

Research Article

Optimal Driving Range for Battery Electric Vehicles Based on Modeling Users' Driving and Charging Behavior

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This paper proposes a simulation approach for the optimal driving range of battery electric vehicles (BEVs) by modeling the driving and charging behavior. The driving and charging patterns of BEV users are characterized by reconstructing the daily travel chain based on the practical data collected from Shanghai, China. Meanwhile, interdependent behavioral variables for daily trips and each trip are defined in the daily trip chain. To meet the goal of the fitness of driving range, a stochastic simulation framework is established by the Monte Carlo method. Finally, with consideration of user heterogeneity, the optimal driving range under different charging scenarios is analyzed. The findings include the following. (1) The daily trip chain can be reconstructed through the behavioral variables for daily trips and each trip, and there is a correlation between the variables examined by the copula function. (2) Users with different daily travel demand have a different optimal driving range. When choosing a BEV, users are recommended to consider that the daily vehicle kilometers traveled are less than 34% of the battery driving range. (3) Increasing the charging opportunity and charging power is more beneficial to drivers who are characterized by high daily travel demand. (4) On the premise of meeting travel demand, the beneficial effects of increased fast-charging power will gradually decline.

1. Introduction

Battery electric vehicles (BEVs) have the outstanding advantages in zero tailpipe emissions, low noise, convenient maintenance, and high energy conversion efficiency. The deployment of BEVs helps to reduce oil dependence, improve air quality, and reduce pollutions and greenhouse gas emissions [1]. Promoting the development of BEVs is considered as one of the promising solutions for the treatment of severe air pollution in metropolises [2]. The incentives, such as subsidies and tax credits, have effectively promoted the public acceptance for switching to BEVs. For instance, in many mega cities in China, like Beijing, Shanghai, and Hangzhou, the number of vehicle license plates issued per month (car ownership) is under strict control, and the local government has also launched the free licensing policies for BEVs [3].

However, due to the limited battery capacity and charging facilities, inconvenient charging is still an

important obstacle to the promotion of BEVs [4]. Compared to the conventional internal combustion engine vehicles (ICEV), BEVs have a shorter driving range, generally 150 km–400 km. Meanwhile, it usually takes hours to charge [5, 6]. Potential customers have repeatedly been found to prefer vehicles with considerably higher available range because of the range anxiety [7]. Although the long driving range design helps to alleviate the user's range anxiety, it results in a higher expenditure on purchase and simultaneously, the affordability and cost-effectiveness is lowered [8]. Optimizing driving range of BEVs based on users' daily travel demand is one of the feasible ways to solve this problem, and it is also the direction of breakthrough for this paper.

The main contribution of this paper is optimizing the driving range for different types of BEV users based on the real-world BEV usage data, specifically including the following: (1) constructing the daily trip chain for BEV drivers

by combining behavioral variables for daily trip and each trip; (2) applying the copula function to examine the dependence between daily travel variables; (3) proposing a simulation framework for the Monte Carlo method to simulate the daily trip chain; and (4) quantifying the fitness of driving range to find the optimal driving range for different drivers.

The remainder of the paper is organized as follows: after a review of relevant literature, Section 3 defines the research problem, followed by the stochastic formulation of driver behavioral models and the procedure of the Monte Carlo simulation in Section 4. Results and discussion are presented in Section 5, and Section 6 concludes this study.

2. Literature Review

Researchers have conducted a series of studies on the travel and charging behaviors of users based on the trajectory data of new energy vehicles (NEVs). In order to understand travel and charging behaviors, many existing studies focused on the distribution of distance traveled per day [5, 9, 10], the start time of charging [11–13], daily vehicle kilometers traveled (DVKT) [10, 12, 14], distance traveled between consecutive charges [5, 15, 16], and battery state of charge (SOC) before and after charging [11, 17, 18]. For example, Wu et al. [9] collected the travel data of 403 plug-in hybrid cars and analyzed the effects of the daily mileage and the mileage between the two charges. Pearre et al. [5] analyzed 470 vehicles with more than 50 days' travel data in Atlanta, USA, and found that the highest probability of DVKT distribution was 19.2–25.6 km; a wide variation in driving distances was observed from different drivers.

Based on the driving behaviors of ICEV and NEV users, how to optimize battery capacity or driving range of electric vehicles (EVs) is studied. Li et al. [19] proposed a hybrid distribution model to describe the daily travel mileage for the purpose of optimizing battery capacity; the testing results indicated that the mixture distribution model could satisfy various drivers. In addition, Dong and Lin [15] proposed the concept of BEV feasibility through a stochastic modeling approach to characterize BEV drivers' behavior. The range of comfort level of the drivers with different driving characteristics was studied to explore solutions to reduce range anxiety. However, although the driving patterns characterizing BEVs are stochastic, the researchers found that the variables are interdependent. After modeling the dependence structure between six variables using a nonparametric copula function, Brady and O'Mahony [20] applied a stochastic simulation methodology to generate a schedule of daily travel and charging profile.

The travel pattern of a particular BEV owner is relatively constant, yet the uncertainties make the travel demand vary from different drivers (i.e., interdriver heterogeneity). Using the data collected from 50 BEVs in Shanghai, China, Yang et al. [11] found the interdriver heterogeneity existing in driving and charging behaviors in terms of distance traveled per day, start time of charging, daily number of charging events, distance traveled between consecutive charges, SOC before and after charging, and time-of-day electricity

demand. Due to the heterogeneities, it is unrealistic for vehicle manufacturers to make the driving range exactly equal to drivers' travel demand. The method of Monte Carlo simulation with the trip chain theory is often used to depict drivers' stochastic behaviors. For example, based on the survey data of National Household Travel Survey (NHTS), Jianfeng et al. [12] fitted the characteristics of the trip chain and analyzed the charging demand by the Monte Carlo simulation. Shuqiang et al. [21] proposed a method to analyze the charging demand of electric vehicles based on the trip chain theory; the Monte Carlo method was applied to explore the probability distribution characteristics of EVs parking time in different regions during one-day travel.

In summary, for the study of optimizing driving range, it is reasonable to consider the correlation between behavior variables and the heterogeneity of users in the modeling process. In addition, practical BEV usage data is rarely utilized to support users daily trip chain reconstruction based on travel and charging behavior. In view of the above methods and shortcomings, this paper proposes a probability distribution model based on the daily user trip chain by considering the correlation between the variables of daily trips and each trip. Combining different scenario settings, users with different driving behavior are analyzed for optimal driving range using Monte Carlo simulation method.

3. Problem Statement

3.1. Daily Trip Chain for BEV Users. The term of "trip chain" has different definitions [22]. To describe each individual's daily movement, we define the trip chain as a sequence of trips bounded by dwells. A trip that commutes between two anchor destinations, such as home to work, or work to home, is powered by electricity, and the dwell between two consecutive trips offers charging opportunities for BEVs.

Assuming BEV drivers leave home in the morning of the travel day with a full battery, the departure time of the first trip T_0 is recorded. With the travel time of the first trip t_1 and the travel speed of the first trip v_1 , the distance traveled and the energy consumed for the first trip are estimated. The departure time for the next trip is determined by the dwell time after the first trip s_1 . Drivers may plug in their vehicles at the dwell place with considerations that the dwell time is long enough, the SOC is below a certain value (SOC before charging: SOC_n'), and the charging facility is available. After the total number of trips N that day, the driver returned home, and daily vehicle kilometers traveled D are recorded. The electric energy consumed by the n -th trip E_n^t can be estimated by the travel time of the n -th trip t_n and the average travel speed of the n -th trip v_n . The energy obtained from the n -th dwell E_n^c is determined by the time length of the n -th dwell s_n and the power of charging facility. Thus, the daily trip chain is formed by the abovementioned determinants, which include a variety of behavioral variables that describe daily trips and each trip. Table 1 summarizes the behavioral variables of the daily trip chain. The distributions of behavioral variables are derived from the BEV dataset collected from Shanghai, China, in the next section. Once the coverage of charging infrastructure is given, the fitness of

TABLE 1: A summary of the behavioral variables of the daily trip chain.

	Number of daily trips N
Variables for daily trips	The departure time of the first trip T_0
	Daily vehicle kilometers traveled D
	The travel time of the n th trip t_n
Variables for each trip	The average travel speed of the n th trip v_n
	Dwell time between two consecutive trips
Variables for charging	s_n
	SOC before charging SOC'_n

the driving range, indicating whether the BEV driving range is capable of covering the daily trip chain, is quantified.

3.2. Correlation between Behavioral Variables. The behavioral variables in the daily trip chain are mutually influential and not independently distributed. Studies have demonstrated the correlation between the variables for daily trips [20] (i.e., number of daily trips N , the departure time of the first trip T_0 , and daily vehicle kilometers traveled D) and applied the copula function to combine the distributions between them. The copula function is called a “join function” or a “dependent function,” which is a function that connects the joint distribution of multiple random variables with their respective marginal distributions [23]. Specifically, in accordance with Sklar’s theorem [24], the continuous random variables x_1, x_2, \dots, x_n with cumulative distribution functions (CDFs) $F_1(x_1), F_2(x_2), \dots, F_n(x_n)$, respectively, are joined by copula C if their joint distribution function can be expressed as

$$F(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)). \quad (1)$$

Further, the three behavior variables of each trip not only affect each other, but also depend on the three variables of daily trip. Equation (2) establishes the link between each trip variable and the daily trip variable:

$$D = \sum_n^{N} t_n \cdot v_n. \quad (2)$$

Daily vehicle kilometers traveled D are the cumulative sum of the travel time of each trip t_n multiplied by the average speed of each trip v_n under the number of daily trips N .

3.3. Fitness of Driving Range. Due to limited battery range and insufficient charging infrastructure, the travel demand of BEV users is likely under constraint. BEV users may check the remaining SOC before each travel. Once the travel distance is beyond the remaining range, drivers have to charge the battery or change the travel plan. This situation is referred to as “range limitation” [15]. The more times the mileage limit occurs, the less user satisfaction will be.

We reconstruct the daily trip chain for BEV users by simulation. The remaining SOC is determined by the energy consumed in the previous travels and the availability of charging opportunity. Once there is no charging opportunity, the situation of “range limitation” may occur when the

remaining battery range is not long enough for the next trip. The trip chain must be terminated as the battery may run out. We count the number of the days with incomplete trip chain and denote it as $\tau(R)$, where R represents driving range. It can be speculated that the larger the battery, the less possibility that the range limitation occurs.

The fitness of driving range θ is defined as

$$\theta = \left(1 - \frac{\tau(R)}{M} \times 100\% \right), \quad (3)$$

where M is the number of travel days for BEV users. The proposed battery fitness measure can incorporate stochastic driver behaviors by incorporating randomly distributed variables in daily trip chain. If the simulated travel days for a BEV are 10,000, the fitness $\theta = 95\%$ means that there are 50 days when the BEV cannot fulfill the traveler’s travel demand.

4. Methodology

4.1. Modeling of Driver’s Behaviors

4.1.1. Data Description. This study makes use of a rich database collected from 50 BEVs over a period of 4–12 months (spanning from June 5, 2015, to June 30, 2016). The dataset is provided by Shanghai Electric Vehicles Data Center (SHEVDC) that is developed to remotely monitor electric vehicles driven across the city. The 50 BEVs, used as personal vehicles, are with the same model of Roewe E50, which is a pure electric passenger car with a 22.4 kW·h battery pack and a claimed driving range of 170 km under NEDC conditions [25].

Vehicle terminals, such as global positioning system data loggers and instruments to measure voltage and current, are installed on BEVs for data collection [26, 27]. The collected data includes turn on time, turn off time, total mileage, SOC, voltage, and current. Vehicles’ driving information includes time-stamped location (i.e., longitude and latitude), spot speed, and azimuth. After data cleaning and consistency check procedure to remove invalid data and possible errors from the record, BEV owners’ driving patterns, such as the trip distance, average travel speed, departure time of each trip, trip time length, SOC before/after each trip, and energy consumed, are extracted.

After the data cleaning of the original dataset, 12,855 valid trips, 7,112 accurate charges, and 7,275 travel days with authentic trips were extracted. Due to the intermittent record, the travel distance between two consecutive charges got 6,244 records. Table 2 summarizes the descriptive statistics of the valid trips and charges.

In terms of travel demand, the indicator that best reflects daily travel demand is the daily travel distance. Its average is 51.6 km, which is only 30% of the battery’s driving range. In addition, the average number of daily trips is 2.97, and the highest value is 9, which can be roughly understood as a daily commute user. For charging habits, the average SOC before charging is 45.6%. This means that the user prefers to start connecting the charging plug when there is still about half of SOC remaining.

TABLE 2: Summary metrics of valid trips and charges.

	Number of samples	Avg.	Med.	Max.	Min.	St.D.
Number of daily trips N	7275	2.97	2	9	1	1.16
The departure time for the first trip T_0	7275	11:23	10:45	23:59	0:00	4:50
Daily vehicle kilometers traveled D (km)	7275	51.6	55.4	95.3	17.5	18.8
Travel time t_n (h)	12855	0.71	0.57	9.12	0.05	0.54
Travel speed v_n (km/h)	12855	19.62	17.04	80	0.25	11.42
Dwell time between two consecutive trips s_n (h)	6244	2.7	1.69	22.15	0.06	2.86
Charging power	7112	3.80	3.21	6.71	1.31	2.64
SOC before charging SOC'_n (%)	7112	45.6	45.4	61.6	18.5	8.3

4.1.2. Modeling Variables for Daily Trips. In order to verify if there is dependence among the variables for daily trips, Pearson's linear correlation which measures a monotonic relationship between variables is estimated and placed in the matrix, R [28]. Pearson's linear correlation derived for the variables representing daily trips: the departure time for the first trip T_0 , daily vehicle kilometers traveled D , and number of daily trips N are given by

$$R = \begin{bmatrix} 1 & -0.23 & 0.51 \\ -0.23 & 1 & -0.35 \\ 0.51 & -0.35 & 1 \end{bmatrix}. \quad (4)$$

Testing the hypothesis of no correlation against the alternative that there is a nonzero correlation was applied to the elements of the correlation matrices [29]. All coefficients in the R matrix are found to be statistically significant assuming a 0.05 level of significance. In the R matrix, there is strong evidence that all variables are correlated and it is important to model the dependence structure between the core variables. According to R (1, 2), daily travel distance is negatively correlated with the first departure time of the day, which means that the later the user travels the earliest day, the shorter the daily travel mileage is. Meanwhile, R (1, 3) shows that the more daily trips, the greater the distance traveled each day. Therefore, after demonstrating the dependencies between the simulated variables, a joint PDF using their respective marginal distributions and a copula function needs to be constructed.

By modeling using copula function, we get the joint distribution result between the three variables for daily trips. If the resulting modeling structure is correct, the original and simulated values of the corresponding variables should have the same distribution. This is studied using the quantile-quantile (Q-Q) plot of the raw and simulated values of the variables (daily vehicle kilometers traveled). Figure 1 shows the Q-Q plot of the raw and simulated values of the variables (daily vehicle kilometers traveled). If the two distributions to be compared are similar, the points in the Q-Q diagram will approximate a straight line. It can be seen from the figure that it approximates a straight line, indicating that the simulated and original data are from the same distribution.

4.1.3. Modeling Variables for Each Trip

(1) **Travel Time t_n .** Figure 2 plots the distribution of travel time for each trip. 54.28% of the travel time is less than 40 minutes. We find that the travel time t_n follows the log-normal distribution [22]. The PDF of t_n is written as

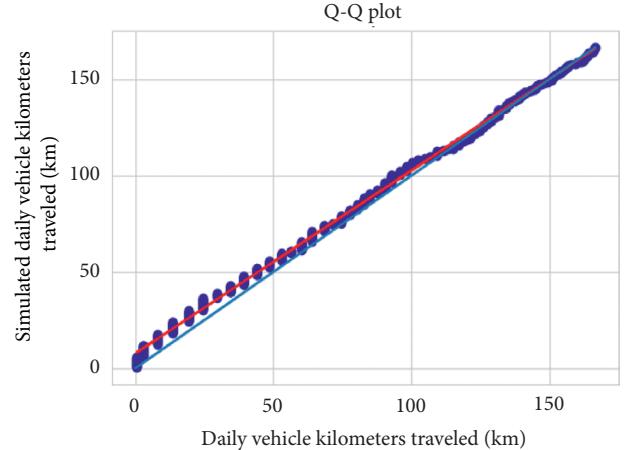


FIGURE 1: Q-Q plot of the simulated and original variable (daily vehicle kilometers traveled).

$$f(t_n) = \frac{1}{\sqrt{2\pi}\sigma t_n} \exp\left[-\frac{1}{2\sigma^2}(\ln t_n - \mu)^2\right], \quad t_n > 0, \quad (5)$$

where $\mu = 2.9115$ and $\sigma = 0.876$.

(2) **Travel Speed v_n .** The travel speed for each trip follows the beta distribution, with an average value of 22.04 km/h (Figure 3). The PDF of travel speed v_n is expressed as

$$p_3(y) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) + \Gamma(\beta)} y^{\alpha-1} (1-y)^{\beta-1}, \quad (6)$$

$$y = \frac{v_n - a}{b},$$

where $\alpha = 2.9339$, $\beta = 3256600$, $a = 0.50467$, and $b = 2399300$.

(3) **Dwell Time between Two Consecutive Trips s_n .** Once a trip is ended, BEV drivers may stop at the destination for a certain period. The dwell time is one of the key factors for charging decision [30]. Figure 4 depicts the distribution of dwell time between two consecutive trips. 57.5% of the dwells last for less than 2 hours, which may not be appropriate for charging with slow charging. The dwell time is estimated by a lognormal distribution. The PDF of s_n is written as

$$p_4(s_n) = \frac{1}{\sqrt{2\pi}\sigma s_n} \exp\left[-\frac{1}{2\sigma^2}(\ln s_n - \mu)^2\right], \quad x > 0, \quad (7)$$

where $\mu = 2.6$ and $\sigma = 1.0147$.

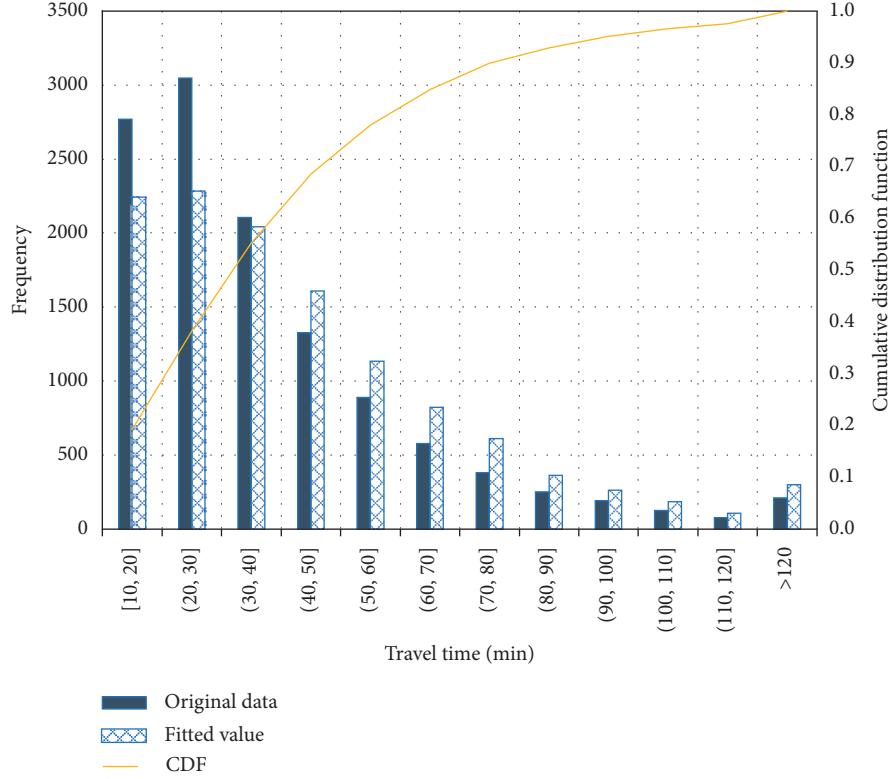


FIGURE 2: The distribution of travel time.

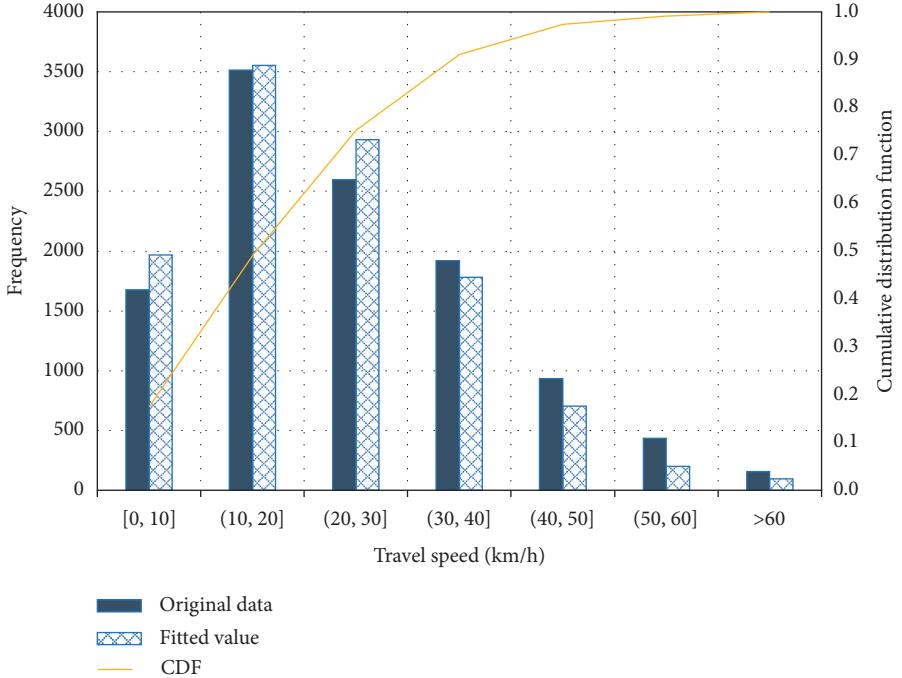


FIGURE 3: The distribution of travel speed.

(4) SOC before Charging, SOC'_n . The SOC before charging is adopted as the threshold for each charging event. Once the remaining SOC is above the threshold, the charging event will not occur [31]. As shown in Figure 5, the preference of the

SOC before charging is not obvious, indicating drivers are likely to charge their vehicles whenever they have charging opportunities. The distribution of SOC'_n is found subject to the Johnson SB distribution. The PDF of SOC'_n is written as

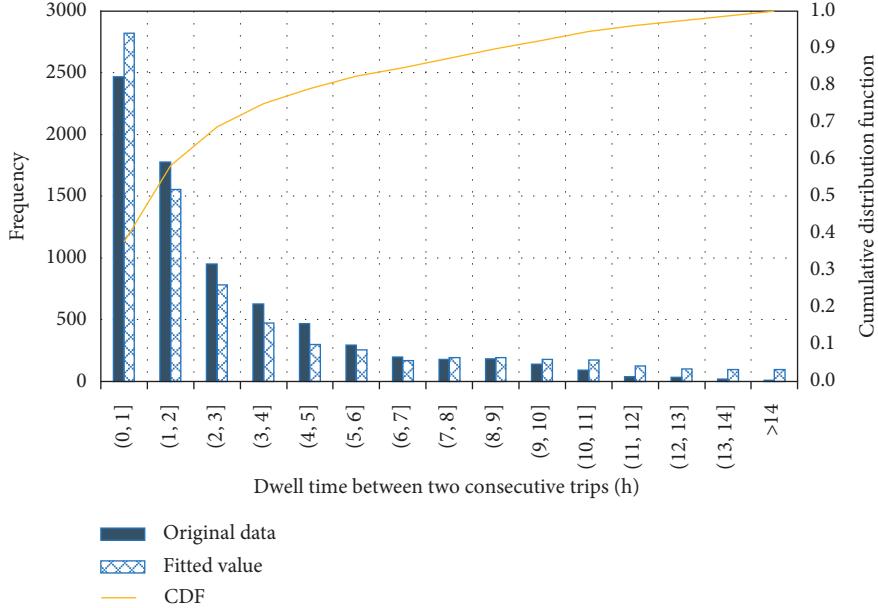


FIGURE 4: The distribution of dwell time between two consecutive trips.

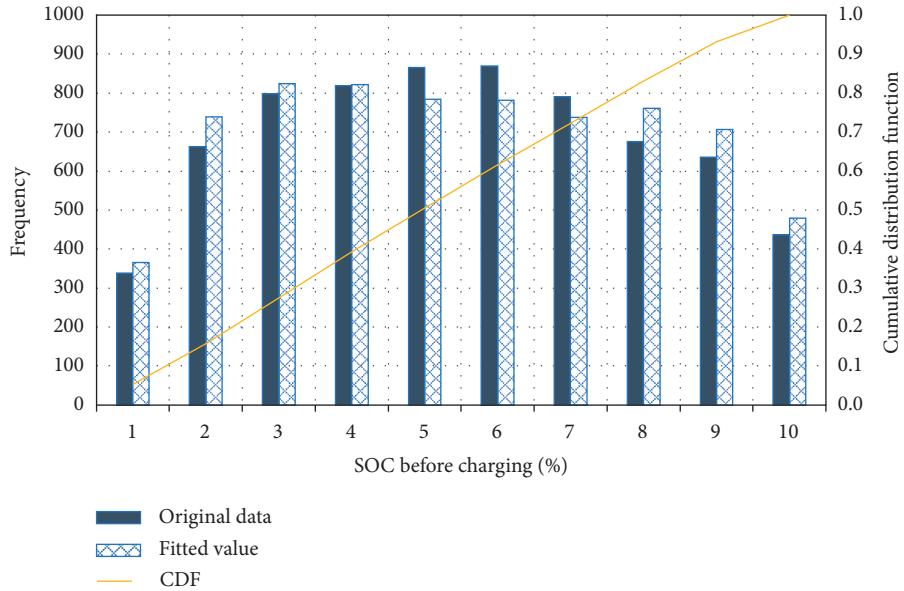


FIGURE 5: The distribution of SOC before charging.

$$p_5(t_n) = \frac{\delta}{\sqrt{2\pi}z(1-z)} \exp\left(-\frac{1}{2}\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)^2\right), \quad \zeta \leq z \leq \zeta + \lambda,$$

$$z = \frac{\text{SOC}'_n - \lambda}{\lambda} \quad (8)$$

where $\gamma = 0.081$, $\delta = 0.242$, $\zeta = 0$, and $\lambda = 100$.

4.1.4. Drivers Heterogeneity. In order to consider the impact of heterogeneity, Yang et al. [11] applied a machine learning method to analyze BEV drivers' habitual behaviors based on

the same sample data. User heterogeneity is mainly reflected in different travel patterns. Daily vehicle kilometers traveled D are not only the core of the behavior variable for daily trips, but also the dependency of each trip variables. Therefore, the research on user heterogeneity in this paper mainly focuses on the optimal driving range of different daily travel users. According to the results of Yang et al. [11], the 50 BEV sample vehicles can be divided into 4 clusters in Table 3 by daily vehicle kilometers traveled D . Obviously, based on the same charging scenario restrictions, users with different travel pattern will have corresponding optimal driving range.

TABLE 3: Summary metrics of different clusters.

Type	Number of vehicles	Avg. daily vehicle kilometers traveled (km)		
		Sample size	Mean	St.D.
Cluster A	34	4406	58.0	42.0
Cluster B	2	240	93.4	44.3
Cluster C	5	1059	31.7	30.1
Cluster D	9	1570	23.3	19.0

4.2. Monte Carlo Simulation

4.2.1. Simulation Assumptions. The data set of this study is based on the Roewe E50, so the initial driving range R during the simulation is also 170 km. That is, the driving range limitation of this study is specifically defined for this vehicle model. Several conditions are set for the simulation context/environment. They are summarized as follows.

Condition 1. Charging places: two scenarios are set for charging locations. In Scenario 1, users can only charge the battery at home when they go back home after the last trip of the travel day. In Scenario 2, the charging facility is available at workplace, and users can choose to charge at the workplace or charge at home. Two time periods for workplace charging are set, i.e., from 09:00 to 16:00 [32].

Condition 2. Energy consumption: the electricity consumed for the n th trip E_n^t (kW) is supposed to be determined by the travel time and travel distance [33]. A linear relationship is found based on the real-world data with the R -squared value of 0.937. It can be written as

$$E_n^t = 0.0038t_n + 0.8358l_n + 0.9829, \quad (9)$$

where l_n (km) is travel distance for the n th trip determined by v_n and t_n .

Condition 3. Charged energy: the amount of electricity charged mainly depends on the charging power and the dwell time. The charging power is assumed as constant, and the charged electricity E_n^c (kW) for the n th dwell can be written as

$$E_n^c = \min(R_n^r + p \times s_n, R), \quad (10)$$

where R_n^r (kW·h) is the remaining range after the n th trip, p is the charging power, and R (kW·h) is the battery capacity.

4.2.2. Simulation Process. Based on the distribution models of drivers' driving and charging behaviors, the Monte Carlo simulation is applied to simulate the trip chain for BEV users. To stabilize the simulation results, the number of the simulated travel days M is set as 10,000. The simulation process is presented in Algorithm 1.

5. Results and Discussion

The charging problem is a key obstacle hindering the development of BEVs. The feasible methods to solve the

charging problem mainly include increasing the charging opportunity and increasing the power of the charging pile. These two feasible methods will be studied to influence the optimal driving range of different users in this section.

5.1. Impact of Workplace Charging. In general, household charging piles mainly apply alternating current (AC), which is mainly divided into two levels. Level 1 operates at 120 VAC (voltage in an alternating current), while Level 2 uses 208 or 240 VAC, and the corresponding charging power ranges from 1.4 kW to 7.2 kW. If the charging pile in public places uses direct current (DC), the charging power can reach 50 kW or more. Although the charging power of Electric Vehicle Supply Equipment (EVSE) is now getting bigger, even more than 100 kW, it takes a long time to spread to the average drivers and to apply to each BEV model [34,35]. Almost all charging events extracted from the dataset are performed using AC Level 2 Electric Vehicle Supply Equipment (EVSE), with an average value of 3.8 kW in Table 2. Thus, by setting three kinds of slow charging power (i.e., the power of 3.5 kW, 7 kW, and 15 kW) at two charging places, the impact of increasing the charging opportunity on the optimal driving range is studied. Given the fitness requirement $\theta = 95\%$, Figure 6 presents the results of optimal driving range in Scenario 1 and Scenario 2.

Whether it is to increase the charging opportunity or the charging power, the value of the optimal driving range can be reduced, because the daily travel demand of users is more easily met. In detail, the daily vehicle kilometers traveled of clusters A and B exceed the average value in Table 2. Compared with Scenario 1, Scenario 2 that increases the charging opportunity at the workplace has a significant effect on reducing the optimal driving range, especially for cluster B with a daily vehicle kilometers traveled value of 93 km. Clusters C and D with smaller travel demand are not sensitive enough to Scenario 1 and 2 with different charging opportunities. When the charging power is 15 kW, the optimal driving range of both clusters is only slightly reduced.

According to the original driving range of the Roewe E50 (170 km), two drivers in cluster B are not suitable for this model unless the charging power and charging opportunities are appropriately increased. Also, the daily travel demand of the 14 users in clusters C and D can be mostly satisfied even if charging only at home and the charging power is 3.5 kW. As the daily vehicle kilometers traveled of cluster A are similar to the average value, it can be found that when the average daily travel distance of the user accounts for about 30%–34% of the battery driving range, the fitness of battery capacity cannot be satisfied. Therefore, users should choose their own BEVs whose daily travel demand is within 34% of the battery driving range.

5.2. Impacts of Fast Charging. In order to understand the impact of fast charging, based on the results of Section 5.1, the benchmark scenario is set to 15 kW at home and at the workplace. Assuming fast charging is only available at workplace, the added charging power of workplaces (CPW)

Input: Practical data of the behavioral variables of the daily trip chain in Table 1

Output: Simulated travel and charging process

Process:

Initial: $M = 10,000$, $m = 1$, $i = 0$.

Step 0: the vehicle is assumed to depart from home with a full battery

Step 1: generate the daily trip, the number of daily trips N , the departure time for the first trip T_0 , and the daily travel distance D using copula function; set $i = 1$

Step 2: generate the travel distance, the average travel speed for each trip, and the dwell time between the two trips by equation (2) on the day m

Step 3: calculate the electricity consumed for the i^{th} trip; check whether the remaining SOC is sufficient for the i^{th} trip. If it is, update the remaining SOC after arriving at the destination, and proceed to Step 4; otherwise, the i^{th} trip is marked as failed with “range limitation,” and choose alternative travel mode to make up for this trip; set $m = m + 1$, and return to Step 0

Step 4: generate SOC before charging SOC_{pre} ; check whether a charging opportunity is available at that time. If the charge is performed, calculate the increased SOC and update the remaining range; otherwise, the remaining range keeps the same

Step 5: check whether i equals N . If it does, move to Step 6; otherwise, $i = i + 1$, and return to Step 2

Step 6: check whether m equals M . If it does, the simulation is terminated; otherwise, set $m = m + 1$, and return to Step 1

ALGORITHM 1: Summary of simulation methodology.

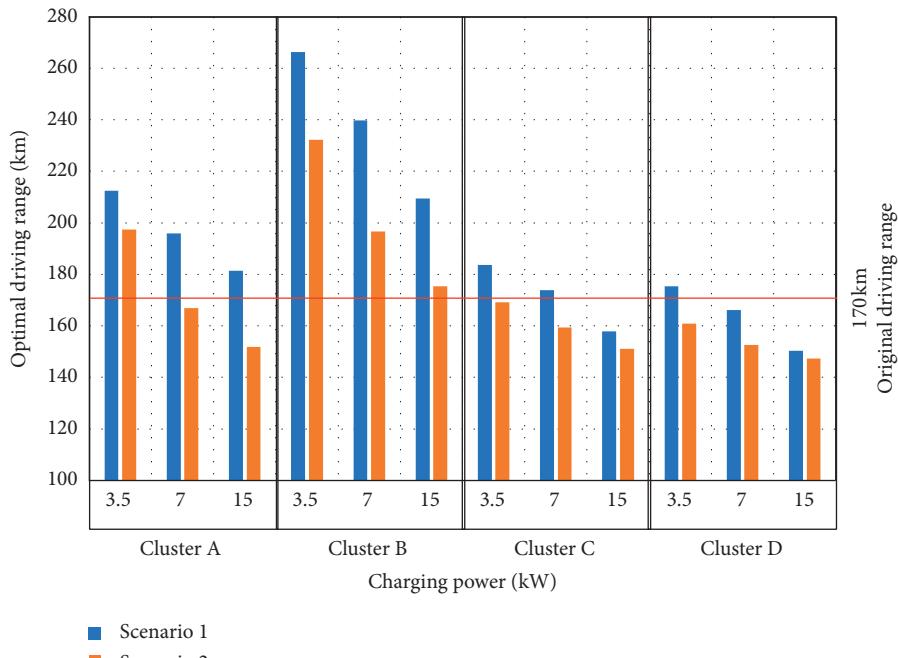


FIGURE 6: Optimal driving range for two scenarios when $\theta = 95\%$.

is set to 30 kW, 45 kW, and 50 kW, respectively. The charging power at home (CPH) is still set to 15 kW. Figure 7 shows a stacked bar chart of relative reduction percentages when the optimal driving range is compared with the values of the benchmark scenario as CPW increases.

Cluster B, which has the largest daily vehicle kilometers traveled, has the largest reduction percentage. When CPW = 50 kW and CPH = 15 kW, the optimal driving range can be reduced by 10.4% compared with the benchmark scenario. Conversely, the cumulative reduction percentage of clusters C and D is in the range of 7.6%–8.4%. The benefits of fast charging are more significant to users with high daily travel demand. Besides, as the CPW increases,

the value of the relative reduction percentage for each cluster gradually decreases. It can be seen that, on the premise of meeting travel demand, the beneficial effects brought by the increase in fast-charging power will gradually weaken.

To sum up, with the increase in daily travel demand of residents, the beneficial effects of charging piles equipped with fast-charging power can be reflected. The government should pay more attention to the layout of the fast-charging piles in the area where residents with large daily travel needs are located. Simultaneously, a reasonable amount of fast-charging power should be studied without the need for blind high power.

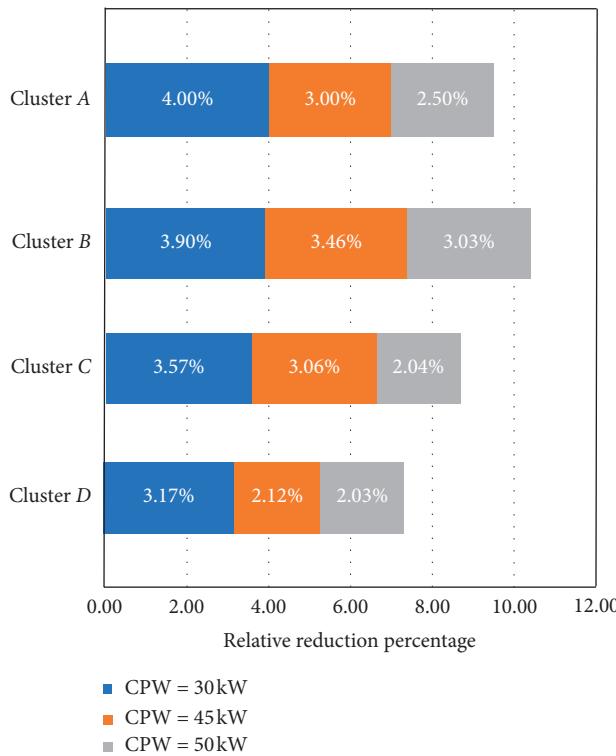


FIGURE 7: A stacked bar chart of relative reduction percentages.

6. Conclusions

Aimed at finding out the optimal driving range considering user heterogeneity in different charging scenarios, this study proposes a simulation modeling method representing BEV users' driving and charging behavior using the real-world in-use data collected from Shanghai, China. The Monte Carlo simulation is adopted to reconstruct BEV users' daily trip chains and quantify the fitness of the driving range. The key findings from the results include the following. (1) The daily travel chain can be reconstructed by variables for daily trips and each trip, and dependencies exist in these variables. (2) According to the results of four clusters, users with different daily travel demand have different optimal driving ranges. When choosing their BEV, users should consider that the daily vehicle kilometers traveled are less than 34% of the battery driving range. (3) Increasing both the charging opportunity and charging power is more beneficial to drivers with large daily vehicle kilometers traveled. (4) With the increase of fast-charging power, this beneficial effect gradually weakens when daily travel demand is met.

The main contribution of this paper is to construct a daily trip chain to analyze the optimal driving ranges of various heterogeneous users. However, due to errors in the vehicle's latitude and longitude in the data source, the restriction is that only the home and workplace are assumed during the daily trip chain. The purpose of daily activities of residents is diverse, not only work and home. Therefore, further enriching the daily trip chain is also the main focus in the future research direction.

Data Availability

The data used to support the findings of this study have not been made available because of confidential issues.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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