

Article

Siting and Sizing of Electric Vehicle Charging Stations Considering Distribution Network Flexibility

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Abstract

The location and capacity of electric vehicle charging stations (EVCSs) directly determine the capital invested and construction costs while also affecting the travelling convenience and economy of electric vehicle (EV) users. Furthermore, the siting and sizing of EVCSs has an impact on distribution network flexibility. Therefore, a method for the siting and sizing of EVCSs that takes into account distribution network flexibility is proposed. Firstly, based on the definition of distribution network flexibility, the flexibility deficit is analyzed, and five flexibility assessment indicators are established. Secondly, the travel characteristics of EVs are simulated based on urban road topology and a trip probability matrix, and a model incorporating users' bounded rationality is adopted to predict the temporal and spatial distribution of EV charging requirements. Furthermore, based on charging requirements and distribution network flexibility deficit, this paper establishes a model for the siting and sizing of EVCSs considering distribution network flexibility. Finally, case studies are conducted with a 29-node transportation network and a 33-node distribution network. The results show that the proposed method can formulate a more reasonable siting and sizing scheme for EVCSs, decrease the flexibility deficit of the distribution network, and reduce the annual comprehensive cost by 11.96%.

Keywords: electric vehicle; charging station; distribution network flexibility; transportation network; charging demand; siting and sizing

1. Introduction

As energy crises and transport-related environmental issues worsen globally, electric vehicles (EVs) have attracted widespread attention worldwide. Compared with traditional fuel vehicles, EVs have a lot of advantages, including zero emissions and no air pollutant emissions. Nevertheless, large-scale popularization of EVs relies on sufficient charging station facilities, which has impacts on both the power system and EV users. Unreasonable deployment of EVCSs may cause increased power loss, voltage fluctuation and supply-demand imbalance [1,2]. In addition, insufficient capacity of EVCSs will lead to severe station congestion and longer charging waiting times. With the development of EVs, there is an urgent need to increase the number of EVCSs. In addition to construction costs and operation costs, the siting and sizing of EVCSs are also affected by distribution network operation conditions. The lack of sufficient flexible regulation capability of the distribution network may force EVCSs to reduce charging power or limit the number of simultaneous charging events, thus lowering service levels. In addition, users' bounded rationality may result in a mismatch between the siting and sizing scheme of EVCSs and



Academic Editor: Kwok Tong Chau

Received: 19 May 2026

Revised: 7 June 2026

Accepted: 10 June 2026

Published: 12 June 2026

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practical conditions. Therefore, it is necessary to establish a reasonable method for the siting and sizing of EVCSs that considers investment costs, service level, distribution network flexibility, and users' bounded rationality.

To achieve more reasonable and efficient siting and sizing of EVCSs, it is essential to clarify the spatiotemporal distribution characteristics of EV charging demands, which has been widely studied. Further integration of EVs may adversely affect the secure operation of a distribution network. Ref. [3] establishes a spatiotemporal transfer framework by adopting travelling route analysis to quantify the uncertainty in the spatial distribution of electric vehicles. On this basis, road conditions, traffic flow, and drivers' driving habits are further considered to improve the accuracy of charging demand forecasting and improve the risk-resisting capability of distribution networks. In Ref. [4], to address uncertainties in EV charging behaviors, historical charging records are converted into time series data. Combining deep learning and reinforcement learning, Ref. [4] proposes a prediction method suitable for the charging power of EVCSs. This algorithm can precisely capture the uncertainties in EV charging loads. With the rising penetration rate of EVs, the spatiotemporal distribution of their charging loads becomes increasingly stochastic. Ref. [5] proposes a new prediction model to forecast EV charging requirements in different areas and at multiple time scales. The model can intuitively reflect the distribution of EV charging demand. Although the above studies have explored various methods for predicting the charging demands of EVs, they all assume that users are absolutely rational. Users follow fixed charging demand conditions during their driving, without considering the impact of users' bounded rationality on the prediction results.

As a key facility for daily EV usage, the siting and sizing of EVCSs are closely related to the driving characteristics of EVs and affected by the operating states and topology of the transportation network [6]. Therefore, in the siting and sizing of EVCSs, relevant scholars have considered not only the construction investment of EVCSs but also charging requirements and traffic conditions. Reasonable siting of EVCSs promotes the rapid development of the EV industry. Ref. [7] quantitatively analyzes factors affecting charging station planning, considers land cost and construction cost, and establishes a charging station planning model. This method features easy implementation and low data processing requirements. Ref. [8] constructs a model for siting and sizing, aiming to achieve minimal construction and users' charging costs. This method provides more reasonable schemes for siting and sizing. To meet the expansion demands of EVCSs, Ref. [9] discusses the growth in dynamic traffic demand caused by social factors and structures a bi-level planning method for EVCSs on expressways. This approach generates more rational construction schemes for charging facilities. To allocate EVCSs for EVs in the early stage of EV development, Ref. [10], using multi-source urban big data, constructs a submodular maximization model to maximize user satisfaction. Finally, a greedy algorithm-based method is adopted to optimize the layout of EVCSs under given budget constraints. The proposed method addresses the optimal siting problem. Unreasonable siting and sizing of EVCSs can exert adverse impacts on the development of EVs. Therefore, Ref. [11] proposes a two-stage method based on regional division and demand distribution for the construction of fast EVCSs in urban transportation networks. The proposed method significantly cuts the capital investment cost of EVCSs. To investigate the optimal siting and sizing of plug-in EVCSs, Ref. [12] investigates the coupling of transportation and power systems under different driving ranges and time-varying demand constraints and establishes a siting and sizing method for EVCSs. Large-scale shared EVs require adequate charging infrastructure to sustain regular operation. Therefore, Ref. [13] analyzes the travel features and the convenience of users. By integrating centralized EVCSs with distributed charging piles, a two-stage planning model is established. The proposed method achieves rational siting-and-sizing schemes for

EVCSs and minimizes the annual total cost. Ref. [14] describes the dynamic characteristics of the transportation network and the environmental benefits associated with carbon emissions. It innovatively proposes a planning strategy based on an improved dynamic user equilibrium model. To promote large-scale EV popularization and realize reliable planning of EVCSs, Ref. [15] proposes a multi-objective method for EVCSs. This model considers user charging convenience, economic benefits, distribution networks, and environmental impacts. Queueing theory is applied to optimize the utilization rate of stations and users' waiting times. Ref. [16] considers the uncertainty in EV arrival rates and service times. A capacity planning model for EVCSs has been established to maximize service quality and improve service quality for customers. The rapid growth of EVs greatly affects power system planning and operation. Ref. [17] considers the market environment and the dual uncertainties in photovoltaic output and load demand. A siting and sizing model integrating photovoltaic systems, energy storage systems and fast EVCSs is established. This method reduces negative impacts from EVs and improves power system operation. The rapid global penetration of electric vehicles requires substantial investment and strategic planning for charging infrastructure. Therefore, Ref. [18] proposes a two-stage optimization framework and develops an efficient hybrid solution algorithm. This approach effectively addresses the complexity of balancing investment cost and user satisfaction, achieving high user satisfaction while maintaining cost-effectiveness. Unreasonable location and capacity of EVCSs impair the economic benefits of station investors and users' charging satisfaction. Against this background, Ref. [19] puts forward an EV charging station planning approach based on Nash bargaining game theory. Numerical results verify that the proposed method realizes balanced benefits among diverse stakeholders. To promote the penetration of EVs, it is essential to construct supporting charging infrastructure. Ref. [20] balances multiple influencing factors and develops a two-stage optimization algorithm to obtain the optimal siting and sizing scheme for EVCSs. The presented method improves both the utilization of charging facilities and users' satisfaction. The above literature investigates the impacts of transportation network characteristics and EV driving features on the siting and sizing of EVCSs. However, these studies only examined aspects such as the cost of EVCSs, user costs, and user satisfaction. They did not explore the operational characteristics of the distribution network.

Large-scale EVCSs can significantly affect the operation of distribution networks. Siting and sizing must consider the features of distribution networks to lessen the construction and operational costs of EVCSs while improving the user servicing level [21,22]. Numerous studies have explored siting and sizing with consideration of distribution networks. Reasonable planning of EVCSs and the expansion of distribution networks support steady growth of EVs and conventional loads. Ref. [23] conducts multi-stage planning of distribution networks and implements siting and sizing. This method determines the location and capacity. It also obtains optimal expansion plans for distribution networks. Growing EV popularity drives charging station expansion and large-scale upgrades of power and traffic networks. Therefore, Ref. [24] discusses the simultaneous expansion of transportation networks, EVCSs, and distribution networks. A bi-level model is constructed for coupled networks. Linearized power flow constraints are introduced into the model to ensure the operational safety of distribution networks. EV development needs coordinated charging station planning combining traffic and distribution networks. Ref. [25] integrates the planning of EVCSs and the promotion of distribution network infrastructure. The method considers the load-carrying capacity of the distribution network. Meanwhile, it determines siting and sizing, the expansion of transportation networks, and the capacity enhancement of power lines. To accommodate more EVs and cut fossil fuel emissions, Ref. [26] discusses the practical constraints of power systems in urban environments, including voltage

regulation requirements, protection equipment upgrading, and distribution network expansion, and establishes a siting model that achieves a balance between construction costs and power network operation costs. This method is highly applicable and has very little error. The above literature investigates the impacts of distribution network stability and economics on siting and sizing. However, these studies have not considered the influence of distribution network flexibility. During the process of siting and sizing, there may be a significant amount of flexibility control costs due to insufficient flexibility.

In order to present the advantages and limitations of the existing solutions more intuitively, the above-mentioned literature is summarized as follows in Tables 1 and 2.

Table 1. Existing solutions for charging demand forecasting and their advantages and limitations.

Existing Solution	Advantage	Limitation
Model-driven	Easy to implement and do not need large amounts of data to support it.	Difficult to guarantee prediction accuracy.
Data-driven	It can capture the complexity of charging behavior and provide highly accurate prediction results.	A large amount of high-quality data is required for support.

Table 2. Existing solutions for siting and sizing and their advantages and limitations.

Existing Solution	Advantage	Limitation
Mathematical programming method	The mathematical logic is rigorous, the optimal solution can be quantified, and the result is theoretically optimal.	In the scenario of coupling large-scale transportation networks and distribution networks, there are many variables, and the solution efficiency decreases.
Optimization algorithm	Suitable for complex coupling models, with flexible modeling capabilities.	There is no guarantee of global optimality, and it is sensitive to parameter variations.

To address the drawbacks of existing studies, this paper puts forward a siting and sizing method for EVCSs considering distribution network flexibility and users' bounded rationality. The proposed method determines the optimal location and capacity of EVCSs. Based on users' bounded rationality, the proposed method obtains the temporal and spatial distribution of EV charging requirements, and the variations in distribution network flexibility are incorporated into the siting and sizing process. Thus, the optimal siting and sizing scheme can be obtained. This method can solve the current mismatch between the quantity of EVCSs and EVs and reduce the impacts of charging station planning on distribution network flexibility. The main contributions of this paper are:

- (1) Aiming at the prediction accuracy of the spatiotemporal distribution of EV charging demands, a prediction model based on a charging urgency perception function is established. This paper considers the characteristics of transportation networks and users' travel behaviors. The Monte Carlo method is adopted to simulate the travel transfer process of EVs in the transportation network, and the charging urgency perception function is integrated to achieve accurate prediction of charging demands. It provides data support for the calculation of user costs in charging station siting and sizing.
- (2) Aiming at the insufficient flexibility of distribution networks, an EV charging station siting and sizing model considering distribution network flexibility is proposed. By comprehensively considering distribution network flexibility, charging station construction costs and user travel costs, the model obtains the best siting and sizing scheme for EVCSs and effectively reduces the annual comprehensive cost.

The remainder of this paper is structured in the following way. The framework of EVCS location and sizing is presented in Section 2. Section 3 establishes the model of distribution network flexibility and quantifies the distribution network flexibility deficit. Section 4 predicts the spatiotemporal distribution of EV charging demand considering users' bounded rationality. Section 5 constructs the siting and sizing model of EVCSs considering distribution network flexibility. Section 6 verifies the effect of this method based on the test systems. Finally, Section 7 concludes the whole paper.

2. Framework for Siting and Sizing for EVCSs

The framework shown in Figure 1 gives a model that could be applied to find and establish the siting and sizing of EVCSs considering the flexibility of the distribution network as well as the bounded rationality of users. The impacts of transportation and distribution network coupling characteristics, distribution network flexibility and users' bounded rationality are considered for siting and sizing decisions. Siting and sizing are realized through three steps: distribution network flexibility modeling, EV charging demand forecasting, and construction of the siting and sizing optimization model.

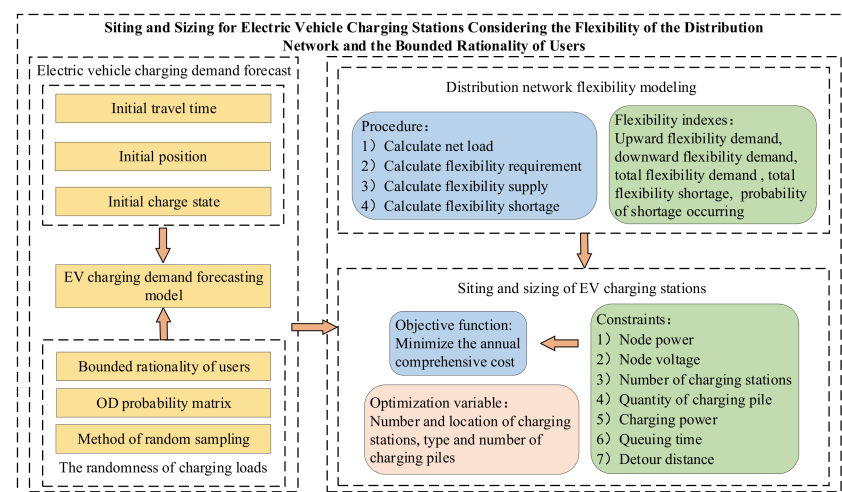


Figure 1. The framework of siting and sizing.

In the modeling of distribution network flexibility, this paper defines distribution network flexibility as the maximum additional output or maximum additional power consumption that flexible resources can provide under the current dispatching scheme. Furthermore, this paper establishes evaluation indexes for distribution network flexibility and comprehensively and quantitatively evaluates the flexibility of the distribution network after the integration of EVCSs.

In the stage of charging demand prediction, based on historical travel rules, this paper generates the initial states, including departure time, state of charge (SOC), and location of EVs, in different areas during the EV charging demand forecasting stage. EV travel trajectories are simulated using an origin–destination (OD) probability matrix, random sampling, and the Dijkstra shortest path algorithm. Based on users' bounded rationality, the travel time and remaining power of EVs are calculated. Finally, the spatiotemporal distribution of charging requirements is obtained, which provides a data foundation for the calculation of users' travel diversion cost [27,28].

In the stage of siting and sizing, this paper considers the regulation cost of distribution network flexibility and users' travel diversion cost, focusing on the capital invested and service level of EVCSs. Taking the minimum annual comprehensive cost as the objective,

an optimization model for siting and sizing is established to obtain a reasonable siting and sizing scheme.

Based on the above framework, this paper establishes an EV charging station siting and sizing model that considers distribution network flexibility and users' bounded rationality.

3. Modeling of Distribution Network Flexibility

Upward flexibility demand, downward flexibility demand, total flexibility demand, total flexibility deficit, and deficit occurrence probability are selected as the assessment indexes of flexibility.

3.1. Calculation of Distribution Network Flexibility Deficit

Distribution network flexibility deficit refers to the power gap that occurs when the maximum up- and down-adjustable capacity provided by various flexible resources in the system cannot fully cover the net load fluctuations. Its calculation mainly includes four steps.

- (1) Calculate the net load of distribution network node i at time t .

$$P_{n.i.t} = P_{c.i.t} + P_{EV.i.t} - P_{re.i.t} \quad (1)$$

where $P_{n.i.t}$ is the net load of the distribution network i -th node at time t . The variables $P_{c.i.t}$, $P_{EV.i.t}$ and $P_{re.i.t}$ are the user loads, EV charging loads and the renewable generation of the i -th node at time t , respectively.

Assume node i is coupled with the transportation network node m . The EV charging load at distribution network node i can be expressed as follows:

$$\begin{cases} P_{EV.i.t} = x_m(r_m^{lo}P_c^{lo} + r_m^{fa}P_c^{fa}) \\ \sum_m^{n_L} x_m = n_{EVS} \end{cases} \quad (2)$$

where x_m is the 0–1 parameter indicating whether the station is constructed at transportation network node m : the value 1 indicates constructing the charging station, and the value 0 indicates otherwise. The variables r_m^{lo} and r_m^{fa} , respectively, are the quantity of slow and fast charging piles at node m participating in charging. The parameters P_c^{lo} and P_c^{fa} represent the rated charging power of slow and fast piles, respectively. The variables n_L and n_{EVS} are the quantity of transportation network nodes and EVCSs, respectively.

$$P_{re.i.t} = P_{pv.i.t} + P_{wt.i.t} \quad (3)$$

where $P_{pv.i.t}$ and $P_{wt.i.t}$ are the photovoltaic power and the wind power generation of distribution network node i at time t , respectively.

- (2) Calculate the flexibility requirements of each node at time t .

$$\begin{cases} X_{i,t}^u = P_{n.i,t+1} - P_{n.i,t}, P_{n.i,t+1} > P_{n.i,t} \\ X_{i,t}^d = P_{n.i,t} - P_{n.i,t+1}, P_{n.i,t+1} < P_{n.i,t} \end{cases} \quad (4)$$

where $X_{i,t}^u$ and $X_{i,t}^d$ are the up and down flexibility requirements, respectively. The parameter $P_{n.i,t+1}$ is the net load of node i at time $t + 1$.

- (3) Calculate the flexible supply of flexible resources at time t .

Considering the fast response capability of distributed gas turbines, this paper takes distributed gas turbines as flexible resources of the distribution network. To quantify

the flexibility supply capability, the output characteristics of distributed gas turbines are modeled as shown in Equation (5).

$$\begin{cases} G_{g,i,t}^u = \min\{P_g^{\max} - P_{g,i,t-1}, R_g^u\} \\ G_{g,i,t}^d = \min\{P_{g,i,t-1} - P_g^{\min}, R_g^d\} \end{cases} \quad (5)$$

where $G_{g,i,t}^u$ and $G_{g,i,t}^d$ are the up and down flexibility supply provided by the gas turbines connected to the i -th node at time t . The variable $P_{g,i,t-1}$ refers to the active power generated by the gas turbine. The parameters R_g^u and R_g^d stand for the up and down ramping rates of the gas turbine unit. The variables $P_g^{\min}$ and $P_g^{\max}$ define the maximum and minimum limits of the gas turbine's active power output range, respectively.

In addition, the active power of the gas turbine is also restricted by the ramping rate.

$$\begin{cases} P_g^{\min} \leq P_{g,i,t} \leq P_g^{\max} \\ P_{g,i,t} - P_{g,i,t-1} \leq R_g^u \\ P_{g,i,t-1} - P_{g,i,t} \leq R_g^d \end{cases} \quad (6)$$

where $P_{g,i,t}$ is the active power output at node i at time t .

- (4) Calculate the flexibility shortage at time t .

A schematic diagram of the flexibility deficit is shown in Figure 2.

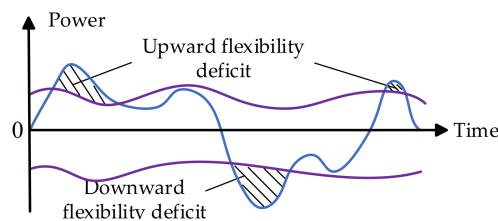


Figure 2. Schematic diagram of the distribution network flexibility deficit.

In Figure 2, the blue curve and the purple curve represent the flexibility demand and the flexibility supply, respectively.

$$\begin{cases} F_{i,t}^u = X_{i,t}^u - G_{g,i,t}^u, G_{g,i,t}^u - X_{i,t}^u \leq 0 \\ F_{i,t}^d = X_{i,t}^d - G_{g,i,t}^d, G_{g,i,t}^d - X_{i,t}^d \leq 0 \end{cases} \quad (7)$$

where $F_{i,t}^u$ and $F_{i,t}^d$ are the up and down flexibility shortages of node i at time t .

3.2. Distribution Network Flexibility Evaluation Index

To quantify the improvement effect of the proposed method on distribution network flexibility, five flexibility indexes are defined as follows:

- (1) Upward flexibility demand: the total upward flexibility demand generated over T time periods.

$$X_i^u = \sum_{t=1}^T X_{i,t}^u \quad (8)$$

where X_i^u is the upward flexibility requirement of node i . The parameter T stands for the quantity of time intervals in a day, and this paper takes 24.

- (2) Downward flexibility demand: the total downward flexibility demand generated over T time periods.

$$X_i^d = \sum_{t=1}^T X_{i,t}^d \quad (9)$$

where X_i^d is the downward flexibility demand of node i .

- (3) Total flexibility demand: the sum of upward flexibility demand and downward flexibility demand.

$$X_i = X_i^u + X_i^d \quad (10)$$

where X_i is the total flexibility demand of node i .

- (4) Total flexibility deficit: the sum of the flexibility shortage that occurs over T time periods.

$$F_i = \sum_{t=1}^T F_{i,t}^u + F_{i,t}^d \quad (11)$$

where F_i is the total flexibility shortage of node i .

- (5) The probability of flexibility deficit: the ratio of the number of time periods with flexibility deficit to the quantity of time periods within T time intervals.

$$B_i = \frac{N_i}{T} \quad (12)$$

where B_i is the probability of node i generating a shortage. The parameter N_i is the quantity of time periods in which node i generates a flexibility shortage.

4. EV Charging Demand Forecasting

To better analyze the driving characteristics and energy consumption of EVs, a simple transportation network is investigated first. Figure 3 depicts a simple transportation network topology in which it is assumed that all roads in the network are two-way.

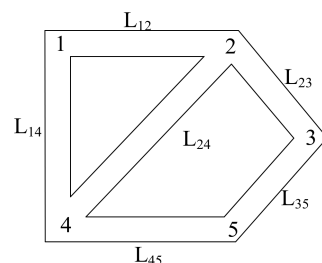


Figure 3. Topology of the simplified transportation network.

The network topology could be described as Equation (13).

$$\left\{ \begin{array}{l} G = (N, L, H, W) \\ N = \{1, 2, 3, \dots, n\} \\ L = \{l_{ij} \mid i \in N, j \in N, i \neq j\} \\ H = \{1, 2, 3, \dots, h\} \\ W = \{w_{ij}^k \mid l_{ij} \in L\} \end{array} \right. \quad (13)$$

where G is defined as the topological map of the traffic network. The variable N is the set of all nodes in the traffic network. The variable n represents the n -th node. The parameter L stands for the full set of roads. The parameters i and j are the starting and ending nodes of this road, respectively. The variable H is used to describe all time intervals that constitute a single day, and h corresponds to the h -th time interval in this set. The parameter W denotes

the collection of impedances generated by road congestion conditions and waiting time at network nodes.

The topology of transportation networks, as shown in Figure 3, is based on the use of the adjacent matrix Z to represent the length of all the road segments. The elements Z_{ij} of matrix Z are assigned according to Equation (14):

$$Z_{ij} = \begin{cases} w_{ij} & , n_{ij} \in L \\ 0 & , n_j = n_i \\ \text{inf} & , n_{ij} \notin L \end{cases} \quad (14)$$

where inf means no direct path between n_i and n_j .

The adjacent matrix Z is ultimately expressed as shown in Equation (15):

$$Z = \begin{pmatrix} 0 & w_{12} & \text{inf} & w_{14} & \text{inf} \\ w_{21} & 0 & w_{23} & w_{24} & \text{inf} \\ \text{inf} & w_{32} & 0 & \text{inf} & w_{35} \\ w_{41} & w_{42} & \text{inf} & 0 & w_{45} \\ \text{inf} & \text{inf} & w_{53} & w_{54} & 0 \end{pmatrix} \quad (15)$$

Combined with the actual development status of EVs, EVs are divided into four categories: taxis, private cars, urban service vehicles, and buses. Meanwhile, the traffic behaviors of EVs are closely related to their initial travel locations and urban areas. According to the main functions and load types, urban areas are divided into residential, working and commercial areas. The relevant assumptions regarding EV travel behavior are given as follows:

- (1) Electric buses follow fixed routes and parking locations; thus, they can be excluded from charging station planning. Private cars mainly travel between residential and working areas. They are generally initially parked in residential areas, and vehicle owners can freely select charging modes. Taxis usually complete shift changes in residential areas, and their initial locations are mostly distributed in residential areas. Urban service vehicles usually depart from working areas.
- (2) EV users exhibit bounded rationality. They will be anxious when the battery power drops. Each user has a reference SOC value. Once the SOC drops below this value, users will deviate from their predetermined route to search for available EVCSs.

Therefore, a charging urgency perception function is introduced. The numerator represents the total energy consumption of the remaining trip, and the denominator denotes the actual available electricity. When the value of the charging urgency perception function exceeds a certain threshold, users will immediately change their travel chains and seek charging piles, thereby generating a charging demand.

$$\eta_k(t) = \frac{F_{ij} \cdot w_{ij}}{SOC_k(t) \cdot E_{\text{cap}} - SOC_{\text{min}} \cdot E_{\text{cap}}} \quad (16)$$

where $\eta_k(t)$ is the perception function of charging urgency. The parameter F_{ij} is the real-time energy consumption per unit mileage on road ij . The variable w_{ij} is the length of road section ij . The variable $SOC_k(t)$ is the SOC of the EV at time t . The parameter SOC_{min} is the safety threshold of the SOC defined by the user. The parameter E_{cap} is the EV battery capacity.

Under the premise of the aforementioned assumptions, this study first generates three core daily parameters for the three categories of EVs, including the travel time t_s , SOC Cap_0 , and position O_i . Destination D_j corresponding to time t_s is then determined via

random sampling, with reference to the OD probability matrix at the same timestamp. On the basis of the preset rule that vehicle drivers select the shortest route toward destination D_j , the Dijkstra shortest path algorithm is utilized to solve the shortest path set R connecting O_i and D_j . Meanwhile, the adjacency matrix is adopted to acquire the road segment distance l_{OD} of each individual route. Ultimately, the charging urgency perception function is applied to confirm the charging demand, and Equation (17) is employed to compute the driving time ΔT_{ij} .

The EV travel time is expressed in Equation (17):

$$\Delta T_{ij} = \frac{l_{OD}}{v} \quad (17)$$

where v is the average speed of the EV.

In case a demand charge is levied when reaching the destination, information on the location and time of the demand to charge will be kept in the matrix G . If there is a demand to charge after arriving at the destination, D_j is used as the new starting point O_i , and the probability matrix at that point is called out. The indicated step is repeated in order to recreate the daily driving path of EVs and eventually arrive at the spatial–temporal distribution of charging demand in 24 h.

5. Siting and Sizing for EVCSs

On account of the distribution network flexibility deficit and the forecasting results of EV charging demands, this section constructs a siting and sizing model considering distribution network flexibility. The regulation cost of EVCSs is characterized by quantifying the flexibility deficit of distribution networks. The calculation of the spatiotemporal distribution of charging needs allows us to measure user costs. Also, it is supposed that the least total cost is the optimization goal, which means that the model takes into account both construction and operation costs of EVCSs, user costs, expansion costs of distribution network capacity, and regulation costs of EVCSs since the distribution network is inflexible. On this basis, the optimal siting and sizing are realized for the coupled transportation–distribution network system.

5.1. Objective Function

This paper considers the construction and operational maintenance cost, users' queuing time cost, users' annual travel diversion cost, annual distribution network capacity expansion cost, and annual regulation cost of EVCSs caused by the distribution network flexibility deficit. However, a function is defined to achieve minimal total cost in Equation (18).

$$\min F = C_H + C_{EV}^{pd} + C_{EV}^{hs} + C_P^u + C_{lhx} \quad (18)$$

where F is the annual comprehensive cost. The parameter C_H is the annual construction operation and maintenance cost. The parameter C_{EV}^{pd} is the annual user waiting time cost. The variable C_{EV}^{hs} is the annual user travel time cost. The variable C_P^u is the annual distribution network expansion cost. The parameter C_{fle} is the annual charging station regulation cost caused by the distribution network flexibility shortage.

(1) The annual construction and operation cost.

$$C_H = C_H^{js} + C_P^{js} + C_H^{yw} + C_P^{yw} \quad (19)$$

where C_H^{js} is the annual construction cost. The variable C_P^{js} is the annual construction cost of the piles. The parameters C_H^{yw} and C_P^{yw} are the annual operation and maintenance costs of EVCSs, respectively.

The annual construction cost of a charging station is

$$C_H^{js} = \sum_{m=1}^{n_L} [x_m (C_m^{la} S_H + C_H^{con} + C_H^{ot})] \cdot R_d \quad (20)$$

where C_m^{la} is the cost of land use per unit area of node i . The variable S_H represents the fixed area of the charging station. The parameter C_H^{con} represents the fixed construction cost of the charging station. The parameter C_H^{ot} represents other investment costs. The variable R_d is an auxiliary variable used for annualization.

$$R_d = \frac{d(1+d)^y}{(1+d)^y - 1} \quad (21)$$

where d is the discount rate. The depreciation period of the EVCS is the parameter y .

$$C_m^{la} = \begin{cases} 1000, & m \in jm \\ 3000, & m \in sy \\ 2000, & m \in gz \end{cases} \quad (22)$$

where jm is a collection of nodes located in residential areas. The parameter sy is a collection of nodes located in commercial areas. The variable gz is a collection of nodes located in working areas.

The annual construction cost of the charging piles is:

$$C_P^{js} = \sum_{l=1}^{n_{EVS}} [r_l^{lo} (C^{lo,cp} + C_l^{la} S_P) + r_l^{fa} (C^{fa,cp} + C_l^{la} S_P)] \cdot R_d \quad (23)$$

where n_{EVS} denotes the total quantity EVCSs in the model. The parameters r_l^{lo} and r_l^{fa} respectively stand for the quantities of slow and fast piles in the l -th charging station. The parameters $C^{lo,cp}$ and $C^{fa,cp}$ are defined as the unit construction investment cost for slow and fast piles, correspondingly. The variable C_l^{la} refers to the unit area land occupancy cost at the node of the l -th charging station. The variable S_P represents the area that needs to be occupied to add one individual pile.

The annual operation cost of the station is:

$$C_H^{yw} = \sum_{m=1}^{n_L} (x_m \cdot C_m^{op.fi}) \quad (24)$$

where $C_m^{op.fi}$ is the annual fixed cost of operating and maintenance of the m -node charging station.

The annual operation and maintenance cost of the charging piles is:

$$C_P^{yw} = \sum_{l=1}^{n_{EVS}} (r_l^{lo} \cdot c^{lo,yw} + r_l^{fa} \cdot c^{fa,yw}) \quad (25)$$

where $c^{lo,yw}$ and $c^{fa,yw}$ respectively represent the annual operation and maintenance cost of the slow and fast charging piles.

(2) The annual user waiting time cost.

Assume that the time interval between vehicle arrivals at the charging station follows an exponential distribution. Moreover, the time taken to charge at the charging station has

an exponential distribution. To give an example, the average queuing waiting time T_q with fast charging piles is:

$$T_q = \frac{(c\rho)^c \rho}{c!(1-\rho)^2 \lambda} P_0 \quad (26)$$

$$P_0 = \left[\sum_{k=0}^{c-1} \frac{1}{k!} \left(\frac{\lambda}{\mu}\right)^k + \frac{1}{c!} \cdot \frac{1}{1-\rho} \cdot \left(\frac{\lambda}{\mu}\right)^c \right]^{-1} \quad (27)$$

$$\rho = \frac{\lambda}{c\mu} \quad (28)$$

where c means the total number of fast charging piles deployed at the charging station. The variable μ stands for the number of vehicles serviced by one fast charger in unit time. The parameter λ refers to the hourly charging service demands submitted to the charging station. The variable P_0 is defined as the reciprocal of EV charging time. The variable ρ characterizes the service strength of the charging pile equipment.

$$C_{EV}^{pd} = C_{uat} \cdot T_{year} \cdot \sum_{l=1}^{n_{EVS}} \sum_{j=1}^{R_l} T_{l,j}^q \quad (29)$$

where C_{uat} is the user's unit waiting time equivalent economic loss. The number of days in one year is T_{year} . The quantity of EVs being charged at the l -th charging station is denoted by R_l . The parameter $T_{l,j}^q$ denotes the waiting time of the j -th EV to the l -th charging station.

(3) The annual user travel time cost.

$$C_{EV}^{hs} = (T_{year} \cdot \sum_{l=1}^{n_{EVS}} \sum_{j=1}^{R_l} (D_{jl}/v)) \cdot C_{uat} \quad (30)$$

where D_{jl} is the distance from the EV j to the l -th station.

(4) The annual distribution network expansion cost.

$$C_P^u = R_d \cdot c^P \cdot \sum_{l=1}^{n_{EVS}} (r_l^{lo} \cdot p_c^{lo} + r_l^{fa} \cdot p_c^{fa}) \quad (31)$$

where c^P is the unit capacity incremental cost.

(5) The annual charging station regulation cost caused by the distribution network flexibility shortage.

$$C_{fle} = c^{fle} \cdot \sum_{i=1}^{n_P} \sum_{t=1}^{24} (F_{i,t}^u + F_{i,t}^d) \cdot R_d \quad (32)$$

where c^{fle} represents the unit flexibility cost. The parameter n_P is the number of nodes.

5.2. Constraints

The flexibility in the distribution network may cause some limitations on the location and capacity of an EVCS, which can be divided into three broad categories: distribution network-related constraints, charging station-related constraints, and EV user-related constraints.

5.2.1. Distribution Network Related Constraints

(1) Nodal power balance constraints.

The power at nodes of the distribution network shall satisfy power balance.

$$P_{i,t} = \sum_{j \in \pi(i)} P_{ji,t} - \sum_{k \in \delta(i)} P_{ik,t}, \forall i \in B \quad (33)$$

$$Q_{i,t} = \sum_{j \in \pi(i)} Q_{ji,t} - \sum_{k \in \delta(i)} Q_{ik,t}, \forall i \in B \quad (34)$$

$$P_{i,t} = P_{c,i,t} + P_{EV,i,t} - P_{re,i,t} - P_{g,i,t} \quad (35)$$

$$Q_{i,t} = Q_{c,i,t} + Q_{EV,i,t} - Q_{re,i,t} \quad (36)$$

where $\pi(i)$ and $\delta(i)$ represent the initial and terminal node sets of the branches that are connected to node i , respectively. The parameter B is the set of all nodes of the power system. The variables $P_{ji,t}$ and $Q_{ji,t}$ are the active power and reactive power of branch ji at time t . The variables $P_{ik,t}$ and $Q_{ik,t}$ are the active power and reactive power of branch ik at time t . The variables r_{ij} and x_{ij} are the resistance and reactance of branch ij , respectively. The parameters $P_{i,t}$ and $Q_{i,t}$ are active and reactive power consumption by node i at time t , respectively. The parameter $P_{g,i,t}$ is the active power produced by the gas turbine at node i at time t . The variables $Q_{EV,i,t}$, $Q_{c,i,t}$ and $Q_{re,i,t}$ are the reactive load of the EV, loads other than the EV, and renewable generation at node i at time t .

(2) Voltage constraints.

$$U_{i,t} = U_{j,t} + (P_{ji,t}r_{ij} + Q_{ji,t}x_{ij})/U_N \quad (37)$$

$$U_{\min} \leq U_i \leq U_{\max} \forall i \in \Omega_N \quad (38)$$

where $U_{i,t}$ and $U_{j,t}$ are the voltages of nodes i and j at time t . The parameter U_N is the reference voltage. The variables $U_{\min}$ and $U_{\max}$ are the minimum and maximum voltages.

5.2.2. Charging Station Related Constraints

(1) The number constraint of EVCSs.

$$n_{\min} \leq n_{EVS} \leq n_{\max} \quad (39)$$

where $n_{\min}$ and $n_{\max}$ are the upper and lower bounds on the quantity of EVCSs.

(2) The number constraint of charging piles.

$$r_{l,\min}^{\text{lo}} \leq r_l^{\text{lo}} \leq r_{l,\max}^{\text{lo}} \quad (40)$$

$$r_{l,\min}^{\text{fa}} \leq r_l^{\text{fa}} \leq r_{l,\max}^{\text{fa}} \quad (41)$$

where $r_{l,\min}^{\text{lo}}$ and $r_{l,\max}^{\text{lo}}$ denote the least and greatest possible number of slow charging piles at the l -th charging station. The variables $r_{l,\min}^{\text{fa}}$ and $r_{l,\max}^{\text{fa}}$ are the least and greatest number of fast charging piles at the l -th charging station.

(3) Charging power constraints of the charging station.

$$P_{l,\max}^{\text{EVS}} = r_l^{\text{lo}} P_c^{\text{lo}} + r_l^{\text{fa}} P_c^{\text{fa}} \quad (42)$$

$$P_l^{\text{EVS}} = R_l^{\text{lo}} P_c^{\text{lo}} + R_l^{\text{fa}} P_c^{\text{fa}} \quad (43)$$

$$\begin{cases} r_l^{\text{lo}} \leq R_l^{\text{lo}} \\ r_l^{\text{fa}} \leq R_l^{\text{fa}} \end{cases} \quad (44)$$

where $P_{l,\max}^{\text{EVS}}$ is the highest possible charging power available at the l -th charging station. Parameter P_l^{EVS} indicates the charging capacity of the l -th charging station. The variables R_l^{lo} and R_l^{fa} are the slow and fast charger demand, respectively, at the l -th EVCS.

5.2.3. EV User Related Constraints

(1) Queueing time constraint.

The service level is affected by the waiting time of users in queues. Therefore, EV traffic behavior is analyzed based on queuing theory. The siting and sizing of EVCs must satisfy the constraint on user queueing time.

$$T_j^q \leq T_{\max} \quad (45)$$

where $T_{\max}$ represents the maximum queue waiting time of users.

(2) Detour distance constraint.

$$D_{jl} \leq D_{\max} \quad (46)$$

where $D_{\max}$ represents the user's maximum detour distance.

6. Case Studies

In this section, the proposed siting and sizing method for EVCs considering distribution network flexibility is analyzed and verified using a test system coupling a 29-node transportation network with a 33-node distribution network (T29-D33 test system).

6.1. Test Case Data

The T29-D33 test system is shown in Figure 4. According to urban land use, the transportation network is divided into three areas, namely, a residential area, a working area, and a commercial area, containing a total of 49 roads. The distribution network is equipped with nine distributed gas turbines, two photovoltaic power sources, and three wind farms.

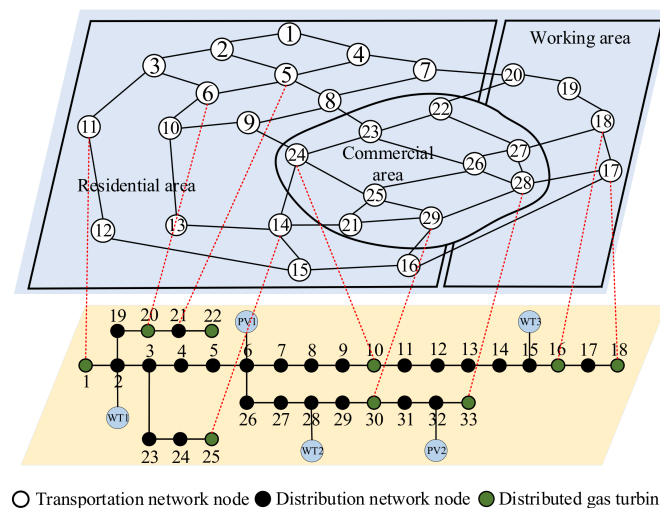


Figure 4. T29-D33 test system.

The parameter settings related to the siting and sizing of charging piles and EVCs are listed in Tables 3 and 4.

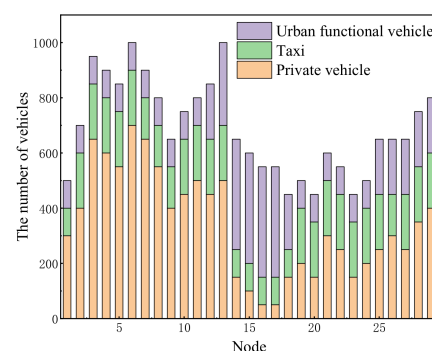
Table 3. Related parameters of charging piles.

Parameters	Charging Piles—Slow	Charging Piles—Fast
Rated charging power	30 kW	70 kW
Investment construction cost	14,724 \$/set	22,086 \$/set
Maintenance cost	294 \$/set/year	441 \$/set/year

Table 4. Related parameters of siting and sizing for EVCSSs.

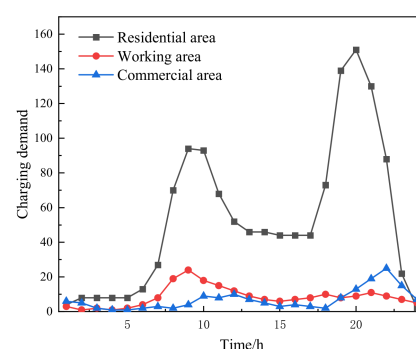
Parameters	Values	Parameters	Values
S_Z	20 Square meters	T_{year}	365 Days
C_Z^{con}	1472 \$	C_{uat}	4.7 \$/h
d	0.08	S_P	20 Square meters
y	20 Year	c^P	53 \$/kVA

The capacity of the EV battery used in the case study is 70 kWh, with an energy consumption of 20 kWh per 100 km and an average driving speed of 40 km/h. It is assumed that the transportation network contains 10,000 private vehicles, 3500 taxis, and 3000 urban functional vehicles. Based on the travel habits of each type of EV, the distribution of their initial locations is shown in Figure 5. Private cars show the highest travel probability at 7:00 a.m., matching the morning commuting peak for work.

**Figure 5.** The initial locations of different types of EVs.

6.2. Charging Demand Forecast

Figure 6 shows the temporal distribution of charging demand in different areas. The charging demand in different areas has significant differences in rising and declining trends. Private cars account for a large proportion in residential and working areas since most private vehicles use the traffic routes within these two areas as their daily commuting paths.

**Figure 6.** Temporal distribution of EV charging demands.

From the perspective of temporal distribution, the demand in the residential area is the highest, with demand peaks occurring in two periods: 8:00–11:00 and 18:00–22:00. The charging demands in the working and commercial areas are lower. Specifically, the demand peaks in the working area appear at 7:00–11:00 and 20:00–23:00, while those in the commercial area occur at 10:00–14:00 and 20:00–23:00.

To explore the influence of users' bounded rationality on charging requirements, two scenarios are set as follows:

Scenario 1: Bounded rationality of EV users is not considered.

Scenario 2: Bounded rationality of EV users is considered.

The spatiotemporal distribution of charging demand under the two scenarios is shown in the following Figures 7 and 8.

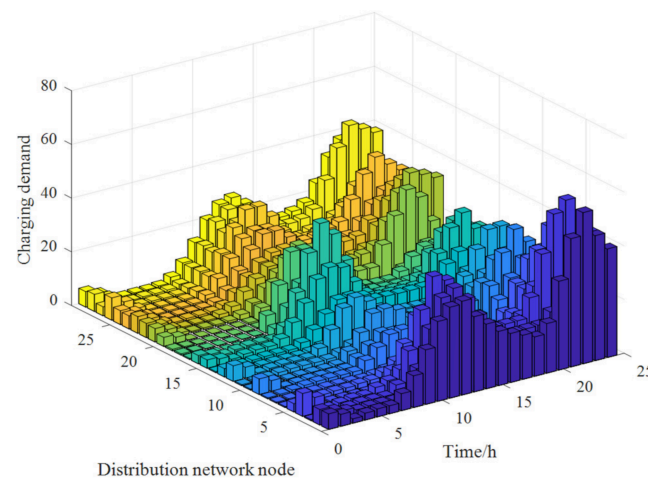


Figure 7. Spatiotemporal distribution of EV charging demand under scenario 1.

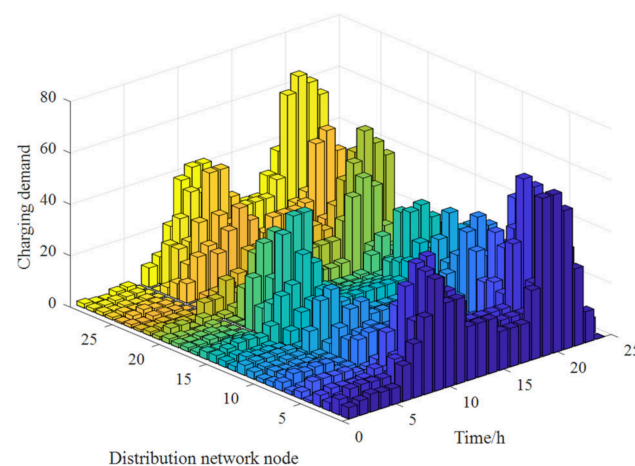


Figure 8. Spatiotemporal distribution of EV charging demand under scenario 2.

In scenario 1, users are assumed to be perfectly rational. Their traveling decisions are made strictly according to the optimal path and minimum energy consumption. The distribution of demand is relatively smooth without extreme power peaks. Since users can accurately calculate the travel time of each road, EV charging demand is effectively guided to the locations with the lowest comprehensive cost across the whole area. Users tend to delay charging until the battery power is nearly exhausted, resulting in a relatively late arrival of the load peak.

In scenario 2, users exhibit bounded rationality. The peaks of EV charging demand become more prominent and emerge much earlier. This is because bounded rationality drives more users to generate charging demand within a specific time. Meanwhile, users tend to charge in advance due to the range anxiety caused by bounded rationality.

Compared with scenario 1, the core advantage of scenario 2 lies in the introduction of bounded rationality characteristics, which breaks the perfect rationality assumption of users adopted in traditional models. In scenario 2, the peak hour of morning charging demand shifts from 12:00 to 9:00, while the peak charging demand rises from 39 to 46, representing an increase of 17.95%. The peak hour of evening charging demand shifts from

22:00 to 20:00, while the peak charging demand rises from 57 to 66, representing an increase of 15.79%. Accordingly, it can more realistically capture users' charging behaviors and provide a larger safety margin for the distribution network.

6.3. Siting and Sizing for EV Charging Stations

EVCSs are limited to a range of eight to 12 sites. Figure 9 shows the annual total cost of charging stations.

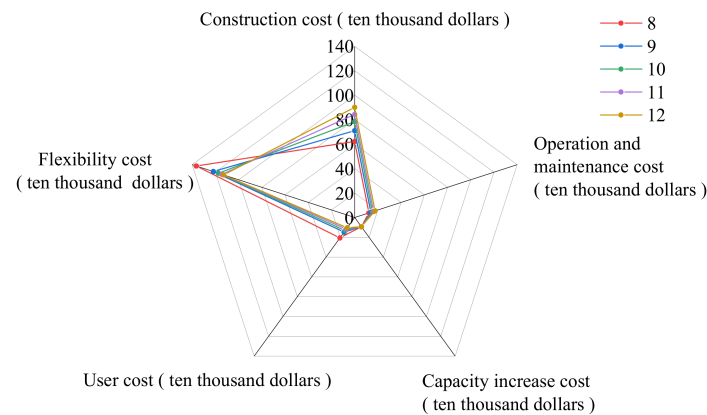


Figure 9. Charging station annual comprehensive cost structure.

The annual total cost is minimized with nine EVCSs (costing 2.31 million \$). Therefore, nine EVCSs are the optimal quantity for this area. These nine EVCSs are deployed at transportation network nodes 5, 6, 11, 14, 17, 18, 24, 28 and 29, which are coupled with distribution network nodes 22, 20, 1, 25, 18, 16, 10, 33 and 30. The layout of EVCSs and the number of piles are presented in Figure 10.

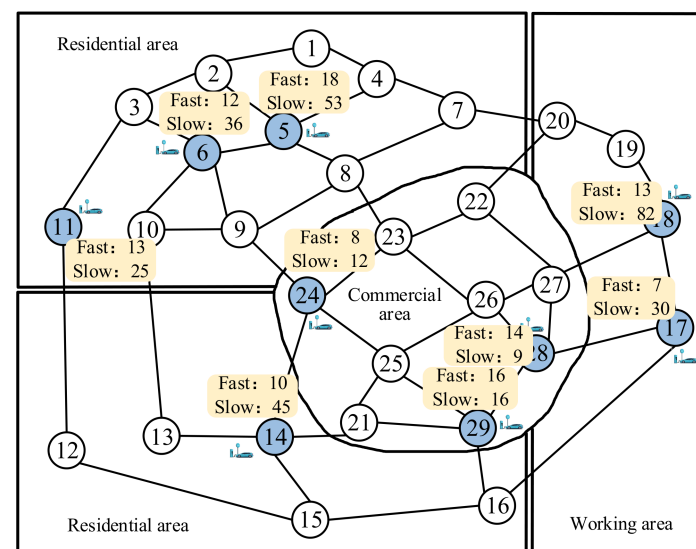


Figure 10. Results of siting and sizing for EVCSs for the T29-D33 test system.

6.4. Analysis of Optimization Results Considering Distribution Network Flexibility

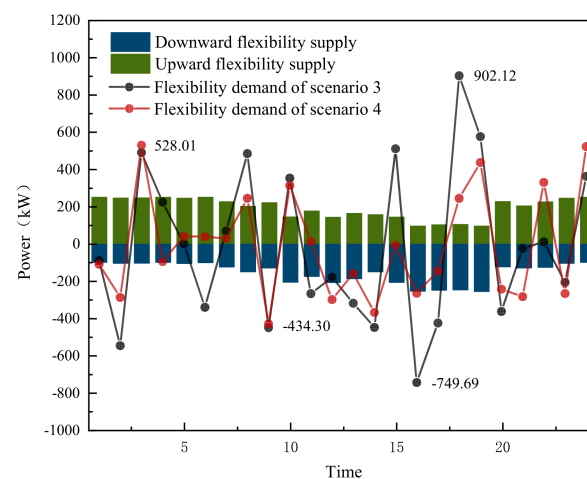
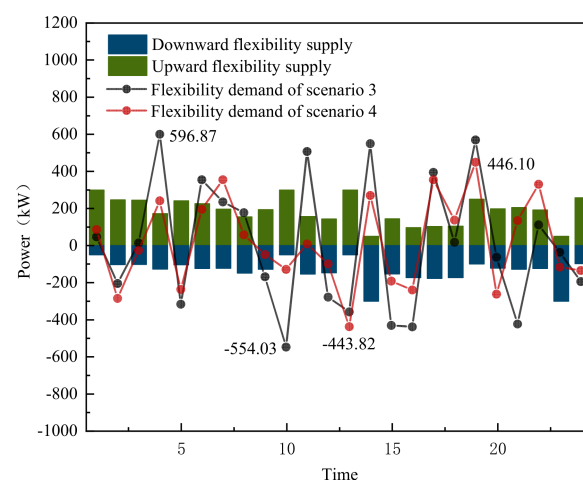
To analyze the impact of flexibility on the siting and sizing of EVCSs, the two scenarios listed in Table 5 are established for comparative analysis.

Table 5. Comparison between scenario 3 and scenario 4 for siting and sizing of EVCSs.

Scenario Number	User Cost	Charging Station Cost	Distribution Network Flexibility Cost
Scenario 3	Considered	Considered	Not considered
Scenario 4	Considered	Considered	Considered

Nodes 5 in the residential area and node 17 in the working area are selected as research objects. These two nodes are coupled with nodes 22 and 18 of the distribution network, respectively. The flexibility supply and demand response characteristics of the above coupled nodes within a 24 h operation cycle are quantitatively analyzed and compared.

As shown in Figures 11 and 12, for distribution network nodes 22 and 18 under scenario 4, the maximum upward flexibility demand decreases by 41.46% and 25.04%, the maximum downward flexibility demand drops by 42.05% and 20.03%, and the maximum flexibility deficit is reduced by 57.59% and 22.02%, respectively. This is because when the influence of distribution network flexibility is considered in the siting and sizing process, the layout of EVCSs and the quantity and capacity configuration of charging piles become more scientific and reasonable. As a result, the flexibility requirements of the two distribution network nodes is reduced, and the deficit is further lowered.

**Figure 11.** Flexibility demands and supplies at node 22 for scenario 3 and scenario 4.**Figure 12.** Flexibility demands and supplies at node 18 for scenario 3 and scenario 4.

The comparison of five flexibility indexes between the two nodes is presented as follows in Tables 6 and 7.

Table 6. Flexibility index comparison of node 22.

	Upward Flexibility Demand/kW	Downward Flexibility Demand/kW	Total Flexibility Demand/kW	Total Flexibility Shortage/kW	Probability of Generating Shortage
Scenario 3	3962	4462	8425	4809	0.667
Scenario 4	2713	3013	5726	2074	0.5
Improvement	31.52%	32.47%	32.04%	56.87%	25.4%

Table 7. Flexibility index comparison of node 18.

	Upward Flexibility Demand/kW	Downward Flexibility Demand/kW	Total Flexibility Demand/kW	Total Flexibility Shortage/kW	Probability of Generating Shortage
Scenario 3	3528	3528	7057	3792	0.667
Scenario 4	2570	2270	4841	1310	0.417
Improvement	27.15%	35.66%	31.4%	65.37%	37.48%

The cost comparison of siting and sizing under the two scenarios is presented in Figure 13.

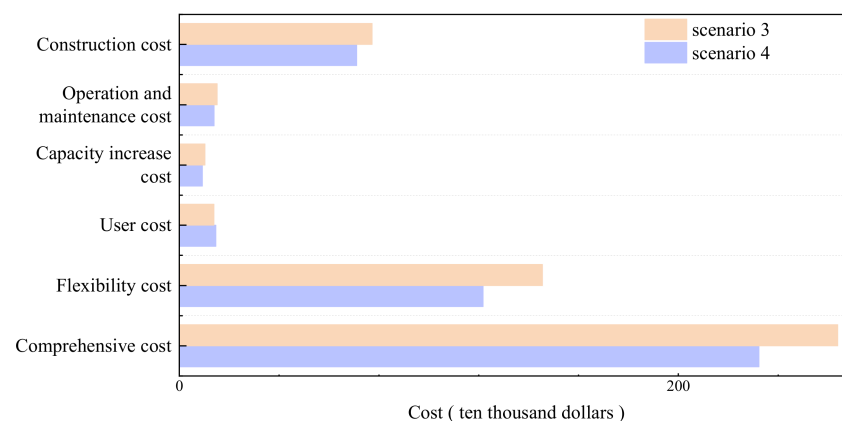


Figure 13. Cost comparison between scenario 3 and scenario 4.

Considering distribution network flexibility in the siting and sizing of EVCSs can reduce the construction cost, operation and maintenance cost, and capacity expansion cost of EVCSs while increasing user cost. Meanwhile, the reduction in the flexibility deficit under scenario 4 significantly cuts the flexibility cost of the distribution network, resulting in an 11.96% lower annual comprehensive cost compared with scenario 3.

6.5. Analysis of the Influence of Combined Installation of Fast and Slow Piles

Three scenarios have been added in order to examine how the installation of fast and slow charging piles will influence the optimization results.

Scenario 5: Only fast charging piles are installed.

Scenario 6: Only slow charging piles are installed.

Scenario 7: A combination of fast and slow charging piles is installed.

The components of the total annual cost for the three scenarios are shown in Table 8.

22, 23, 24, 27, 28, 29, 30, 31, 32, and 33 belong to the residential area. Nodes 1, 2, 3, 4, 16, 17, 18, 19, and 25 belong to the working area. Nodes 5, 6, 7, 8, 9, 10, 21, and 26 belong to the commercial area. The distribution network is equipped with 10 distributed gas turbines, two photovoltaic power sources, and three wind farms.

The layout of EVCSs and the number of piles are presented in Figure 15.

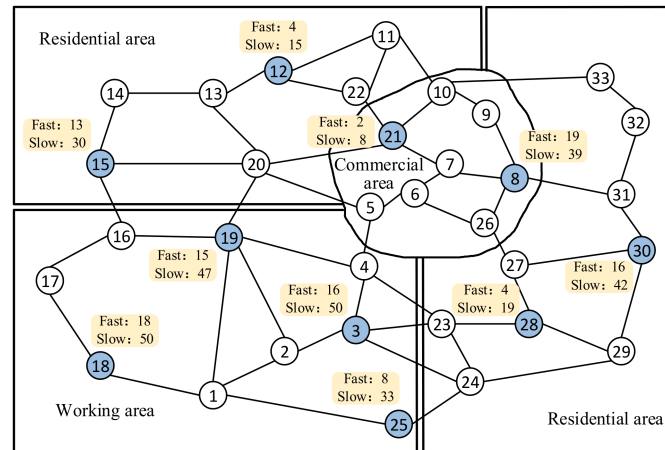


Figure 15. Results of siting and sizing for EVCSs for the T33-D33 test system.

The minimum annual total cost of 2.38 million dollars is reached with 10 EVCSs for the T33-D33 test system. Therefore, 10 EVCSs are the optimal quantity for this area. These 10 EVCSs are deployed at transportation network nodes 3, 8, 12, 15, 18, 19, 21, 25, 28 and 30, which are coupled with distribution network nodes 29, 16, 24, 2, 20, 4, 8, 31, 12 and 17.

To analyze the impact of distribution network flexibility on the siting and sizing of EVCSs, the two scenarios listed in Table 9 are established for comparative analysis.

Table 9. Comparison between scenario 8 and scenario 9 for siting and sizing of EVCSs.

Scenario Number	User Cost	Charging Station Cost	Distribution Network Flexibility Cost
Scenario 8	Considered	Considered	Not considered
Scenario 9	Considered	Considered	Considered

The cost comparison of EVCS siting and sizing under the two scenarios is presented in Figure 16.

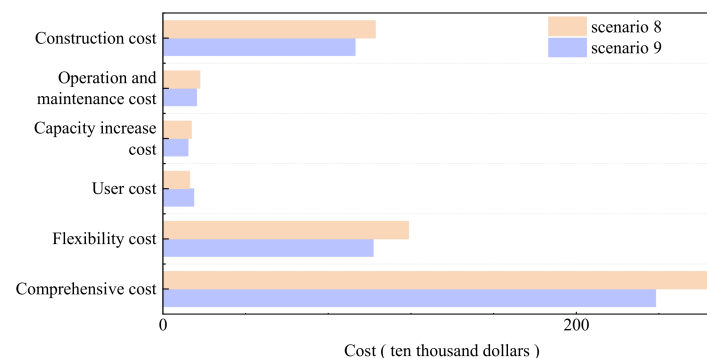


Figure 16. Cost comparison between scenario 8 and scenario 9.

As shown in Figure 16, the reduction in the flexibility deficit under scenario 9 significantly reduces the distribution network's flexibility cost by 14.32% and decreases the annual comprehensive cost by 10.49%.

The above results verify that the proposed method is applicable to the T33-D33 test system, which demonstrates its universality.

7. Conclusions

This paper plans the siting and sizing of EVCSs considering the flexibility of the distribution network and the limited rationality of the consumer. Case studies are conducted with the coupled system of a 29-node transportation network and a 33-node distribution network. The conclusions are summarized as follows:

- (1) The proposed siting and sizing method for EVCSs can effectively balance economic benefit and service level, achieving the minimization of annual comprehensive cost. Verified by case studies, the proposed model can generate reasonable siting and sizing schemes for EVCSs under given constraints, and the annual comprehensive cost is reduced by 11.96%.
- (2) Compared with traditional siting and sizing methods for EVCSs, the planning results become more practical when considering distribution network flexibility and users' bounded rationality. Meanwhile, the system flexibility deficit is reduced by 16.38%, and all flexibility indexes of the distribution network are improved by more than 25%.
- (3) Compared with the scheme that adopts a single type of charging piles, the combined deployment of fast and slow charging piles better conforms to the spatiotemporal distribution characteristics of actual charging demand. It reduces construction and operation–maintenance costs while effectively reducing users' charging waiting time and travel transfer time and improving the service level.
- (4) The given approach is also validated through a combined system of a transportation network with 33 nodes and a distribution network with 33 nodes. These findings suggest that the approach would decrease the distribution network flexibility deficiency by 14.32% and the total annual comprehensive cost of the network by 10.49%. This supports the applicability of the proposed method in general.

However, there remain certain limitations in this study.

- (1) This paper mainly explores the integration impacts of EVs as power loads while ignoring V2G technology. In future research, V2G technology can be utilized to integrate EVs as mobile energy storage resources for unified dispatching. By establishing a two-direction interaction mechanism between EVs and distribution networks, EVs can be guided to participate in the flexibility market. The flexible regulation potential of EVs can be fully exploited, and the regulation capability of EVs on distribution network flexibility can be considered during charging station siting and sizing.
- (2) This study only considers the coupling relationship between EVCSs and distribution networks, without involving other energy sources of EVCSs. It is essential to promote the integrated planning of EVCSs with rooftop photovoltaic systems, on-site energy storage devices and hydrogen energy supply facilities. This can provide references for the siting and sizing of EVCSs under the background of integrated energy systems.
- (3) This paper fails to consider uncertain factors such as extreme weather, increased traffic flow on holidays and temporary transportation network control. Random fluctuations and scenario disturbances could be introduced into the charging station planning model in future research. A self-adaptive siting and sizing method is established to make EVCSs adaptable to complex and changeable external environments.

Author Contributions: J.C.: conceptualization, methodology, original writing, formal analysis, and validation. X.L.: conceptualization and supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data is available in a publicly accessible repository. The data of the IEEE-33 bus system is openly available at <https://matpower.org/docs/ref/matpower6.0/case33bw.html> (accessed on 9 December 2025). The data of the transportation network with 29 nodes is from the appendix of the paper “A Spatial-temporal Charging Load Forecast and Impact Analysis Method for Distribution Network Using EVs-Traffic-Distribution Model”, available at <http://ntps.epri.sgcc.com.cn/djgxcb/CN/10.13334/j.0258-8013.pcsee.161470> (accessed on 9 December 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EVCS	electric vehicle charging station
EV	electric vehicle
EVs	electric vehicles
SOC	state of charge
OD	origin–destination
$P_{n,i,t}$	net load of distribution network node i
$P_{c,i,t}$	user load of node i
$P_{EV,i,t}$	EV charging load of node i at time t
$P_{re,i,t}$	renewable energy output of node i at time t
x_m	0–1 variable to show whether the station is constructed at transportation network node m
r_m^{lo}	number of slow charging piles of distribution network node m participating in charging
r_m^{fa}	number of fast charging piles of distribution network node m participating in charging
p_c^{lo}	rated charging power of slow piles
p_c^{fa}	rated charging power of fast piles
n_L	quantity of transportation network nodes
n_{EVS}	number of EVCSs
$P_{pv,i,t}$	photovoltaic power generation of the distribution network
$P_{wt,i,t}$	wind power generation of the distribution network
$X_{i,t}^u$	upward flexibility requirement
$X_{i,t}^d$	downward flexibility requirement
$P_{n,i,t+1}$	net load
$G_{g,i,t}^u$	upward flexible supply
$G_{g,i,t}^d$	downward flexible supply of the gas turbine at node i of the distribution network
$P_{g,i,t-1}$	active power output
R_g^u	upward climbing rate
R_g^d	downward climbing rate
p_g^{min}	minimum active power output
p_g^{max}	maximum active power output
$P_{g,i,t}$	active power output
$F_{i,t}^u$	upward flexibility shortage
$F_{i,t}^d$	downward flexibility shortage
X_i^u	upward flexibility demand of node i
T	number of time periods
X_i^d	downward flexibility demand of node i
X_i	total flexibility demand of node i
F_i	total flexibility shortage of node i
B_i	probability of node i generating a shortage
N_i	number of time periods in which node i generates a flexibility shortage
G	topological map of the transportation network
N	set of all nodes
n	the n -th node

L	set of all roads
i	starting nodes of this road
j	ending nodes of this road
H	set of time intervals in a day
h	h -th time interval
W	set of impedances formed by road congestion and nodal waiting time
inf	no direct path between nodes n_i and n_j
$\eta_k(t)$	perception function of charging urgency
F_{ij}	real-time energy consumption per unit mileage on road ij
ω_{ij}	length of road section ij
$SOC_k(t)$	SOC of the EV
SOC_{min}	safety threshold of the SOC defined by the user
E_{cap}	battery capacity of the EV
v	average speed of the EV
F	annual comprehensive cost
C_H	annual construction operation and maintenance cost
C_{EV}^{pd}	annual user waiting time cost
C_{EV}^{hs}	annual user travel time cost
C_p^u	annual distribution network expansion cost
C_{fle}	annual charging station regulation cost caused by distribution network flexibility shortage
C_H^{is}	cost of land use per unit area of node i
S_H	fixed area
C_H^{con}	fixed construction cost
C_H^{ot}	other costs
R_d	an auxiliary variable used for annualization
d	discount rate
y	depreciation period of the charging station
jm	collection of nodes located in residential areas
sy	collection of nodes located in commercial areas
gz	collection of nodes located in working areas
r_l^{lo}	number of slow piles
r_l^{fa}	number of fast piles
$C^{lo.cp}$	unit construction investment cost of slow charging pile
$C^{fa.cp}$	unit construction investment cost of fast charging pile
C_l^{la}	land use cost per unit area
S_p	area required to increase a single charging pile
$C_m^{op.fi}$	annual fixed operation and maintenance cost
$c^{lo.yw}$	annual operation and maintenance cost of slow charging piles
$c^{fa.yw}$	annual operation and maintenance cost
c	number of fast piles
μ	quantity of vehicles completed for the unit time service
λ	quantity of charging requirements per hour to the charging station to receive services
P_0	reciprocal of EV charging time
ρ	service strength of the charging pile
C_{uat}	user's unit time equivalent economic loss
T_{year}	number of days in one year
R_l	number of EVs charging
$T_{l,j}^q$	waiting time
D_{jl}	distance
c^P	unit capacity increase cost
c^{fle}	unit flexibility cost
n_p	number of nodes
$\pi(i)$	set of the first nodes
$\delta(i)$	set of the last nodes

B	set of nodes in the power grid
$P_{ji,t}$	active power
$Q_{ji,t}$	reactive power
$P_{i,t}$	the consumed active power
$Q_{i,t}$	the consumed reactive power
$P_{g,i,t}$	the injected active power
$Q_{EV,i,t}$	reactive load of EV generation
$Q_{c,i,t}$	loads other than EV generation
$Q_{re,i,t}$	renewable generation
$U_{i,t}$	voltages of node i
$U_{j,t}$	voltages of node j
U_N	reference voltage
$U_{\min}$	minimum voltages of each node
$U_{\max}$	maximum voltages of each node
$n_{\min}$	lower limits of the number of EVCSs
$n_{\max}$	upper limits of the number of EVCSs
$r_{l,\min}^{\text{lo}}$	minimum number of slow piles
$r_{l,\max}^{\text{lo}}$	maximum number of slow piles
$r_{l,\min}^{\text{fa}}$	minimum number of fast piles
$r_{l,\max}^{\text{fa}}$	maximum number of fast piles
$p_{l,\max}^{\text{EVS}}$	maximum charging power that the l -th charging station can provide
p_l^{EVS}	power of the l -th station
R_l^{lo}	number of requirements for charging with slow charging piles in the l -th charging station
R_l^{fa}	quantity of charging requirements for charging with fast piles
$T_{\max}$	maximum queue waiting time of users
$D_{\max}$	users' maximum detour distance

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