ACCSCIENCE PUBLISHING

Design+

ARTICLE

Capacity design of electric vehicle charging station based on queuing theory

Hong Zhang[1,2]* and Feifan Shi[1]

[1]Transportation Institute of Inner Mongolia University, Hohhot, China

[2]Inner Mongolia Engineering Research Center for Intelligent Transportation Equipment, Hohhot, China

Abstract

To increase the utilization rate of charging facilities and promote electric vehicles (EV), charging infrastructure should be built in a rational manner. The deployment strategy of public fast-charging stations (CS) determines whether charging demand can be met efficiently. Early CS planning has achieved some success. In the past, little is known about the charging behaviors and preferences of EV users, leading to a lack of relevance in the decisions made for the government-led CS construction. To address these issues, we used data on charging orders collected from public fast-CS s in cities for the summer and winter of 2023 to analyze charging user behavior patterns and build a more realistic model. Using queuing theory, we analyzed the facility size and operational metrics of public fast-CSs. Based on this, a capacity optimization model for public fast-CS was established to optimize the facility configuration of CSs by considering two factors: Investment cost and time cost. The optimal charging equipment configuration scheme for the public fast-CS is an 800 kVA charging box variable and 8 charging terminals, and the proposed facility scheme reduces the comprehensive cost by 28.1% and the user's dwell time by 41.16%. If more consideration is given to the experience of EV users, the number of charging terminals can be set to 9.

Keywords: Electric vehicle; Queuing theory; Fast-charging station; Capacity decision

***Corresponding author:**
Hong Zhang
(zh-hong@imu.edu.cn)

Citation: Zhang H, Shi F. Capacity design of electric vehicle charging station based on queuing theory. *Design+*. 2025;2(2):4225. doi: 10.36922/dp.4225

Received: July 12, 2024

1st revised: July 30, 2024

2nd revised: August 6, 2024

3rd revised: August 15, 2024

Accepted: August 21, 2024

Published online: March 24, 2025

Copyright: © 2025 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons AttributionNoncommercial License, permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

In light of the growing focus on greenhouse gas emissions and climate change, electric vehicles (EVs) have garnered increasing attention.[1] The popularity of EVs as an alternative mode of transport that no longer relies on fossil fuels has been on the rise in recent decades.[2] The widespread adoption of EVs has become a pivotal factor in achieving emissions reduction objectives.[3] A number of factors are impeding the advancement of EVs. One of the most significant obstacles is the inconvenience of charging. This is a significant deterrent for potential EV users.[4] The lack of charging infrastructure may directly hinder the promotion of EVs.[5] Thus, there is a pressing need to design and develop charging stations (CS) that can accommodate a diverse range of customer classes, distinguished by their varying charging preferences, needs, and technological requirements.[6] The establishment of public fast-CSs represents a crucial aspect of EV infrastructure, facilitating the rapid replenishment of energy in urban

road environments. The expansion of such stations, in particular, has been identified as a key factor influencing EV sales.[7] In recent years, the optimization of public fast-CS capacity has emerged as a significant research topic. The determination of an optimal facility configuration scheme for CS represents a pivotal aspect of this optimization. Despite the advent of advanced charging technology, the limitations of CS capacity result in prolonged wait times, particularly during peak hours. These extended wait times have the potential to deter individuals from adopting EV.[8] The lengthy charging times require that the optimal utilization of the available CS capacity is crucial for enhancing the overall experience and the effective utilization of the charging infrastructure.

Early studies of CS capacity tended to focus solely on meeting charging demand. A number of studies have investigated maximizing traffic capture to minimize the number of charging facilities. Upchurch *et al.*[9] propose that peak hour demand data be employed to assess site capacity, thereby ensuring that the number of vehicles charging simultaneously at a given site does not exceed the maximum site capacity in the event of a worst-case scenario. Wang *et al.*[10] employed the updated traffic statistics to ascertain the aggregate demand for regular and fast-charging facilities. On the basis of the average daily engaged working hours of a charger, the service capacity at each CS was thus determined. Bai *et al.*[11] propose a cell-based model for determining the location, capacity options, and service type of EV CSs to meet all potential charging needs. Brandt *et al.*[12] presented a case study applying prescriptive analytics to the placement of charge points in urban areas. They used the strategic triangle framework, which evaluates public value creation through the interconnected dimensions of value, legitimacy, and operational capacity, as a starting point to assess prescriptive analytics initiatives in the public sector. Çelik and Ok[13] used Arena 14 simulation software to model station traffic and optimize charging unit types and quantities. Based on the results of EV load forecasting, a location model with the lowest users travel cost has been established.[14] The location of CS was optimized by a genetic algorithm to obtain the location and capacity library of CS.

Aside from the construction cost, social equity, and other aspects, some researchers also consider that the configuration strategy of CSs is a key problem. Zhu *et al.*[15] proposed a novel model for the planning of plug-in EV (PEV) CS. The objective was to minimize the total cost, including the cost of the CS and the cost to users. The model simultaneously handles the location of the CS and the number of chargers to be established in each CS. Loni and Asad[16] determined the optimal size, type of charging, and location of CS based on trade-offs between minimizing site development costs, maximizing social equity capture, and meeting EV charging demand. Mei *et al.*[17] employed a simulation approach to model the actual demand for charging and optimize the configuration of charging piles. This is done with the objective of reducing the uneven spatial distribution of charging demand and improving the overall utilization efficiency of regional CS.

A more accurate representation of the charging process can be achieved by considering queuing for charging in situations where demand exceeds capacity at the CS. Researchers have employed queuing theory to develop a model that integrates the characteristics of CS, including charging times, waiting times, and other factors, to determine the optimal size of a CS. This model utilizes queuing theory to estimate the average waiting times at CS based on average arrival and service rates. The planning of CS capacity is typically conducted through the estimation of average waiting time costs. Yang *et al.*[18] used the M/M/s/N queuing model to develop PEV charging dynamics and co-optimized CS configurations (i.e., number of chargers and waiting space) through a comprehensive benefit-cost analysis. Chen *et al.*[19] modeled drivers at each charging facility as the M(t)/M/n queue and approximated the average queuing time and probability of waiting time as functions of facility capacity and demand arrival rate. Wu *et al.*[20] developed a robust optimization problem with queue theory and used it to measure the exact charging demand or its distribution. Xiao *et al.*[21] proposed an optimal location model to determine the optimal locations and capacities of EV charging infrastructure to minimize the comprehensive total cost, which considers the charging queuing behavior with finite queue length and various siting constrains. Assuming that drivers would not stop to queue at CS when none of the charging piles are available, Zhang *et al.*[22] employed the M/M/n/n Queuing System to solve the Optimal Charging Pile Assignment. Mishra *et al.*[23] proposed a queueing mechanism that accounts for the demand distribution over time. Then, a statistical approximation approach was proposed to estimate the total unsatisfied EVs within a CS for the given port allocation as a derived random variable. Zhang *et al.*[24] proposed a three-period model for the location and capacity planning of CS. During the capacity design process, the model incorporates the M/M/c/N queuing theory with capacity constraints. The proposed approach optimizes both the location and the number of CS. Most of these studies used simulation data and lacked real charging operation data to optimize the capacity of CS from the perspective of user behavior.

One part of the researchers only considered the charging facilities to fulfill the users' charging needs, while the other part of the researchers regarded the CS planning

as a comprehensive problem, considering the aspects of demand and cost. The last part is the CS planning with queuing theory approach. In this investigation, we collected operational data from a public fast-CS. This data allowed us to analyze charging behaviors such as the departure and arrival of EV users and charging duration. This analysis was used to establish a CS capacity optimization model based on EV charging behaviors. The CS was used as an example to illustrate how the number of charging terminals at the fast CS can be optimized to determine the best facility configuration scheme. The model considers both the investment cost and the user time cost to ensure the convenience of EV users while reducing the waste of charging resources. The following paragraphs present the principal research methods of this paper.

(1) Analysis of user charging behavior preferences. Based on the collected CS operation data, the arrival and departure process, charging duration, and charging power of EV users were analyzed. The real CS operation data was used to determine the parameters of the capacity optimization model and to provide support for CS capacity optimization.
(2) Queuing theory was employed to calculate CS operation indexes and establish a CS capacity optimization model based on queuing time and other indexes. The model considers two optimization objectives: CS investment cost and user time cost. Constraints such as queuing time and facility utilization rate were set.
(3) The optimal charging terminal capacity of public fast-CSs was determined through a case study, thereby reducing the investment cost of CSs and the user's stay time.

2. Data and methods

2.1. Data

We collected charging operation data from a standard fast-CS in Hohhot. The order data at three CS for June and December 2023 were collected. The fast CS is equipped with 15 single-gun fast-charging terminals, which can provide fast-charging service for 15 EVs at the same time. The data we obtained include charging start time, end time, charging power, charging cost, charging duration, and charging end reason. These data are crucial to understand the pattern of EV charging demand and utilization rate in the city. In Table 1, we describe in detail each of the data collected and their meanings to better understand and utilize this information.

The objective of our data collection initiative is to conduct a comprehensive analysis of the charging behavior of EV users. A better understanding of users' charging preferences allows decision makers to make informed decisions. This data are crucial for optimizing the operation and planning of CSs. By analyzing users' charging behaviors, it is possible to identify peak hours, increase the utilization rate of CS, and reduce users' waiting time. This data can be used by decision makers to develop appropriate solutions that enhance user experience. This data not only facilitates a more comprehensive understanding of users' charging requirements but also serves as a valuable reference for the future construction of urban EV charging infrastructure.

Table 1. Charging data and its meaning

Typology	Meaning
Start time	Time when the user starts charging
End time	Time for user to end charging
Charging capacity	Electricity delivered throughout the charging process (kWh)
Charging fees	Charge for electricity and charging services
Charging duration	Duration from start to end of charging
Reason for end of charging	Reasons for aborting charging (draw, app abort, vehicle reaches required SOC, etc.)

Abbreviation: SOC: State of charge.

2.2. User charging behavior characteristics

A day was divided into 24 time periods to facilitate the calculation and analysis of the frequencies of arrival and departure of EVs at the CS in a month. We calculated the number of charging vehicles per time period based on their arrival/departure times. For charging events that span multiple time periods, we distributed the number of charging vehicles proportionally to each time period. Using this approach, we obtained data on the arrival and departure of charging vehicles within each time period in a day, as shown in Figure 1. These data provide us with detailed information on the use of the CS, including information on peak charging times, analysis of the utilization of the charging facilities, and other aspects.

Figure 1 shows that the start and end times of charging orders follow roughly the same trend. There are two distinct peak charging periods at the public fast-CS: a peak charging period from 10:00 a.m. to 2:00 p.m., followed by a slight decrease in the number of charging vehicles, and another peak charging period from 7:00 p.m. to 10:00 p.m., followed by a sharp decrease in the number of charging vehicles until the number of charging vehicles reaches a minimum at 4:00 a.m., and then a slow increase to the peak charging period at noon the next day.

If the time span is extended to 1 month as in Figure 2, the average number of charging orders H per day at the CS is 132 vehicles. The number of charging vehicles varies

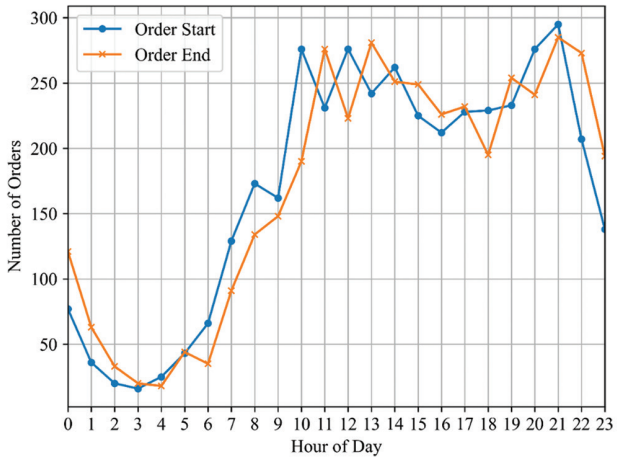

Figure 1. Hourly charging trends at charging stations

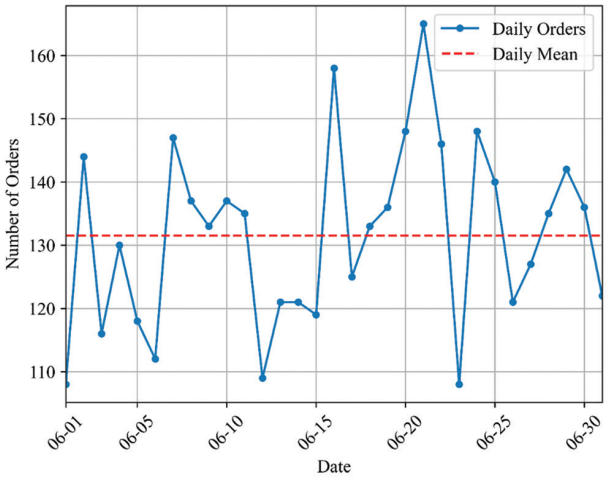

Figure 2. Daily charging trends at charging stations

significantly over different days in a month, with a clear pattern of days with more charging orders and days with fewer charging orders. It can be observed that the days with fewer charging orders are mostly weekends. We can conclude that people are more likely to choose public fast-CS on weekdays. On non-working days, people may choose to charge at private CS more often, or they may choose not to charge due to reduced commuting needs.

The arrival intervals of charging vehicles can indicate the level of user demand for charging facilities and usage patterns. Shorter arrival intervals may indicate higher demand for charging and more frequent use of charging facilities. Observing arrival intervals provides insight into the use of charging facilities. Shorter intervals may indicate that facilities are being used heavily. Understanding the arrival intervals of charging vehicles can help plan and optimize the layout and capacity of charging facilities. If the arrival intervals at a location are short, it may be necessary to increase the capacity of the charging facility at that location. As shown in Figure 3, charging vehicle arrival intervals follow a negative exponential distribution. The negative exponential distribution has a unique parameter λ. The mathematical expectation of the negative exponential distribution, $1/\lambda$, implies that $1/\lambda$ events occur per minute, that is, on average, an event occurs every λ minutes. The time interval for EVs to start charging satisfies the parameter λ of the negative exponential distribution to be 9.47, which means that on average every 9.47 min there is a vehicle charging at this public fast-CS.

The charging habits of different EV users vary greatly, which is reflected in the charge start state of charge (SOC) and charge power. Users with EV mileage anxiety tend to start charging when the vehicle has a lot of power left and choose to charge until the battery is full. Another group of users tends to spread out the charging time, that is, each charging time is shorter as long as it can meet their travel needs. Due to the different usage habits of EV users, the length of EV charging time also varies. As shown in Figure 4, the charging time of most EV users is between 40 min and 1 h, and the charging time of some users who use fragmented time charging is shorter, <30 min. Only a few users have a charging time longer than 80 min. The frequency histogram of charging time is fitted with a normal distribution. It can be seen that the frequency distribution of EV charging time is basically normal, and its normal distribution parameter is mean mu = 47.25, standard deviation std = 17.39. This means that most of the charging time in this charging time distribution is concentrated in about 47 min.

The charging power of an EV reflects the charging speed: The higher the power, the shorter the charging time. The charging power depends on the SOC of the battery, the power of the on-board charger, the output power of the charging pile, and even the weather can affect the charging speed. The power of AC charging is mostly 3.3 kW or 6.6 kW. DC fast-charging can reach 60 kW or 120 kW, while EVs equipped with 800V high-voltage platforms can reach fast-charging speeds of more than 350 kW. Figure 5 shows a bimodal distribution, with EV charging power concentrated at two peaks: 18 kW and 40 kW. It can also be found that although charging piles support charging speeds above 120 kW, EVs with charging power above 100 kW are currently relatively few.

2.3. Charging service system and operational indicators

The queuing theory is an effective approach for the study of the aggregated EV charging behaviors. This approach

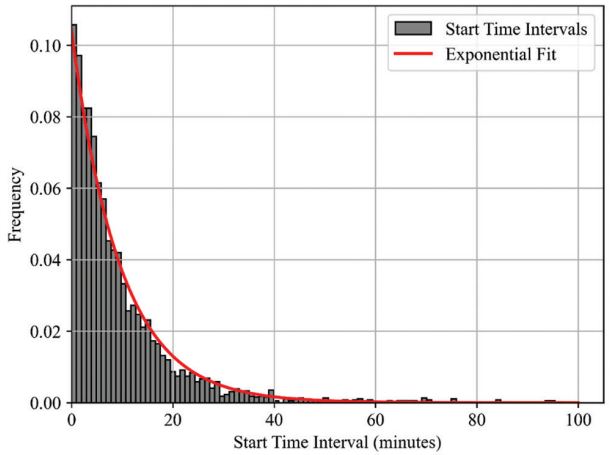

Figure 3. Distribution fitting for vehicle arrival interval frequency at charging stations

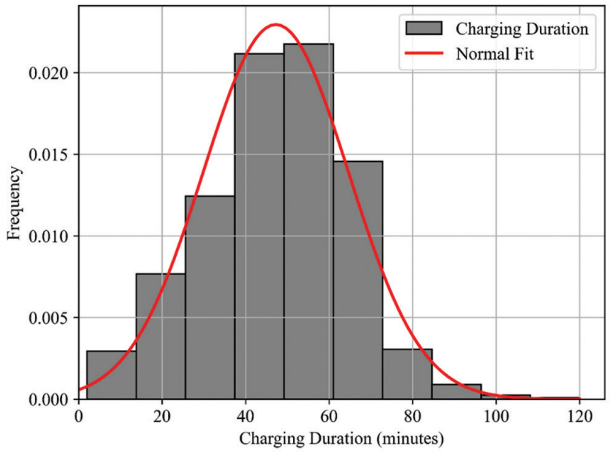

Figure 4. Distribution of charging duration

considers various uncertainties in the EV charging process.[1] The number of charging devices at public fast-CS is limited. During peak charging hours, EV users may need to queue up to receive charging services. CS can be considered a queuing system in which customers are represented by EVs, where reception corresponds to charging devices and providing service means charging. Its operation logic is: When the charging vehicle arrives at the CS, if the charging equipment is available, the vehicle directly selects the charging equipment for charging. If the charging equipment is all occupied during the peak period, the charging vehicle needs to queue up and wait for the completion of the service of the vehicle in charging to accept the service. The process of charging vehicle accepting service is a queuing process, so the charging service system can be studied according to the queuing theory. The service rules of the charging

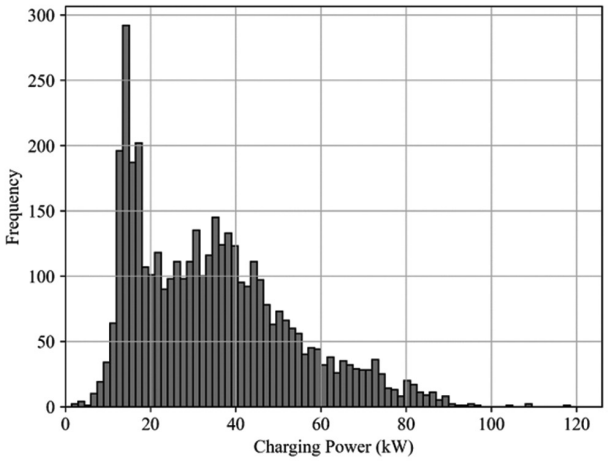

Figure 5. Charging power distribution

service system are first-come-first-served. The system does not impose a limit on the queue length of charging vehicles, provided that the vehicles entering and leaving the public fast-CS are in equilibrium. Two key parameters of the queuing system are a random variable describing the time between customer arrivals and a random variable describing the service time. In the charging service system, these two parameters are a random variable describing the time interval between the arrival of an EV at a public fast-CS and a random variable describing the time at which an EV receives charging service, respectively. These two random variables usually conform to specific probability distributions. After the statistical analysis of the arrival time interval and charging duration in the actual operation data of a CS in Hohhot City as described in Section 2.2, the time interval for EVs to arrive at the public fast-CS obeys the negative exponential distribution, and the time for EVs to receive charging service obeys normal distribution. The number of charging equipment in the public fast-CS is assumed to be s. According to the queuing theory, the queuing model of the charging service system is *M/G/s*. The schematic diagram of the charging service system is shown in Figure 6.

The operation indicators of the charging service system include service intensity, average queue length, average waiting time, and so on. By analyzing the calculation of the charging service system service indicators, we can improve the structure of the charging service system to optimize the key indicators of the charging service system and better meet the needs of users. The premise of the charging service system is that the number of EVs entering the public fast-CS and the number of EVs leaving the public fast-CS are equal, that is, the service system can achieve dynamic equilibrium. Equation I is the equilibrium equation of the charging service system.

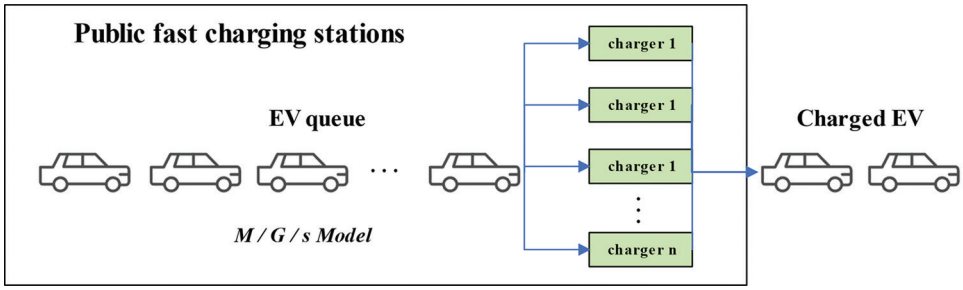

Figure 6. Charging service system

$$\begin{cases} \mu P_0 = \lambda P_1 & \\ (n+1)\mu P_{n+1} + \lambda P_{n-1} = (\lambda + n\mu) P_n & 1 \leqslant n < s \\ s\mu P_{n+1} + \lambda P_{n-1} = (\lambda + s\mu) P_n & s \leqslant n \end{cases} \quad \text{(I)}$$

Where P_n represents the probability that there are n cars receiving charging service in the public fast-CS; n is the number of electric cars that are receiving charging service; s represents the number of charging piles in the charging service system; $1 \leq n < s$, all the n cars in the system are receiving charging service; $s \leq n$, there are only s electric cars receiving charging service in the system; and the n-s electric cars need to queue up to receive charging service. After the system reaches equilibrium, using the recursive method to solve Equation Ⅰ, the probability of various states of EVs receiving charging services can be obtained as Equation Ⅱ.

$$P_0 = \frac{1}{\sum_{n=0}^{s-1} \frac{1}{n!}(\frac{\lambda}{\mu})^n + \frac{1}{s!(1-\rho)}(\frac{\lambda}{\mu})^s}$$

$$P_n = \begin{cases} \frac{1}{n!}(\frac{\lambda}{\mu})^n P_0 & n \leq s \\ \frac{1}{s!s^{n-s}}(\frac{\lambda}{\mu})^s P_0 & s < n \leq N \end{cases} \quad \text{(II)}$$

Where P_0 denotes the idle rate of the charging device (the probability that there is no vehicle charging in the CS); P_n denotes the probability that exactly n EVs are charging in the CS. In the formula, $\rho = \lambda/\mu s$, μs denotes the average service rate of the system, and ρ is called the service intensity or facility utilization rate, and the service system will not form an infinite queue only if the facility utilization rate $\rho < 1$.

For the stochastic service system of *M/G/s* model, there is no formulaic derivation analysis of the queuing system of this model in the current operations research theory. The common *M/G/s* queuing model and *M/G/s* model have differences, so the research generally uses the formulaic derivation of *M/G/s* queuing model combined with Kingman's classical law of congestion (law of congestion) to obtain the formula for the operational metrics of *M/G/s* queuing model service system.[25] The metrics of *M/G/s* queuing system are shown in Equations III to VI:

$$L_q = \sum_{n=s+1}^{\infty} (n-s) p_n = \frac{(s\rho)^s \rho}{s!(1-\rho)^2} p_0 \quad \text{(III)}$$

$$W_q = \frac{L_q}{\lambda} \quad \text{(IV)}$$

$$L_s = L_q + \rho = \frac{(s\rho)^s \rho}{s!(1-\rho)^2} p_0 + \frac{\lambda}{\mu} \quad \text{(V)}$$

$$W_s = \frac{L_s}{\lambda} \quad \text{(VI)}$$

In the above equation, L_q is the average queue length, W_q is the average waiting time, L_s is the average captain, W_s is the average captain, and W_s is the average time of stay. The waiting time for the *M/G/s* queuing model can be calculated by using Equation VII.

$$W_q^G = W_q \times \frac{1 + c_s^2}{2} \quad \text{(VII)}$$

Here c_s denotes the coefficient of variation of the service time, $c_s = \sigma_s / E(x)$; c_s is the ratio of the standard deviation to the mean of the normal distribution obeyed by the service duration.

2.4. CS capacity optimization model

2.4.1. Objective function

The number of charging piles and charging power will not only have an impact on the investment cost of the builder but also on the user's charging service experience and waiting time. Current CSs usually use high-low voltage integrated charging box-type transformer, which contains a transformer and charging master control box. An integrated box transformer can be connected to multiple

charging terminals to realize the satisfaction of charging demand through the flexible distribution of power, as shown in Figure 7. Therefore, CS can freely choose how many charging terminals to configure according to the actual situation. For a fixed-capacity integrated charging box transformer, if a large number of charging terminals are connected, when all terminals are charged at the same time, the average charging power obtained by each terminal will be relatively low. On the contrary, if the number of connected charging terminals is small, the charging power obtained by each terminal will be relatively high.

The number of charging terminals and charging power are the key optimization elements in the CS optimization model. To minimize the sum of the investment cost of the CS and the cost of the user's waiting time, we established a CS capacity optimization model. In this model, we converted the cost into cost per unit time and incorporated it into the objective function, and the optimization goal was to minimize the integrated social cost of each CS, as in Equation VIII.

$$\min F_k = \gamma_1 F_{ik} + \gamma_2 F_{tk} \tag{VIII}$$

In Equation VIII, F_k denotes the integrated social cost per unit time of public fast-CS k, which is the sum of investment cost and user time cost. F_{ik} is the cost of spreading the investment cost of public fast-CS k into unit time. F_{ik} is the time cost of users per unit time in public fast-CS k. γ_1 and γ_2 denote the weighting coefficients of the two optimization objectives of the public fast-CS's investment cost and the user's time cost, respectively; $\gamma_1 + \gamma_1 = 1$. The description of each cost and its components are as follows.

The investment cost of a public fast CS k is the cost of building and operating the CS. The investment costs include the following. Charging equipment costs, including the purchase and installation of high-low voltage integrated charging box-type transformers and several charging terminals. Station land costs, including the cost of charging spaces, queuing areas, and user lounges. The station construction costs encompass the purchase and installation of charging equipment, lighting systems, monitoring systems, and smart access control gates, as well as the construction expenses for user waiting lounges. Station operation cost, the distribution cost of all electric facilities in the station, and the labor cost required for daily inspection and maintenance. The investment cost can be expressed by Equations IX and X.

$$F_{ik} = \frac{d(1+d)^r}{(1+d)^r - 1}\left(\frac{c_{xb} + c_{pd} + c_{\mathrm{td}} + c_{js}}{365\times 24} + \frac{c_{zd} + c_{wh}}{365\times 24}\times \mathrm{s}\right) \tag{IX}$$

$$c_{pd} = \frac{P_{\mathrm{xb}}\alpha}{\beta} \tag{X}$$

In the formula, r is the operating years of the station; d is the current discount rate; c_{xb} is the price of the high-low voltage integrated box-type transformer; c_{pd} is the distribution cost

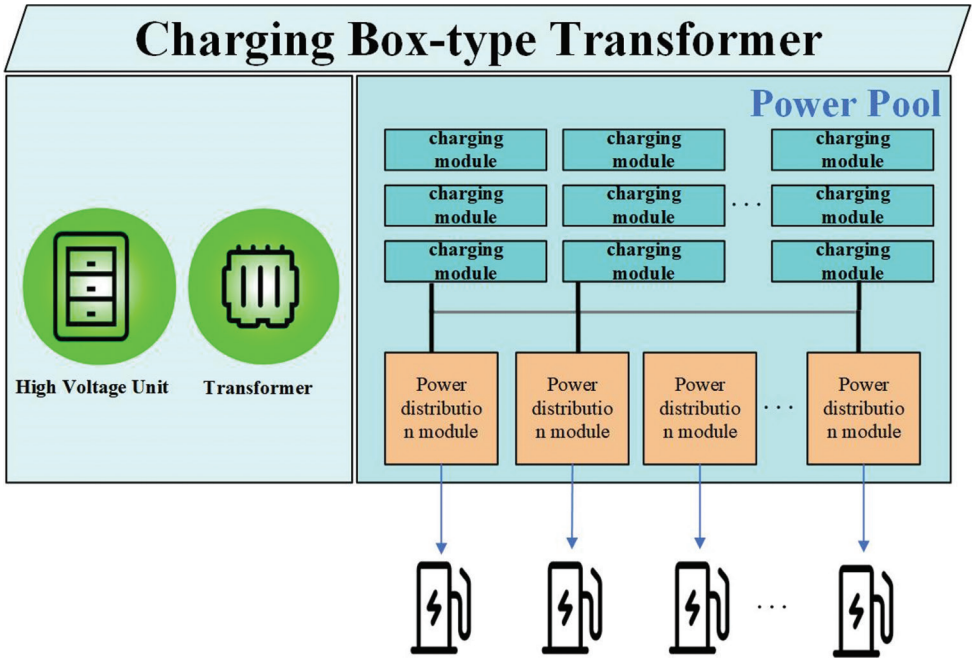

Figure 7. High-low voltage integrated charging box-type transformer structure

of the box-type transformer; c_{td} is the land cost of the station; c_{js} is the construction cost; c_{zd} is the unit price of the charging terminals; c_{wh} is the cost of inspection and maintenance of the individual terminals; and s is the number of charging parking spaces in the station. P_{xb} denotes the power of the integrated box-type transformer; α is the distribution cost (yuan/kVA); and β is the optimal load factor.

User time cost, including the queuing time for users waiting for vacant charging spaces and the waiting time for EV charging, as in Equations XI and XII. CS operation hours are divided into peak and off-peak periods. The number of CS terminals in off-peak period is larger than the number of EVs, and EVs can be charged without queuing and can receive a larger charging power. In the peak period, the CS will be swarmed with charging vehicles queuing up for charging. This paper focuses on the study of the user's time cost during the peak charging period.

$$F_{tk} = c_t \left(W_q^{\ G} + W_{ct} \right) \frac{H}{24} \quad \text{(XI)}$$

$$W_{ct} = q / P \quad \text{(XII)}$$

In the formula, c_t is the average time cost of EV users, and W_{ct} is the charging time, and it is related to the power of the charging terminal. $P=P_{xb}/s$ denotes the power allocated to the charging terminal; H denotes the number of charging vehicles per day; q denotes the battery capacity of the EV; and s is the number of charging terminals.

There are usually two modes of construction of public fast CSs: Investment construction and joint construction. Investment construction generally means that the investor-operator of the CS bears the cost of the land and builds the CS by itself. Co-construction means that the investor-operator and the landowner build the CS together in a cooperative mode, and the land is expropriated free of charge. When the CS is constructed based on the investment construction mode, the investing operator often bears the larger portion of the land rent. In such a situation, more attention should be paid to the investment cost of the investor. The value of the weight coefficient is suggested to be $\gamma_1 > \gamma_2$, so that the optimization model will pay more attention to reduce the investment cost. Under the co-construction model, since there is no land cost, the investment cost only includes the equipment cost and construction, operation, and maintenance cost. Using this model, how to reduce the user time cost is key. The value of the weighting coefficient is suggested to be $\gamma_1 > \gamma_2$, so as to ensure that the comprehensive social cost is lower.

2.4.2. Constraint condition

Facility optimization of public CSs is a complex decision problem that involves multiple factors, including the utilization of charging equipment, waiting time of users, and cost-benefit analysis. Multiple constraints need to considered in optimizing problem. By comprehensively considering the needs of investors and users, we can formulate a public CS facility optimization plan that can both ensure return on investment and enhance user experience. This enables formulating a public CS optimization plan that ensures return on investment while enhancing user experience through improved service quality and operational efficiency.

(A) Facility utilization constraints

From the investor's perspective, facility utilization should exceed a certain value. Facility utilization is critical to return on investment. Investors put money into a public CS project with the expectation that they will recover their investment and realize a profit within a reasonable period of time. If the facility utilization rate is too low, it means that the payback period will be extended and the return on investment will be affected. Therefore, it is essential for investors to set an appropriate lower limit for facility utilization. Determining the facility utilization needs to take into account not only the size and cost structure of the investment but also market demand and competitive conditions to ensure the sustainability of the project.

From the user's perspective, the utilization rate of the facility should not be >1. The utilization rate of the charging equipment is directly related to the user's experience and satisfaction. Users often choose to use public CSs for convenience and urgency, meaning they expect the CS is immediately available when they need it, rather than having to wait for it. A facility utilization rate of 1 means that the facility is always in use, which can significantly reduce user satisfaction. Therefore, to improve the user experience, it is important to ensure that the utilization rate of the charging facilities is <1. This means that corresponding measures need to be taken in the planning and management of equipment. Thus, the number of devices available and the layout design need to be reasonably optimized, and the users should be guided to effectively plan the charging time. Under the ideal circumstances, the users would be able to use the charging equipment quickly and easily when they need it, thus enhancing their satisfaction.

Facility utilization rate, as a key indicator, directly affects the payback period and the profitability of the project as well as the charging experience of users. The planning and design of public CSs should ensure that the project can recover the investment cost in a reasonable period of time and avoid prolonged waiting time for charging; therefore, the facility utilization rate should be constrained, as in Equation XIII.

$$\rho_t<\rho<1 \quad \text{(XIII)}$$

(B) Waiting time limit

We need to consider not only the return on investment for the investor and the equipment utilization but also the reasonability of the queuing time. Thus, the efficiency of CSs and user satisfaction needs to reach a good balance. Through queuing theory, we can calculate the average queuing time and charging time under different numbers of charging terminals, directly reflecting the efficiency of users waiting for charging. For users, a long waiting time will seriously affect their experience and satisfaction. To ensure that the queuing time of users is not too long, we need to introduce a limit. The waiting time should be set to less than the maximum queuing time, as in Equation XIV. This maximum queuing time can be determined based on the user's needs, behavioral habits, and expectations of the charging service.

$$W_s \le W_t \quad \text{(XIV)}$$

Taking into account the above analysis of the objective function and constraints, the public fast-CS capacity optimization model can be expressed as Equation XV.

$$\begin{cases} \min F_k = \gamma_1 F_{ik} + \gamma_2 F_{tk} \\ s.t.\ \ \rho_t < \rho < 1,\ W_s \le W_t \end{cases} \quad \text{(XV)}$$

2.5. Case analysis

We collected data about the operation of a public fast-CS in Hohhot. The time distribution of the arrival process and service process of the charging service system of this fast-CS has been analyzed as described in Section 2.2. It is known that the arrival interval time obeys a negative exponential distribution with parameter 9.47, so the number of vehicles arriving at the CS per unit time is λ = 0.106. The charging duration obeys a normal distribution with parameter 47.25; then the number of vehicles that can be served per unit time is μ = 0.021.

The production method is a method of determining the cost of time based on the value that the traveler can create. The production method assumes that travelers are engaged in productive activities if they are not waiting. They can create national income or gross national product. In the queuing theory model, when considering the time cost of EV users, it is a common method to use the production method, which is calculated as in Equation XVI.

$$W_p = \frac{P_G}{T_G \times N_P} \quad \text{(XVI)}$$

In the formula, W_p is the cost per unit of time to the user calculated according to the production method; P_G is the gross national product expressed in monetary terms; T_G is the work hours of the laborer; N_p is the number of workers; and T_G=D×T_w/5, where D is the number of working days in the year; and T_w is the average weekly working hours.

The gross domestic product and other data of Hohhot City in 2022, as shown in Table 2, were obtained from the Hohhot City 2023 Statistical Yearbook.

Substituting the data in Table 2 into Equation XVI, the average user time cost in Hohhot in 2022 can be obtained as 86.85 yuan by the production method.

The parameters of the public fast-charging capacity optimization model are set as follows. The operating life of the station r is set to 10 years. The discount rate d is set at 5%. The charging facilities of the public fast-CS adopt split charging equipment, including high and low voltage integrated charging box transformer and charging terminal. The price of 800 kVA charging box-type transformer c_{xb} is 520,000 yuan. The unit price of the charging terminal c_{zd} is 6,000 yuan. The land cost of the public fast CS c_{td} is 2 million yuan. The construction cost of the station c_{js} is 100,000 yuan. The annual inspection and maintenance cost of each terminal c_{wh} is 1,000 yuan. The distribution cost per unit capacity α is 5000 yuan/kVA, and the load ratio of the transformer is set to 80%. The distribution cost of the charging box transformer c_{pd} can be calculated to be 5 million yuan. The battery capacity of the EV q is set to 60 kWh and the maximum queuing time that EV users can tolerate is set to 10 min. The time cost for EV users is 86.85 yuan/h. Since there is a land cost for this station, the weighting factor is set to γ_1 = 0.6, γ_2 = 0.4.

The facility utilization rate of a public CS is calculated as $\rho = \lambda/\mu s$. For the charging service system not to form an infinite queue, ρ should be ≤1. Substituting the values of λ and μ, s = 5.06, the minimum number of charging terminals in the public fast-CS is determined as 6. The facility utilization rate of the public fast-CS ρ should be greater than a certain minimum value ρ_t to ensure the sustainable operation of the CS. By setting ρ_t = 0.3, the maximum number of charging terminals in the public fast CS is determined as 16.

When the number of charging terminals is >13, the charging power allocated to a single charging terminal will be <60 kW, which means that the charging time for EVs will

Table 2. Statistical data of Hohhot in 2022

Year	Employment number	Gross domestic product	Weekly working hours	Number of working days
2022	1.574 million people	332910.46 million yuan	48.9 h	249 days

be >1 h. The charging waiting time for EV users is longer. Taking the above analysis into account, the maximum value of the number of charging terminals in a public fast-CS is 13. By considering the above two constraints of facility utilization rate and charging waiting time, the number of charging terminals in the capacity optimization model of public fast-CS is limited to between 6 and 13.

3. Results

In the previous section, the parameters of the public fast-CS capacity optimization model are set and the constraints are analyzed. After calculation, the optimal configuration of the public fast-CS is obtained, as shown in Figure 8. By analyzing the charging service system by queuing theory, we found that with six charging terminals, the charging of EVs in the charging service system could be satisfied by applying the highest power at the charging terminals, but the queuing time of EV users was found as long as 73.6 min. When the number of charging terminals was increased to 7, the queuing time decreased significantly to 11 min, exceeding the maximum queuing time that users can tolerate (i.e., 10 min). When the number of charging terminals was increased to 8 and 9, the queuing time was 3 min and 1 min, respectively. With a continued increase of number of charging terminals, the queuing time dropped to 0 and did not change significantly.

The charging facility of this CS is a split-type charging equipment, and the charger is placed in an integrated charging box-type transformer. When charging, the transformer distributes power to a plurality of charging terminals, thereby charging a plurality of EVs, so the power for charging EVs is closely related to the number of charging terminals. As the number of charging terminals increases, the charging power of a single charging terminal decreases, resulting in a longer charging time for the EV. When the number of charging terminals is 8, the total time for queuing and charging is 39 min. When there are eight charging terminals, total time is 39 min. Any number fewer or >8 results in total time exceeding 40 min.

Public fast-CSs configured with different charging terminals entail different investment costs and user time costs. Figure 9 shows the investment costs, user time costs, and social costs in each case for a fast-CS configured with 6 – 13 charging terminals.

It can be found that the comprehensive cost of the charging service system is lowest when eight charging terminals are configured. When the charging terminals are <8, the user time cost is affected by the queuing time, and the user time cost decreases with the increase of the number of terminals. When there are more than eight charging terminals, the user time cost increases with

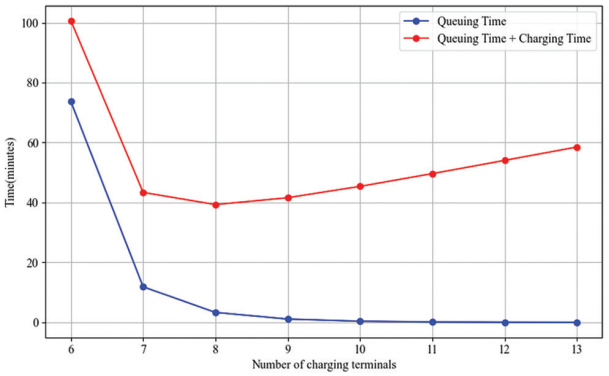

Figure 8. Electric vehicle users' queuing time for charging

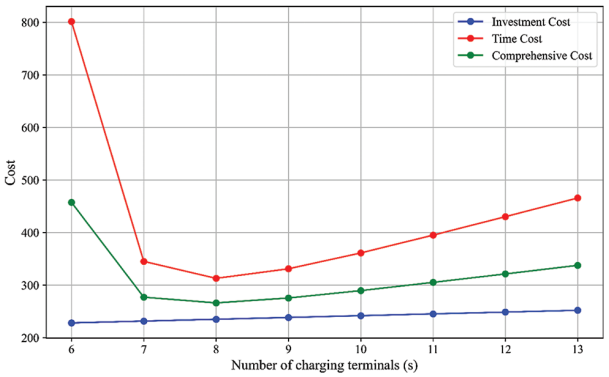

Figure 9. Charging service system costs

the number of terminals because the charging power becomes smaller and the charging time is prolonged. The investment cost increases linearly and slowly as the number of terminals increases because the investment cost of CS mainly comes from the fixed investments such as land rent and box-type transformer, (a compact, enclosed unit integrating transformer and charging components which is less affected by the number of charging terminals.

The queuing time, facility service rate, and the cost of each for public fast-CSs configured with different numbers of charging terminals are shown in Table 3. The sojourn time is the total time that the user stays in the CS, including queuing time and charging time.

4. Discussion

The findings of this study provide valuable insights into the optimization of public fast-CS capacity, particularly in urban settings where charging demand exhibits distinct temporal patterns. The proposed model, which integrates queuing theory with real-world operational data, offers a practical approach to balancing investment costs and user time costs. The results indicate that configuring 8 charging terminals for an 800 kVA charging box transformer is the

Table 3. Analysis of public fast-charging station costs and queuing systems

Number of charging terminals	Power (kW)	Investment cost (yuan/h)	User time cost (yuan/h)	Comprehensive cost (Yuan/h)	Staying time (min)	Facility utilization
6	133	228.23	801.46	457.53	100.67	0.84
7	114	231.66	345.18	277.07	43.36	0.72
8	100	235.09	312.96	266.24	39.31	0.63
9	89	238.51	331.13	275.53	41.59	0.56
10	80	241.94	361.28	289.67	45.38	0.50
11	73	245.36	395.12	305.26	49.63	0.46
12	67	248.78	430.25	321.37	54.04	0.42
13	62	252.21	465.84	337.66	58.51	0.39

optimal solution, reducing the comprehensive cost by 28.12% and the user's stay time by 41.76% compared to the original configuration of 15 terminals. This optimization not only enhances the operational efficiency of the CS but also significantly improves the user experience by minimizing queuing times.

The analysis of charging behavior revealed two distinct peak periods: One during midday (10:00 a.m. to 2:00 p.m.) and another in the evening (7:00 p.m. to 10:00 p.m.). These findings align with previous studies that have identified similar patterns in urban charging demand. The observed differences in charging duration and power further highlight the diverse needs of EV users, ranging from those with "mileage anxiety" who prefer longer charging sessions to those who utilize fragmented time for shorter charges. This heterogeneity underscores the importance of a flexible charging infrastructure that can accommodate varying user preferences.

The application of queuing theory in this study allows for a more accurate representation of the charging process, particularly during peak hours when demand exceeds capacity. By modeling the arrival and service times as negative exponential and normal distributions, respectively, the study was able to calculate key operational metrics such as average queuing time and facility utilization rate. These metrics are crucial for evaluating the performance of CSs and informing capacity planning decisions. The results suggest that a facility utilization rate of 0.63 strikes an optimal balance between minimizing user waiting times and ensuring a reasonable return on investment for station operators.

The study also highlights the trade-offs between the number of charging terminals and the power allocated to each terminal. While increasing the number of terminals reduces queuing times, it also decreases the charging power per terminal, leading to longer charging durations. This trade-off is particularly relevant for fast- CSs, where users expect quick turnaround times. The proposed configuration of eight terminals with an average charging power of 100 kW effectively addresses this issue, providing a balance between fast charging and reduced queuing.

From a policy perspective, the findings of this study have important implications for the planning and deployment of EV charging infrastructure. The optimization model can serve as a valuable tool for decision-makers in both the public and private sectors, enabling them to design CSs that are both cost-effective and user-friendly. In addition, the study's emphasis on real-world data enhances the practical applicability of the model, making it a useful resource for urban planners and CS operators.

Future research could explore the integration of advanced technologies, such as dynamic power allocation and smart charging systems, to further optimize CS performance. In addition, the relationship between CS capacity and the development of EV technology, such as higher-voltage platforms and faster charging speeds, warrants further investigation. Finally, the model could be extended to consider the impact of renewable energy integration and grid stability, which are increasingly important factors in the transition to sustainable transportation.

5. Conclusion

The results of this study show that eight charging terminals are the optimal number for alleviating waiting time at the station. The average charging power of the charging terminals is 100 kW, which can meet the fast charging needs of most vehicles. The queuing time of the charging service system of the public fast CS is 3 min, which is shorter than the longest queuing time that users can tolerate, and the sojourn time is 39.31 min. The facility utilization rate is 0.63, which is greater than the minimum facility utilization rate. The user cost is 312.96 yuan/h, which is the lowest among all the scenarios. The investment cost is 235.09 yuan/h.

The composite cost is 266.24 yuan/h, which is the lowest of all scenarios. If the decision maker places high emphasis on the comprehensive cost, then the number of charging terminals in the public fast CS should be set to 8. If the user experience is more preferred, then 9 or 10 charging terminals should be selected to avoid queuing or reduce the queuing time of users.

Our optimized solution is compared with the charging station's original configuration consisting of one 800kVA box-type charging transformer and 15 charging terminals. The comprehensive cost of the original scheme is calculated to be 370.39, and the sojourn time is 67.5 min. The public fast-CS configuration optimization model proposed in this study saves a huge cost and significantly reduces the user's stay time at the CS. The configuration of eight charging terminals reduces the comprehensive cost by 28.12% and the sojourn time by 41.76% compared to the original configuration.

In this study, a CS capacity optimization model was established by analyzing the operation data of public fast-CSs in Hohhot City, and the model was solved to draw the following conclusions. Characterization of the charging behavior of CS users shows that there is an obvious time distribution characteristic of charging demand, and there are two peak hours. There are also differences in users' charging duration and charging power. These data provide an important reference for CS planning and operation. Based on queuing theory analysis, a mathematical model of the charging service system is established and key operational indicators, such as average queue length and average waiting time, are calculated. This provides a theoretical basis for evaluating and optimizing CS performance. The CS capacity optimization model considers two objectives, investment cost, and user time cost, and sets constraints such as facility utilization rate and maximum waiting time. By solving the model, the optimal configuration of eight charging terminals is obtained. Compared with the original configuration scheme of 15 charging terminals, the optimized scheme of 8 charging terminals reduces the comprehensive cost by 28.12% and the user's stay time by 41.76%, which significantly improves the operational efficiency and user experience of the CS.

This study proposes more practical and operable suggestions in the optimization of CS capacity. The findings would help to promote the development and improvement of urban EV charging infrastructure. In future research, the relationship between CS capacity optimization and the development of charging equipment technology, as well as the combination with urban EV development planning, can be further explored to improve the operational efficiency and service quality of CSs.

Acknowledgments

None.

Funding

This work was supported by the Natural Science Foundation of Inner Mongolia Autonomous Region of China under grant 2023MS07014; and "Inner Mongolia Science and Technology Achievement Transfer and Transformation Demonstration Zone, University Collaborative Innovation Base, and University Entrepreneurship Training Base" Construction Project (Supercomputing Power Project) under grant 21300 – 231510.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Hong Zhang
Methodology: Feifan Shi
Writing–original draft: Feifan Shi
Writing–review & editing: Hong Zhang

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data for used in the study can be obtained at: https://10.6084/m9.figshare.26014237.

References

1. Huang X, Wu D, Boulet B. Metaprobformer for charging load probabilistic forecasting of electric vehicle charging stations. *IEEE Trans Intell Transp Syst*. 2023;24(10): 10445-10455.

   doi: 10.1109/TITS.2023.3276947

2. Li H, Son D, Jeong B. Electric vehicle charging scheduling with mobile charging stations. *J Clean Prod*. 2024;434:140162.

   doi: 10.1016/j.jclepro.2023.140162

3. Du Z, Zheng L, Lin B. Influence of charging stations accessibility on charging stations utilization. *Energy*. 2024;298:131374.

   doi: 10.1016/j.energy.2024.131374

4. Zhao T, Li N, Kong N, Xie X. Optimal location of electrical vehicle charging stations with both self-and valet-charging service. *IEEE Trans Autom Sci Eng*. 2023.

doi: 10.1109/TASE.2023.3321412

5. Wu J, Su H, Meng J, Lin M. Electric vehicle charging scheduling considering infrastructure constraints. *Energy*. 2023;278:127806.

   doi: 10.1016/j.energy.2023.127806

6. Bayram IS, Tajer A, Abdallah M, Qaraqe K. Capacity planning frameworks for electric vehicle charging stations with multiclass customers. *IEEE Trans Smart Grid*. 2015;6(4):1934-1943.

   doi: 10.1109/TSG.2015.2406532

7. Ma SC, Fan Y. A deployment model of EV charging piles and its impact on EV promotion. *Energy Policy*. 2020;146:111777.

   doi: 10.1016/j.enpol.2020.111777

8. Zhang X, Chan KW, Li H, Wang H, Qiu J, Wang G. Deep-learning-based probabilistic forecasting of electric vehicle charging load with a novel queuing model. *IEEE Trans Cybern*. 2020;51(6):3157-3170.

   doi: 10.1109/TCYB.2020.2975134

9. Upchurch C, Kuby M, Lim S. A model for location of capacitated alternative-fuel stations. *Geogr Anal*. 2009;41(1):85-106.

   doi: 10.1111/j.1538-4632.2009.00744.x

10. Wang H, Zhao D, Meng Q, Ong GP, Lee DH. A four-step method for electric-vehicle charging facility deployment in a dense city: An empirical study in Singapore. *Transp Res A Policy Pract*. 2019;119:224-237.

    doi: 10.1016/j.tra.2018.11.012

11. Bai X, Chin KS, Zhou Z. A bi-objective model for location planning of electric vehicle charging stations with GPS trajectory data. *Comput Indus Eng*. 2019;128:591-604.

    doi: 10.1016/j.cie.2019.01.008

12. Brandt T, Wagner S, Neumann D. Prescriptive analytics in public-sector decision-making: A framework and insights from charging infrastructure planning. *Eur J Oper Res*. 2021;291(1):379-393.

    doi: 10.1016/j.ejor.2020.09.034

13. Çelik S, Ok Ş. Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning. *Heliyon*. 2024;10(7):e29153.

    doi: 10.1016/j.heliyon.2024.e29153

14. Cao W, Wan Y, Wang L, Wu Y. Location and capacity determination of charging station based on electric vehicle charging behavior analysis. *IEEJ Trans Electr Electron Eng*. 2021;16(6):827-834.

    doi: 10.1002/tee.23378

15. Zhu Z, Gao Z, Zheng J, Du H. Charging station planning for plug-in electric vehicles. *J Syst Sci Syst Eng*. 2018;27:24-45.

    doi: 10.1007/s11518-017-5352-6

16. Loni A, Asadi S. Data-driven equitable placement for electric vehicle charging stations: Case study San Francisco. *Energy*. 2023;282:128796.

    doi: 10.1016/j.energy.2023.128796

17. Mei Z, Que Z, Qiu H, Zhu Z, Cai Z. Optimizing the configuration of electric vehicle charging piles in public parking lots based on a multi-agent model. *Phys A Stat Mech Appl*. 2023;632:129329.

    doi: 10.1016/j.physa.2023.129329

18. Yang Q, Sun S, Deng S, Zhao Q, Zhou M. Optimal sizing of PEV fast charging stations with Markovian demand characterization. *IEEE Trans Smart Grid*. 2018;10(4): 4457-4466.

    doi: 10.1109/TSG.2018.2860783

19. Chen R, Qian X, Miao L, Ukkusuri SV. Optimal charging facility location and capacity for electric vehicles considering route choice and charging time equilibrium. *Comput Oper Res*. 2020;113:104776.

    doi: 10.1016/j.cor.2019.104776

20. Wu T, Fainman E, Maïzi Y, Shu J, Li Y. Allocate electric vehicles' public charging stations with charging demand uncertainty. *Transp Res D Transp Environ*. 2024;130:104178.

    doi: 10.1016/j.trd.2024.104178

21. Xiao D, An S, Cai H, Wang J, Cai H. An optimization model for electric vehicle charging infrastructure planning considering queuing behavior with finite queue length. *J Energy Storage*. 2020;29:101317.

    doi: 10.1016/j.est.2020.101317

22. Zhang Y, Wang Y, Li F, Wu B, Chiang YY, Zhang X. Efficient deployment of electric vehicle charging infrastructure: Simultaneous optimization of charging station placement and charging pile assignment. *IEEE Trans Intell Transp Syst*. 2020;22(10):6654-6659.

    doi: 10.1109/TITS.2020.2990694

23. Mishra S, Mondal A, Mondal S. Charging station siting and sizing considering uncertainty in electric vehicle charging demand distribution. *IEEE Trans Intell Transp Syst*. 2024;25:12709-12721.

    doi: 10.1109/TITS.2024.3384537

24. Zhang J, Wang Z, Miller EJ, *et al*. Multi-period planning of locations and capacities of public charging stations. *J Energy Storage*. 2023;72:108565.

    doi: 10.1016/j.est.2023.108565

25. Eick SG, Massey WA, Whitt W. The physics of the Mt/G/∞ queue. *Oper Res*. 1993;41(4):731-742.

    doi: 10.1287/opre.41.4.731