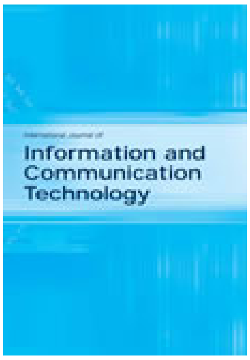


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Electric vehicle charging station planning based on the development of distribution networks and coupled charging demand

Daqing He, Yunuo Chen, Linwei Li, Dunchu Chen, Wenwu Li

Article History:

Received:	13 December 2024
Last revised:	21 January 2025
Accepted:	22 January 2025
Published online:	31 March 2025

Electric vehicle charging station planning based on the development of distribution networks and coupled charging demand

Daqing He*, Yunuo Chen and Linwei Li

China Three Gorges University,
Yichang, Hubei, 443100, China
Email: 19071390633@163.com
Email: 289932588@qq.com
Email: 24495456@qq.com
*Corresponding author

Dunchu Chen and Wenwu Li

Hubei province Key Laboratory of
Cascade Hydropower Station Operation and Control,
Yichang, Hubei, 443100, China
Email: 1375417160@qq.com
Email: liwenwu7508@ctgu.edu.cn

Abstract: Current research on charging station planning overlooks the evolution of power distribution networks and oversimplifies charging demand without considering the traffic characteristics of electric vehicles (EVs), leading to voltage deviations due to high charging loads. This paper proposes a bi-level optimisation model to simulate EV charging demand based on road networks. Charging demand is forecasted through road network simulation, and simplified charging needs are clustered with road weights. The model then optimises the power distribution network topology, as well as the location and capacity of charging stations. The upper level optimises the power network structure, while the lower level optimises the layout and capacity of charging stations. Case studies show that the clustering algorithm based on road weights effectively simplifies the data while retaining the spatiotemporal characteristics of charging demand. The proposed bi-level planning model significantly mitigates voltage deviations caused by high charging loads.

Keywords: charging station planning; distribution network planning; clustering; electric vehicles; EVs; bilevel optimisation; distribution network; article swarm optimisation.

Reference to this paper should be made as follows: He, D., Chen, Y., Li, L., Chen, D. and Li, W. (2025) 'Electric vehicle charging station planning based on the development of distribution networks and coupled charging demand', *Int. J. Information and Communication Technology*, Vol. 26, No. 6, pp.62–97.

Biographical notes: Daqing He is currently pursuing his Masters degree and is a graduate student. His research interests focus on distribution network planning. He is affiliated with the School of Electrical and New Energy, China Three Gorges University.

Yunuo Chen is currently pursuing his Masters degree and is a graduate student. His research interests focus on new energy forecasting. He is affiliated with the School of Electrical and New Energy, China Three Gorges University.

Linwei Li is currently pursuing his Masters degree and is a graduate student. His research interests focus on permanent magnet direct-drive wind power generation. He is affiliated with the School of Electrical and New Energy, China Three Gorges University.

Dunchu Chen is currently pursuing his Masters degree and is a graduate student. His research interests focus on the application of artificial intelligence in the power system. He is affiliated with the School of Electrical and New Energy, China Three Gorges University.

Wenwu Li holds a Doctoral degree and is a Professor. His research interests are in distribution network planning. He is affiliated with the School of Electrical and New Energy, China Three Gorges University.

1 Introduction

Electric vehicles (EVs) serve as both a mode of transportation and a mobile load, influenced by the dual factors of charging station layout and traffic flow information. The uncertainty and spatiotemporal distribution characteristics of their charging demands pose new challenges for the planning of distribution networks and the establishment of charging stations.

The primary steps in charging station planning include the construction of road network models, the forecasting of EV charging demands, the establishment of planning models, and their solutions.

During the planning and design phase of charging infrastructure, the core issue lies in predicting the charging demand for EVs. Typically, this prediction process involves a comprehensive analysis of key factors such as the regional road traffic network, travel patterns of EVs, and user charging behaviours. Accurately and reasonably predicting the charging load of EVs to obtain its spatiotemporal distribution characteristics is crucial for supporting the decision-making process of building and expanding charging infrastructure. It is also a prerequisite step for the site selection planning of charging facilities.

In the initial phase of research, researchers primarily conducted preliminary predictive analysis of the charging load of EVs based on static data. For example, they used historical operational data from charging stations for related studies. With continuous technological advancements and gradually expanding research perspectives, the methods for predicting the charging load of EVs have begun to focus more on dynamically describing the driving and charging behaviours of EVs. Currently, the methods for predicting the charging load of EVs can be mainly divided into the following two categories:

1.1 EV charging load forecasting method based on historical operation data of charging stations

The demand for EV charging is influenced by a variety of factors, including EV travel behaviour, user types, and traffic conditions. Some scholars have conducted research on predicting charging demand based on a large amount of historical operational data from charging stations.

Tian and Zhang (2019) constructed an integrated vehicle-pole platform to collect operational data of EVs and charging data of charging piles, thereby generating a heat map of EV usage. This study aimed to minimise the payback period as the objective function and built a charging station location and capacity model, which was solved using a differential evolution algorithm. Liu et al. (2016) conducted in-depth data mining on the historical data of EV charging stations, analysed the fluctuation characteristics of the sample data, and constructed a charging prediction model based on the combination of freshness function and cross-entropy, aiming to predict the short-term charging load of EVs. Leou et al. (2015) used the actual charging station data statistically collected on-site, described the charging frequency and initial charge level of EVs using Poisson distribution, uniform distribution, and roulette selection methods, and established a charging station load forecasting model based on this. Zhang et al (2022) integrate real ride-hailing trip data through data mining to uncover user travel habits. Zhu et al. (2019) utilised big data and machine learning techniques to evaluate the real-time data of EV charging stations and proposed a data stream-based streaming logistic regression model, which charging station operators can use for optimisation planning.

1.2 Charging demand forecasting method for simulating EV travel characteristics

Zhang et al. (2014) analysed the parking patterns of various types of vehicles and used Monte Carlo simulation techniques to simulate the travel, parking, and charging behaviours of vehicles, thereby predicting the temporal and spatial distribution of vehicle charging loads. Tang and Wang (2016) adopted a graph theory approach, combined with a Markov decision process, to simulate the transfer behaviour of EVs within the road network, in order to predict their charging demand. Xu et al. (2016) based on the theory of travel chains, effectively simulated the travel patterns of EV users, divided the study area into five categories based on land use functions and geographical attributes – residential areas, office areas, tourist areas, commercial areas, and educational areas – and comprehensively considered the traffic flow of each area to complete the prediction of EV charging loads. Song et al. (2020) simulated the driving characteristics of EVs based on the topological structure of the transportation network and the travel data matrix, and on this basis, completed the prediction of the temporal and spatial distribution of charging demand. Li et al. (2019) constructed travel chain models of different complexities based on vehicle travel datasets and used the shortest path algorithm to determine travel routes, in order to predict the distribution of EV charging loads. Zang et al. (2021) proposed a 'time-traffic' road impedance model that accounts for road impedance to describe changes in vehicle positions. Tian et al. (2010) analysed the travel patterns of traditional vehicles and simulated the initial charging time, daily driving mileage, and battery capacity of EVs through probabilistic statistical methods, thereby calculating the total power of charging loads. Luo et al. (2024) employs Monte Carlo sampling to simulate EV charging demands and uses time-of-use clustering and Gaussian mixture models to simplify data samples. Xing et al. (2020a) proposed an EV routing planning and charging navigation strategy based on real-time traffic information, simulating EV driving behaviour through the traffic OD method.

Previous literature has conducted extensive research on the prediction of EV charging demand. However, the predicted demand is overly complex and not particularly beneficial for computational efficiency. Moreover, clustering simplification for charging demand can not only streamline the calculation process but also enhance the accuracy of planning results to improve overall planning benefits. Therefore, as mentioned above, some research teams, such as Luo et al. (2024), have used time-based clustering methods based on road distances in their planning. However, these studies frequently use traditional clustering algorithms that are solely based on the concept of distance, which may not be the most accurate representation of the actual travel costs for EVs as a mode of transportation. It is worth noting that the travel costs for EVs are not only related to the distance travelled but are also significantly affected by actual road conditions, such as traffic congestion and road types. These factors are often overlooked in these simplified models.

In planning the location and capacity of charging stations, it is necessary to consider not only the load-bearing capacity of distribution lines and the interests of charging station investors but also the charging costs for EV users. A rational layout of charging stations can reduce the energy consumption and queuing time for users during their charging trips. Reference Wang et al. (2023), Gao et al. (2022), Pennington et al. (2024), Gutierrez and Ladisch (2024), Rouso et al. (2024), and Ullah et al. (2024) involves EVs in the voltage regulation of distribution networks. Jiang et al (2019) forecast the spatiotemporal distribution of EV charging demands to minimise investment costs for charging stations and charging costs for users. Yan et al. (2021) use neural network algorithms to predict the ownership of EVs and employs an improved PSO algorithm to optimise the location and capacity of charging stations. Tian et al. (2021) evaluate the acceptance capacity of distribution networks for charging station access schemes using an entropy-weighted analytic hierarchy process (AHP) method.

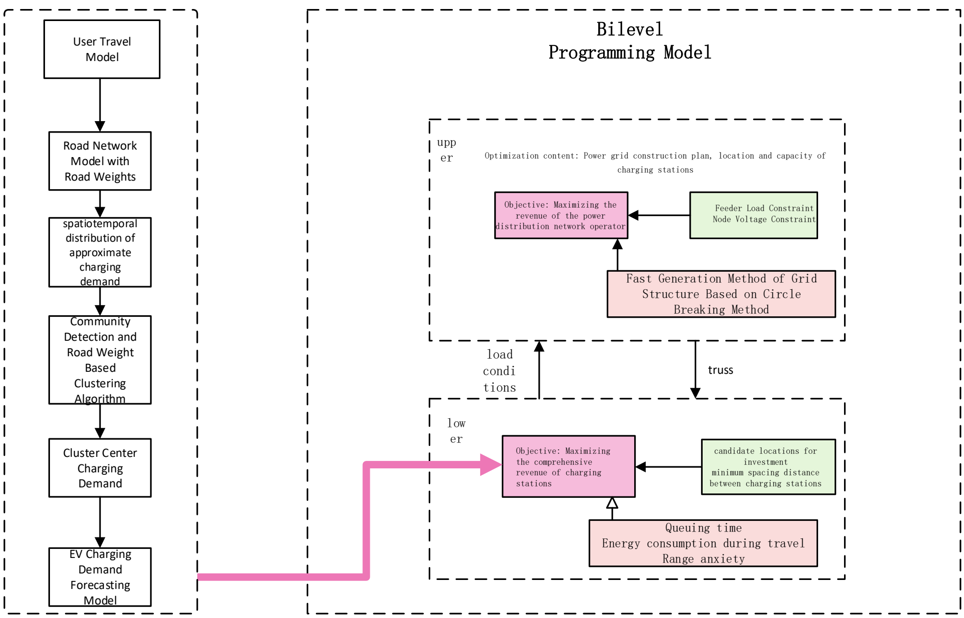
In summary, existing research has studied aspects such as the prediction of charging demands (Yang et al., 2022; Lu et al., 2022; Wang et al., 2022; Kautish et al., 2024; Zhang et al., 2022; Zang et al., 2021) and user charging costs, but there are still the following shortcomings. For the prediction of charging demand, the results are often too complex to calculate, and the methods used to simplify charging demand do not fully reflect the traffic characteristics of EVs; for the planning of charging stations, the coupling relationship between charging demand and distribution networks has not been fully reflected, and there is little consideration of the interaction between charging stations and distribution networks during the planning process. Merely guiding users to charge orderly to mitigate the node voltage deviation caused by the access of a large number of EV charging loads to the distribution network is not a long-term solution. Instead, it leads to the distribution network topology planning being unable to adapt to the randomness of EV user growth and charging demand, and the planning of charging stations is restricted by the fixed distribution network, making it difficult to meet the needs of EV users. This paper proposes a charging station planning method that combines spatiotemporal charging demand with the development of distribution networks to solve the aforementioned problems. The research content is as follows:

1. The generation of the spatiotemporal distribution of EV charging demand begins with the basic classification of EV users. Monte Carlo simulation is used to sample and generate vehicle data and related driving information for each user. A road network model is established that simulates road conditions using road weights, and the travel patterns of different types of EVs are analysed based on trip chain theory. A single EV model is constructed, and the Dijkstra algorithm is used to confirm the movement trajectories of EV users within the road network model. Combining the charging habits of different types of users and confirming their charging times and locations based on the current battery charge level (SOC) of the vehicle to generate a rough spatiotemporal distribution of charging demand. Then, road weights are introduced into a clustering algorithm based on BFS to accurately depict the spatiotemporal distribution of charging demand.
2. A two-layer planning model for the construction of distribution network lines and the location and capacity determination of EV charging stations is established. Taking the IEEE33-node distribution network system as an example, for the grid and EV charging station location and capacity determination, this paper establishes a grid-station two-layer planning model. The upper-layer grid planning aims to maximise the total revenue of the distribution company, which includes the construction, operation and maintenance costs, and revenue from electricity sales. The constraint condition is the voltage deviation of the distribution network nodes, and a fast generation method for the expansion scheme of the distribution network topology structure is optimised using a grid structure based on the breaking circle method. The lower-layer charging station planning aims to maximise the comprehensive revenue of the charging station (comprehensive revenue: construction cost, operation and maintenance cost, user cost, network loss cost, and revenue from electricity sales). The constraint conditions are the locations for investment and construction selected in the clustering process, the minimum spacing between charging stations, and the voltage deviation of the distribution network nodes. The actual investment location and construction capacity of the charging stations are optimised based on the spatiotemporal distribution of charging demand at the clustering centres. During the iterative solution process of the model, the lower layer plans the location and capacity of the charging station based on the distribution network line structure given by the upper layer, according to the spatiotemporal distribution of charging demand. The upper layer then superimposes the charging load given by the lower layer onto the conventional load of the distribution network to confirm the optimal grid construction scheme under the current load conditions. After iteration, the model will provide the optimal grid construction scheme and the capacity and investment address of the charging stations. Based on this planning result, the Newton-Raphson method is used to solve the distribution network node deviation. Compared with the results of disorderly investment in charging stations, it is shown that the charging station access scheme after planning has less impact on the distribution network than random access, which is more conducive to the safe and stable operation of the distribution network.

2 Overall technical framework

This paper proposes a planning approach for EV charging stations based on the development of distribution networks and coupled charging demands. By employing Monte Carlo sampling, road network simulation, the incorporation of road weights, and utilising breadth-first search (BFS) for community detection, we cluster and generate charging demands that align with the mobility characteristics of EVs. Subsequently, a bi-level optimisation model is constructed, with the upper level optimising the topology of the distribution network and the lower level optimising the siting and capacity configuration of charging stations. This ensures that the planning scheme can take into account both the stability of the distribution network and the charging demands of EV users, as depicted in Figure 1 of the technical framework.

Figure 1 Overall technical framework for charging station planning (see online version for colours)



As depicted in the figure, for charging demands, this paper employs Monte Carlo sampling to obtain a substantial amount of basic information on EV users; for the road network model, the concept of road weights is introduced to reflect traffic conditions on road segments; the Dijkstra algorithm is utilised to determine the travel paths of each EV user within the road network based on start and end nodes, combining the sampled EV-related data to calculate the energy consumption of users' travel, and obtaining the spatiotemporal distribution of charging demands for all system EV users based on the charging logic of different types of vehicle users.

Based on a clustering algorithm that integrates BFS and cluster evaluation (Davies-Bouldin Index (DBI)), road weights are used to cluster the charging load at different road nodes during various time periods to their corresponding cluster centre nodes, ensuring that the influence range of each cluster centre does not overlap or intersect by utilising BFS for community detection. The clustered charging demands can be referenced for lower-level charging station planning, with the assumption that EV users depart from the cluster centres to charge at the nearest charging stations, and that cluster centres can also serve as potential locations for charging stations.

Regarding the framework and EV charging station siting and capacity determination, this paper establishes a bi-level planning model for network and station. The upper-level network planning aims to maximise the total revenue of the distribution network operator by optimising the expansion plan of the distribution network topology. The lower-level charging station planning aims to maximise the comprehensive revenue of the charging stations, optimising the actual location and construction capacity of charging stations based on the spatiotemporal distribution of charging demands at cluster centres.

3 Road network model and EV charging demand forecast

EVs, as a mode of transportation, are influenced by the road network structure and real-time traffic conditions in their navigation and travel. Therefore, when predicting EV charging demands, it is necessary to establish a road network model to simulate the driving behaviour of EVs and accurately forecast users' charging demands based on energy consumption models and charging habits.

3.1 Road network-power grid coupling model

The road network refers to the physical structure of roads and transportation systems within a city or region, primarily used for vehicle passage and navigation. The travel paths of EV users are influenced by the structure of the road network. Regarding the distribution network, EVs are a relatively special type of load; they possess both the characteristics of a mode of transportation and a mobile load. Their charging behaviour and demands can impact the load distribution and nodal voltage of the distribution network. Therefore, when studying the charging load of EVs, the nodes of the distribution network are mapped directly into the road network as road network nodes, establishing a road network-distribution network coupling model to map the spatiotemporal distribution of EV charging load in the road network into the nodes of the distribution network.

3.1.1 Road network model

The road network model employs graph-theoretic analysis for modelling (Cui, 2013), and the topological mathematical model of the road network is described as equation (1):

$$\begin{cases} G = (V, E, K, W) \\ V = \left\{ v_i \ / \ i = 1, 2, 3, \ldots, n \right\} \\ E = \left\{ v_{ij} \ / \ v_{ij} \in V, v_i \in V, v_j \in V, i \neq j \right\} \\ K = \{ k \ / \ k = 1, 2, 3, \ldots, 24 \} \\ W = \left\{ w_{ij}^k \ / \ v_{ij} \in E, k \in K \right\} \end{cases} \tag{1}$$

In the equation, G represents the overall road network model; v denotes the set of all nodes in G; E signifies the set of all road segments; W is the collection of road segment weights; K indicates the set of time periods divided.

In further discussion, the segment weight W is defined as a quantitative indicator of road travel costs, and its quantitative research can be based on parameters such as segment length, travel speed, travel time, and travel expenses. In view of the time-varying dynamic characteristics of the urban internal road network and the complexity of multiple intersections, this paper adopts a time-flow model for modelling and analysis. This study focuses on the distribution of EV charging loads within urban roads. In the urban road network, many intersection nodes are usually controlled by traffic lights, and vehicle travel is not only affected by the impedance of the road segment but also encounters time delays at the intersection nodes. Therefore, the road resistance in the urban road can be expressed as:

$$W_{ij}^{K} = Cv_i + Rv_{ij} \tag{2}$$

In the equation: C_{vi} represents the node impedance model; R_{vi} represents the road segment impedance model.

According to the classification criteria for urban traffic conditions, the saturation S is adopted as an evaluation indicator: unobstructed ($0 < S < 0.6$), slow-moving ($0.6 < S \le 0.8$), congested ($0.8 < S \le 1.0$), and severely congested ($1.0 < S \le 2.0$). Given the differences in the capacity of road intersections and road sections, models for road section impedance and node impedance under different saturation levels can be constructed accordingly.

The road segment impedance model

$$Rv_{ij} = \begin{cases} R^1 v_{ij} : t_0\,(1+\alpha(S)\beta), & (0 < S \le 1.0) \\ R^2 v_{ij} : t_0\left(1+\alpha(2\text{-}S)^{\beta}\right), & (1.0 \le S \le 2.0) \end{cases} \tag{3}$$

In the equation: saturation $S = \dfrac{Q}{C}$ represents the degree of congestion. The degree of saturation depends on the actual vehicle flow and the maximum allowable vehicle flow on the road. The higher the travel speed of vehicles on the road section, the lower the saturation value, and vice versa. Q is the traffic flow on the road segment, C is the capacity of the road segment; t_0 is the travel time at zero flow; α, β are impedance influence factors.

Node impedance model

$$Cv_i = \begin{cases} C^1 v_i : \dfrac{9}{10}\left[\dfrac{c(1-\gamma)^2}{2(1-\gamma S)} + \dfrac{S^2}{2q(1-S)}\right], & (0 < S < 1.0) \\ C^2 v_i : \dfrac{c(1-\gamma)^2}{2(1-\gamma S)} + \dfrac{1.5(S-0.6)}{1\text{-}S}, & (S > 0.6) \end{cases} \tag{4}$$

In the equation: c represent 'signal cycle' or 'signal light cycle'; γrepresent green signal ratio; q represent vehicle arrival rate on the road segment.

Combining equation (3) with equation (4) yields the complete road segment weight model:

$$w_{ij}^k = \begin{cases} R^1 v_{ij} + C^1 v_i, & 0 < S \le 0.6 \\ R^1 v_{ij} + C^2 v_i, & 0.6 < S \le 0.8 \\ R^2 v_{ij} + C^1 v_i, & 0.8 < S \le 1.0 \\ R^2 v_{ij} + C^2 v_i, & 1.0 < S \le 2.0 \end{cases} \tag{5}$$

3.2 Single electric vehicle charging demand forecasting method

EVs can be categorised into three major classes based on their usage: private cars, taxis, and public vehicles. Building upon this classification, to analyse the full-day travel distribution characteristics of EVs, an origin-destination (OD) matrix is employed to delineate their starting and destination points (Yan and Luo, 2022). Monte Carlo sampling is utilised to assign travel origin and destination locations, as well as departure and return times, for each EV. The Dijkstra algorithm is then applied for route guidance, and ultimately, by integrating the energy consumption models and corresponding charging habits of various types of EV users, the travel mileage of each EV is quantified into charging demands at corresponding nodes.

3.2.1 EV Battery parameter model

Based on the classification statistics of EVs, the battery capacity of different types of EVs is distributed according to the gamma distribution (Zhang et al., 2024) as shown in equation (6).

$$C_{bat} = \frac{1}{\beta_t^{\alpha_t} \Gamma(\alpha_t)} C_p^t(i)^{\alpha_t - 1} e^{-\frac{C_p^t(i)}{\beta_t}} \tag{6}$$

In the equation: α_t and β_t are the parameters of the gamma distribution, $\Gamma(\alpha_t)$ is the normalisation constant of the gamma distribution, and the $C_p^t(i)$, parameters for the battery capacity of the three types of EVs are specified. Based on common EV data (Luo et al., 2024), the specific parameters are detailed in Appendix Table A1.

3.2.2 Electric vehicle battery parameter model

According to the 'urban road engineering design specifications,' a model for the EV energy consumption per unit distance on urban roads is established, as follows:

$$E_m = 1.5 \frac{w_{ij}^k(t)}{V_{car}} + \left(0.21 - 0.001 * w_{ij}^k\right) * w_{ij}^k \tag{7}$$

In the equation: V_{car} represents the average travel speed of the road segment, which is obtained through Monte Carlo sampling.

3.2.3 EV charging demand forecasting process

At each distribution network node a vehicle reaches, the remaining state of charge (SOC) of the vehicle is calculated:

$$T_{SOC_1} = T_{SOC_0} - \frac{E_{m1}}{0.9C_{bat}} \tag{8}$$

$$T_{SOC_2} = T_{SOC_1} - \frac{E_{m2}}{0.9C_{bat}} \tag{9}$$

In the equation: T_{SOC_0} represents the initial SOC, T_{SOC_1} and T_{SOC_2} represent the current and the estimated SOC upon arrival at the next node; C_{bat} denotes the battery capacity; E_{m1} signifies the cumulative energy consumption generated by all the road segments travelled by the vehicle, E_{m2} indicates the estimated energy consumption to the next distribution network node private cars $T_{SOC_2} < 0$, then slow charging is required, while for public and taxi vehicles $T_{SOC_2} < 0.5$ fast charging is needed.

Fast charging:

$$T_{fast} = \left(0.5 - T_{SOC_0}\right)\frac{C_{bat}}{P_{fast}} \tag{10}$$

Slow charging:

$$T_{fast} = \left(0.5 - T_{SOC_1}\right)\frac{C_{bat}}{P_{slow}} \tag{11}$$

According to the QC/T 841-2010 standard 'EV conductive charging interface,' the destination slow charging power P_{slow} is set at 12kW, and the fast charging power P_{fast} at the charging station is set at 60kW.

Based on the user's charging time, the start and end time periods for each user's charging within the distribution network are obtained. The calculation formula is as follows:

Private car charging start t_{start} and end times t_{end}:

$$\begin{cases} t_{floor} = \dfrac{L_D}{0.9V_{car}} \\ t_{start} = t_{floor} \\ t_{end} = t_{floor} + T_{slow} \end{cases} \tag{12}$$

In the equation: In the equation, represents the average speed of the vehicle V_{car} represents the cumulative mileage of vehicles at the current node, and L_D represents the cumulative time of vehicle travel at the current node.

For public and taxi vehicles, the start and end times of charging are as follows:

$$\begin{cases} t_{floor} = \dfrac{L_D}{0.9V_{car}} \\ t_{start} = t_{floor} \\ t_{end} = t_{floor} + T_{fast} \end{cases} \tag{13}$$

Based on the user's charging time, the charging load for each user within the distribution network is obtained, $P_{i,k}$ that is, the charging demand of the user at node k at time moment i. The calculation formula is as follows:

Private cars:

$$P_{i,k} = T_{slow} * P_{slow} \tag{14}$$

Public and taxi vehicles:

$$P_{i,k} = T_{fast} * P_{fast} \tag{15}$$

In the equation, k represents the moment determined by the corresponding start t_{start} and end times t_{end} of charging.

The charging demand of each EV during the same period is accumulated to the corresponding road network node to obtain the spatiotemporal distribution of 24-hour EV charging demand.

3.3 Clustering algorithm with introduced road weights

Given the large number of EVs and the complexity of the transportation network structure, directly applying each EV's demand data to subsequent charging station planning problems would significantly increase the complexity of model solving. This paper proposes the introduction of road network weights during the clustering process, employing an improved clustering algorithm based on BFS and central node updates. The main steps of the algorithm are as follows:

3.3.1 Cluster main steps

The process is illustrated in Figure 2:

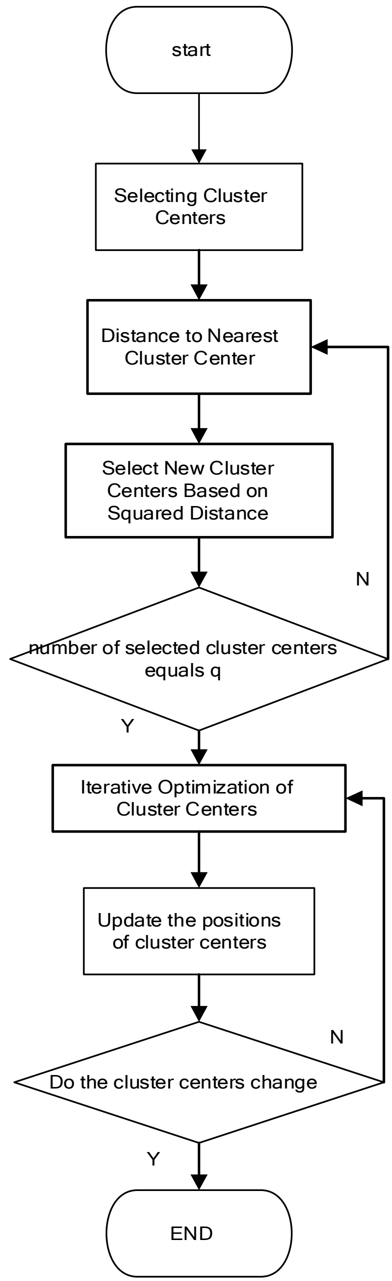
The specific details are as follows:

1 Initialisation: select qq traffic network nodes as initial cluster centres. Utilise the BFS method, starting from the chosen initial centres to expand, ensuring that each initial cluster centre effectively covers the surrounding nodes.

2 Node allocation: calculate the shortest path distance from each node where charging demand data is located to the qq cluster centres, and assign it to the category of the nearest cluster centre.

3 Iterative optimisation: in each iteration, readjust the allocation of nodes based on the road weights to all cluster centres. For each cluster centre, calculate the total road weight of the covered nodes, and select the node with the minimum weight as the new cluster centre.

Figure 2 Clustering flowchart



3.3.2 Davies-Bouldin index

The DBI is a metric for assessing the quality of clustering. It measures the effectiveness of clustering by calculating the compactness within each cluster and the separation between different clusters.

The smaller the DBI value, the better the clustering effect (Liu et al., 2023).
This index is defined as:

$$I_{DBI} = \frac{1}{q}\sum_{\substack{i=1 \\ j\neq i}}^{q} \max\left(\frac{c_i + c_j}{D_{i,j}}\right) \tag{16}$$

In the equation: q represents the number of cluster centres, c_i and c_j are the average distances from node i and node j to their respective cluster centres, and $D_{i,j}$ is the road network weight from cluster centre i to cluster centre j.

4 Network-station bi-level planning model

To address the issue of distribution network topology planning not being adaptable to the randomness of charging demands and to meet the EV charging demands generated by road network simulation and community clustering, this paper establishes a bi-level planning model. The upper level is the distribution network topology planning layer, which optimises the construction plan of the network structure with the goal of maximising the benefits for the distribution company; the lower level aims to maximise the benefits of charging stations by optimising the construction location and capacity.

4.1 Upper model

4.1.1 Objective function

When constructing the network structure, it is necessary to consider the comprehensive benefits of the distribution network constructor. Therefore, the total benefits for the distribution company are proposed, which are composed of operational and maintenance costs, expansion costs, and the transaction benefits of users:

$$\max F = -C_{inv} - C_{main} + C_{trans} \tag{17}$$

In the equation, C_{inv} represents the equivalent annual cost of distribution network expansion, which includes the construction of new lines and interconnection lines; C_{main} denotes the operational and maintenance costs of the distribution network; C_{trans} sales signifies the revenue from electricity sales of the distribution network.

Distribution network expansion

$$C_{inv} = \frac{(d+1)^m}{d(d+1)^m - 1}\sum_{i,j} x_{ij} L_{ij} C_{line} \tag{18}$$

In the equation, *dd* represents the discount rate for the construction of the network structure; *mm* is the service life of the lines; i and j are nodes within the distribution network; x_{ij} is a binary variable indicating whether the line between nodes i and j is constructed or not; L_{ij} is the length of line ij; and C_{line} are the construction cost parameters per unit length of line *ijij*, as shown in Appendix Table A2

operational and maintenance costs:

$$C_{main} = \mu C_{inv} \tag{19}$$

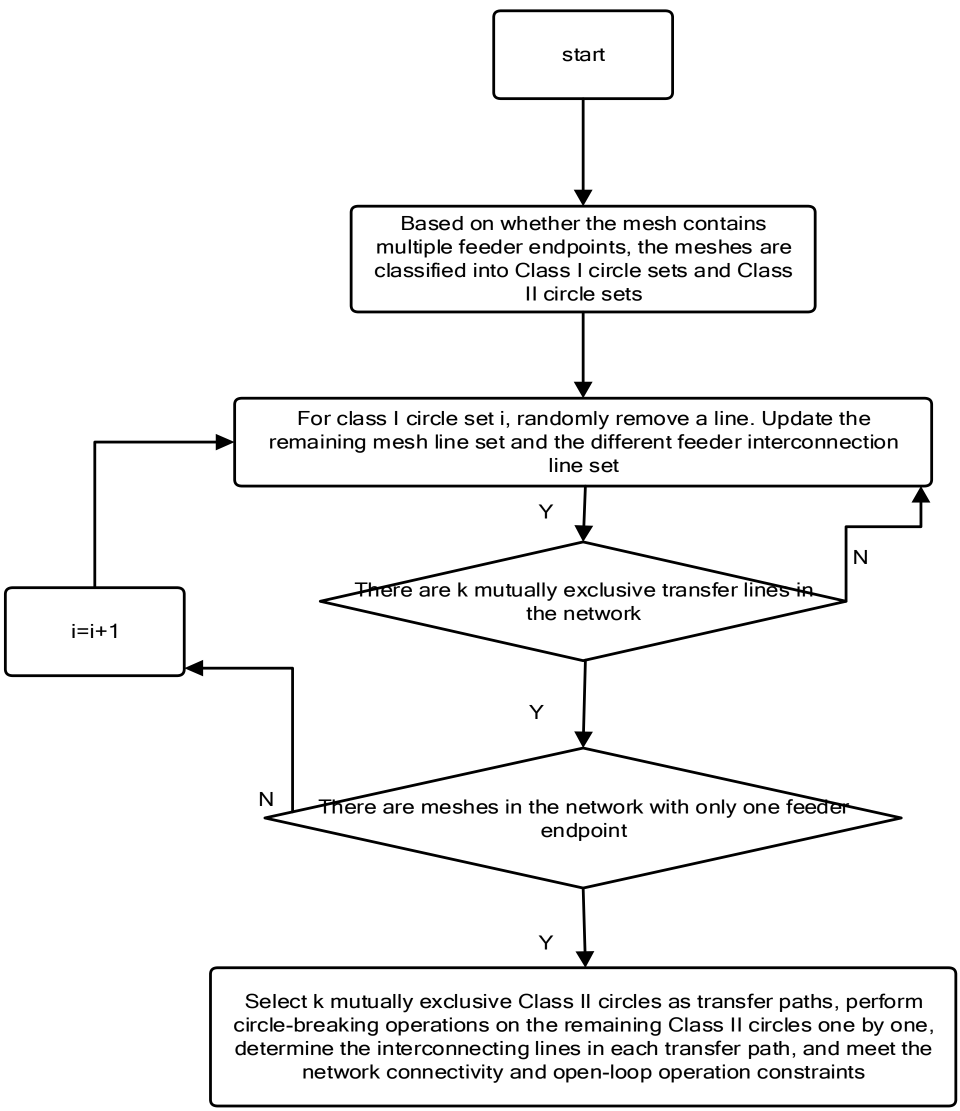
In the equation, μ represents the proportion of operation and maintenance costs.

Distribution network electricity sales revenue

$$C_{trans} = \sum_{t=1}^{24} \sum_{i=1}^{N_{node}} C_{sold,t} P_{i,t} \tag{20}$$

In the equation, N_{node} represents the number of nodes; $C_{sold,t}$ is the electricity selling price at time t; $P_{i,t}$ is the charging power at node i at time t.

Figure 3 Loop-breaking method



4.1.2 Constraints

Node voltage constraints

$$U_{b\min} \le U_b \le U_{b\max} \tag{21}$$

In the equation, U_b represents the per-unit value of the node voltage; U_{bmin} is the lower limit of the per-unit node voltage; U_{bmax} is the upper limit of the per-unit node voltage.

4.1.3 Fast generation method for network topology structure

During the iterative process of generating the network structure, the loop-breaking method (Lu et al., 2022) is used to improve the solution speed, and the steps are in Figure 3.

4.2 Lower model

4.2.1 Objective function

When planning the location and capacity of EV charging stations, the total benefits of the charging stations, which are composed of construction costs, operational and maintenance costs, user costs, network loss costs, and electricity sales revenue, are considered. The planning of EV charging stations is constructed to maximise the total benefits:

$$\max F = -C_I - C_{EV} - C_L + C_B \tag{22}$$

In the equation, C_I represents the average annual investment cost of the k^{th} charging station; C_{EV} and C_B are the annual user cost and the annual electricity sales revenue of the charging station, respectively; C_L is the annual network loss cost of the charging station. For related parameters, see Appendix Table A3.

Average annual investment cost:

$$C_I = \sum_{i\in\varphi}\sum_{k=1}^{N_C}\left(C_{J,i,K} + C_{M,i,K}\right) \tag{23}$$

$$C_{J,i,K} = \frac{r_0\left(r_0+1\right)^{n_0}}{r_0\left(r_0+1\right)^{n_0\text{-}1}}\left(N_{ch,i,K}c_{ch} + A_{i,k}C_{f,i,K} + C_{o,i,K}\right)C_{M,i,K} = \beta_k C_{J,i,K} \tag{24}$$

N_c is the total number of charging stations to be constructed φ is the set of nodes where charging station candidates are located; $C_{J,i,k}$, $C_{M,i,K}$ and $C_{o,i,k}$ are the construction cost, operational cost, and other costs at node ii for the k^{th} charging station, respectively; r_0 is the discount rate; n_0 is the operational life of the charging station; C_{ch} is the unit price of a charging pile; $N_{ch,iK}$, $A_{i,k}$, $C_{fi,K}$ and β_k are the number of charging piles, the area occupied by a single charging pile, the rental cost per unit area, and the proportion of operational and maintenance costs to construction costs at node ii for the k^{th} charging station, respectively. See Appendix Table A3 for related parameters.

Annual user cost:

$$C_{EV} = 365C_j \tag{25}$$

In the equation: C_j daily user cost.

The daily user cost, which is composed of energy consumption costs during travel, travel time costs, and queuing time costs:

$$C_j = \min \sum_{k=1}^{N_c} \left(\sum_{t=1}^{24} c_{ev,t,k} \right) \tag{26}$$

$$c_{ev,t,k} = \sum_{n=1}^{N_{i,c}} \left(c_t t_{n,k,d} + c_{n,k,e} P_{b,t} + c_t t_{n,k,w} \right) \tag{27}$$

In the equation: $C_{ev,t,k}$, $N_{i,c}$ represent the user cost and the number of charging demand clusters heading to the k^{th} charging station during time period t, respectively; $t_{n,k,d}$, $t_{n,k,w}$ represent the average travel time and the average waiting time for charging from the n^{th} cluster centre to the k^{th} charging station, with the waiting time being determined by subsequent formulas; c_t and $c_{n,ke}$ represent the unit time cost for charging users and the average energy consumption during travel from the n^{th} cluster centre to the k^{th} charging station, respectively

Charging station annual network loss cost:

$$C_L = 365 P_c \sum_{i=1}^{24} P_{L,i} \tag{28}$$

In the equation: $P_{L,i}$ represents the network loss during period i, and P_c c is the cost coefficient

$$P_{L,i} = \sum_{m \neq l}^{N_{node}} \left| I_{ml} \right|^2 R_{ml} \tag{29}$$

In the equation: I_{m1} denotes the absolute value of the branch current between nodes m and l; represents the branch resistance between nodes m and l.

Charging station annual electricity sales revenue:

$$C_B = \left(365 \sum_{t=1}^{24} P_{b,t} P_{i,t} \right) \tag{30}$$

$P_{b,t}$ represents the unit electricity selling price at the charging station during period t, $P_{i,t}$ is the charging power at node ii during period t.

If the arrival process of vehicles at various charging stations follows a Poisson distribution, according to queue theory (Xing et al., 2020b; Ratnaweera et al., 2004), the average waiting time T_w in the system is:

$$T_w = \frac{\left(N_{ch,k} \rho \right)^{N_{ch,k}} \rho}{N_{ch,k}!(1-\rho)^2 \varepsilon} P_0 \tag{31}$$

$$P_0 = \left[\sum_{n=0}^{N_{ch,k}-1} \frac{1}{n!} \left(\frac{\varepsilon}{\mu} \right)^n + \frac{1}{N_{ch,k}!(1-\rho)} \left(\frac{\varepsilon}{\mu} \right)^{N_{ch,k}} \right]^{-1} \tag{32}$$

$$\rho = \frac{\varepsilon}{N_{ch,k}\mu} \tag{33}$$

$N_{ch,k}$ represents the number of charging machines in the charging station; ε is the average charging time for a single charging pile, μ is the average number of users arriving per unit of time, which is the reciprocal of the EV charging duration; ρ is the utilisation rate of the charging machines ($\rho < 1$).

4.2.2 Constraints

Distance constraints

$$u_s \geq u_{\min} \tag{34}$$

In the equation, the distance between any two charging stations is greater than or equal to the minimum distance limit

Charging pile quantity constraints

$$\sum_{k=1}^{N_c} N_{ch,k} P_{ch} \geq E_{\max} \tag{35}$$

P_{ch} represents the charging power of the charging pile; E_{max} is the maximum value of the charging demand from all clustering centres. This constraint sets the minimum number of charging piles to be constructed.

Charging station construction node constraints:

$$\sum_{c=1}^{N_a} a_c \geq N_c \; a_c \in A_{alt} \tag{36}$$

a_c is a binary variable that takes the value of 1 if a charging station is constructed at node cc, and 0 otherwise; A_{alt} and N_a represent the set of potential charging station locations and the number of potential locations, respectively.

Node voltage constraints:

$$U_{b\min} \leq U_b \leq U_{b\max} \tag{37}$$

U_b represents the per-unit value of the node voltage; U_{bmin} is the lower limit of the per-unit node voltage; Ub_{max} is the upper limit of the per-unit node voltage (Zhao and Yang, 2024).

5 Planning model solution algorithm

Particle swarm optimisation (PSO) is a global optimisation algorithm inspired by the foraging behaviour of bird flocks. It gradually approaches the optimal solution of a problem through collaboration and information sharing among individual particles. PSO has the advantages of simplicity and high computational efficiency, and thus has been widely applied in fields such as nonlinear optimisation and distributed system design. However, traditional PSO algorithms have revealed some issues in practical applications, such as being prone to getting stuck in local optima in complex, multimodal search spaces, leading to insufficient global search performance. This is especially evident when the particle swarm tends to converge towards the end of optimisation, where search efficiency significantly decreases. To address this, this paper employs a probabilistic mutation method based on single-dimensional search quantities to improve PSO (MPSO). By introducing a dynamic mutation mechanism, probabilistic positional adjustments are made to certain dimensions of particles during the optimisation process, thereby enhancing the algorithm's global search capability and convergence speed. Unlike traditional PSO, MPSO improves the ability of particles to escape local optima through moderate disturbances near local optimum points, while also making the search process more flexible and diverse.

5.1 Principles of algorithms

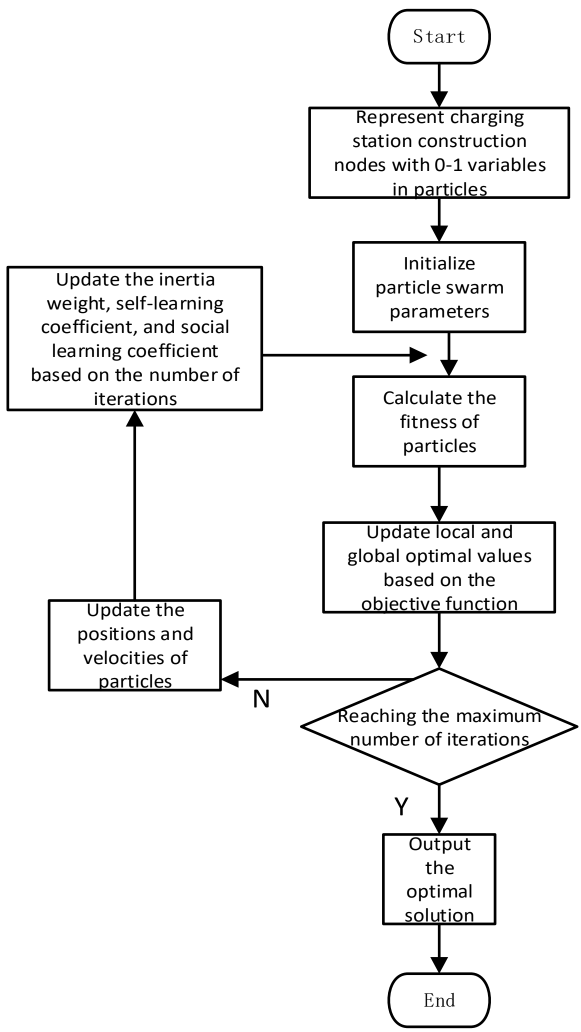
The improvement focus of MPSO lies in the dynamic variation operation of particles. The core idea is based on the statistics of historical search volume on a single dimension, to probabilistically vary dimensions with higher search concentration, allowing particles to explore areas that have not been fully accessed. First, each particle's search space is divided into several intervals by dimension, with each interval representing an independent search subspace. As particles iteratively update, the algorithm statistically tracks the historical access volume of each interval in real-time, serving as a basis for judging the degree of search in that area. When a specific interval of a dimension is frequently accessed, it indicates that the search in that interval is becoming overly concentrated, which could lead the algorithm to get stuck in local optima. To avoid this issue, the algorithm triggers a probabilistic variation mechanism in that interval, resetting the particle's position to a less searched interval for further exploration. The probability of variation is inversely proportional to the historical access volume of the target interval; the lower the access volume, the higher the probability of the particle jumping into it. This design ensures that particles can dynamically and evenly cover the entire search space.

During this process, the overall position update of particles still follows the inertia weight and acceleration term formulas of traditional PSO. However, the introduction of the variation mechanism interferes with the position on individual dimensions of particles. The position of the varied particles is no longer limited by local optima but probabilistically jumps into new areas based on the historical access distribution. Such operations not only increase the randomness of the search but also effectively break the premature convergence problem caused by particle clustering. Through this dynamic variation mechanism, MPSO achieves full exploration of the search space while maintaining a high ability to discover global optimal solutions.

5.2 Advantages of the algorithm

The improved MPSO algorithm has shown significant improvements in performance and applicability compared to traditional PSO. Firstly, MPSO significantly enhances the diversity of particles by introducing a probabilistic mutation mechanism. In traditional PSO, the position update of particles usually relies on the current global best solution and individual historical best solutions. This mechanism can quickly approach the optimal area in the early stages of search, but in the later stages of optimisation, it may fall into local optima due to the excessive concentration of particles around the global best point. MPSO, on the other hand, dynamically adjusts the positions of particles, increasing attention to less explored areas, thus avoiding premature convergence of the particle swarm.

Figure 4 Improved particle swarm optimisation



Secondly, MPSO performs outstandingly in terms of optimisation efficiency. By triggering mutations in high-frequency search intervals, MPSO reduces the number of ineffective searches, allowing the algorithm to find the global optimal solution in a shorter time. Moreover, since the goal of probabilistic mutation is to improve the global exploration ability of the particle swarm, MPSO is particularly suitable for high-dimensional nonlinear optimisation problems and has shown strong adaptability in the optimisation of complex multimodal functions. In addition, while improving global performance, MPSO retains the simplicity and ease of implementation of traditional PSO algorithms. The introduction of the dynamic mutation mechanism does not significantly increase computational complexity, and its framework remains simple and flexible, making it easy to apply in various practical scenarios. Therefore, this paper employs an improved PSO algorithm (Lu et al., 2009) to solve the EV charging station planning model established. The process is illustrated in Figure 4.

6 Case study analysis

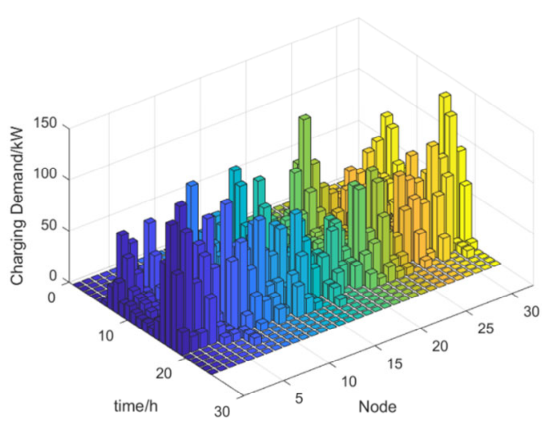
Based on the EV path planning experiment, this paper predicts the spatiotemporal distribution of EV charging demand and its impact on the distribution network through a specific example. The IEEE-33 distribution network model is selected in this paper and coupled with the road network model to form an interactive model. MATLAB code is used to program the road network topology and road weights, and the planning scheme is solved to verify the effectiveness of the bi-level planning model proposed in this paper. The road network topology diagram, specific data of the distribution network, EV parameters, and charging station parameters are shown in Appendix.

6.1 Electric vehicle charging demand forecasting results

6.1.1 Electric vehicle charging demand forecasting results

A total of 1,000 EVs are planned to be put into operation, and the charging demand at each node for each period of 24 hours is shown in Figure 5.

Figure 5 Time-space distribution of charging demand within 24 hours (see online version for colours)

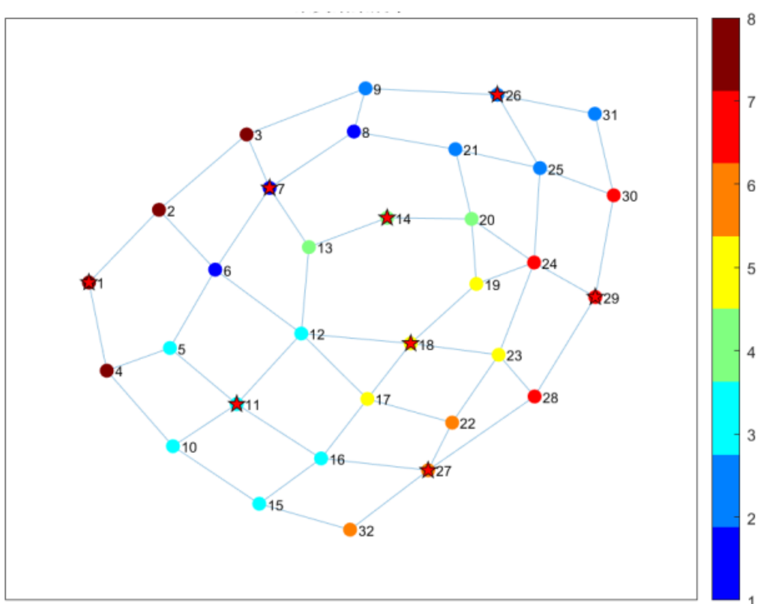


As shown in the diagram, it is clear that the charging demand for EVs exhibits a 'double peak' pattern over the temporal dimension. Specifically, this pattern manifests as two distinct peak periods, one in the morning and the other from evening to night. In terms of spatial distribution, the charging demand also shows regular characteristics. To be precise, between 8:00 AM and 10:00 AM, the charging demand is mainly concentrated near the nodes 9, 15, and 22; whereas during the afternoon period from 17:00 to 20:00, the charging demand shifts to the nodes 2, 5, 15, and 32, and the demand is generally higher. The occurrence of this phenomenon can be attributed to private car users who, after completing their morning commutes, tend to charge their vehicles at their destinations for use the next day. The evening to night charging peak is influenced by a combination of public and private vehicles, as people finish work and start returning to their starting points during this time, resulting in higher charging demand in these areas. It is evident that there are significant differences in the geographical distribution of EV charging demand across different time periods. Therefore, it is particularly crucial to study and predict EV charging demand by incorporating road network analysis. This approach aids in the rational planning of charging infrastructure layout to meet the charging needs of different areas at various times, thereby enhancing the efficiency and convenience of the charging network.

6.1.2 Clustering results

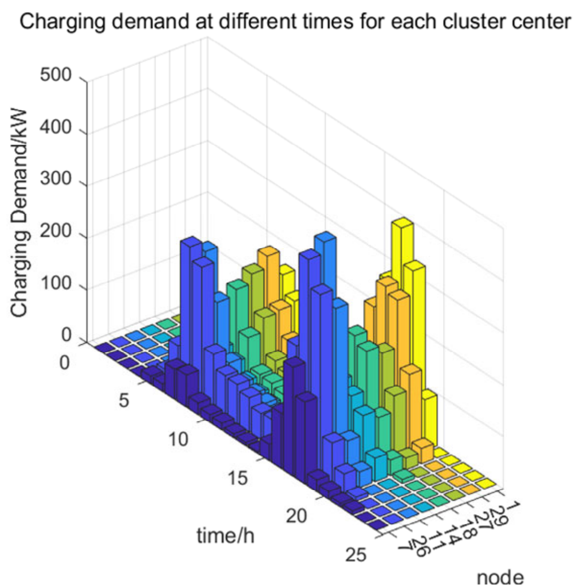
The optimal clustering results, derived through iteration with reference to the DBI parameter, are shown in the following Figure 6:

Figure 6 After clustering the charging needs, the cluster centres and their influence ranges are reflected in the road network (see online version for colours)



As shown in the Figure 6, the asterisks represent the cluster centres corresponding to the distribution network node numbers and the positions of the road network nodes. A total of eight cluster centres were generated in the figure, each represented by a different colour to show their influence areas. Observing the influence areas, it can be seen that Cluster Centre 11, located on the west side, covers the widest area, reaching 6 nodes. This is because this area is set as the starting point for most private cars, belonging to a residential area where the roads are generally clear and the road impedance is generally low, resulting in less user travel loss. The central and eastern parts of the road network model have more cluster centres, and most of the covered areas are smaller. This is due to the road network model simulating congested traffic conditions, making it difficult for users to travel in this area, and the cost of going to charging stations is higher. The 24-hour charging demand for each cluster centre node is shown in Figure 7:

Figure 7 The time-space distribution of charging demand at each cluster centre after 24 hours of clustering (see online version for colours)



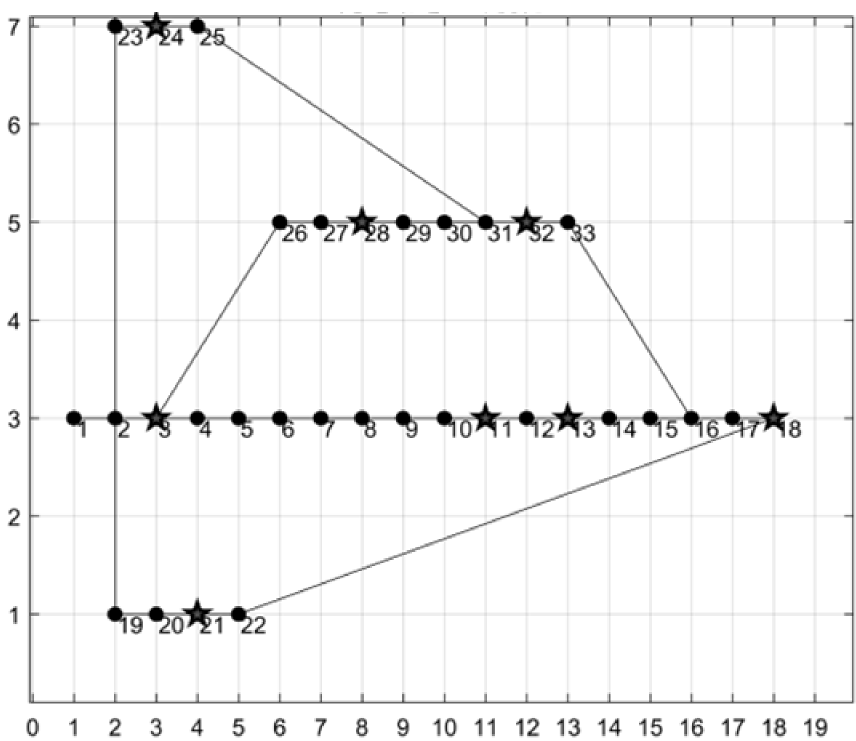
As shown in the Figure 7, the charging demand after clustering has been greatly simplified compared to before clustering, and the number of cluster centres and the corresponding charging demand can serve as a reference in the planning process of EV charging stations. Therefore, in the subsequent iterations of the bi-level planning model, the initial iteration will propose the deployment of 8 charging stations, and the initial locations will be set at the nodes where the cluster centres are located.

6.2 Charging station and network planning results

The planning scheme for lines and charging stations derived from MATLAB code programming is shown in Figure 8:

As shown in Figure 8, the distribution network topology, combined with the site selection and capacity planning for charging stations, not only meets the needs of the distribution network under normal load conditions but also successfully addresses the spatial and temporal distribution of EV charging demands through the implementation of a two-layer optimisation strategy. The study spans a time frame of 20 years, during which the upper-level planning objective function achieved an optimal result with a value of 2.43 million Yuan. In scenarios with a smaller number of charging stations, although the construction and operational costs are relatively low, EV users have to travel longer distances to reach the charging stations, which not only increases their travel time but may also lead to longer waiting times at the stations, thus making the total charging cost relatively high. However, as the number of charging stations gradually increases, although the construction and operational costs will rise, the travel distance and waiting time for EV users to reach the charging stations will decrease accordingly, which helps to reduce the users' charging costs. Based on the planning model we proposed and the number of cluster centres shown in Figure 6, the most suitable number of EV charging stations to invest in and build within this area is determined to be 8. Such planning enables the lower-level planning objective function to achieve an optimal result, with a value of 3.54 million Yuan. Specific details on the capacity investment can be referenced in Table A6 in the appendix.

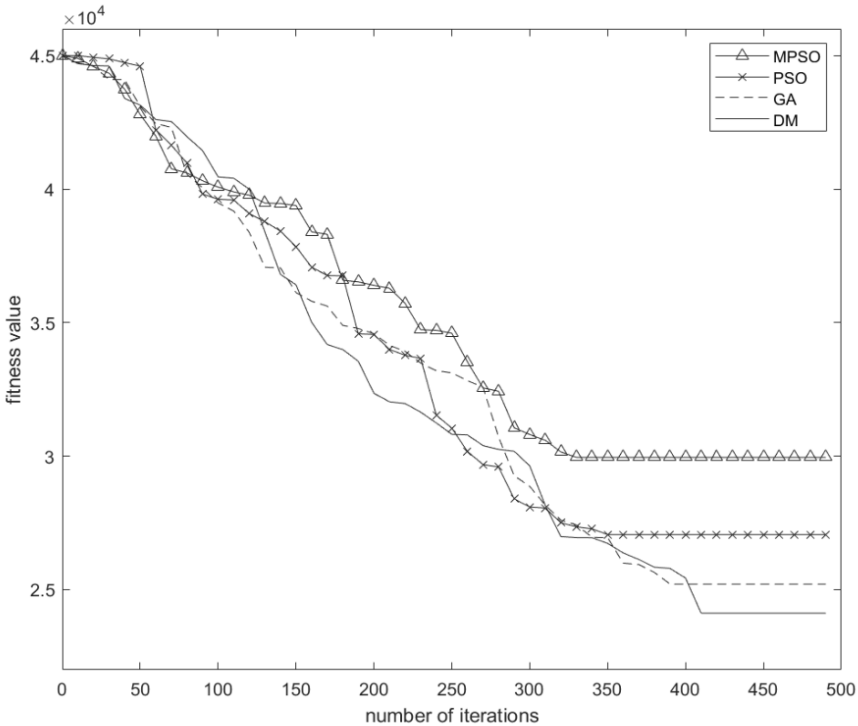
Figure 8 Distribution network lines and charging station planning map



6.3 Comparative analysis of algorithmic calculation efficiency

Case analysis indicates that MPSO, compared to traditional PSO and other optimisation algorithms, can better balance the interests between charging station operators and users, further verifying its application value in practical engineering problems. Figure 9 is a comparative diagram:

Figure 9 MPSO algorithm efficiency compared to other traditional algorithms chart



In Figure 9, the iteration efficiency comparison among MPSO, traditional PSO, genetic algorithm (GA), and differential evolution (DM) is shown. It is evident that although MPSO's ability to find the optimal value is slightly weaker in the initial iterations, as the iterations progress, it achieves the best numerical results among the four algorithms. Moreover, its computational speed is only second to the differential evolution algorithm. Therefore, in terms of optimisation ability and solution speed, MPSO can ensure the global optimality of the final results by preventing premature convergence to local optima, and it can also enhance the solution efficiency to some extent.

6.4 Cluster validity verification based on confidence level

Confidence level is an important indicator for measuring the reliability of clustering results, reflecting the representativeness of the cluster centres to the actual fluctuation of charging demand. The higher the confidence level, the more accurately the cluster centres can capture the characteristics of the charging demand of nodes; conversely, when the confidence level is low, the clustering results may not fully reflect the fluctuation characteristics of charging demand. To verify the effectiveness of the charging demand clustering method based on road weight, this paper introduces different confidence levels (Wang, 2023), taking 85%, 90%, 95%, and 100% as examples, limiting the number of iterations to 1,000, and analysing the representativeness of the cluster centres to the charging demand and its impact on the planning results of charging stations under various confidence levels.

As shown in Table 1, under a 100% confidence level, the cluster centres can fully capture the fluctuation of charging demand for all nodes. In this case, the planning scheme for charging stations strictly optimises based on the clustered charging demand. Although the construction cost of charging stations in high-confidence schemes is higher, due to the smaller number and reasonable layout of charging stations, the queuing time for users during peak hours is significantly reduced, and the charging cost is greatly decreased. At the same time, stable grid operating conditions further increase the electricity sales revenue of charging stations, maximising the overall economic benefits. In addition, high-confidence schemes can better balance the distribution network load, reducing the risk of high load on distribution network lines during the same period, thereby effectively controlling the node voltage deviation.

Table 1 Cost and revenue of EV charging station planning schemes at different confidence levels

Cost and revenue (10,000 Yuan)	*100%*	*95%*	*90%*	*85%*
Average annual investment cost	20.5	19.8	18.6	17.5
User charging cost	7.2	8.0	9.1	10.3
Average annual electricity sales revenue	24.5	23.8	22.4	21.0
Total revenue from charging stations (20 years)	354.4	338	326	310

In contrast, under a lower confidence level (such as 85%), due to the weakened ability of the cluster centres to capture the fluctuation of charging demand, some of the larger fluctuations in charging demand are not fully reflected. This clustering result leads to a significant increase in the number of charging stations in the planning scheme, and the layout of charging stations becomes overly dispersed. Although dispersed charging stations are beneficial for the charging experience of EV users and reduce the charging cost for users, each charging station requires additional land purchase costs, and the planning scheme with a large number of small-capacity charging stations significantly increases the construction cost of charging stations. Moreover, too many users charging on the distribution network at the same time will lead to a significant increase in line load peaks, causing node voltage deviation to worsen, and the voltage of some nodes may even drop significantly. At the same time, larger node voltage deviations may affect the operational stability of grid equipment, indirectly reducing the electricity sales revenue of charging stations, and lowering the overall economic benefits.

By comparing the results of different confidence levels, it can be seen that the change in confidence level directly affects the simplification of charging demand and the quality of planning schemes. In high-confidence schemes (such as 100%), the number of charging stations is smaller and the layout is more reasonable, most users can charge orderly based on queuing theory, the distribution of distribution network load is evenly distributed, and node voltage deviation is significantly reduced. While low-confidence schemes (such as 85%) result in lower planning costs for charging stations due to the overly dispersed charging demand, but the charging cost increases, and the operational safety of the distribution network is also adversely affected.

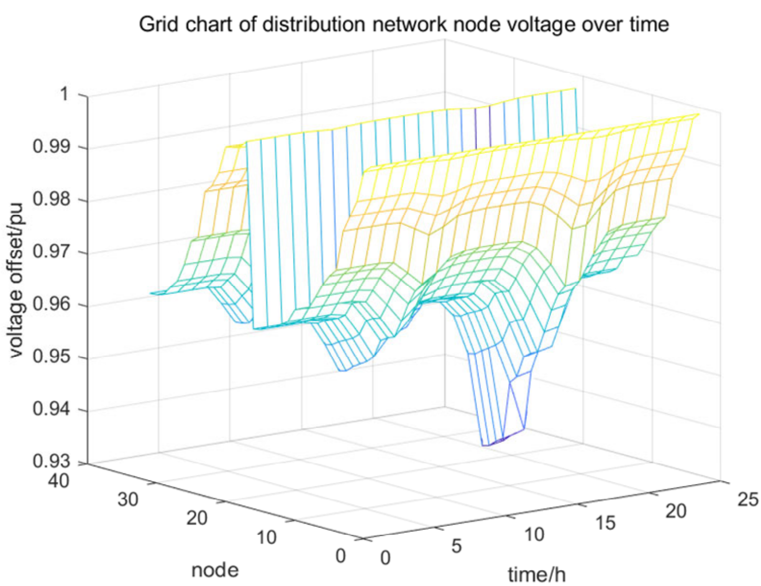
In summary, introducing confidence level as a measure can significantly enhance the scientific nature of clustering methods and the rationality of charging station planning. Especially in high-confidence levels, the planning scheme can more accurately reflect the distribution of charging demand, optimise the operation of the distribution network, and balance investment returns with user needs.

6.5 Comparison of node voltage deviation in high/low confidence level planning results

In distribution network planning, node voltage deviation refers to the deviation between the actual voltage of a node and the reference voltage, usually expressed as a percentage. When the node voltage deviation is too large, it may affect the safe and stable operation of the distribution network, and could even damage user equipment. The base voltage adopted in the study is 10kV and the base capacity is 10 MVA. On this basis, the charging station load is combined with traditional loads, and the planning results under different confidence levels (100% and 85%) are compared. The fixed number of iterations is set to 1,000, and the voltage deviation of each node is analysed.

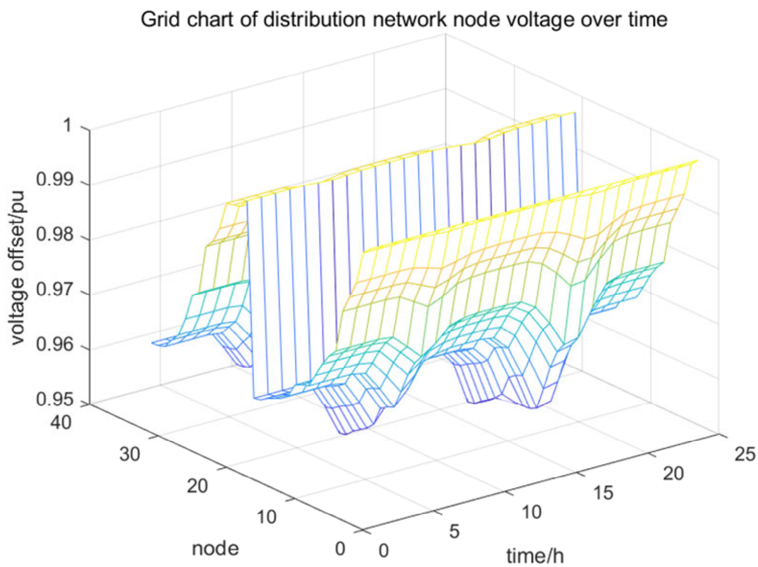
As shown in Figure 10, at an 85% confidence level, due to the more dispersed prediction of charging demand, the number of charging stations invested in the planning results is larger, leading to a more decentralised layout of charging stations. Although this planning approach reduces the load pressure on individual charging stations, the simultaneous connection of too many users to the distribution network for charging at certain times causes a sharp increase in the load on the distribution network lines, further triggering a significant drop in node voltage. As a result, the voltage deviation of some nodes even exceeds –5%, indicating that this planning scheme cannot effectively alleviate the voltage deviation problem during peak charging demand.

Figure 10 Node voltage deviation corresponding to the planning results at 85% confidence level (see online version for colours)



In contrast, as shown in Figure 11, at a 100% confidence level, the prediction of charging demand is more concentrated, and the number of charging stations in the planning results is relatively small, but the layout is more reasonable. Most users' charging behaviour is based on a queuing theory model and proceeds in an orderly manner. Due to the centralised distribution of charging stations after planning, the load on the distribution network is more effectively allocated at the same time, significantly reducing the line load pressure, thereby significantly improving the deviation of node voltage, with the maximum deviation being only –4.4%. These results indicate that the planning scheme at a high confidence level can not only retain the distribution characteristics of charging demand but also effectively reduce the instantaneous load on the distribution network, optimising the stability of node voltage.

Figure 11 Node voltage deviation corresponding to the planning results at 100% (see online version for colours)



In summary, the charging demand clustering method based on road weights significantly enhances the scientific nature of distribution network planning through a two-layer optimisation. In the planning results at a high confidence level, the charging load is more reasonably allocated, which not only improves computational efficiency but also optimises the safety and stability of grid operation. This further verifies the practical application value of the method proposed in this paper for charging station planning and distribution network optimisation.

7 Conclusions

This paper proposes a two-layer optimisation model based on road network simulation of EV charging demand, and the conclusions drawn from typical case analysis are as follows:

Using road network simulation to generate the charging demand of EVs ensures that the charging demand data has both spatial and temporal dimensions, providing more realistic and detailed charging load distribution information for charging station planning.

The clustering algorithm with the concept of road weight, while ensuring the distribution characteristics of charging demand, effectively clusters the charging demand in space and maintains the characteristics of peak and valley changes in EV charging demand over time, which is conducive to subsequent calculations.

The two-layer optimisation model fully considers the development needs of both sides during the process of distribution network topology expansion and charging station site selection and capacity planning, reducing the voltage deviation of the distribution network.

Further research needs to consider the impact of EVs as mobile energy storage devices participating in V2G (vehicle to grid) (Fesli and Ozdemir, 2024; Tetik Kollugil et al., 2024) on the planning of charging stations and the operation of distribution networks.

Declarations

All authors declare that they have no conflicts of interest.

Data availability statement

The datasets used and analysed during the current study available from the corresponding author on reasonable request.

References

Cui, M. (2013) *Research on Real-Time Travel Time Collection Method Based on Simplified Road Network Model*, Chongqing University, Chongqing, China.

Fesli, U. and Ozdemir, M.B. (2024) 'Electric vehicles: a comprehensive review of technologies, integration, adoption, and optimization', *IEEE Access*, Vol. 12, pp.140908–140931.

Gao, T., Huang, X., Yang, Z., Wang, H., Wen, X., Zhao, Q. and Ding, H. (2022) 'A grouping strategy and day-ahead scheduling method of electric vehicles for peak shaving', in *2022 IEEE 5th International Electrical and Energy Conference* (*CIEEC*), pp.2676–2681, IEEE.

Gutierrez, D.M. and Ladisch, M.R. (2024) 'Electric vehicles, biofuels, and transitions in transportation energy', *Industrial Biotechnology*, Vol. 20, No. 1, pp.21–25.

Hou, H., Wang, Y., Wu, X. et al. (2023) 'Scheduling strategy for electric vehicle charging and discharging considering range anxiety psychological effect on a long time scale', *High Voltage Technology*, Vol. 49, No. 1, pp.85–93, DOI: 10.13336/j.1003-6520.hve.20211581.

Jiang, X., Feng, Y.T., Xiong, H., Wang, J. and Zeng, Q. (2019) 'Electric vehicle charging station planning based on travel probability matrix', *Transactions of China Electrotechnical Society*, Vol. 34, No. S1, pp.272–281, DOI: 10.19595/j.cnki.1000-6753.tces.l80131.

Kautish, P., Lavuri, R., Roubaud, D. and Grebinevych, O. (2024) 'Electric vehicles' choice behaviour: an emerging market scenario', *Journal of Environmental Management*, Vol. 354, p.120250.

Leou, R.C., Su, C.L. and Teng, J.H. (2015) ‘Modelling and verifying the load behaviour of electric vehicle charging stations based on field measurements’, *Generation Transmission and Distribution Iet*, Vol. 9, No. 11, pp.1112–1119.

Li, H., Du, Z., Chen, L. et al. (2019) ‘Electric vehicle charging load prediction model based on travel prediction and V2G evaluation’, *Automation of Electric Power Systems*, Vol. 43, No. 21, pp.88–96.

Liu, S., Zhou, Z., Liu, Y. et al. (2023) ‘Degradation stage division of AC contactor contact system based on vibration signals’, *High Voltage Technology*, Vol. 49, No. 12, pp.4971–4981, DOI: 10.13336/j.1003-6520.hve.20221773.

Liu, W., Long, R., Xu, X. et al. (2016) ‘Short-term charging load forecasting model for electric vehicles considering data freshness and cross-entropy’, *Automation of Electric Power Systems*, Vol. 40, No. 12, pp.45–52.

Lu, T., Yao, E., Jin, F. and Yang, Y. (2022) ‘Analysis of incentive policies for electric vehicle adoptions after the abolishment of purchase subsidy policy’, *Energy*, Vol. 239, p.122136.

Lu, Z., Yang, G., Zhang, X. et al. (2009) ‘Application of improved binary particle swarm optimization algorithm in distribution network reconfiguration’, *Power System Protection and Control*, Vol. 37, No. 7, pp.30–34.

Luo, P., Yang, Z., Zhang, J., Yang, Q., Lv, Q. and Wu, Q. (2024) ‘Planning of electric vehicle charging stations considering multi-scenario charging demand forecasting’, *High Voltage Technology*, pp.1–20, https://doi.org/10.13336/j.1003-6520.hve.20231438.

Pennington, A.F., Cornwell, C.R., Sircar, K.D. and Mirabelli, M.C. (2024) ‘Electric vehicles and health: a scoping review’, *Environmental Research*, Vol. 251, Pt. 2, p.118697.

Ratnaweera, A., Halgamuge, S.K. and Watson, H.C. (2004) ‘Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients’, *IEEE Transactions on Evolutionary Computation*, Vol. 8, No. 3, pp.240–255.

Ruoso, A.C., Ribeiro, J.L.D. and Olaru, D. (2024) ‘Electric vehicles' impact on energy balance: three-country comparison’, *Renewable and Sustainable Energy Reviews*, Vol. 203, p.114768.

Song, Y., Lin, S., Tang, Z. et al. (2020) ‘Probability modelling of spatiotemporal distribution of electric vehicle charging load based on dynamic traffic flow’, *Automation of Electric Power Systems*, Vol. 44, No. 23, pp.47–56.

Tang, D. and Wang, P. (2016) ‘Probabilistic modelling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles’, *IEEE Transactions on Smart Grid*, Vol. 7, No. 2, pp.627–636.

Tetik Kollugil, E., Sarıca, K. and Topcu, Y.I. (2024) ‘Electric vehicles as an emission mitigation option: expectations and reality’, *Clean Technologies and Environmental Policy*, pp.1–22.

Tian, L., Shi, S. and Jia, Z. (2010) ‘’A statistical modelling method for electric vehicle charging power demand’, *Power System Technology*, Vol. 34, No. 11, pp.126–130.

Tian, M., Tang, B., Yang, X. et al. (2021) ‘Electric vehicle charging station planning considering both charging demand and power distribution network accommodation capacity’, *Power Grid Technology*, Vol. 45, No. 2, pp.498–509, DOI: 10.13335/j.1000-3673.pst.2020.0636.

Tian, P. and Zhang, L. (2019) ‘Charging station location planning model based on revenue analysis’, *Power Big Data*, Vol. 22, No. 12, pp.58–66.

Ullah, I., Zheng, J., Jamal, A., Zahid, M., Almoshageh, M. and Safdar, M. (2024) ‘Electric vehicles charging infrastructure planning: a review’, *International Journal of Green Energy*, Vol. 21, No. 7, pp.1710–1728.

Wang, C. (2023) ‘A method for identifying and evaluating energy meter data based on big data analysis technology’, *International Journal of Information and Communication Technology*, Vol. 23, No. 4, pp.424–445.

Wang, H., Jia, Y., Shi, M., Xie, P., Lai, C.S. and Li, K. (2022) ‘A hybrid incentive program for managing electric vehicle charging flexibility’, *IEEE Transactions on Smart Grid*, Vol. 14, No. 1, pp.476–488.

Wang, W., Huang, H., Xu, Y. et al. (2023) 'Research on voltage regulation strategies of electric vehicles participating in active distribution network', *Guangdong Electric Power*, Vol. 36, No. 10, pp.93–104.

Xing, Q., Chen, Z., Leng, Z. et al. (2020a) 'Electric vehicle routing planning and charging navigation strategy based on real-time traffic information', *Proceedings of the CSEE*, Vol. 40, No. 2, pp.534–550.

Xing, Q., Chen, Z., Zhang, Z., Xu, X., Zhang, T., Huang, X. and Wang, H. (2020b) 'Urban electric vehicle fast-charging demand forecasting model based on data-driven approach and human decision-making behavior', *Energies*, Vol. 13, No. 6, p.1412.

Xu, Q., Cai, T., Liu, Y et al. (2016) 'Planning of electric vehicle charging stations considering driver behavior habits and travel chains', *Automation of Electric Power Systems*, Vol. 40, No. 4, pp.59–65.

Yan, G., Liu, H., Han, N. et al. (2021) 'Optimal method for location and capacity planning of electric vehicle charging stations considering spatiotemporal distribution status', *Proceedings of the CSEE*, Vol. 41, No. 18, pp.6271–6284, DOI:10.13334/j.0258-8013. pcsee. 202001.

Yan, L. and Luo, Q. (2022) 'Planning of electric vehicle charging stations based on improved sparrow search algorithm', *Guangdong Electric Power*, Vol. 35, No. 9, pp.56–66.

Yang, Z., Huang, X., Gao, T., Liu, Y. and Gao, S. (2022) 'Real-time energy management strategy for parking lot considering maximum penetration of electric vehicles', *IEEE Access*, Vol. 10, pp.5281–5291.

Zang, H., Shu, X., Fu, Y., Wei, Z. and Sun, G. (2021) 'Multi objective planning of urban electric vehicle charging stations considering multi demand scenarios', *Power System Protection and Control*, Vol. 49, No. 5, pp.67–80, DOI: 10.19783/j.cnki.pspc.200579.

Zhang, H., Hu, Z., Song, Y. et al. (2014) 'A method for predicting electric vehicle charging load considering spatial and temporal distribution', *Automation of Electric Power Systems*, Vol. 38, No. 1, pp.13–20.

Zhang, J., Feng, W., Tan, Y. et al. (2024) 'A health prediction method for new energy vehicle power batteries based on AACNN-LSTM neural network', *International Journal of Information and Communication Technology*, Vol. 24, No. 5, pp.74–94.

Zhang, M., Xu, L., Yang, X., Wu, Z. and Zhang, Q. (2022) 'Research on the planning of electric vehicle charging stations based on the spatiotemporal distribution characteristics of charging demand', *Power System Technology*, Vol. 47, No. 1, pp.256–268, DOI: 10.13335/j.1000-3673. pst.2022.0427.

Zhao, Q. and Yang, L. (2024) 'Real-time monitoring system for power distribution network faults based on deep learning technology', *International Journal of Information and Communication Technology*, Vol. 25, No. 5, pp.18–39.

Zhu, J., Yang, Z., Guo, Y., Zhang, J. and Yang, H. (2019) 'Short-term load forecasting for electric vehicle charging stations based on deep learning approaches', *Applied Sciences*, Vol. 9, No. 9, p.1723.

Appendix

Figure A1 Topology of IEEE 33-node distribution network

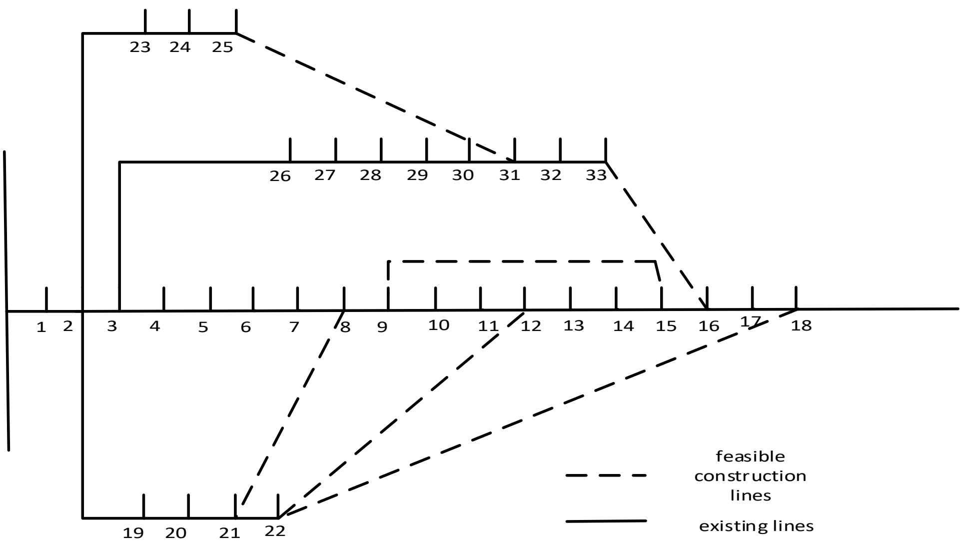


Figure A2 Calibrated road weights network topology map

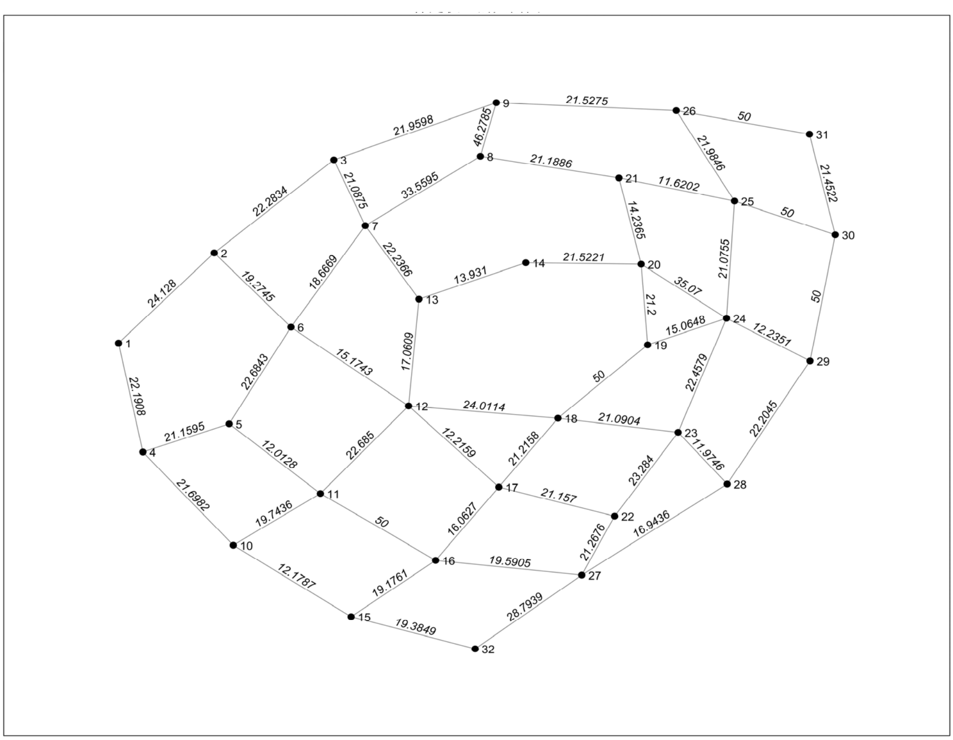


Figure A3 DBI index and 24-hour cumulative charging demand (see online version for colours)

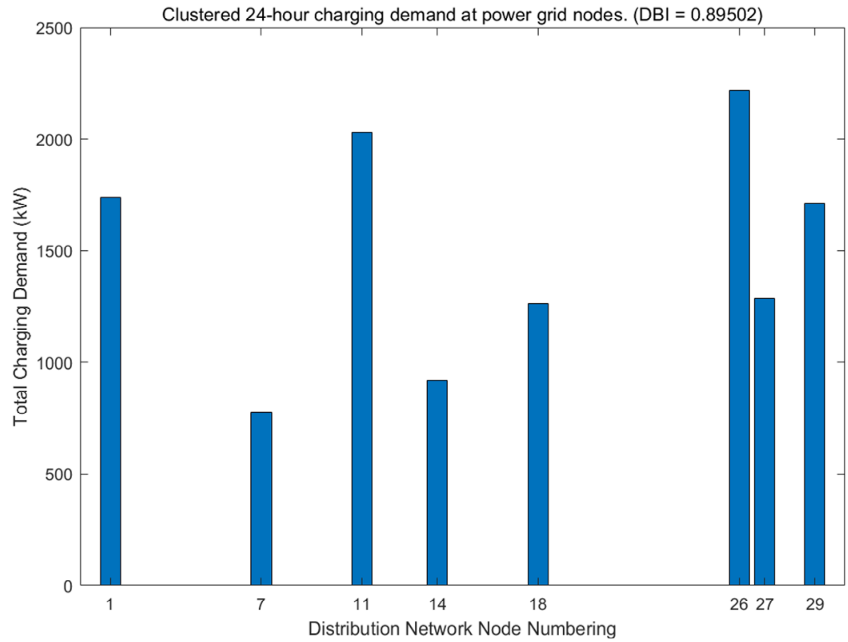


Figure A4 Algorithm comparison (see online version for colours)

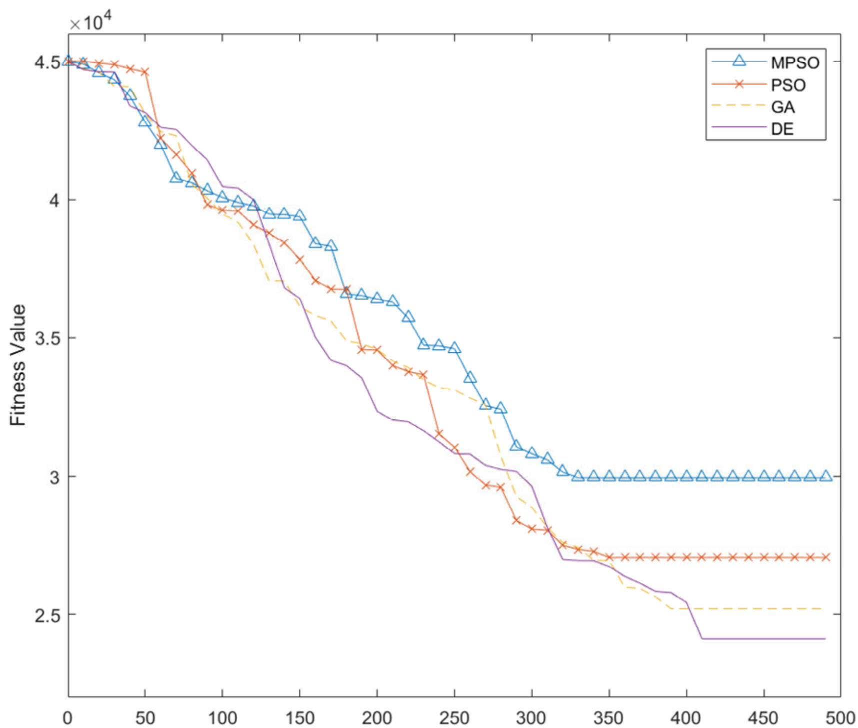


Table A1 Summary table of travel and charging characteristics indicators and parameters for three types of vehicles

TYPE	*Private*		*Public*		*Taxi*	
Start Time	Normal distribution N(8, 1^2)		Normal distribution N(6, 0.5^2)		Normal distribution N(6, 0.5^2)	
Return time	Normal distribution N(17, 1^2)		Normal distribution N(17, 1^2)		Normal distribution N(17, 1^2)v	
Battery capacity	Gamma distribution	C_p^1 = 60KW·h α_1 =10.08 β_1 = 0.08	Gamma distribution	C_p^2 = 60KW·h α_2 =4.5 β_2 =6.3	Gamma distribution	C_p^3 = 90KW·h α_3 = 8.7 β_3 = 3.2
Initial SOC			Normal distribution N(0.6, 0.1^2)			
Average speed	Normal distribution N(40, 1^2)		Normal distribution N(30, 2^2)		Normal distribution N(45, 1^2)	

Table A2 Grid planning related parameters

Investment node	*Number of charging piles*
Grid construction discount rate	0.12
Line service life	20 Years
Construction cost per unit length of line	3,000 Yuan/metre
Electricity selling price (peak, flat, valley)	1.2/0.8/0.4 (Yuan/kw·h)

Table A3 Charging station planning model parameters

Basic parameters	*Value*	*Basic parameters*	*Value*
Discount rate	0.12	Operation and maintenance cost conversion factor	0.02
Charging station operation years	20 years	Charging power of a charging pile/kW	60
Price of charging pile	10,000 Yuan/unit	Charging power of a charging pile/%	95
Charging station auxiliary facilities cost	30,000 Yuan/seat	User charging service fee/(Yuan·(kW·h)–1)	0.8
User time cost/(Yuan·h^{-1})	50	Land price/(Yuan/m^2)	14,500
Area occupied by a single charging pile	2.5m2/unit	Electricity selling price (peak, flat, valley)	1.6/1/0.6 (Yuan/kw·h)

Table A4 Cluster centre and pulled node list

Cluster centre corresponding distribution network node number	*Distribution network nodes pulled by the cluster centre*
7	6 7 8
26	9 21 25 26 31
11	5 10 11 12 15 16
14	13 14 20
18	17 18 19 23
27	22 27 32
29	24 28 29 30
1	1 2 3 4

Table A5 IEEE33 distribution network line data

Line number	*Starting node*	*Endpoint node*	*Line resistance*	*Line reactance*
1	1	2	0.0922	0.047
2	2	3	0.493	0.2511
3	3	4	0.366	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.819	0.707
6	6	7	0.1872	0.6188
7	7	8	0.7114	0.2351
8	8	9	1.03	0.74
9	9	10	1.044	0.74
10	10	11	0.1966	0.065
11	11	12	0.3744	0.1238
12	12	13	1.468	1.155
13	13	14	0.5416	0.7129
14	14	15	0.591	0.526
15	15	16	0.7463	0.545
16	16	17	1.289	1.721
17	17	18	0.732	0.574
18	2	19	0.164	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083
23	23	24	0.898	0.7091
24	24	25	0.896	0.7011
25	6	26	0.203	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.059	0.9337

Table A5 IEEE33 distribution network line data (continued)

Line number	*Starting node*	*Endpoint node*	*Line resistance*	*Line reactance*
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.963
31	31	32	0.3105	0.3619
32	32	33	0.341	0.5302
33	8	21	2	0.3122
34	9	15	2	0.622
35	12	22	2	0.423
36	18	33	0.5	0.555
37	25	29	0.5	0.535

Table A6 Charging station investment nodes and capacities

Investment node	*Number of charging piles*
3	4
11	5
13	4
18	3
21	4
24	5
28	6
32	5

Table A7 Conventional load of distribution network

Node number	*Active power (KW)*	*Reactive power (KVA)*
1	0	0
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20
7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80

Table A7 Conventional load of distribution network (continued)

Node number	*Active power (KW)*	*Reactive power (KVA)*
15	60	10
16	60	20
17	60	20
18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40