Research Article

Prediction of Charging Requirements for Electric Vehicles Based on Multiagent Intelligence

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Received 19 October 2021; Revised 29 March 2022; Accepted 18 April 2022; Published 19 May 2022

1.Introduction

Innovative transportation technologies have emerged continuously in recent years. Electric vehicles (EVs) have advantages of low cost and low greenhouse gas emissions [1]. Because EVs utilize electricity instead of gasoline, their application can reduce fossil energy consumption when electricity is generated from other energy sources and can effectively alleviate the global energy shortage [2]. Therefore, the EV market has garnered the attention of several governments. The EV market is rapidly developing with government incentives and automaker investments [3, 4]. Globally, EVs have been widely adopted over the last decade. In 2020, plug-in EV sales surpassed 3.24 million vehicles compared to 2.26 million in the previous year, a year-on-year growth of 43%, accounting for a 4.2% share of all new car sales [5]. Today, China, Germany, and the United States lead the world in the number of registered EVs [6]. According to the “2020 Global New Energy Vehicle Development Report: Centennial Changes of Automobiles” [7], the number of EVs is expected to continuously increase in the next few years. The total number of passenger vehicles sold in China in 2020 was 2.0178 billion [8]. Based on current trends, the sales of new energy vehicles in China will reach 4.29 million by 2025. According to the "Circular of the General Office of the State Council on Printing and Issuing the Development Plan of New Energy Automobile Industry [9]" (The State Council, China, 2020), China’s new energy vehicles will account for approximately 20% of the total sales of new vehicles by 2025, and the stock of EVs will reach a high level. However, more EVs have a higher electricity demand, which increases the peak load on the power grid, as well as the expansion expenditure and challenges required to operate the grid [10–12]. Therefore, charging service
providers need to balance the conflict between providing more charging infrastructure to meet the demand and ensure their own profits from charging services.

Various challenges have been encountered in the development of charging infrastructure. For example, the utilization rate of public charging equipment units (called “piles”) varies significantly in different regions, resulting in “zombie” charging infrastructure in some areas and extreme scarcity of charging infrastructure in others, and this has caused considerable waste of resources [13]. Moreover, charging service providers have proven that they are unable to deal with the peak load and fluctuation in the charging demand on the grid [14]. Several recent studies have been conducted on the optimal deployment of charging infrastructure, mostly based on mathematical optimization models. However, other studies have focused on different factors, such as the driver’s total excess driving distance [15, 16], covered path flows [17, 18], social welfare [19], greenhouse gas emissions [20], user costs [21], and trip distance [22]. While different factors affecting the optimal deployment of charging infrastructure have been considered, all optimization models in these studies are based on charging demands. Therefore, accurately forecasting the charging demand is essential for optimizing the deployment of charging infrastructure.

Another challenge for charging service providers is how to reduce the peak load and fluctuation in demand on the grid. The total charging demand is a result of the charging behavior of individual users, and the demand distribution in a charging system is an aggregation of the charging behavior of users in the charging system according to a certain pattern. Numerous factors can affect the users’ charging choices, such as the state of charge (SOC) [23], parking duration [24], trip distance [25], charging price [26], and charging cost [27]. Demographic factors, such as age, gender, income, and education, are also major factors that can influence charging choices [28]. Pan et al. [29] recently advanced this research using a discrete choice model to demonstrate the heterogeneity of charging choices. However, the abovementioned factors are hard to convey using a driver charging behavior model based on mathematical modeling, and it is difficult to perceive the comprehensive role of these factors in charging decision-making.

Regarding the aforementioned challenges, in this study, we apply a multiagent system (MAS) to predict the charging demand distribution, and we further investigate the relationship between the operational efficiency of the charging infrastructure and deployment of charging piles in different functional areas. Our study contributes to the current research on EVs in four ways.

(i) First, for large-scale charging demand prediction, a data-driven multiagent system is used. The charging demand distribution in the simulation system is an aggregation of the agents’ charging behavior based on real-world user behavior.

(ii) Second, a heterogeneous agent model is proposed with bounded rationality and adaptive behavior.

The agent’s charging decision is not just influenced by range anxiety, but also by considerations such as charging price and parking duration. Agents decision parameters are iteratively changed in days at the same time.

(iii) Third, the indexes for evaluating the operational efficiency of charging infrastructure in various functional areas are developed. The charging request rejection rate, public charging pile utilization rate, and charging load deviation are proposed to access the service level of charging infrastructure operator.

(iv) Forth, the temporal and spatial implications of various pricing strategies and the deployment of charging infrastructure are explored. In comparison to a constant price, a dynamic TOU price can better guide customers’ charging behavior and transfer peak load, and when combined with charging infrastructure deployment optimization, it can increase the charging service’s efficiency.

The remainder of this paper is organized as follows. Section 2 summarizes recent studies on charging behavior and charging demand distribution. In Section 3, some basic model assumptions are described, and a charging demand prediction model is proposed by analyzing the trip chain characteristics and charging choice model. Section 4 presents our simulation results for different areas under different charging price scenarios and investigates the differences in operating efficiency under different charging infrastructure configurations. Finally, conclusions, policy recommendations, and prospective research directions are provided in Section 5.

2. Literature Review

The charging demand distribution is determined by the charging behavior of the individual EV drivers. Understanding the charging behavior of users is extremely important for predicting charging demand [30]. The following section summarizes the current state of research on psychological factors before exploring more into the findings on market factors. Following that, the state of the research field in EV charging prediction is discussed.

The first pilot studies focused mainly on psychological factors is range anxiety [31] during the decision-making process. Subsequent studies expanded the factors, to include charging location [32], duration or frequency [27, 33], charging mode [34], charging time choice [35], and the deployment of public charging infrastructure [25, 36, 37]. Other pilot studies consider the heterogeneity of user types and charging conditions and find the factors driving people’s charging behavior including the state of charge (SOC) [23], parking duration [24], cost of charging [25, 38], and demographic factors (e.g., age, gender, income, and past charging experiences) [27]. Using these factors, Li et al. [39] and Pan et al. [29] further described and explained charging behavior. The preceding studies
provide us the motivation for designing the agent’s charging decision.

In addition, market factors such as charging prices and infrastructure service capacity can alter the charging behavior, which in turn affects the charging demand distribution. Thus, charging service providers must adopt appropriate pricing strategies to guide their orderly charging choices. Accordingly, several studies have proposed different strategies, such as the time-of-use pricing strategy based on a mathematical scheduling model, which has the objective of minimizing the peak-to-valley load ratio [40]; the charging price optimization model, which has the objective of minimizing power loss in the distribution network by considering the charging load and nodal voltage amplitude limitations [41]; the maximization of the economic benefits of EVs on both the grid and user end [42]; and the reduction of the peak-to-valley difference and minimization of charging cost and duration [43]. Several further studies propose strategies based on charging service level such as online time and power of charging facilities [44]. Other studies [45–47] propose methods to influence the charging behavior by improving charging efficiency through optimizing the deployment of charging stations. These studies guide us for configuring the environment of a multi-agent simulation system.

According to the research methods used, related studies on forecasting charging demand can be classified into three categories. The first category of studies is the Monte Carlo model- (MCM-) based simulation [48], which consider various factors including demographics (e.g., age, gender, education, etc.) [48], workdays [49], road conditions, and temperature [50]. The second category is the Markov-chain method. Owing to the difference in charging demands in different areas, a spatial Markov chain is utilized to describe the movement of EVs between different areas [51,52]. An EV generally has three operating states: driving, parked and charging, and parked without charging. By analyzing the probability of these three states, Fotouhi et al. [52] predicted the charging demand in a simulation study. The third category includes the big-data-based methods. Xydas et al. [52] adopted data mining technology to identify the point demand characteristics in different areas and evaluated the potential risks of charging loads to the distribution network. Mirzaei et al. [53] and Helmus et al. [54] employed probability and cluster analysis. Jahangir et al. [56] proposed a charging demand prediction model based on neural networks, using historical data such as arrival time, departure time, and trip distance.

From the perspective of system emergence, each driver’s charging decision has an effect on the market’s charging demand. Charge demand forecasting must take into account not only the influencing factors on driver charging decisions, but also the market factors of charging infrastructure. The complex interaction between these factors is difficult to model mathematically or traditional prediction model. As a result, this study will employ the multiagent simulation method, which will allow for a more comprehensive prediction.

### 3. Model Formulation

To investigate the charging demand distribution, EV user travel behavior, and EV user charging choice in different areas, we first analyzed EV user travel behavior and then utilized a prediction model that captures EV user charging choice behavior and demand.

#### 3.1. Assumptions

For simplicity, the model formulation in this study is developed under the following assumptions: Table 1 summarizes and defines the main notations used in this study.

1. Only travels within a city are considered. Moreover, EVs and conventional vehicles have the same traveling features in terms of the average distance per trip and average daily travel distance.
2. Assume that the charging power is 7 kW without considering the travelers’ choice of charging pile power and adopt the power load to evaluate the charging demand; that is, the unit of charging demand is kW.
3. EV drivers make charging choices when they arrive at their destination. If the traveler decides not to charge, the utility is zero. Otherwise, charging starts at the time the traveler arrives at the destination.
4. For travel purposes, urban areas can be divided into different functional areas. In this study, urban areas are divided into three functional areas: home (H), workplace (W), and other areas (O). Home is regarded as the origin and destination of each trip chain; that is, the place EV drivers start and finish their daily travel.
5. Real-world daily travel data from the National Household Travel Survey (NHTS) 2017 database are directly employed in this study. Travel data include the daily travel trajectories of travelers. There is a certain degree of heterogeneity in the travel data of the different travelers.

#### 3.2. Travel Behavior Analysis

To analyze charging patterns, it is necessary to study travel behavior characteristics. The trip chain characteristics include the following three elements: origin and destination (OD), time, and speed. OD comprises information on the origin of travel, trip distance, and destination. Time includes travel and parking durations. Speed refers to the average speed of movement during each period. Different travel characteristics are connected in a certain order to form a trip chain. Using the trip chain of the EV drivers, it is possible to accurately describe the daily travel trajectory of each traveler.

Each trip chain reflects the purpose of the travelers. Previous studies were mostly based on a probability transition matrix to determine a traveler’s destination transition. This method can reflect neither the true trajectories of a traveler nor the heterogeneity of EV drivers. For example, the trip chain of a particular traveler may be [H-W-O-O-...
The characteristics of a trip chain can be accurately obtained based on a real travel trajectory. The ODs of EVs are travel origin and destination. For example, in [H-W-H], there are two trips: the first trip is from home to workplace (OD of origin and destination. For example, in [H-W-H], there are then visits three other places before returning home. /K_he ODs of EVs are travel characteristics of a trip chain can be accurately obtained

In existing studies, the state transition probability matrix method is often employed to determine travel destinations. In other words, the transfer of EV destinations at different times follows a certain probability distribution. Based on this probability, the next destination can be predicted [48, 51]. In the current study, based on real-world NHTS 2017 data, the daily travel trajectory of each traveler is obtained by connecting the ODs of that traveler in a day. Subsequently, the traveler’s trip chain is simulated based on real-world travel data. When the number of samples is negligible, the random error in determining the travel destination based on the state transition probability is large. Thus, using extensive real-world travel data for simulation is more in line with the travel characteristics and makes the model scalable.

According to data from the Annual Report on the Development of Beijing Transportation [58], and Zhang et al. [48], the Burr Type XII model is utilized as the probability density function \( f(t_0|a, c, k) \) of the departure time of the first trip, as follows:

\[
  f(t_0|a, c, k) = \frac{k c^a (t_0/a)^{c-1}}{(1 + (t_0/a)^a)^{k+c+1}},
\]

where \( t_0 \) is the departure time of the first trip, \( a \) is a range parameter, and \( c, k \) are shape parameters.

Parking duration determines the maximum recharge time at the destination and is a key factor affecting users’ charging choices. It is related to the purpose of the trip and varies at different destinations. Based on the results of Zhao et al. [59], we assumed that the parking duration in each functional area followed a generalized extreme value distribution. Thus, the probability density function of parking duration in workplace areas can be expressed as follows:

\[
  f_w(x) = \frac{1}{\text{scale}_w} \exp\left\{ -\left(1 - x_w \right)^{1/c_w}\left(1 - c_w x_w \right)^{1/c_w-1} \right\},
\]

where
Similarly, the probability density function of the parking duration at home and other functional places can be expressed as

$$f_{h/o}(x) = \frac{1}{\text{scale}_{h/o}} \exp\left\{-(1 - c_{h/o}X_{h/o})^{1/c_{h/o}} \right\} (1 - c_{h/o}X_{h/o})^{1/c_{h/o}-1},$$

where

$$X_{h/o} = \frac{t^{(l,t)}_P - \text{loc}_{h/o}}{\text{scale}_{h/o}},$$

where $t^{(l,t)}_P$ is the parking duration of traveler $i$ arriving at time $t$, loc is a range parameter, and scale is a normalization parameter.

Road conditions and driving speed vary at different times of the day. The speed during rush hours is significantly lower than that during off-peak hours. Wang et al. [60] collected speed data on various types of roads at five-minute intervals. Through data screening and processing, 2,521 valid data pieces were obtained. By analyzing the speed characteristics of vehicles in different space and time dimensions, Wang et al. [60] obtained vehicle speed data on urban roads.

Even when there is light traffic, the vehicle speed is limited by road design and laws. According to the regulations stated in the Regulation on the Implementation of the Road Traffic Safety Law of the People’s Republic of China, the speed of vehicles on urban roads must not exceed 70 km/h (Chinese State Council 2005). Based on the results of Wang et al. [60] and the Chinese government regulations, the average speed values during the different time periods illustrated in Figure 1 are used in our study.

The travel trajectory is obtained by simulating the travel activities of the trip chain using the aforementioned probability distribution. Figure 2 presents the simulation process.

### 3.3. Charging Choice and Demand Prediction Model

Charging choices are affected by several factors, and different EV drivers may make different choices, thereby reflecting their heterogeneity. The primary factors driving a traveler’s charging choices are the current SOC, expected power consumption of the next trip, parking duration, charging price, and range anxiety, which is a psychological state that reflects the traveler’s level of anxiety over losing power when the SOC is below a certain level. The SOC at the beginning of a day determines the maximum distance of a single trip. The higher the initial SOC, the greater the maximum distance of a single trip. Thus, the initial SOC also affects the charging behavior. The probability density function of the initial SOC ($SOC_0$) is expressed by the following equation [61]:

$$f(SOC_0) = \begin{cases} aSOC_0^{\alpha - 1}, & 0 < SOC_0 \leq 1, \\ 0, & \text{others} \end{cases},$$

where $SOC_0$ is the initial SOC, and $\alpha$ is a shape parameter.

A traveler’s heterogeneity is also reflected in range anxiety, which represents their risk preference attitude. In this study, anxiety ranges from 0 to 1, and a larger value suggests that a traveler is more risk-averse. According to the results of Ma et al., the probability density function of range anxiety is expressed by the following equation [61]:

$$f(A_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(A_i - \mu)^2}{2\sigma^2}\right),$$

where $A_i$ is the range anxiety of traveler $i$, $\mu$ is the mean of the range anxiety, and $\sigma$ is the variance of the range anxiety.
In our study, a utility function $U$, is introduced to describe the charging choice [62]. Assuming the parking duration of traveler $i$ arriving at time $i$ is $t_p^{(i)}$, the SOC is $SOC_i^{t_p}$, battery capacity is $C_B$, and time to fully charge the battery is $t_{SOCM}^{(i)}$, then the effective charging duration is $\min\{t_p^{(i)}, t_{SOCM}^{(i)}\}$ and the change in the SOC is $\Delta SOC_i^{t_p}$, as follows:

$$\Delta SOC_i^{t_p} = \min\{t_p^{(i)}, t_{SOCM}^{(i)}\} \frac{P}{C_B}.$$  

(9)

If $C_i$ is the charging price during $i$, and $C_a$ is the average price, the utility function $U$ is formulated as

$$U_C^{(i)}(C_t, C_a, \Delta SOC_i^{t_p}, A_i) = (1 + A_i)\Delta SOC_i^{t_p}C_B - \Delta SOC_i^{t_p}C_a,$$  

(10)

where $C_a$ is the following weighted average electricity price:

$$C_a = \left( \frac{C_p|\text{Span}_p| + C_f|\text{Span}_f| + C_v|\text{Span}_v|}{|T|} \right),$$  

(11)

where $\text{Span}_p$ is the set of peak-valley hours for charging, $\text{Span}_f$ is the set of flat hours for charging, $\text{Span}_v$ is the set of valley hours for charging, and $|\cdot|$ is the length of a set of periods. It is easy to prove (as in Appendix) that $U$ satisfies the following conditions:
Condition 1: When the charging price in other hours increases, the utility in the current hour increases, i.e., \( \partial U / \partial C_i > 0 \), where \( C_i \) represents the charging price in non-\( t \) hours.

Condition 2: When the charging price in \( t \) increases, the utility of the user in \( t \) decreases, i.e., \( \partial U / \partial A_i > 0 \), where \( A_i \) is the charging price in \( t \).

Condition 3: When the user's range anxiety \( A_i \) increases, the utility of the same charge increases, i.e., \( \partial U / \partial A_i > 0 \), where \( A_i \) is the range anxiety level of traveler \( i \).

If the utility value is positive, the user's benefit of choosing to charge exceeds zero; if it is negative, the user's benefit of choosing to charge is below zero. Therefore, the charging decision-making process for EV drivers is expressed as follows:

(i) To ensure that the vehicle can complete the daily trip, the user sends a charging request, regardless of the current conditions if the following condition is met:

\[
SOC_i^t - \frac{d_{t+1}}{R} \leq 0.2, \tag{12}
\]

(11) indicates that when the result of the current power minus the power consumption of the next trip is less than 20\%, a charging request is submitted, which is consistent with the specifications of the current EV battery protection systems.

(ii) In addition, when the following conditions are met, a charging request is submitted as well:

\[
\left( \begin{array}{c} SOC_i^t \leq A_i \ OR \ SOC_i^t - \frac{d_{t+1}}{R} \leq A_i \end{array} \right) AND U^f_{i,j} \tag{13}
\]

(12) indicates that when a traveler experiences range anxiety, a charging request is not submitted immediately. The user further considers whether the utility of charging exceeds zero, and charging is selected only if the utility is greater than zero.

In summary, the probability of charging increases with a lower SOC, next trip requiring greater energy consumption, longer parking duration, lower charging price, and higher level of range anxiety.

In several existing studies, it is assumed that the number of charging piles is sufficiently large to prevent charging congestion; therefore, the charging demand is computed according to computer simulations of the trip chain. However, under practical conditions, the number of charging piles is limited, and the order in computer simulations does not accurately represent the arrival order of different EV drivers at destinations in the real world. For example, traveler one arrives at the workplace at 9:30 a.m., and traveler two arrives at the same workplace at 9:40 a.m. According to existing studies, because traveler one is generated earlier in the simulation, even though they arrive 20 min later than traveler two, traveler one will make the charging decision first because traveler two has not yet been simulated. Clearly, it is impractical to let the late-arriving traveler charge before the early-arriving traveler. Particularly when the charging infrastructure is limited, this approach will affect the reliability of the charging demand prediction to a certain extent.

Given that the current battery technology allows 2-3 days of daily travel activities at full charge, travel activities and charging choices are separately simulated in our study. First, the daily travel activities of all EV drivers are simulated, and EV drivers traveling at different time periods are sorted according to the order of arrival to obtain travel activity data. The charging choice of each traveler is then made based on the order of arrival. The charging choice and travel trajectory are combined to predict the charging demand. The simulation process is provided in Figure 3.

4. Simulation Results and Discussion

This section presents the simulation results of different areas (i.e., residential, workplace, and other areas) under different charging price scenarios (i.e., constant and time-of-use prices).

The simulations in this study are based on Python, and experiments were conducted using the PyCharm platform. The NHTS 2017 dataset was used, which included 193,028 travel data after screening.

It should be noted that because of existing policies and regulations in China, we have no access to the location data of Chinese travelers; hence, we chose to use a substitute with the NHTS 2017 location data, which reflect only the number of daily trips and travel purposes of travelers, not other relevant variables of the trip chain. The NHTS 2017 location data largely represent the location data of Chinese travelers in these two aspects. First, the average number of daily trips in the NHTS 2017 dataset is 3.14, and statistical data from the Annual Report on the Development of Beijing Transportation [58] indicates that the average number of private car trips per working day is 3.33, while the average number of trips per holiday is 3.20. From a statistical point of view, the distribution and parameter values of the number of trips in are not significantly different from those in China. Second, from the perspective of travel purposes, the Annual Report reveals that commuter travel accounts for 47.1% of total travel in Beijing, while commuter travel accounts for approximately 40% of total travel in NHTS 2017 (excluding travel for school). Because the NHTS 2017 dataset supplies only these two aspects of location data (the number of daily trips and travel purposes), its influence on the overall trip chain simulation is weak and limited. This study intends to solve charging infrastructure challenges in China; therefore, the distribution and parameter selection of other relevant variables of the trip chain are mainly based on the travel characteristics of Chinese travelers.

The results of the relevant reports from the China Academy of Urban Planning and Design reveal that the average density of public charging piles in southern cities of China is 20.6 sets/km², and in northern cities, it is
11.5 sets/km². According to the current rate of infrastructure deployment by the Chinese government, the proportion of new residential parking construction or reserved charging facilities should reach 100%, and large public buildings and parking lots should not be less than 10%. Based on the above data and combined with the relevant urban area data and current situation of the overall vehicle-pile ratio in China’s public sector, this study sets the number distribution parameters of charging piles in different functional areas, as presented in Table 2.

The basic system and probability distribution parameters are summarized in Tables 2 and 3, respectively.

4.1 Analysis of Charging Demand Distribution. The charging demand distribution varies in different areas under different charging price scenarios. As explained in the previous section, when charging prices are equal in different periods, price does not affect the charging choice behavior, and charging decisions are only influenced by range anxiety.
Thus, this section presents the simulation of different scenarios by considering two charging price schemes (i.e., time-of-use charging and constant prices) and then analyzes the charging demand distribution in different functional areas.

4.1.1. Scenario 1: Time-Of-Use Charging Price Scheme. According to (10), the utility function of a traveler choosing to charge is as follows:

\[ U_C^{(t)}(C_t, C_a, \Delta SOC_t^i, A_i) = (1 + A_i)\Delta SOC_t^i C_a C_o - \Delta SOC_t^i C_o^2 C_i. \]

(14)

In this case, the charging price \( C_t \) varies with time and can be determined using (14) as follows:

\[ C_t = \begin{cases} C_p, & t \in \text{Span}_p; \\ C_f, & t \in \text{Span}_f; \\ C_v, & t \in \text{Span}_v. \end{cases} \]

(15)

The charging choice is determined based on the following two conditions:

(a) \( SOC_t^i - d_{n+1}/R \leq 0.2 \)

(b) \( (SOC_t^i \leq A_i) \text{ or } SOC_t^i - d_{n+1}/R \leq A_i \)

When either of the above conditions is met, a charging request is submitted.

4.1.2. Scenario 2: Constant Charging Price Scheme. When the charging prices in each period are equal, i.e., \( C_t = C_a \), by substituting it into the utility function, it is known that \( U_C^{(t)}(C_t, C_a, \Delta SOC_t^i, A_i) > 0 \) is always true. In this case, Condition (2) in equation (13) is transformed into \( SOC_t^i \leq A_i, OR SOC_t^i - d_{n+1}/R \leq A_i \); that is, the charging choice is made by considering only the range anxiety. This charging decision-making behavior is referred to as the disorderly charging behavior, and the charging choice is determined by the following conditions:

\[ \begin{align*}
&a) SOC_t^i - d_{n+1}/R \leq 0.2 \\
b) SOC_t^i \leq A_i \text{ or } SOC_t^i - d_{n+1}/R \leq A_i \\
\end{align*} \]

Similarly, when either of the above two conditions is satisfied, a charging request is submitted.

Figures 4(a)–4(d) illustrate a comparison of the charging demand distribution in different areas (i.e., total, residential, workplace, and other areas) under different charging prices.

As illustrated in Figures 4(a) and 4(b), with the current charging pile configuration, most of the charging demand is in residential areas in the time-of-use charging price scenario (Scenario 1), and the charging load is significantly reduced during peak demand hours compared with the constant charging price scenario (Scenario 2). The charging demand in Scenario 1 peaks between 10:00–12:00 and 18:00–20:00, while the charging demand peaks in Scenario 1 occur at approximately 12:00 and 17:00. The time-of-use pricing strategy significantly reduces the charging demand in the evening (18:00–20:00), but a new charging demand peak is created at 17:00, indicating that the time-of-use pricing strategy only shifts the peak charging demand and does not reduce it. A reasonable explanation for this phenomenon is that, on the one hand, the residential electricity consumption mode has changed significantly. Accordingly, the previous peak-valley time division is not consistent with the current demand mode, which makes the time division insufficiently accurate. On the other hand, the

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**Table 2: Basic parameters.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recharge mileage ( R )</td>
<td>180 km</td>
</tr>
<tr>
<td>Battery capacity ( C )</td>
<td>32 kWh</td>
</tr>
<tr>
<td>Charging power ( P )</td>
<td>7 kW</td>
</tr>
<tr>
<td>Maximum SOC ( SOC_{id} )</td>
<td>0.8</td>
</tr>
<tr>
<td>Charging price in peak hours ( C_p )</td>
<td>1.0436 Yuan/kWh</td>
</tr>
<tr>
<td>Charging price in flat hours ( C_f )</td>
<td>0.6768 Yuan/kWh</td>
</tr>
<tr>
<td>Charging price in valley hours ( C_v )</td>
<td>0.3923 Yuan/kWh</td>
</tr>
<tr>
<td>Number of charging piles in residential areas ( N_h )</td>
<td>10000</td>
</tr>
<tr>
<td>Number of charging piles in workplace areas ( N_w )</td>
<td>1500</td>
</tr>
<tr>
<td>Number of charging piles in other areas ( N_o )</td>
<td>2000</td>
</tr>
</tbody>
</table>

**Table 3: Probability distribution parameters.**

<table>
<thead>
<tr>
<th>Trip characteristics</th>
<th>Probability distribution</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial departure time</td>
<td>Burr type XII</td>
<td>( \alpha = 7.986, c = 6.696, k = 0.609 )</td>
</tr>
<tr>
<td>Single trip distance</td>
<td>Log-normal distribution</td>
<td>( \mu_d = 11.4, \sigma_d = 2.7 )</td>
</tr>
<tr>
<td>Parking duration in residential and other areas</td>
<td>Generalized extreme value distribution</td>
<td>( loc_{hlo} = 68.52, scale_{hlo} = 41.761, c_{hlo} = -0.657 )</td>
</tr>
<tr>
<td>Parking duration in workplace areas</td>
<td>Generalized extreme value distribution</td>
<td>( loc_{w} = 438.445, scale_{w} = 164.506, c_{w} = 0.234 )</td>
</tr>
<tr>
<td>Initial SOC</td>
<td>Power distribution</td>
<td>( a = 4.352 )</td>
</tr>
<tr>
<td>Range anxiety</td>
<td>Normal distribution</td>
<td>( \mu = 0.466, \sigma = 0.179 )</td>
</tr>
</tbody>
</table>
time-of-use pricing strategy will not change once set and lacks dynamic adjustment mechanisms to adjust the price flexibly according to real-time charging demand. This limitation of the time-of-use pricing strategy calls for future research on real-time dynamic pricing mechanisms.

Figures 4(c) and 4(d) illustrate the charging demand distribution in the workplace and other areas, respectively. With the current charging pile configuration, Scenario 1 reduces the load during the evening peak to some extent, and no significant change is observed for other periods. In addition, the charging demand in other areas is at full load for most of the day because several travel destinations belong to the “other areas” category, and more charging choices occur in these areas, resulting in high charging demand. However, there are more hours of charging infrastructure at full capacity in areas other than workplaces. In the workplace, the full-demand period is from 7:00–12:00 (6:00–19:00 in Scenario 1 and 6:00–22:00 in Scenario 2). In general, charging demands in workplace areas are lower than those in other areas. The predicted charging demand distribution in the two scenarios suggests that the time-of-use pricing strategy has a few limitations in reducing the peak-valley difference, thereby highlighting the importance of flexible and variable pricing strategies for charging service providers.

4.2. Operational Efficiency of the Charging System. The charging system comprises EV drivers, charging service providers, and a power grid. In this section, based on the charging demand distribution model, we investigate the influence of charging infrastructure deployment in different functional areas on the operational efficiency of the charging system.

The operational efficiency of the charging system is measured using three indices: the average charging request rejection rate, average charging pile utilization rate, and charging load deviation. The average charging request rejection rate is the average value of the charging request rejection rate over all periods. For charging service providers, a lower average charging request rejection rate is preferable, as high congestion rates cause potential customer loss and, thus, profit loss. The average charging pile utilization rate is the average value of the utilization rates over all periods.
periods. For charging service providers, a higher utilization rate is preferable. The charging load deviation is the standard deviation of the charging demand distribution. For the grid, a smaller load deviation means less fluctuation on the grid, and thus, lower operating costs. The average charging rejection rate $\beta$, average charging pile utilization rate $\mu$, average charging load $D$, and charging-load deviation $\sigma$ are computed as follows:

$$
\begin{align*}
\beta &= \frac{\sum_{t=1}^{T} \hat{\beta}_t}{T\mu}, \\
\mu &= \frac{\sum_{t=1}^{T} \hat{H}_t}{T\overline{D}}, \\
\overline{D} &= \frac{\sum_{t=1}^{T} D_t}{T\sigma}, \\
\sigma &= \sqrt{\frac{\sum_{t=1}^{T} (D_t - \overline{D})^2}{T}}.
\end{align*}
$$

Based on the above indices, we study the effect of the number of charging piles in different functional areas on operational efficiency (Figures 5–7). The subplots ((a-c) in Figures 5–7) illustrate how the indices change with the number of charging piles in residential, workplace, and other areas, respectively. The red solid line represents the average charging request rejection rate, green solid line represents the average charging pile utilization rate, and blue solid line represents the charging load deviation.

4.2.1. Influence of the Number of Charging Piles in Residential Areas on Operational Efficiency. The changes in the operational efficiency of the charging system are analyzed by altering only the number of charging piles in the residential areas, and the results are illustrated in Figure 5.

The charging request rejection rate in all the three functional areas decreases with an increasing number of charging piles in residential areas (NR) and then remains unchanged (Figure 5). This finding suggests that as the number of charging piles increases, the charging demands are gradually satisfied; however, at a certain level, where the maximum charging demands are met, the rejection rate stabilizes. It is noteworthy that the increased number of charging piles in residential areas has the same effect on the rejection rate in workplace areas and other areas (as illustrated in Figures 5(b) and 5(c)), suggesting transferrable charging demands between the three functional areas. Therefore, the operational efficiency of the charging system can be improved by optimizing the density of charging piles in different functional areas. A similar trend was observed in terms of the charging pile utilization rate. Increasing the number of charging piles increases user satisfaction; however, after a certain level, charging pile utilization decreases, resulting in a waste of resources. In addition, the charging load deviation in residential and other areas increases with the increasing number of charging piles before stabilizing, which indicates that, with an increasing number of charging piles, the charging demand fluctuation and randomness of charging choices increase, which may cause disorderly charging and challenge grid operation.
4.2.2. Influence of the Number of Charging Piles in Workplace Areas on the Operational Efficiency of the Charging System.

The changes in the operational efficiency of the charging system are analyzed by changing only the number of charging piles in the workplace areas, and the results are presented in Figure 6.

The influence of the number of charging piles in workplace areas on the charging request rejection rates in...
each functional area indicates the same trend as that in residential areas, which indicates that the charging demands are transferrable between different functional areas. In general, the charging pile utilization rate trends are the same for all three functional areas. Moreover, when the number of charging piles in workplace areas is negligible, the charging pile utilization rate remains low, but the utilization continues to remain low even when the number is increased, indicating a saturated charging demand and, thus, a low demand for charging infrastructure in workplace areas. The charging load deviation in both workplace areas and other areas increases with an increase in the number of charging piles in workplace areas, whereas the load deviation in residential areas decreases. The difference is more obvious when the number of charging piles in the workplace area is negligible. One possible reason is that most users rely on home charging, and when there is insufficient charging infrastructure in residential areas, they tend to charge in a disorderly manner, increasing the charging demand fluctuation. As the number of charging piles in workplace areas increases, people have more opportunities to charge at the workplace, thereby reducing charging choices during peak hours and charging demand fluctuations in residential areas.

4.2.3. Influence of the Number of Charging Piles in Other Areas on the Operational Efficiency of the Charging System. The changes in the operational efficiency of the charging system are analyzed by changing only the number of charging piles in other areas, and the results are illustrated in Figure 7.

The charging load deviation in residential areas decreases as the number of charging piles in the workplace increases (Figure 7). From the travel data, EV drivers can be divided into two categories: commuters whose trip chain includes the workplace, and noncommuters whose trip chain does not include the workplace. The noncommuter trip chain contains additional functional areas, and with an increasing number of charging piles in other functional areas, noncommuters tend to charge in these areas, thereby increasing the charging load there (as illustrated in Figure 7(c)). Subsequently, when noncommuters return from other functional areas to residential areas, they avoid charging during peak hours when the charging price is higher, thereby reducing the charging load fluctuation in residential areas.

5. Conclusion

In the present study, a charging demand distribution model was created based on spatiotemporal travel characteristics and charging choices. Unlike previous studies, this study considered the heterogeneity of EV drivers and introduced a utility function in the charging choice model, which can be extended to different decision-making models under different pricing strategies. In addition, the travel trajectory and charging behavior were separated in the simulation, and this addressed the limitations of previous studies in dealing with limited charging resources and improving the charging demand distribution prediction accuracy.

The charging demand distribution results under Scenarios 1 and 2 illustrated that although the time-of-use pricing strategy reduces the charging demand fluctuation to some extent, it shifts the peak charging demand without reducing the peak-valley differences. The additional findings are presented as follows. First, the natural attributes of residential areas granted users longer charging durations and greater flexibility; therefore, at-home charging was the preferred method for most users. Second, charging demand was low in the workplace. Therefore, the number of charging piles in workplace areas was reduced during planning and construction, and more piles were placed in other areas. This strategy not only increased the convenience of charging and relieved range anxiety, but also transferred the charging demand in residential areas to other areas, reducing the charging demand fluctuation in residential areas. Third, charging demand was transferrable between different functional areas, and different charging infrastructure configurations achieved the same operational efficiency. The focus of service providers was on the charging request rejection rate or charging pile utilization rate, the focus of the grid was on load deviation, and the focus of the government was on the operational efficiency of the entire charging system.

Future research could examine optimizing the construction of charging infrastructure in residential areas, and how deploying charging infrastructure in different functional areas will affect the operational efficiency of the charging system. Other studies could investigate a more flexible real-time charging price mechanism to reduce the peak-valley differences and charging demand fluctuation. Current charging prices mainly include the electricity price and service charge, whereas the profit of the charging service operator mainly comes from the service charge. As future research seeks to develop a real-time and flexible dynamic pricing mechanism, it could analyze charging pile utilization rate data with the help of big data methods to grasp the usage patterns of users while considering market acceptance and consumer satisfaction.

Appendix

Proof of Conditions

Substituting equations (10) into (9), we obtain the following:

\[
U = (1 + \Delta A)\Delta SOC_iC_e \left( C_p|\text{Span}_{i}| + C_{\rho}|\text{Span}_{\rho}| + C_i|\text{Span}_{i}| \right) \\
\frac{T}{T} - \Delta SOC_iC_eC_t
\]

(A.1)

Assume that \( t \in \text{Span}_i \); that is, the current period is the peak charging period, \( C_t = C_p \). Subsequently, by substituting \( C_t = C_p \) into equation (A.1), we obtain the following:
\[ U = (1 + A_i) \Delta SOC_i C_p \left[ C_f |\text{Span}_f| + C_i |\text{Span}_i| + C_p |\text{Span}_p| \right] / T - \Delta SOC_i C_p C_p. \] (A.2)

The first-order partial derivatives of the utility function \( U(\bullet) \) with respect to the electricity prices \( C_f \) and \( C_p \) in the nonpeak period in equation (A.2) are given by

\[ \frac{\partial U}{\partial C_f} = (1 + A_i) \Delta SOC_i C_p \left[ |\text{Span}_f| / T \right] > 0. \] (A.3)

\[ \frac{\partial U}{\partial C_p} = (1 + A_i) \Delta SOC_i C_p \left[ |\text{Span}_p| / T \right] > 0. \] (A.4)

Similarly, it can be proved that Condition (1) is satisfied when the current hour is a flat period or valley hour. This completes the proof of Condition (1).

Similar to the proof of Condition (1), suppose \( t \in \text{Span}_p \), \( C_f = C_p \), and then the first-order partial derivative of the utility function \( U(\bullet) \) with respect to the electricity price \( C_p \) of the peak period in equation (A.3) is expressed as follows:

\[ \frac{\partial U}{\partial C_p} = \left( 1 + A_i \right) \frac{|\text{Span}_p|}{T} - 1 \right) \Delta SOC_i C_p. \] (A.5)

In this study, \( |\text{Span}_p| = 8 \), \( T = 24 \), \( 0 < A_i \leq 1 \), 
\[-2/3 < (1 + A_i)|\text{Span}_p|/T - 1 \leq -1/3 < 0 \); thus, \( \partial U/\partial C_p < 0 \).

Similarly, it can be proved that Condition (2) is satisfied when the current hour is a flat or valley hour. This completes the proof of Condition (2).

The first-order partial derivative of the utility function \( U(\bullet) \) with respect to \( t A_t \) in equation (A.2) is expressed as follows:

\[ \frac{\partial U}{\partial A_t} = \Delta SOC_i C_p \left[ C_f |\text{Span}_f| + C_i |\text{Span}_i| + C_p |\text{Span}_p| \right] / T > 0. \] (A.6)

This completes the proof of Condition (3).

### Data Availability

Some or all data, models, or code generated or used during the study are available from the corresponding author upon request, including the coordinate date of nodes in the case studies.

### Additional Points

1. A data-driven multiagent framework is adopted for large-scale charging requirements prediction.
2. A heterogeneous agent model is proposed with bounded rationality and adaptive behavior.
3. The indexes for evaluating the operational efficiency of charging infrastructure in various functional areas are developed.
4. The temporal and spatial implications of various pricing strategies and the deployment of charging infrastructure are explored.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

### References


