collect and briefly describe the connection data of electric vehicles from the existing internet of vehicle systems, and then explain how to identify the fast charging behavior and its influence factors from historical data. Finally, the overall distribution of the trajectory data and its fast charging behavior are analyzed.
3.1. Data Collection

BEV connected data used in this paper was collected by the vehicle-mounted information collection and transmission terminal. The terminal equipment consists of MCU, OBD module, GPS satellite positioning module, wireless communication (GPRS) module, a storage module, a power management module, and other hardware modules (Figure 1). The equipment can monitor the working status of the electronic control system of the engine and other modules of the vehicle in real-time during the operation of the vehicle. Additionally, it can also provide various working conditions data of the vehicle. The terminal installed in the BEV transmits the vehicle charging and discharging state data to the monitoring platform periodically by using the GPRS wireless transmission technology for a specified period (usually 10 seconds).

Figure 1. Vehicle Terminal of the battery electric vehicles (BEVs).

In this research, 130 vehicles with relatively regular travel patterns were selected from a large number of historical data of Beijing’s private BEVs for seven months. All these vehicles come from the same car company in China, and the electrical converters/inverters, electric motor type, battery types and battery technologies of these vehicles are the same. The interval between each group of driving data is 10 s. The data content mainly includes the terminal number, charging and discharging status, driving range, power battery SOC (state of charge), discharge target, longitude, latitude, mileage, and acquisition time (see Table 1). The battery state of charge (SOC) is defined as the ratio of the remaining capacity to the battery capacity, which is used to reflect the remaining capacity of the battery.

| Time     | Terminal Code | Lat     | Lon     | Charging State | Running Mode | Speed | Accumulated Mileage | Total Voltage | Total Current | SOC     | Insulation Resistance | Effective Positioning |
|----------|---------------|---------|---------|----------------|--------------|-------|----------------------|---------------|---------------|---------|-----------------------|-----------------------|
| 2018/2/1 12:05 | 101760 | 39.98901 | 116.3368 | 3 | 25.1 | 25.1 | 196.1 | 342 | 39.6 | 46 | 3315 | 1 |
| 2018/2/1 12:05 | 101760 | 39.98901 | 116.3368 | 3 | 22.3 | 22.3 | 196.1 | 346 | -10.8 | 46 | 3430 | 1 |
| 2018/2/1 12:05 | 101760 | 39.98901 | 116.3368 | 3 | 23.2 | 23.2 | 196.1 | 341 | 42 | 46 | 3455 | 1 |
| 2018/2/1 12:06 | 101760 | 39.98901 | 116.3368 | 3 | 31.4 | 31.4 | 196.1 | 341 | 40.8 | 45 | 3425 | 1 |
| 2018/2/1 12:06 | 101760 | 39.98901 | 116.3368 | 3 | 34.1 | 34.1 | 196.1 | 347 | -23.8 | 45 | 3395 | 1 |
| 2018/2/1 12:06 | 101760 | 39.98901 | 116.3368 | 3 | 24.6 | 24.6 | 196.1 | 344 | 21.9 | 45 | 3380 | 1 |
| 2018/2/1 12:06 | 101760 | 39.98901 | 116.3368 | 3 | 14 | 14 | 196.1 | 342 | 29.3 | 45 | 3495 | 1 |
| 2018/2/1 12:06 | 101760 | 39.98901 | 116.3368 | 3 | 29.9 | 29.9 | 196.1 | 344 | 14.3 | 45 | 3370 | 1 |

3.2. Fast Charging Behavior and Influence Factors Identification

Charging behavior is closely related to the user’s daily trip characteristics [43], so the analysis should be combined with the above. In this paper, the historical data are divided according to distinct day and vehicle to determine the charging and discharging process within a day. The process contains much information about time, space, methods, and activities, and the information is interrelated and interactive. It is worth noting that when the charging process or discharging process continues to the next day after the zero points, the entire charging or discharging process is divided into the previous day.
The following data handlers were executed. First, the charge and discharge data are divided according to the collected status data. In order to avoid classification errors caused by state data errors, the classification results are verified according to the changes of SOC with time series. Then a single charging and discharging process are intercepted according to the time difference between adjacent data. Next, we distinguish fast charge and slow charge process according to current performance. The slow charging is defined as the standard EV charge from the 110V/15A outlet as specified in Chevy Volt’s specifications [44]. The fast charge is defined as the EV charging strategy when EVs can be charged at a higher voltage and current to achieve a faster charging duration. The fast charge can be accomplished by charging from a 240V/30A outlet [15]. Finally, the day trajectory information of each car is determined according to the starting time of the charging process.

Based on the above processing, the fast charging behavior of day trajectory and its influencing factors data is extracted. If there is a fast charge in the charging process of day trajectory, it is the day trajectory of fast charge. At the same time, the starting time, state of the initial charge, travel distance, travel time duration, number of fast charging, duration, and electric quantity of fast charging of the day were recorded. In addition, historical weather information is collected to record the weather, average temperature, and wind scale on the day of trajectory (these data were collected from the internet).

3.3. Data Summary

Using seven months of BEV data, a total of 15,752 trajectories were identified according to distinct day and vehicle, in which 11,349 are non-charging, 1620 are only fast charging, 2242 are only slow charging, and 541 are fast and slow charging (see Table 2). The proportion of the non-charging to the charging of the day trajectories is 2.5:1, which indicates that the driver of the BEV usually travels short distances to reduce charging. Such a large amount of empirical data is precious and helpful for conducting comprehensive analysis later.

| Total Trajectories | Non-Charge | Charge Behavior |
|--------------------|------------|-----------------|
|                    |            | Fast | Slow | Fast and Slow |
| 15,752             | 11,349     | 1620 | 2242 | 541           |

This study focuses on the fast charging behavior. Hourly distributions of fast charging behavior over time of day is first examined, as shown in Figure 2. In detail, the number of fast charging progress to start per hour for 24 h was determined. Meanwhile, the probability density of the fast charging cases that happened within each hour was also collected. Then a time series plot with x representing charging start time (in hours) and y representing number of the fast charging cases or probability density volume was plotted. It was found that fast charge cases have a significant rise after the morning rush hour. Additionally, most of the BEV fast charging behavior occurred during the daytime after 10 a.m., especially in the 1 p.m. to 4 p.m. afternoon period. Since some vehicles generated charging demand after driving in the morning rush hour, the charging event increased significantly at 10 a.m.
In addition, most of the trip is during the daytime, and the vehicles need to be charged after a period of driving, so the fast charging behaviors are concentrated in the afternoon. Most of the trip has ended at night when users tend to choose a fixed slow charge over a fast one.

Additional analysis is conducted on the distributions of fast charging time duration. Firstly, the range of charging time value is segmented; that is, the range of the total charging time value is divided into a series of intervals. Then the charging situation were calculated in each interval. Figure 3 presents this distribution. The fast charging time duration of EVs was concentrated between 40 to 80 minutes, especially between 50 to 60 minutes.

The impact of weather is found by comparing the proportion of fast charging happening during different weather days (see Figure 4). In sunny, cloudy, rainy, and snowy weather, the frequency of rapid charging behavior varies from 0.12 to 0.14, with little difference. This is because there are few snow days in the data, and only sleet and light snow, so the influence on charging behavior in a day is not apparent. However, the overall frequency of fast charging is only about 13%, which indicates that BEV users try to avoid fast charging.
4. Analysis of Influence Factors Upon Fast Charging Behavior

The large amount of matched day trajectory data presented in Table 1 record the detailed travel status as well as charging behavior of each individual vehicle (i.e., fast charging, slow charging, fast and slow charging or no-charging). We could statistically analyze the large amount of day trajectories to describe the relationships between the charging behavior and some important factors. Such a statistical approach demonstrates promising value. For example, Wu et al. [45] and Botsford [46] suggest a correlation between driver’s decision behavior and his/her current driving conditions. Following this methodological spirit, all these relationships could be depicted as different figures and the inner correlation could be derived from the large amount of day trajectories data directly.

4.1. Battery Modeling of Fast Charging Behavior

Battery modeling, mainly including battery state of charge (SOC) and battery capacity, are the main factors affecting the performance of electric vehicles. The battery capacity reflects the maximum driving range of a BEV. The SOC is used to reflect the remaining capacity of the battery. When SOC = 0, the battery discharge is complete, and when SOC = 100, the battery is fully charged.

The battery capacity of BEVs adopted in this study is basically the same, so we consider SOC firstly. Taking the SOC at the start time (start-SOC) as the X-axis, the proportion of fast charging as the Y-axis, the relationship between start-SOC and the proportion of fast charging is plotted in Figure 5. From this figure, we find that the start-SOC is negatively correlated with the fast charging behavior. If the start-SOC is between 0 and 10, more than 50% of BEVs would choose fast charge during their trip, and if the start-SOC is over 30, the proportion of the fast charging behavior would reduce to 15%. In other words, as the start-SOC decreases, the proportion of fast charging significantly increases.
4.2. Driving Behavior of Fast Charging Behavior

Driving behavior has a significant impact on the variations in fast charging behavior. The main information of driving behavior includes time-origin, travel time duration, driving distance and driving speed.

BEV users tend to choose the slow charging mode when they arrive at the residential area at the end of the night travel, so the later the time-origin of trip, the less likely users are to choose the fast charging halfway. The orange line in Figure 6. shows that between 6 a.m. and 8 p.m., the earlier the trip starts, the higher the proportion of fast charging will be. The blue bar chart shows the overall distribution of the day trajectories starting from each time of day, with a significant surge in travel starting from morning and evening rush hours.

It is well known that the longer a BEV travels, the greater the power consumption and the higher the possibility of charging. Based on the data we collected, the relationship between the travel time duration of the BEV and the day trajectory is shown in Figure 7. From the blue bars, we can see that the total number of trips decrease as the travel time duration increases. The reason is simple; most of the drivers choose a short trip, for the range of BEVs is short. The red lines indicate that as the travel time increases, the proportion of day trajectories with charging behavior increases. That is because once the driver chooses a long trip, the drivers have to stop and take time to charge. The yellow blue bars show that the number of fast charging decreases as the travel time duration increases. That is
because the number of total trips is little, and even as the proportion of the fast charging behavior increases, the number of fast charging decreases.

Figure 7. The travel time duration vs. fast charging behavior.

The distance a BEV travels has a great influence on whether the day trajectory has fast charging or not. Obviously, when the distance of the day trajectory is much larger than the initial driving range of the BEV, the BEV needs to be charged. Based on the data of private BEVs, this paper draws the relationship between the EV day trajectory distance and the fast-charging day trajectory ratio, as shown in Figure 8. From the figure, we find that the ratio of the day trajectories with fast-charging is positively related to the day trajectory distance. As the distance traveled by EVs increases, the probability of fast charging of the day trajectory increases. Most of the day trajectories travel within 50 km. This phenomenon indicates that most users are accustomed to traveling short distances.

Figure 8. The driving distance vs. fast charging behavior.

Vehicle speed is the first factor to consider when studying vehicle mileage power consumption. Similarly, the average driving speed of the trip is also an important factor influencing the charging behavior of the day trajectory. We first calculated the average velocity of each day trajectory, and then determined the number of day trajectories in each velocity interval and the proportion of day trajectories with fast charging at an interval of 5. As shown in Figure 9, the driving speed is concentrated at 30–40 km/h. The reason for this phenomenon is that EV users generally have the endurance mileage anxiety, so that most EVs are driving in the city, so the average driving speed of EVs is generally low. In addition, when the driving speed interval is different, the proportion of day trajectories with rapid charge is also very different.
4.3. Weather and Environmental Data of Fast Charging Behavior

Weather and environmental data is mainly considered real-time data. Historic weather patterns also play a significant role in predicting weather conditions in the future. Weather and environmental data include temperature, season, weeks properties, wind direction, wind speed, and chance of rain or snow [47].

When the temperature is too high or too low, drivers use air conditioning or heat. This will increase the amount of power consumed per mile, increasing the need for BEVs to be recharged. Figure 10 shows the proportion of day trajectories with fast charging in different average temperature intervals. Low and high temperatures result in more energy being used to either heat or cool the vehicle, which increases the fast charging behavior significantly.

The travel purpose of weekdays and weekends is not the same, and different day trajectories may be generated. We plotted the quantity distribution diagram of the all-day trajectories and the day trajectories with fast charging from Monday to Sunday as shown in Figure 11. It can be seen that the number of total day trajectories and the day trajectories with fast charging during the week and weekend are basically the same.
In the process of driving, the intensity of wind will affect the resistance of the vehicle, thereby affecting the power consumption and charging demand. We divided wind force into \( \leq \) level 3, level 3–4, level 4–5, and level 5–6, and plotted the proportion of sunrise track with rapid charging under different wind forces, as shown in Figure 12. With the increase of wind power, the possibility of fast charge in the day trajectory increases.

Different users could have different fast charging decisions under the same circumstances, so user habit is an important concept in fast charging behavior analysis. We only think about the effects of the fast charging status of the last day trajectory (last-fast status) here.

In this paper, the day trajectory with fast charging behavior is counted as 1, and the day trajectory status with no fast charging behavior is counted as 0. Then the state combination of the previous status and target day trajectories is: 0–0, 0–1, 1–0, 1–1. The four combinations of day trajectories were listed in Table 3. It can be seen from the table that the case of 0–0, that is, the last and the target day trajectory all have no charge behavior of 77%, which indicates that most private car users try to avoid the charging behavior during the day trajectory. In the case of the second 1–1, the last and the target day trajectory charge accounted for 16%, indicating that users with fast charging habits are more likely to charge the next day trajectory.

| Charging Behavior | 0–0 | 0–1 | 1–0 | 1–1 |
|-------------------|-----|-----|-----|-----|
| Percentage        | 77% | 5%  | 2%  | 16% |
5. Significant Factors Analysis of Fast Charging Behavior

In this study, the factors affecting the fast charging behavior of BEVs mainly include battery modeling (i.e., start-SOC), driving behavior (i.e., time-origin, travel time duration, driving distance, and driving speed), weather and environmental (i.e., day of week, wind power, temperature, and rain and snow weather), and even user habit (i.e., the fast charging status of last day trajectory). The description and digitization statistics of the potential factors is shown in Table 4.

| Factor               | Description                                                                 | Digitization                                                                 |
|----------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------|
| start-SOC            | The SOC of BEV at the start of target day trajectory.                       | The percentage of the remaining capacity in the battery capacity. Value is 0–100%. |
| time-origin          | The start time of target day trajectory.                                    | The hour corresponding to the start time.                                     |
| travel time duration | The total travel time duration of target day trajectory.                    | The total distance traveled, unit km.                                         |
| driving distance     | The total driving distance of target day trajectory.                        | Driving distance/travel time duration, unit km/h.                            |
| day of week          | The weekly property on the day for the target day trajectory.               | "1" represents weekday and "0" weekend.                                       |
| wind scale           | The wind scale on the day for the target day trajectory.                    | Level 3 and below is "0", level 3–4 is "1" ...                               |
| temperature          | The average temperature for the target day trajectory.                      | Average of the highest and lowest temperatures of the day, unit degrees Celsius.|
| weather              | The weather condition on the day for the target day trajectory.             | "1" represents rain or snow weather and "0" others.                           |
| last-fast-status     | The fast charging behavior of the last trajectory.                          | "1" represents yes and "0" no.                                                 |

Based on seven-tenths of the data in each group, Statistic Package for Social Science was applied to fit the regression model. The fitting results are provided in Table 5. Both T-test and one-sample Kolmogorov-Smirnov test show that the residuals are normally distributed. Besides, ANOVA test was applied and the results show that the proposed regression model has a good fit of the data. The desirable goodness of fit indicates that we can use the proposed regression model to predict fast charging based on significant influence factors.

| Variable          | Group(a) | Group(b) | Group(c) |
|-------------------|----------|----------|----------|
| start-SOC         | -0.017   | P < 0.01 | -0.017   | P < 0.01 | -0.015   | P < 0.01 |
| time-origin       | 0.000    | P > 0.05 | 0.000    | P > 0.05 | 0.000    | P > 0.05 |
| travel time       | 0.000    | P > 0.05 | 0.000    | P > 0.05 | 0.000    | P > 0.05 |
| distance          | 0.013    | P < 0.01 | 0.012    | P < 0.01 | 0.011    | P < 0.01 |
| speed             | -0.008   | P > 0.05 | -0.007   | P > 0.05 | -0.002   | P > 0.05 |
| wind power        | 0.061    | P < 0.05 | 0.008    | P < 0.05 | 0.026    | P < 0.05 |
| temperature       | 0.011    | P < 0.01 | 0.010    | P < 0.01 | 0.008    | P < 0.01 |
| last-fast-status  | 2.282    | P > 0.05 | 2.175    | P > 0.05 | 2.244    | P > 0.05 |
| constant          | -1.499   | P > 0.05 | -1.492   | P > 0.05 | -1.665   | P < 0.01 |

Only variables which are statistically significant at the significance level of 0.05 are included in Table 5. The results show that the start-SOC, time-origin, travel time duration, driving distance, driving speed, and temperature are significant influential factors.

When the travel starts at different time periods, the probability of charging on the way varies greatly. When the travel chain ends at night, BEV users will choose the slow charging mode after arriving at the residential area. Moreover, the later the time-origin, the less likely it is to fast charge in the middle. Whether the start-SOC of a BEV is enough to complete the following journey is the key to whether the battery will be charged in the driving process. The travel time duration and driving distance can directly determine whether the electric quantity of the BEV can complete the trajectory. The longer the travel time duration and driving distance, the more likely the BEV is to be charged. Low and high temperatures result in more energy being used to either heat or cool the vehicle, which reduces the remaining driving range significantly [48]. This increases the probability of charging. According to the rules of BEV users, those who have the habit of fast charging will often fast
charge on the way. Therefore, users who have the fast charging in the last day’s trajectory are more likely to fast charge the today’s trajectory.

The impact of the day of week and weather is not significant. Different travel purposes during the week and the weekend will generate different trajectories and charging behaviors. This paper only considers whether there is rapid charging every day, so the influence of weekly distribution is not obvious. In the data of this study, there is a very small amount of snow weather, and only light snow and sleet. This does not have a significant impact on road conditions, nor does it have a significant impact on charging behavior.

To sum up, the final retained significant influencing factors are: start-SOC, time-origin, travel time duration, driving distance, driving speed, wind power, temperature and last-fast-status. From the regression coefficient (B), we can see the change direction of each variable’s interpretation of the dependent variable. The coefficient of start-SOC and driving speed is negative, indicating that the lower the start-SOC and driving speed are, the easier it is to charge.

6. Fast Charging Behavior Prediction

Based on real private BEV data, the significant relationship between the main potential factors and fast charging happen in one day trajectory. Another purpose of this study is to investigate whether the factors’ data with significant influence can be utilized to estimate fast charging. Thus, a binary logistic regression model is proposed for predicting if there is a fast charging behavior in a day trajectory. For that, we randomly divided three sets of data sets in a ratio of 7:3 and seven-tenths of the data in each group were used to construct the model. Another three tenths of data were used to verify the model accuracy.

6.1. A Prediction Model Based on Significance Factors

Since a driver’s fast charging behavior is a binary variable, a binary logistic regression model is applied to describe the correlation between all impact factors and drivers’ fast charging behavior (fast charging and non-fast charging). If we define fast charging and non-fast charging as “1” and “0”, respectively, a standard logistic regression model for a driver’s fast charging behavior can be described as Equation (1):

\[
\logit[\pi_i] = \log\left(\frac{\pi_i}{1 - \pi_i}\right) = \alpha + \beta X_i
\]

where \(\pi_i\) is the probability that trajectory \(i\) is a fast charging trajectory and \(1 - \pi_i\) is the probability that trajectory \(i\) is a non-fast charging trajectory; \(X_i = (x_{1,i}, x_{2,i}, \ldots, x_k,i)\) represents a vector of all significant factors which impact the charging behavior of trajectory \(i\) (the significant factors are listed in Table 5); \(\alpha\) is an intercept parameter; and \(\beta\) is a vector of the coefficients of the corresponding factors. \(\alpha\) and \(\beta\) are estimated by the method of maximum likelihood estimation (MLE). The likelihood function is constructed as Equation (2). By maximizing the log likelihood expression shown in Equation (3), the estimate of the new intercept parameter \(\alpha\) and coefficient vector \(\beta\) can be obtained accordingly.

\[
L(\beta) = \prod_{i=1}^{n} \left\{ \pi(x_i)^{y_i} [1 - \pi(x_i)]^{1-y_i} \right\}
\]

\[
LL(\beta) = \ln(L(\beta)) = \sum_{i=1}^{n} \left[ y_i \ln[\pi(x_i)] + (1 - y_i) \ln[1 - \pi(x_i)] \right]
\]

Based on seven-tenths of the data of each group, \(\alpha\) and \(\beta\) are estimated. The results of \(\alpha\) and \(\beta\) are listed in Tables 6 and 7.

| Parameter | Group(a) | Group(a) | Group(a) |
|-----------|---------|---------|---------|
| \(\alpha\) | -1.499  | -1.492  | -1.665  |
Table 7. $\beta$ for different groups.

| Parameter          | Group(a) | Group(a) | Group(a) |
|--------------------|----------|----------|----------|
| start-SOC          | -0.017   | -0.017   | -0.017   |
| time-origin        | 0.000    | 0.000    | 0.000    |
| travel time duration| 0.000    | 0.000    | 0.000    |
| driving distance   | 0.013    | 0.012    | 0.012    |
| driving speed      | -0.008   | -0.007   | -0.007   |
| wind power         | 0.061    | 0.008    | 0.008    |
| temperature        | 0.011    | 0.010    | 0.010    |
| last-fast-status   | 2.282    | 2.175    | 2.175    |

6.2. Model Validation

Based on Equation (1), the probability that the target day trajectory has charging behavior can be described by a logical distribution, as shown in Equation (4):

$$p(Y_i = 1/X_i) = \pi_i = \frac{e^{(\alpha + \beta X_i)}}{1 + e^{(\alpha + \beta X_i)}} \quad (4)$$

where $Y_i$ denotes the charging behavior of day trajectory $i$. $Y_i = 1$ means the day trajectory $i$ is a charging chain. The output is the probability that the target vehicle $i$ is fast charging behavior. The final decision is that $p_i > 0.5$ is a charging chain, and is calculated through Equation (5):

$$y = bool(p_i > 0.5) \quad (5)$$

The function $y = bool(x)$ is Boolean function, when $x$ is true, $y = 0$, the day trajectory has charging behavior; otherwise, the day trajectory has no charging behavior.

To examine the applicability and accuracy of the proposed model, a case study was conducted based on three-tenths of trajectories’ data. By applying Equation (4) presented in the models, the probability of the day trajectories of each training set having fast charging behavior is predicted. Then Equation (5) in the models is applied to determine whether the day trajectories of each training set has fast charging behavior. By comparing the predicted value with the true value, the prediction accuracy of the three groups of data is 88.33%, 88.08% and 91.68%, respectively (The predication accuracy is defined as the ratio between correct fast charging prediction number and actual fact charging number).

In order to evaluate the performance of the proposed model, different models were established based on the liner regression method (ULR) and multiple linear regression method (MLR). To compare the performance of all these models, the receiver operating characteristics (ROC) curves are plotted and the areas under the curve (AUC) of these models are calculated. ROC curves and AUC are frequently used to compare the performance of different methods [49]. ROC curve directly shows which model is dominant, and the model with larger AUC also indicates better performance.

The prediction results for different methods were listed in Table 8. Figure 13(a), (b) and (c) show the ROC curves and AUC values for different models, respectively. The larger the AUC, the better the prediction results. The ROC curve of binary logistic model is closest to the upper left corner, indicating the logistic model has the best prediction results. The second-best model is MLR model, and the ULR model has the worst prediction results.
Table 8. Charging behavior prediction based on different methods.

| Prediction Model | Factors                      | AUC  |
|------------------|------------------------------|------|
|                  |                              | (a)  | (b)  | (c)  |
| logistics        | Significant                  | 0.823| 0.842| 0.841|
|                  | All                          | 0.759| 0.788| 0.780|
|                  | Start-SOC                    | 0.512| 0.499| 0.521|
|                  | Time-origin                  | 0.559| 0.546| 0.561|
|                  | Travel time duration         | 0.664| 0.677| 0.694|
|                  | Driving distance             | 0.672| 0.696| 0.697|
|                  | Driving speed                | 0.533| 0.552| 0.524|
|                  | Day of week                  | 0.502| 0.505| 0.494|
|                  | Wind power                   | 0.524| 0.514| 0.531|
|                  | Temperature                  | 0.554| 0.572| 0.585|
|                  | Weather                      | 0.530| 0.533| 0.531|
|                  | Last-fast-status             | 0.667| 0.699| 0.683|

Figure 13. ROC curves.
7. Conclusions

In order to improve the BEV’s charging efficiency, it is essential to understand the factors that affect the charging behavior of BEV users. In this paper, seven months of data collected by 100 private BEVs, and over 15,752 trajectories, are captured according to distinct day and vehicle. Based on the fast charging situation in the day trajectory, we further divided these trajectory cases into four categories: "no charging behavior," "with fast charging," "with slow charging," and "with fast and slow charging." The classification results show that since most of the day trajectories are in a "no charging behavior" state, BEV users usually travel short distances to reduce charging. Additionally, in the day trajectory with charging behavior, there are 2161 fast charging behaviors and 2783 slow charging behaviors. Considering the urgency of charging in the driving process of BEVs, this study only considers the fast charging behavior.

Based on the day trajectory data, this paper studies the relationship between the fast charging situation in the day trajectory and the critical factors such as start-SOC, time-origin, travel time duration, driving distance, driving speed, wind power, day of the week, temperature, weather, and last-fast-status. Statistical analysis shows that as the start-SOC of the BEV decreases, the number of day trajectories with fast charging increases significantly. As the travel time duration increases, the proportion of the day trajectory with fast charging behavior increases. As the distance traveled by the EV increases, the possibility of fast charging of the day trajectory increases. Furthermore, users with fast charging habits are more likely to fast charge the next day trajectory.

In addition, based on the above influencing factors, we determined the significant impact of start-SOC, time-origin, travel time duration, driving distance, driving speed, wind power, temperature, and last-fast-status. According to these significant influencing factors, we established a binary regression model to describe the relationship between significant influencing factors and charging behavior. We further use three-tenth trajectories data to validate this model. The results show that the regression model has a significant performance with a prediction accuracy rate of 89.36%. However, the accuracy of the prediction model is still not very high, and the false alarm rate is relatively high. The potential reason is that some important factors (i.e., the electrical converters/inverters, electric motor types, battery types, etc.) were not included in our analysis. Besides, our data analysis results may help the governments to refine the demand-side management policies, but this topic needs much more data and deeper work. All these will be left for our future research.

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