

Article

Site and Capacity Planning of Electric Vehicle Charging Stations Based on Road–Grid Coupling

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Abstract

To address the rapidly growing demand for charging stations (CSs) and the associated challenges posed by the expansion of electric vehicles (EVs), this study proposes a collaborative planning method integrates user demand considerations with operational constraints at the grid level. Based on graph theoretical principles, static topology models of the road network and distribution grid were constructed. A dynamic origin–destination (OD) prediction framework was then formulated by jointly considering traffic flow variations, battery energy consumption, user charging behavior, and ambient temperature, in which an enhanced gravity model is coupled with the Floyd algorithm. Charging load characteristics were quantified through Monte Carlo simulation, and K-means++ clustering was further applied to identify spatial charging demand hotspots. On this basis, a multi-objective optimization model was established to simultaneously balance the annualized cost of charging stations, user costs, and voltage deviation in the distribution network. To solve the resulting high dimensional problem, a collaborative optimization mechanism was designed by integrating a weighted Voronoi diagram with a multi-objective particle swarm optimization (MOPSO) algorithm, enabling dynamic service area partitioning and global capacity optimization. Case analysis demonstrates that the proposed method reduces user time costs by 15.8%, optimizes queue delay by 42.2%, and improves voltage stability, maintaining fluctuations within 5%. It also balances the interests of charging station operators, users, and distribution networks, with only a slight increase in construction costs. These results offer valuable theoretical and practical insights for charging infrastructure planning.

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1. Introduction

The global pursuit of carbon neutrality has accelerated the adoption of electric vehicles. As an environmentally friendly mode of transportation, electric vehicles (EVs) have been widely promoted, resulting in a rapid growth in their ownership [1]. However, the rapid increase in EV adoption has substantially intensified charging demand, posing significant challenges for charging station planning [2]. Inadequate planning not only worsens traffic conditions [3] but also jeopardizes power system operation, leading to issues

such as voltage violations and aggravated peak–valley load fluctuations [4]. Charging station planning requires the coordinated consideration of transportation networks, power grids, and user behaviors, for which traditional methods are often insufficient to handle. Therefore, more comprehensive and in-depth research on charging station planning is urgently required.

In the field of EV charging load forecasting, a wide range of methods has been proposed to capture spatiotemporal demand characteristics. Reference [5] develops a travel-chain-based approach combined with geographic information systems to model user mobility and charging behavior. Reference [6] adopts a game-theoretic framework, specifically a Stackelberg game, to represent user charging preferences and interactions, thereby enhancing spatiotemporal prediction accuracy. Reference [7] integrates multi-source traffic and power grid data with travel chain theory to reconstruct vehicle trajectories and associated charging events. More recently, data-driven methods have gained increasing attention in this field. Reference [8] employs graph-based deep learning models, such as GCN-based architectures, to fuse road-network characteristics with meteorological information for charging demand prediction. Reference [9] proposes a deep learning framework that incorporates weather conditions, temporal patterns, and user attributes to improve short-term charging load forecasting at charging stations. Reference [10] applies Monte Carlo simulation combined with optimization techniques to evaluate the impacts of EV charging behavior on power grid operation. Reference [11] introduces multi-model forecasting strategies to better capture complex temporal variations in charging demand. Reference [12] leverages digital-twin-based battery state estimation to enhance the realism of EV energy consumption and charging behavior modeling.

Despite these advances, existing charging load forecasting studies often exhibit several limitations. First, many approaches either neglect real-time traffic dynamics or rely on simplified routing assumptions, such as shortest-path travel or destination-only charging, which restrict their applicability in complex urban environments. Second, user charging preferences, traffic congestion evolution, and battery energy consumption are frequently modeled in a partially decoupled manner, limiting the ability to capture their joint influence on spatiotemporal charging demand formation. Moreover, the outputs of forecasting models are typically treated as static inputs for downstream planning problems, without considering feedback effects from infrastructure deployment and grid constraints.

Regarding charging station site selection, a variety of planning models have been developed to balance economic efficiency, user convenience, and system reliability. Reference [13] proposes a planning model that incorporates multiple types of charging piles and mobile emergency resources and formulates the siting problem as a mixed-integer programming framework to minimize social costs under uncertainty conditions. Reference [14] develops a collaborative planning framework for fast and slow charging stations by integrating Wardrop's user equilibrium with charging–discharging management, thereby addressing load fluctuation mitigation and investment trade-offs. Reference [15] presents a user-satisfaction-oriented model that considers detour distance, queuing time, and charging cost and applies heuristic optimization algorithms to support multi-user charging decision-making. Reference [16] introduces a bi-level planning model to capture the interactive relationship between users and the power grid in charging station deployment. Reference [17] employs an agent-based simulation framework combined with Bayesian optimization to identify optimal charging station locations under heterogeneous urban traffic conditions.

Although these studies provide valuable insights into charging station siting, most existing approaches rely on static or weakly adaptive representations of charging demand. Spatial demand patterns are often predefined or assumed to be time-invariant, and the

dynamic redistribution of demand induced by traffic congestion and user behavioral adaptation is rarely considered. Furthermore, clustering or hotspot identification techniques are typically applied as standalone preprocessing steps, without being embedded into an iterative planning framework that links site selection with service-area evolution and capacity decisions.

In terms of charging station capacity configuration with road–grid coordination, a number of studies have explored integrated optimization mechanisms for EV charging infrastructure. Reference [18] develops an EV charging optimization model within a coupled road–grid network based on hierarchical graph theory and real-time pricing strategies, aiming to reduce user costs and alleviate network congestion. Reference [19] proposes a road–electricity coupling model grounded in an improved user equilibrium principle to coordinate EV charging strategies with distribution-network dispatching. Reference [20] introduces an integrated capacity configuration approach that combines queuing theory, Monte Carlo simulation, and multi-objective optimization to balance economic performance and user satisfaction. Reference [21] employs a hybrid particle swarm optimization framework to jointly optimize charging station siting and capacity allocation under dynamic demand conditions. Reference [22] presents a multi-objective optimization model that incorporates uncertainties in charging demand and grid operation and analyzes trade-offs through Pareto front exploration.

From a methodological perspective, most existing studies focus on one or two aspects of the EV charging infrastructure problem in isolation. Spatiotemporal demand forecasting, hotspot identification, service-area partitioning, and capacity optimization are often addressed sequentially rather than within a unified framework. In many road–grid coupled models, traffic flow is simplified, and charging demand is treated as exogenous, limiting the ability to capture iterative feedback among traffic congestion, user charging behavior, service-area reshaping, and grid feasibility constraints. As a result, the integration of behavior-driven demand formation, adaptive service-area modeling, and grid-feasible capacity optimization into a dynamically coupled planning loop remains insufficiently explored.

Based on the above methodological analysis, several critical limitations can be identified in the existing literature on EV charging load forecasting, station siting, and road–grid coordination.

First, many existing studies treat traffic dynamics, user charging behavior, and grid operational constraints in a partially decoupled or sequential manner. As a result, feedback effects among congestion evolution, charging demand redistribution, and grid feasibility are often insufficiently captured. Second, road–grid coupled planning frameworks commonly rely on static or simplified service-area representations. These approaches rarely model how charging station capacity decisions interact with time-varying traffic conditions to reshape spatial demand allocation in a dynamic manner. Third, although advanced techniques such as clustering-based hotspot identification, service-area modeling, and meta-heuristic optimization have been individually applied, their integration into a unified, behavior-driven, and dynamically coupled planning loop remains insufficiently explored. Compared with many existing road–grid coupled planning frameworks, which often assume simplified or static routing conditions or treat charging demand as an exogenous input to grid feasibility analysis, the present study establishes an explicitly coupled planning mechanism. In the proposed framework, traffic-dependent routing, SOC-based user charging decisions, and distribution-grid voltage constraints are iteratively updated within a unified optimization loop. This structural integration enables charging station deployment decisions to simultaneously reflect time-varying congestion

effects, energy consumption dynamics, and grid operational feasibility, thereby distinguishing the proposed methodology from sequential or loosely connected road–grid approaches.

These gaps motivate the development of a comprehensive road–grid collaborative planning framework that jointly captures spatiotemporal charging demand formation, adaptive service-area partitioning, and grid-feasible capacity optimization.

This study develops a collaborative planning framework for electric vehicle charging stations that integrates user demand orientation with grid-level operational constraints. The proposed method enhances the accuracy of charging load forecasting, improves the rationality of site selection, and supports coordinated decision making across users, charging station operators, and power grids. A comprehensive optimization mechanism is further established to achieve global capacity configuration and dynamic service area allocation. The primary contributions of this study are as follows:

1. This study proposes a dynamic, behavior-driven charging load prediction method, which integrates dynamic traffic flow, battery energy consumption, user charging behavior, and ambient temperature. By combining an improved gravity model, the Floyd algorithm, travel chain modeling, and Monte Carlo simulation, the method enables refined spatiotemporal forecasting in complex travel scenarios.
2. This study proposes a data-driven hotspot identification method based on K-means++ clustering, which extracts spatial charging demand patterns and provides a quantitative foundation for charging station siting.
3. This study develops a unified multi-objective planning and capacity optimization framework that jointly accounts for charging station construction and O&M costs, user travel and time costs, and distribution-network voltage performance. By integrating a weighted Voronoi-based service area partitioning scheme with a multi-objective particle swarm optimization algorithm, the proposed framework achieves dynamic capacity allocation while balancing system economics, user convenience, and grid security. The proposed framework is designed as a planning-oriented decision-support tool, aiming to evaluate charging station deployment strategies with coupled road–grid interactions over a representative planning horizon. It is not intended to model real-time operational control or instantaneous traffic and charging fluctuations but rather to support strategic planning decisions at the system level.

The remainder of this paper is organized as follows: Section 2 presents the dynamic charging load prediction method. Section 3 introduces the hotspot identification process and the multi-objective planning model. Section 4 details the collaborative capacity optimization mechanism. Section 5 provides the solution framework and planning process. Section 6 presents case studies and simulation analyses. Finally, Section 7 concludes the findings of this work.

2. Foundation Model Construction

This section establishes the fundamental modeling framework for collaborative charging station planning, which serves as the basis for subsequent optimization processes. The framework integrates static network topology, dynamic system characteristics, and user travel and charging demand profiles, thereby providing accurate and rigorous mathematical support for the upcoming load forecasting and collaborative optimization.

To provide a clear overview of the proposed modeling framework and the interaction among its key modules, Figure 1 summarizes the overall workflow of the road–grid coupled collaborative planning approach.

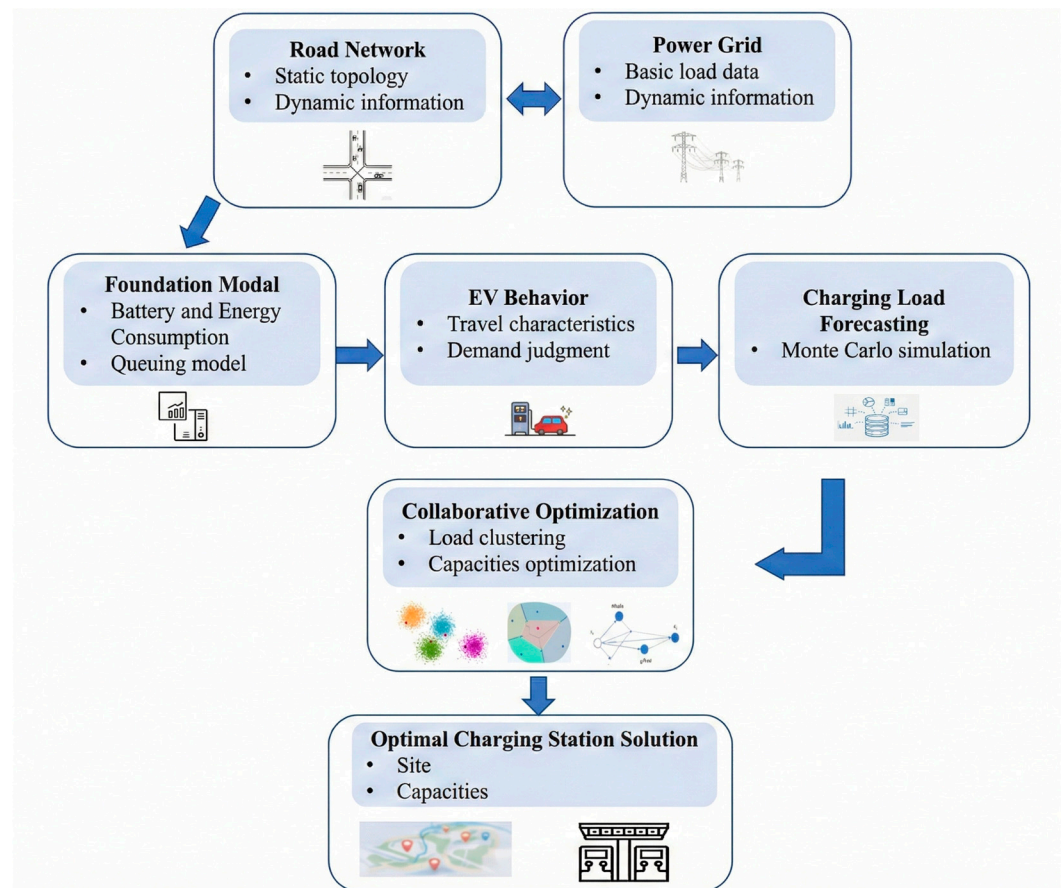


Figure 1. Overall workflow of the proposed road-grid coupled collaborative planning framework.

The framework integrates road-network traffic dynamics, EV behavior modeling, charging station service modeling, charging load forecasting, and grid-aware collaborative optimization to obtain optimal station location and capacity deployment decisions.

The proposed modeling framework adopts a modular structure, in which traffic loading, EV behavior simulation, service-area partitioning, and optimization are organized as loosely coupled components. This structure allows the framework to be applied to urban systems of different scales through appropriate spatial partitioning and parallel computation, without changing the underlying modeling logic.

2.1. Road Network Modeling

As a fundamental component of collaborative charging station planning, the road network must accurately represent both its static topological structure and its dynamic traffic characteristics. Graph theory provides a concise and rigorous framework for modeling transportation networks [23], enabling effective simulation and analysis of complex traffic flows. The static topological structure of the road network can be expressed as

$$\Phi_R = (P_r, E_r, D, T) \quad (1)$$

$$\begin{cases} P_r = \{p_i, (x_i, y_i) \mid i = 1, 2, \dots, n\} \\ E_r = \{e_l, (p_i, p_j), L_l \mid l = 1, 2, \dots, m\} \\ D = \{d_{ij} \mid (p_i, p_j) \in E_r\} \end{cases}$$

where Φ_R represents the road network topology. P_r is the set of nodes in the road network. E_r is the road in Φ_R . L_l is the set of roads in the network. m is the total number of road segments. D is the adjacency matrix of the road network, with d_{ij} denoting the path length between two adjacent nodes p_i, p_j .

For bidirectional representative road segments, the corresponding adjacency matrix D can be constructed accordingly. Taking the network connectivity shown in Figure 2 as an example, the adjacency matrix is given by

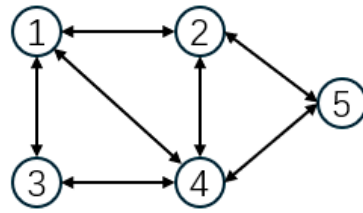


Figure 2. Road network connection relationship.

$$D = \begin{bmatrix} 0 & d_{12} & d_{13} & d_{14} & \text{inf} \\ d_{21} & 0 & \text{inf} & d_{24} & d_{25} \\ d_{31} & \text{inf} & 0 & d_{34} & \text{inf} \\ d_{41} & d_{42} & d_{43} & 0 & d_{45} \\ \text{inf} & d_{52} & \text{inf} & d_{54} & 0 \end{bmatrix} \quad (2)$$

where d_{ij}, d_{ji} indicate that the roads are two-way with consistent traffic conditions. Inf denotes that the road nodes are not connected.

Static topology alone cannot capture real traffic behavior as vehicle speed and traffic conditions vary significantly over time. Vehicle speed directly affects EV energy consumption; while idealized models assume constant driving speed and uniform energy consumption per kilometer, real traffic environments exhibit strong temporal variability influenced by road capacity, congestion levels, and traffic volume. To describe these effects more accurately, a flow–speed–energy–consumption model is introduced [24]. The relationship between vehicle speed and road traffic volume is given by

$$\begin{cases} V_{ij}(t) = \frac{v_{ij,0}}{1 + (\lambda_{ij}(t))^\beta} \\ \beta = a + b\lambda_{ij}^n \end{cases} \quad (3)$$

$$\lambda_{ij}(t) = \frac{q_{ij}(t)}{C_{ij,0}} \quad (4)$$

where $V_{ij}(t)$ is the speed of the vehicle on road segment (i, j) at time t . λ_{ij} is the congestion coefficient of the road. $v_{ij,0}$ is the zero flow speed (speed limit) of the road. $q_{ij}(t)$ is the real time traffic flow volume. $C_{ij,0}$ is the maximum capacity of the road. A, b, n are the adaptive coefficients for different road grades.

The parameters of the flow–speed function are selected based on the settings reported in established traffic assignment studies, particularly the density-based travel-time formulation proposed in [24]. These parameter values have been widely used in network-level traffic modeling to capture the monotonic degradation of travel speed under increasing flow conditions. In our implementation, the reference parameters are applied as baseline values and subjected to internal consistency checks. Minor adjustments are introduced to reflect local road characteristics, such as link type and nominal capacity, ensuring that the resulting speed patterns remain reasonable for the studied urban network. Specific parameter settings can be found in Appendix A.

Plausibility checks are conducted to assess the realism of the simulated traffic dynamics. Specifically, the spatiotemporal speed patterns generated by the model are compared with typical urban traffic operation statistics reported in authoritative public monitoring sources, such as the “2025 Annual Report on Urban Road Network Density and Operational Conditions in China.” The simulated congestion distribution and peak-period speed reduction trends exhibit qualitative consistency with the reported average urban speeds and congestion characteristics, supporting the plausibility of the adopted traffic representation at the planning level.

The adopted flow-speed formulation is further designed to remain numerically stable under peak-hour and highly congested conditions. Travel speed is bounded by predefined lower limits and decreases monotonically with increasing traffic flow, preventing non-physical outcomes such as negative speeds or abrupt oscillations when congestion intensifies. Under severe congestion conditions, the model produces progressively reduced but finite travel speeds, which lead to longer travel times and higher energy consumption in a physically interpretable manner. These congestion effects are consistently propagated to downstream routing and charging load simulations through the time-dependent impedance matrix, ensuring that abnormal traffic conditions are reflected as increased travel burden rather than numerical instability.

Overall, the road network model provides a stable and interpretable macroscopic traffic state that serves as a reliable input for subsequent EV routing, energy consumption estimation, and charging demand simulation within the proposed road-grid coupled planning framework.

2.2. Electric Vehicle Modeling

A comprehensive representation of EV behavior is essential for accurate load forecasting and collaborative planning. This section constructs EV related models from four aspects: battery capacity, energy consumption, charging-demand judgment, and user travel characteristics.

Battery performance is strongly influenced by ambient temperature. Based on empirical lithium-ion battery test data that quantify the impact of temperature on capacity degradation [25], the temperature capacity relationship is formulated as

$$C_B(T) = \xi_0 + \xi_1 T + \xi_2 T^2 + \xi_3 T^3 \quad (5)$$

where $C_B(T)$ is the battery's relative capacity percentage at temperature. ξ is the fitting coefficient.

Electric vehicle energy consumption also varies with vehicle speed due to changes in aerodynamic and rolling resistance [26]. This relationship is characterized through the speed-energy consumption model:

$$EC_{ij,t} = \frac{\varsigma_1}{V_{ij}(t)} + \varsigma_2 V_{ij}(t) + \varsigma_3 V_{ij}(t)^2 + \varsigma_4 \quad (6)$$

where $EC_{ij,t}$ is the road segment speed influenced by real time traffic condition. ς is the energy consumption coefficient.

In addition, air-conditioning usage contributes significantly to total energy consumption during EV operation. The temperature-power relationship and the corresponding start-stop behavior of the system are modeled as

$$P_{ac}(T) = k_T (T + \theta_1)^2 + \theta_2 \quad (7)$$

where $P_{ac}(T)$ is the variation in air-conditioning power consumption affected by temperature, in kW. k_T, θ_1, θ_2 are fitting coefficients.

EV users exhibit both rigid and elastic charging demand. Electricity price signals are among the most consistent and influential drivers of EV charging decisions, especially in time-of-use or dynamic pricing schemes [27]. Rigid demand occurs when the battery SOC drops below a safety threshold SOC_{min} during driving. Elastic demand may arise after a trip is completed, even when SOC remains above SOC_{min} , due to behavioral inertia or electricity-price considerations. To describe this dual decision mechanism, a dynamic charging threshold is introduced:

$$\varepsilon_t = \theta_d + \beta_d \cdot SOC_{need} - \alpha \left(\frac{C_t}{C_{ref}} \right) SOC_{base} \quad (8)$$

where ε_t is the dynamic charging threshold at time t . θ_d is the base preference threshold. β_d is the behavioral inertia coefficient, and SOC_{need} is the minimum SOC required for the next day's travel. α is the electricity price sensitivity coefficient. SOC_{base} is the base SOC reference value.

In this work, the charging decision mechanism is parameterized using real-world tariff structures and electricity pricing rules adopted in the studied region. Charging decisions are triggered by SOC conditions and evaluated against time-varying electricity prices, allowing charging timing and station selection to emerge endogenously as price-responsive outcomes. This modeling approach aligns with established findings on price-driven EV charging behavior.

Realistic modeling of EV mobility patterns requires a detailed characterization of user travel behavior. Three key components are considered: initial departure time, initial SOC distribution, and parking-time duration.

Based on the U.S. National Household Travel Survey (NHTS) dataset [28,29], the initial departure time of private EV users is assumed to follow a normal distribution:

$$f(t_s) = \frac{1}{\sigma_{t_s} \sqrt{2\pi}} e^{-\frac{(t_s - \mu_{t_s})^2}{2\sigma_{t_s}^2}} \quad (9)$$

where t_s represents the initial departure time; μ_{t_s}, σ_{t_s} represents the expectation and standard deviation.

The initial SOC prior to trip departure is similarly modeled using a normal distribution [30]:

$$f(SOC_{ini}) = \frac{1}{\sigma_{SOC_{ini}} \sqrt{2\pi}} e^{-\frac{(SOC_{ini} - \mu_{SOC_{ini}})^2}{2\sigma_{SOC_{ini}}^2}} \quad (10)$$

where SOC_{ini} represents the initial SOC of the electric vehicle; $\mu_{SOC_{ini}}, \sigma_{SOC_{ini}}$ represents the expectation and standard deviation.

Parking durations at intermediate stops are modeled using a generalized extreme value (GEV) distribution, with parameters varying across functional zones:

$$f(t_p; k_p, \sigma_p, \mu_p) = \frac{1}{\sigma_p} \left[1 + k_p \left(\frac{t_p - \mu_p}{\sigma_p} \right) \right]^{-1 - \frac{1}{k_p}} \cdot e^{-\left[1 + k_p \left(\frac{t_p - \mu_p}{\sigma_p} \right) \right]^{\frac{1}{k_p}}} \quad (11)$$

where t_p represents the parking time of electric vehicles in the corresponding functional area; the distribution parameters of k_p, σ_p, μ_p are specifically determined by the functional area where it is located.

2.3. Charging Station Modeling

At the planning level, detailed station-level arrival records are often unavailable, making empirical identification of EV arrival distributions difficult. As a result, aggregated EV arrivals at public charging stations are commonly modeled as a Poisson process in planning-oriented queueing studies. This assumption provides a tractable and robust approximation of stochastic arrivals with large user populations and independent charging decisions and has been widely adopted in high-impact EV charging infrastructure research [31]. To characterize user waiting behavior at charging stations, an M/M/s queueing model is employed in this study. The model assumes a Poisson arrival process and exponential service-time distribution, with s parallel charging units. The model captures station congestion and quantifies user waiting time through standard queueing indicators, including the probability of waiting, average queue length, and expected waiting duration:

$$\rho = \lambda / \mu \quad (12)$$

$$P_0 = \left[\sum_{n=1}^{s-1} \frac{\rho^n}{n!} + \frac{\rho^s}{s!} \frac{s}{s-\rho} \right]^{-1} \quad (13)$$

$$P_n = \begin{cases} \frac{1}{n!} \rho^n \cdot P_0, & 0 < n < s \\ \frac{\rho^s}{s! \cdot s^{n-s}} \cdot P_0, & n > s \end{cases} \quad (14)$$

$$W_q = \frac{\sum_{n=s}^{\infty} P_n}{\mu s - \lambda} = \frac{\frac{\rho^s}{s!} \cdot \frac{s}{s-\rho} \cdot P_0}{\mu s - \lambda} \quad (15)$$

where P_0 is the probability that the queue is empty. P_n is the probability that the queueing process is in state n . W_q is the expected waiting time in the queue. n represents the state of the queueing system. $\rho = \lambda/\mu$ is the utilization rate of the queueing process.

In this model, the service rate μ represents the average charging service capability of a single charger. It is determined by the assumed fixed charging power of the charger and the typical charging energy demand of EV users. By adopting a fixed charging power for each charger type, variations in service duration are implicitly reflected through differences in EV charging demand rather than through fluctuating charging power. This abstraction provides a stable and interpretable representation of charging service processes that is suitable for planning-oriented queueing analysis.

In this study, all EV-related parameters are defined consistently for a single representative vehicle category, namely, private passenger EVs. This modeling choice is motivated by the fact that private passenger EVs constitute the dominant share of urban public charging demand, and their charging behaviors exhibit substantial variability driven primarily by travel patterns, state-of-charge conditions, and temporal factors rather than by vehicle class differences. By adopting a unified representative vehicle type, the proposed framework focuses on capturing behavior-driven charging demand variability while avoiding additional uncertainty introduced by multiple vehicle categories. This design ensures modeling clarity, computational tractability, and reproducibility, while remaining suitable for planning-oriented analysis of urban charging infrastructure.

With respect to fleet heterogeneity, variations in battery capacity and charging power are represented through a representative parameter setting that reflects mainstream market configurations. These parameters are treated as configurable inputs in the simulation

framework, allowing alternative battery sizes or charging power levels to be incorporated in a scenario-based manner without altering the core modeling structure.

3. EV Charging Load Forecasting Method

Accurate spatiotemporal forecasting of EV charging load is essential for collaborative planning of charging stations. Building on the system models established in Section 2, this section develops a dynamic charging load prediction framework capable of capturing heterogeneous driving behaviors, real time traffic conditions, and stochastic charging decisions. The framework integrates dynamic OD prediction, path planning, travel chain modeling, charging-demand extraction, and Monte Carlo-based simulation to generate refined load profiles for each charging station.

3.1. Dynamic OD Prediction Based on the Improved Gravity Model

Due to the difficulty of obtaining complete real-time traffic data for the study area, this study adopts a time-segmented dynamic OD prediction method based on an improved gravity model [32]. By integrating road network topology, functional zoning characteristics, and temporal distribution patterns, a multi-level traffic volume prediction framework is developed to generate simulated traffic demand, forming the basis for subsequent path planning and flow distribution. The gravity-based formula for calculating the travel volume between nodes is given as follows:

$$OD(i, j) = \frac{W_i \cdot W_j}{1 + d_{ij}} \quad (16)$$

where $W_i \cdot W_j$ represents node i and the weight of node j , reflecting population density, d_{ij} is the shortest distance between nodes.

A temporal distribution function is introduced to divide the daily OD matrix into 24 hourly intervals, accentuate tidal traffic patterns during morning and evening peaks, and generate a dynamic OD matrix $OD(i, j)$ for each time period. The specific steps are as follows:

1. Allocate differentiated node weights based on functional zoning.
2. Improve the gravity model by incorporating three components of attraction factors, impedance functions, and distance sensitivity to simulate travel uncertainty.
3. Adjust the spatiotemporal distribution model to distinguish peak and off-peak periods and highlight users' temporal travel preferences.
4. Apply a dynamic allocation algorithm that adopts the all-or-nothing (AON) assignment method, assuming that all travelers choose the shortest paths and focusing on macro-level traffic prediction.

3.2. Dynamic Optimal Path Selection

Multiple path combinations may exist between any two nodes (i, j) in the road network. In the conventional Floyd algorithm, the initial adjacency matrix (i.e., actual travel distance) is used as the weight for determining the optimal path between nodes. Since users typically prioritize minimizing travel time, this paper improves the weight matrix by using the shortest travel time as the optimization objective of the Floyd algorithm. The improved equivalent distance matrix $W(t)$ is defined as follows:

$$W(t) = \frac{D}{V_{ij}(t)} \quad (17)$$

The specific algorithmic procedure is as follows:

1. Determine the road adjacency matrix D , the origin node, and the destination node.
2. Use the Floyd algorithm to obtain the n shortest path and its corresponding set of segments.
3. Remove the last segment of the n -th shortest path, and then remove the remaining segments one by one to construct m subgraphs.
4. Apply the Floyd algorithm to each subgraph to obtain the candidate set of shortest paths between the origin and destination nodes.
5. Remove duplicate paths from the candidate set, sort them by length, and select the shortest one as the $i + 1$ -th shortest path.
6. Repeat steps (3)–(5) until N shortest paths are obtained, and determine the user's travel path using the road impedance function model.

After these steps, the improved Floyd-based path search method can systematically identify and summarize optimal paths between all nodes in the road network under the specified conditions. Because traffic flow varies dynamically throughout the day, path choices for the same OD pair may differ across time periods as traffic conditions change. Nevertheless, the selected path is always guaranteed to be the optimal choice under prevailing traffic conditions. It should be noted that the OD-based AON assignment provides a macroscopic approximation of the network traffic state, including link flows and congestion-dependent, time-varying speeds. The subsequent EV-level Monte Carlo simulation is performed conditionally on this macroscopic traffic state to capture heterogeneous routing and charging behaviors, thereby forming a coherent macroscopic-microscopic modeling linkage rather than independent or conflicting modeling steps.

3.3. Travel Chain

Based on users' travel categories and the functional zoning settings of the road network, the travel process is classified into five types: commuting, shopping, entertainment, returning home, and other activities. According to the number of stopover points, travel chains are categorized into simple and complex types [33] and further divided into six categories as illustrated in Figure 3.

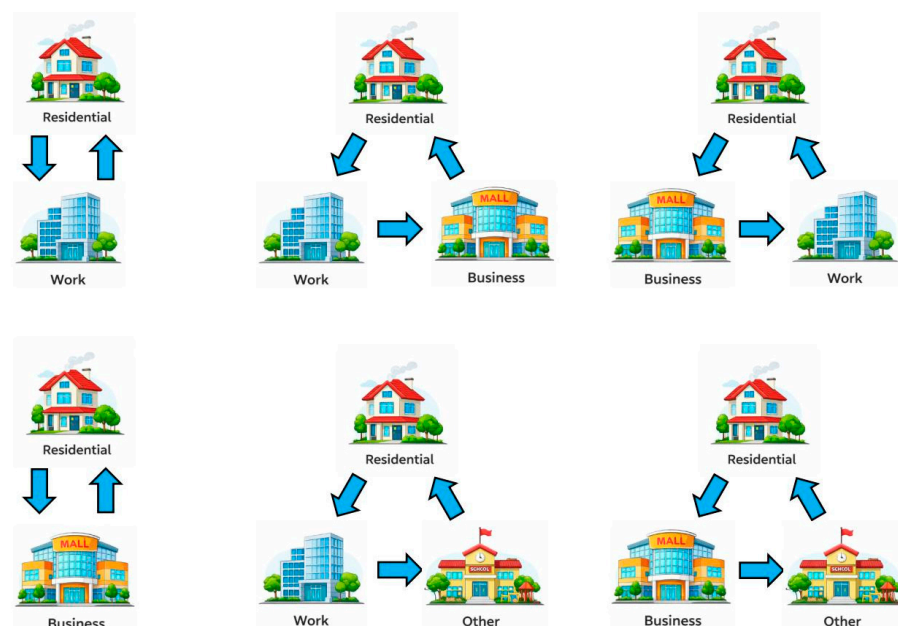


Figure 3. Travel chain.

3.4. Monte Carlo Simulation

By applying the Monte Carlo method [10] and integrating users' travel chain information with the relevant probabilistic distribution models, EV users are randomly sampled to simulate their travel behaviors. Based on the detailed road information within the integrated road network, the driving process of each electric vehicle is dynamically simulated, and the corresponding SOC consumption is continuously tracked. This procedure determines and records the specific temporal and spatial patterns of charging load generation. After all EVs have been simulated, the charging load results at each node are superimposed to obtain the predicted spatiotemporal distribution of EV charging demand. The flowchart of the proposed load forecasting model is illustrated in Figure 4.

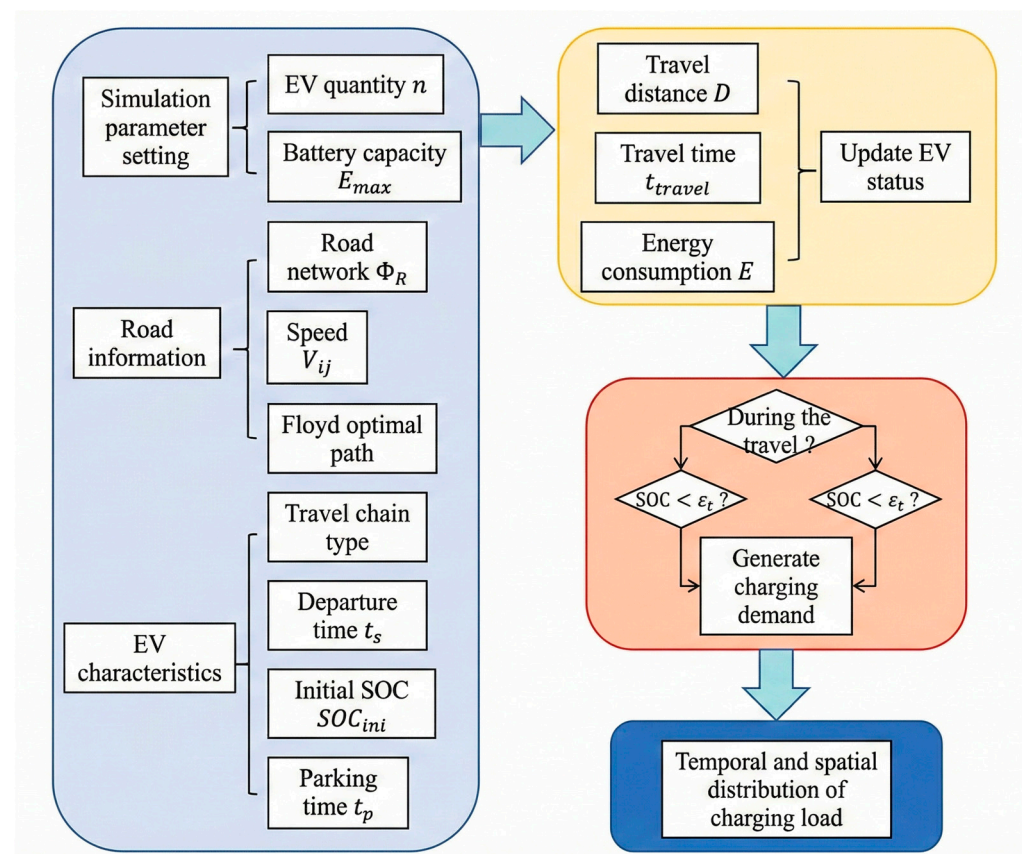


Figure 4. Load forecasting model flowchart.

The detailed procedure is as follows: First, simulation parameters and input data are initialized, including the number of EVs, battery capacity, road network topology, traffic speed, and user travel characteristics such as departure time, travel chain type, initial state of charge (SOC), and parking duration. Based on the road network and real time traffic conditions, the Floyd algorithm is applied to determine optimal travel paths. During vehicle movement, travel distance, travel time, and energy consumption are continuously calculated, and the SOC of each EV is dynamically updated. When SOC drops below the predefined threshold during driving or at the end of travel, the corresponding network node will trigger the charging demand. Finally, by aggregating charging events across all simulated vehicles and time steps, the temporal and spatial distribution of EV charging load is obtained.

4. Spatiotemporal Load Clustering and Hotspot Detection

Accurate characterization of the spatiotemporal distribution of EV charging loads is essential for charging station planning. Although the charging load forecasting results obtained in the previous section provide high temporal resolution, the resulting data are high-dimensional and spatially heterogeneous. As a result, their direct applicability to site-selection and capacity optimization problems is limited.

To extract representative spatial demand patterns and reduce the complexity of subsequent optimization, as described in this section, the K-means++ clustering method for load curve [34] was applied to identify charging demand hotspots. By clustering road network nodes with similar daily charging load profiles, stochastic spatiotemporal load data were transformed into a structured set of demand regions, providing objective and computationally efficient candidate locations for charging station deployment.

Before applying the K-means++ clustering algorithm, the number of clusters K needs to be specified. In this study, K was determined using the elbow method, which evaluates the trade-off between clustering compactness and model complexity by analyzing the within-cluster sum of squares as K increases. In our implementation, the elbow point corresponds well with the functional-zone-based partitioning adopted in the case study, and the resulting K values provide a reasonable balance between hotspot resolution and computational efficiency.

Since the clustering was performed separately within predefined functional zones, moderate variations in K mainly affect the spatial granularity of detected hotspots rather than altering the overall demand concentration pattern. Accordingly, K was treated as a planning-resolution parameter rather than a hyperparameter requiring extensive sensitivity analysis. For this reason, the detailed elbow-curve analysis is not explicitly presented in the main text. Nevertheless, the elbow-based K selection was implemented and verified during the experimental process, and the proposed framework can accommodate alternative K values if different planning resolutions are desired.

It should be noted that the clustering was performed over a predefined set of candidate nodes, which were screened in advance to ensure physical feasibility in terms of land use and accessibility to the distribution network. Therefore, the identified hotspots correspond to feasible planning locations rather than abstract spatial points.

The clustering procedure was implemented through the following steps.

1. Data preprocessing and feature construction

The daily charging load data of each road network node were collected at a 15 min sampling interval, yielding a 96-point load curve for each node. Based on this curve, a feature vector x_i was constructed to characterize the load profile of node i :

$$x_i = [lon_i, lat_i, D_i, D_{peak,i}, R_i, T_{peak,i}, StdDev_i] \quad (18)$$

where lon_i, lat_i represents the node coordinates; D_i represents the total daily demand of the node; $D_{peak,i}$ represents the daily peak load of the node; R_i represents the load rate; $T_{peak,i}$ is the peak time; and $StdDev_i$ represents the standard deviation of the load.

2. Data normalization

Because different features (e.g., total demand and temporal distribution) vary widely in scale, normalization was applied to prevent any single attribute from dominating the clustering process. All feature values were standardized before clustering.

$$x'_{i,t} = \frac{x_{i,t} - \min x_{i,t}}{\max x_{i,t} - \min x_{i,t}} \quad (19)$$

where $x'_{i,t}$ represents the load characteristics of the data point i at the t moment, and the load set x is updated after normalization.

3. K-means++ clustering process

- Initial centroid selection: Randomly select one sample from the normalized dataset C_1 as the first clustering center.
- Distance calculation and probability allocation: For each sample x in the dataset, compute its minimum distance $D(x)$ to all currently selected centers.
- Probabilistic selection: Select the next center according to formula (20), indicating that samples farther from existing centers have higher selection probability.

$$P(x) = \frac{D(x)^2}{\sum_{x \in X} D(x)} \quad (20)$$

- Iterative selection: Repeat the above two steps until K initial cluster centers are obtained.
- Standard K-means iteration: Using the optimized initial centroids, perform the standard K-means iterations by assigning each sample to the nearest centroid, recalculating cluster means, and updating centers until convergence or the iteration limit is reached.

Based on the above analysis, Algorithm 1 presents a step-by-step description of the proposed K-means++-based spatiotemporal load clustering and charging-demand hotspot identification procedure.

Algorithm 1. Spatiotemporal charging load clustering and hotspot identification.

Input:

- Road network node set $v = \{1, 2, \dots, 38\}$
- Node-level daily charging load curves $L_i(t), t = 1, 2, \dots, 96$
- Number of clusters K

Output:

- Charging demand hotspot set $\mathcal{H}$
- Cluster assignment of each road network node

1: For each road network node $i \in v$

- Collect its daily charging load curve

$$L_i = [L_i(1), L_i(2), \dots, L_i(96)]$$
- Extract spatial coordinates (lon_i, lat_i)

2: For each node i , construct the feature vector

$$x_i = [lon_i, lat_i, D_i, D_{peak,i}, R_i, T_{peak,i}, StdDev_i]$$

3: Normalize all feature vectors using standardization:

$$x'_{i,t} = \frac{x_{i,t} - \min x_{i,t}}{\max x_{i,t} - \min x_{i,t}}$$

To obtain the normalized dataset X'

4: Initialize cluster centers using the K-means++ strategy:

- Randomly select the first centroid
- For each remaining centroid, select node i with probability

$$P(x) = \frac{D(x)^2}{\sum_{x \in X} D(x)}$$

5: Repeat until convergence:

- Assign each node iii to the nearest centroid based on Euclidean distance
- Update each cluster centroid as the means of assigned feature vectors

6: Identify cluster centroids as charging demand hotspots $\mathcal{H}$

Output:

-
- Cluster labels for all road network nodes
 - Hotspot set $\mathcal{H}$, used as candidate locations for subsequent station planning
-

5. Collaborative Optimization Framework for Charging Station Deployment

In the previous section, demand hotspots were identified, and the initial candidate sites for charging stations were extracted through clustering analysis. Building on this foundation, this section addresses the comprehensive problem of charging station siting and capacity configuration. This task constitutes a large-scale system optimization problem that must simultaneously consider the objectives of three stakeholders: station operators, EV users, and the distribution network. Because these objectives are often conflicting, traditional single-objective methods are insufficient for achieving balanced planning decisions.

To overcome this challenge, this section develops a multi-objective optimization framework that jointly minimizes the overall system cost and the voltage deviation of the distribution network. To handle the high dimensionality and nonlinearity of the planning problem, a coordinated optimization mechanism is introduced by integrating a weighted Voronoi diagram [35] with a multi-objective particle swarm optimization algorithm (Voronoi-MO-PSO) [36]. This mechanism enables dynamic partitioning of charging station service areas and achieves globally optimized capacity allocation across candidate sites.

5.1. Construction of Multi-Objective Optimization Model

5.1.1. Objective Function

In this study, the charging station deployment problem is formulated as a planning-oriented optimization that jointly considers economic performance from both the station operator and EV user perspectives while strictly satisfying distribution-network voltage security requirements. The charging station planning problem is multi-objective by nature, involving station-side cost, user-side cost, and grid voltage security. In this study, grid voltage security is enforced as a mandatory feasibility requirement via constraint handling/penalty mechanisms. Under grid-feasible conditions, the station-side and user-side economic objectives are combined using a weighted-sum preference strategy, resulting in a scalarized constrained optimization problem solved by MOPSO.

The planning problem in this study involves three stakeholders: the charging station operator, EV users, and the distribution-network operator. Accordingly, the objective design is structured into three components: station-side economic cost F_1 , user-side generalized cost F_2 , and grid-side voltage quality indicator F_3 .

In particular, the grid-side voltage requirement represents an operational security constraint and must be satisfied. Therefore, the optimization follows a “feasibility-first” logic: solutions that violate voltage constraints are penalized or rejected, and the economic objective is optimized within the feasible region. The following subsections explain each component and its physical meaning.

The cost on the charging station side covers the initial investment during the construction stage and the maintenance expenses during the operation period, and they are uniformly annualized.

$$F_1 = f_i + f_m \quad (21)$$

where f_i represents the construction cost of the power station; f_m represents the operation and maintenance cost of the power station.

The construction cost (annualized) mainly includes land purchase and investment in charging pile equipment:

$$f_i = \frac{1}{T} \sum_{j=1}^J X_j \frac{r_0(1+r_0)^T}{(1+r_0)^T - 1} (S \cdot C_{land} + C_{pile} \cdot N_{pile}) \quad (22)$$

$$C_{land} \in \{C_{land,H}, C_{land,W}, C_{land,B}, C_{land,O}\} \quad (23)$$

$$S = (1 + \varpi) s_{pile} \cdot N_{pile} \quad (24)$$

where J represents the set of charging stations; X_j is a binary decision variable ranging from 0 to 1. r_0 represents the average depreciation rate; T represents the expected service life of the charging station; S represents the land area occupied for the construction of the charging station. C_{land} , C_{pile} represent the land cost and charging pile cost corresponding to the location of the charging station. N_{pile} represents the estimated number of charging station piles to be constructed; ϖ is the proportional coefficient of the parking space area to the area occupied by the facilities. s_{pile} represents the construction area of a single charging pile parking space.

The operation and maintenance (O&M) costs of charging stations are closely related to their construction costs. In general, stations with higher construction expenditures and a larger number of chargers incur correspondingly higher O&M costs. This relationship can be represented proportionally to the construction cost, expressed as follows:

$$f_m = \kappa f_i \quad (25)$$

where κ is the ratio of operation and maintenance cost to construction cost.

In summary, F_1 increases with the number of deployed chargers and the required land area, while the O&M cost is modeled as proportional to the investment scale. This formulation allows the planning model to capture the trade-off between increasing service capability and the associated infrastructure cost.

User cost includes the travel cost, charging cost and time cost which is expressed as

$$F_2 = f_d + f_c + f_t \quad (26)$$

Travel cost primarily originates from the energy consumed by route to the charging station:

$$f_d = \frac{(E_d + E_{ac}) \times C_E}{C_B(T)} \quad (27)$$

$$E_d = \sum_{k=1}^K \sum_{l \in L_{k,j-j}} X_{i,k} \cdot EC_{l,t} \cdot d_l \quad (28)$$

$$E_{ac} = \sum_{k=1}^K E_{ac,k} = \sum_{k=1}^K \sum_{l \in L_{k,j-j}} X_{i,k} \cdot K_{ac}(T) \cdot P_{ac}(T) \cdot \frac{d_l}{V_l(t)} \quad (29)$$

Here, the travel cost is determined by the total route distance and the congestion-dependent travel speed, which captures how traffic conditions influence energy consumption during access to charging stations.

Charging cost refers to the expense incurred by users for the energy replenished at the charging station:

$$f_c = \sum_{k=1}^K \sum_{i=1}^I X_{i,k} \cdot (SOC_{ex} - SOC_{i,k}) \cdot E \cdot C_E \quad (30)$$

The time cost represents the total time incurred by a user from the moment a charging demand is triggered until the charging process is completed. It consists of three components: travel time to the station, queuing time at the station, and the actual charging time. It is expressed as

$$f_t = (T_{travel} + T_{queue} + T_{charge}) \times C_T \quad (31)$$

$$T_{travel} = \sum_{k=1}^K \sum_{l \in L_{k,j-j}} X_{i,k} \cdot \frac{d_l}{V_l(t)} \quad (32)$$

$$T_{queue} = \sum_{k=1}^K \sum_{l=1}^I X_{i,k} \cdot W_q \quad (33)$$

$$T_{charge} = \frac{E_d + E_{ac} + E_c}{\mu_{charge} \cdot P_c} \quad (34)$$

$$E_c = \sum_{k=1}^K \sum_{i=1}^I X_{i,k} \cdot (SOC_{ex} - SOC_{i,k}) \cdot E \quad (35)$$

To improve power supply quality, system voltage deviation is included as an optimization objective. The root mean square error of the three-phase nodal voltage is used as the evaluation metric, expressed as

$$F_3 = \sqrt{\frac{1}{3N_{t,grid}} \sum_{t=1}^{N_{t,grid}} \sum_{\phi \in \{A,B,C\}} (V_{\phi}(t) - V_{nominal})^2} \quad (36)$$

where F_3 is the voltage deviation objective function. $N_{t,grid}$ is the number of time intervals for power flow analysis. ϕ represents the phase, which can be A, B, or C in a three-phase system. $V_{nominal}$ denotes the rated voltage of the distribution network.

Since F_1, F_2, F_3 have different physical units and orders of magnitude, a normalization procedure is adopted to ensure numerical comparability. The economic objective is formed by combining station-side and user-side costs, while voltage security is enforced through the constraint-handling and penalty mechanism. As a result, the optimization minimizes a weighted economic objective under grid-security constraints, which is suitable for iterative meta-heuristic solvers. The specific formula is as follows:

$$\min F = \omega_1 \bar{f}_{eco} + \omega_2 \bar{f}_{grid} + P_{voltage} \cdot \Pi_{violation} \quad (37)$$

$$f_{eco} = F_1 + F_2 \quad (38)$$

$$f_{grid} = F_3 \quad (39)$$

$$\bar{f}_n = \frac{f_n - f_n^{\min}}{f_n^{\max} - f_n^{\min}}, n \in \{eco, grid\} \quad (40)$$

$$P_{voltage} = k_p \cdot \left[\sum_{t,\phi} \max(0, (V_{\phi}(t) - V_{nominal})^2) + \sum_{t,\phi} \max(0, (V_{\min} - V_{\phi}(t))^2) \right] \quad (41)$$

where ω_1 ω_2 are the weighting coefficients for the objective functions. f_{eco} is the system economic objective function, defined as the sum of the annualized cost on the station side and the total daily cost on the user side. f_{grid} is the distribution-network-side voltage deviation objective function. $\tilde{f}_n$ is the normalization function using the Min–Max scaling method. $P_{voltage}$ is the voltage violation penalty function. $\Pi_{violation}$ is the voltage violation indicator coefficient.

It should be noted that the station-side cost and user-side cost are expressed in the same monetary unit and are directly aggregated to form the overall economic objective. Therefore, the trade-off between charging station operators and EV users is structurally embedded in the economic objective itself, rather than being regulated by additional preference weights. The weighting coefficients introduced in the objective function are used to balance the normalized economic objective and grid-side voltage quality.

5.1.2. Constraints

$$V_{\min} < V_j(t) < V_{\max}, \forall j, t \quad (42)$$

$$I_{br} \leq I_{br, \max}, \forall br, t \quad (43)$$

$$P_{i, m} \leq P_{\max, m} + \Delta P_m \quad (44)$$

$$\begin{cases} \sum_{j=1}^{N_{flow}} P_j + \sum_{j=1}^{N_{flow}} P_{ch, j} - P_{loss} = \sum_{j=1}^{N_{flow}} P_{load, j} \\ \sum_{j=1}^{N_{flow}} Q_j + \sum_{j=1}^{N_{flow}} Q_{ch, j} - Q_{loss} = \sum_{j=1}^{N_{flow}} Q_{load, j} \end{cases} \quad (45)$$

$$N_{ch, \min} < \sum X_j < N_{ch, \max} \quad (46)$$

$$N_{pile, \min} < N_{ch, pile} < N_{pile, \max} \quad (47)$$

$$D_{m, \max} \leq D_{grid, \max} \quad (48)$$

$$0 \leq T \leq T_{\max} \quad (49)$$

where $V_{\min}$ $V_{\max}$ represent the minimum and maximum voltage constraints of the power grid; $I_{br, \max}$ is the maximum branch current constraint; $P_{\max, m} + \Delta P_m$ is the capacity constraint of the transformer; Equation 42 represents the system power balance constraint; $N_{ch, \min}$ and $N_{ch, \max}$ represent the minimum and maximum number constraints of charging stations in the road network, respectively. $N_{pile, \min}$ $N_{pile, \max}$ represent the minimum and maximum constraints on the number of piles within the station. $D_{grid, \max}$ is the inter-station service radius constraint; the maximum service life constraint of the charging station is $T_{\max}$.

5.2. Collaborative Optimization Algorithm Based on Voronoi-MO-PSO

Based on the hotspot identification results obtained in the previous section, where K-means++ clustering is used to extract representative charging demand regions and reduce the candidate search space, the charging station planning problem is further formulated as a joint location–capacity optimization task under road–grid coupling conditions.

The optimization model developed in the previous section is a nonlinear, multivariable, and constrained problem. A key challenge lies in the strong coupling between the service areas of charging stations and their capacity configurations, where adjustments in one dimension directly influence the other. To address this interdependence, this section introduces a collaborative optimization framework termed Voronoi-MO-PSO, which integrates a weighted Voronoi diagram with a multi-objective particle swarm optimization algorithm. The multi-objective charging station planning problem is solved using a weighted-sum scalarization strategy combined with strict voltage-feasibility enforcement. After normalization, economic performance and grid-side voltage quality are integrated into the objective function, and candidate solutions are evaluated with feasibility and penalty mechanisms. This formulation enables the optimization algorithm to search for representative planning solutions with specified preference settings, while ensuring that voltage-security requirements are satisfied throughout the optimization process. This framework enables dynamic partitioning of station service areas while simultaneously performing global capacity optimization, thereby achieving coordinated and efficient planning.

It should be emphasized that the contribution of this framework does not lie in the individual novelty of K-means++, weighted Voronoi partitioning, or MOPSO, which have been widely used in related studies. Instead, the novelty lies in their problem-driven integration into a unified and interactive planning loop.

Specifically, K-means++ provides a demand-driven initialization by identifying spatiotemporal charging hotspots, thereby narrowing the solution space. The weighted Voronoi mechanism introduces a capacity-aware and dynamically adjustable representation of charging service areas, allowing demand allocation to respond explicitly to planning decisions. Building on this adaptive service-area modeling, MOPSO is employed to solve the resulting constrained multi-objective planning problem under road-grid coupling conditions. The iterative interaction between service-area redistribution and capacity deployment enables congestion mitigation and demand shifting effects to be captured during the optimization process, which constitutes the core conceptual contribution of the proposed framework.

5.2.1. Algorithm Framework

The Voronoi-MO-PSO algorithm embeds a weighted Voronoi diagram into the multi-objective particle swarm optimization (MOPSO) framework, enabling dynamic partitioning of service areas and forming a closed loop feedback mechanism. The operating principles of the framework are summarized as follows:

1. Decision variable: The number of charging piles configured at each charging station is used $N = [n_1, n_2, n_3, n_4, n_5]$ as the optimization decision variable.
2. Optimization engine: A multi-objective PSO algorithm is employed to explore the solution space and identify the optimal capacity configuration scheme.
3. Dynamic coupling: For each candidate capacity configuration generated by the PSO, the weighted Voronoi diagram is applied to reallocate service areas according to the current capacities, and the associated economic cost and voltage deviation are subsequently evaluated.
4. Constraint handling: A penalty function mechanism incorporates voltage safety constraints into the optimization objective, guiding the search toward feasible solutions that balance economic efficiency and operational safety.

Through this interaction mechanism, spatial service area allocation and numerical capacity optimization are tightly coupled within a unified iterative framework.

5.2.2. Weighted Voronoi Diagram Model

The traditional Voronoi diagram partitions a continuous geometric space, whereas real road networks are composed of discrete nodes. To reconcile this mismatch, this study employs a discretized weighted Voronoi allocation method defined directly on the road network nodes. For a road network G consisting of 38 nodes and a set of five candidate charging stations $CS = \{CS_1, CS_2, CS_3, CS_4, CS_5\}$, the assignment of each network node to a charging station CS_i is mathematically defined as follows:

$$Station(x) = \arg \min_i \left(\frac{d(x, CS_i)}{w_i} \right) \quad (50)$$

where $d(x, CS_i)$ represents the actual shortest path distance of node x to the station i ; w_i represents the comprehensive influence weight of the charging station, reflecting the relative strength of the service capacity of the site; and $\arg \min$ indicates the return of the charging station representation that minimizes the entire function, rather than the actual distance itself.

5.2.3. Dynamic calculation Model of Comprehensive weights

To ensure that the Voronoi-based partitioning reflects not only spatial proximity but also heterogeneous station capabilities and traffic conditions, a dynamic composite weight model is introduced. A weighted Voronoi diagram is constructed on the discrete nodes of the road network. Node assignment to charging stations is dynamically determined by the ratio between each node's shortest path distance to a station and the station's composite influence weight. This mechanism enables adaptive and rational service area partitioning that reflects both spatial structure and operational characteristics.

$$w_i = \alpha_1 w_{pile,i} + \alpha_2 w_{access,i} \quad (51)$$

$$w_{pile,i} = \tau_1 + \tau_2 \frac{n_i - \min(N)}{\max(N) - \min(N)} \quad (52)$$

$$w_{access,i} = \tau_3 + \tau_4 \frac{\bar{T}_{i,t} - \min(\bar{T}_t)}{\max(\bar{T}_t) - \min(\bar{T}_t)} \quad (53)$$

where $w_{pile,i}$ is the capacity weight. $w_{access,i}$ is the accessibility weight. $\bar{T}_{i,t}$ is the average travel time to charging station i during time period T . τ is normalization scaling coefficient.

The composite station weight is constructed as a linear combination of capacity-related and accessibility-related factors to jointly reflect infrastructure adequacy and user convenience. A linear aggregation is adopted for three main reasons: (1) it provides an interpretable and transparent trade-off between the two drivers, which is suitable for planning-oriented decision-making; (2) it is computationally efficient and numerically stable when the weighted Voronoi partition is repeatedly updated within the MOPSO iterations; and (3) it serves as a baseline formulation that can be naturally extended to nonlinear or data-driven aggregation functions when additional calibration data become available. This weighting model ensures that service area partitioning is determined not only by each station's inherent capacity but also by real time variations in road network traffic conditions, thereby enabling spatiotemporal dynamic optimization of service boundaries.

5.2.4. Multi-Objective Particle Swarm Optimization Algorithm

To efficiently solve the resulting nonlinear and constrained multi-objective problem, a MOPSO algorithm with embedded voltage constraints is developed for joint service area partitioning and capacity optimization.

In the proposed framework, each particle represents a candidate charging station capacity configuration, expressed as

$$X_k = [N_1^{(k)}, N_2^{(k)}, \dots, N_M^{(k)}] \quad (54)$$

where $N_i^{(k)}$ denotes the number of charging piles allocated to station i by particle k , subject to capacity constraint (47).

(1) Initialization

At the beginning of the algorithm, the swarm size and maximum iteration number are specified. Particle positions X_k and velocities V_k are randomly initialized within the feasible capacity region. Each particle's initial position is recorded as its personal best solution $P_{best,k}$, and a global Pareto archive is initialized to store non-dominated solutions.

(2) Voronoi-Based Allocation and Fitness Evaluation

For each particle in the swarm, a weighted Voronoi diagram is constructed based on the current capacity configuration X_k . Using the discrete road network formulation introduced in Section 5.2.2, each network node is assigned to a charging station according to the weighted shortest path distance, thereby dynamically determining the service area of each station.

Based on the resulting service area partitioning, charging loads within each region are aggregated and mapped to the corresponding nodes of the distribution network. Power flow analysis is then performed to obtain node voltages over the scheduling horizon. The particle fitness is evaluated using the multi-objective function vector

$$F(X_k) = [F_1(X_k), F_2(X_k), F_3(X_k)] \quad (55)$$

To ensure grid security, voltage constraints are incorporated using a constraint dominating rule. Solutions satisfying all voltage limits are always preferred over infeasible ones, while infeasible solutions are compared based on the severity of voltage violations. This mechanism guides the search process toward Pareto optimal solutions that simultaneously satisfy economic and operational requirements.

(3) Particle Update and Feasibility Repair

After fitness evaluation, each particle updates its velocity and position according to the standard MOPSO update equations:

$$V_k^{t+1} = \omega V_k^t + c_1 r_1 (P_{best,k} - X_k^t) + c_2 r_2 (G_{best,k} - X_k^t) \quad (56)$$

$$X_k^{t+1} = X_k^t + V_k^{t+1} \quad (57)$$

where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are uniformly distributed random variables.

Since charging station capacities are discrete decision variables, a rounding operator and boundary handling strategy are applied after each update to ensure integer valued and feasible capacity configurations. The updated particle position is then re-evaluated in the next iteration through Voronoi allocation and load-grid coupling analysis.

(4) Termination and Solution Selection

The iterative optimization process continues until the maximum iteration number is reached or convergence criteria are satisfied. The final solution is selected from the global Pareto archive according to planning preferences, yielding an optimal charging station

capacity configuration that balances station investment, user cost, and distribution-network voltage performance.

The overall optimization procedure of the proposed Voronoi-MO-PSO framework is summarized in Algorithm 2.

Algorithm 2. Voronoi-MO-PSO-based collaborative optimization for charging station capacity planning.

Input:

- Road network $G(V,E)$ with 38 nodes
- Candidate charging station set $CS = \{CS_1, CS_2, CS_3, CS_4, CS_5\}$
- Feasible capacity bounds $N_i^{\min}, N_i^{\max}$
- Initial demand data and traffic information
- PSO parameters (ω, c, r)
- Swarm size N_p , maximum iterations $T_{\max}$

Output:

- Best grid-feasible charging station capacity configuration N^* under the weighted economic objective

1: Initialize swarm size N_p , and iteration counter $t = 0$

2: Randomly initialize particle positions

$$X_k^{(0)} = [n_{1,k}, n_{2,k}, n_{3,k}, n_{4,k}, n_{5,k}]$$

and velocities $V_k^{(0)}$ within feasible bounds

3: Set personal best $P_{\text{best},k} = X_k^{(0)}$ for all particles

4: Initialize global best solution G_{best}

5: **While** $t < T_{\max}$ **do**

6: **for** each particle $k = 1, \dots, N_p$ **do**

7: Compute composite station weights w_i using (51)–(53)

8: Construct discrete weighted Voronoi diagram on road network

$$\text{Station}(x) = \arg \min_i \left(\frac{d(x, CS_i)}{w_i} \right)$$

9: Aggregate charging loads within each service area

10: Map charging loads to distribution network nodes

11: Perform power flow analysis to obtain node voltages

12: Evaluate multi-objective fitness vector

$$F(X_k) = \{C_{\text{station}}, C_{\text{user}}, V_{\text{dev}}\}$$

13: Apply voltage-feasibility rule (feasible solutions are always preferred) and compute penalty for infeasible ones

14: Update $P_{\text{best},k}$ using feasibility-first comparison under the weighted objective

15: Update G_{best} as the best among all $P_{\text{best},k}$

16: **end for**

17: Set global guide as the current global best solution G_{best}

18: **for** each particle $k = 1, \dots, N_p$ **do**

19: Update velocity

$$V_k^{t+1} = \omega V_k^t + c_1 r_1 (P_{\text{best},k} - X_k^t) + c_2 r_2 (G_{\text{best}} - X_k^t)$$

20: Update position

$$X_k^{t+1} = X_k^t + V_k^{t+1}$$

21: Apply rounding and boundary handling to ensure feasibility

22: **end for**

23: $t = t + 1$

24: **end while**

25: Set $N^* = G_{\text{best}}$ (the best grid-feasible solution under the weighted objective)

26: Return N^*

6. Case Studies

6.1. Parameter Settings

In this study, a representative urban road traffic network consisting of 38 nodes and 63 road segments was used, as shown in the figure. Based on planning requirements, the network is divided into five functional zones: Residential Area 1, Residential Area 2, the Working Area, the Industrial Area, and Other Areas. Following [37], roads are categorized into Grade I and Grade II, corresponding to urban arterial roads and secondary arterial roads, with zero flow speeds set to 60 km/h and 40 km/h, respectively. The mapping between functional zones and network nodes, along with detailed road information, is provided in Table 1.

Table 1. Functional areas covering nodes.

Functional Area	Overlay Nodes
Residential H1	1, 2, 3, 8, 9, 10, 13, 17
Residential H2	23, 24, 28, 31, 32, 36, 37, 38
Work W	4, 5, 6, 7, 11, 12, 15, 16
Business B	14, 20, 21, 22, 26, 27, 35
Other O	18, 19, 25, 29, 30, 33, 34

This study adopts the IEEE 33-node distribution network as the network framework. The charging station nodes in the road network are coupled with their corresponding nodes in the distribution network, and the charging loads within each station’s service area are mapped to the associated grid nodes. The topology of the coupling relationship between the road network and the power system is shown in Figure 5. The black dots represent actual road nodes and current nodes. The red star and square represent the deployment locations of charging stations in the road network and power flow, while the red dashed line represents the node mapping relationship of the road network and power grid

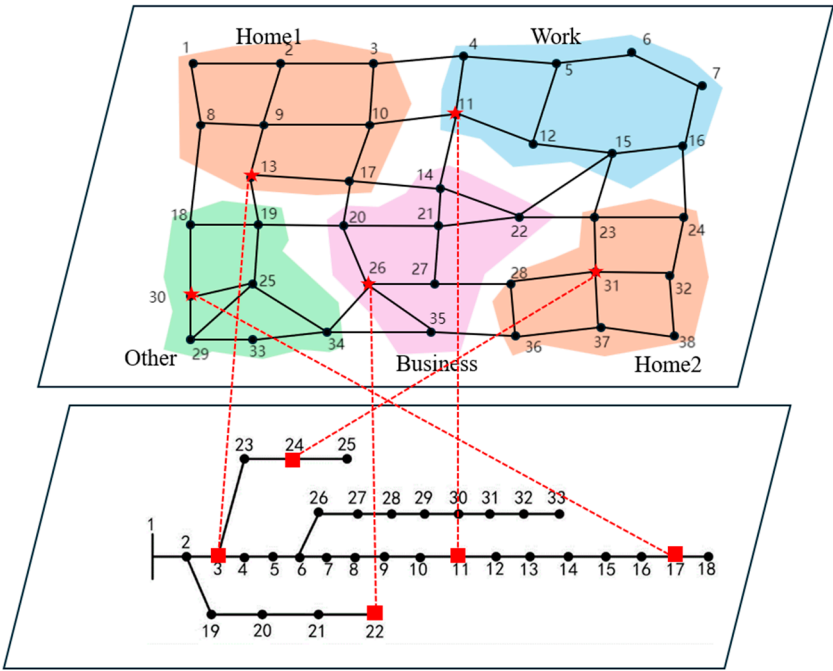


Figure 5. Schematic diagram of circuit and electrical coupling.

In this study, the functional zoning of the study area (e.g., residential, workplace, and commercial zones) is treated as a representative and quasi-static planning input. This is because the proposed framework aims to validate the road–grid coupled collaborative planning mechanism with typical daily traffic and charging demand patterns, while the deployment of charging infrastructure is generally planned on a medium- to long-term horizon. Nevertheless, the proposed framework is extensible: when updated land-use data or mobility statistics are available, the node weights and OD demand intensity can be updated accordingly to support time-varying functional zoning.

Referring to the parameter specifications for different road classifications provided in [38], the corresponding road grade settings used in this study are summarized in Appendix A. These parameters serve as the foundational inputs for modeling traffic flow, capacity constraints, and speed–flow relationships across the urban road network.

The parameters of the multi-objective particle swarm optimization algorithm were configured as follows: the swarm size was set to 30, the maximum number of iterations to 50, the inertia weight to 0.7, and both the cognitive and social learning factors to 1.5.

The simulation was conducted on the MATLAB R2024b platform using a one-day time window, with data sampled every 5 min, resulting in 288 time intervals. The number of EVs in the simulation was set to $n=20000$. In the case study, the battery capacity of private EVs was set to 40 kWh, and the charging power was assumed to be 50 kW, representing a typical fast-charging configuration for urban private vehicles. The Monte Carlo simulation was performed using a single large-sample realization rather than multiple repeated runs. With a population size of $n = 20000$ EV agents, the aggregated charging load profiles and station-level performance indicators exhibit stable macroscopic characteristics suitable for planning-oriented analysis. This design choice allows the framework to capture heterogeneous EV behaviors while maintaining computational efficiency and result interpretability at the system level.

To evaluate the effectiveness of the proposed method and assess the optimization impact of each processing step on charging station planning, four case scenarios were designed. The specific settings are as follows:

Case 1: Baseline scenario, in which neither user demand nor power grid performance is considered. The initial site layout and capacity configuration are provided in Table 2.

Case 2: User-demand-oriented scenario, where load data are clustered and charging station locations are updated accordingly.

Case 3: Service area optimization, in which the service areas of charging stations are updated using Voronoi-diagram-based partitioning.

Case 4: Comprehensive collaborative optimization, integrating road–grid coupling and iteratively optimizing station capacities using a multi-objective particle swarm optimization algorithm.

To ensure a fair evaluation of the proposed collaborative planning framework, we compared multiple structured baseline scenarios with the same road–grid simulation settings. Specifically, Scenario 1 represents the non-optimized deployment baseline, Scenario 2 evaluates location-only optimization without capacity adjustment, and Scenario 3 presents the joint optimization of station location and capacity. This progressive comparison is used to quantify the incremental effectiveness of each module and to avoid biased conclusions caused by inconsistent assumptions.

Table 2. Original case setup.

Functional Zone of the Charging Station	Station Road Node	Station Grid Node	Capacity
H1	13	3	60
H2	31	24	60
W	11	11	80

B	26	22	50
O	30	17	20

6.2. Results and Analysis

The spatiotemporal distribution of system-wide EV charging load is shown in Figure 6. From a temporal perspective, charging demand remains low between 00:00 and 06:00, representing residual demand from the previous day. A notable increase occurs between 07:00 and 10:00 due to morning commuting activities. A second rise appears from 12:00 to 15:00, driven by midday travel. The evening period from 19:00 to 22:00 exhibits the highest demand as users return home and initiate charging, forming the daily peak load. From a spatial perspective, morning and evening peak nodes correspond primarily to work area and residential area nodes, respectively. At midday, the spatial distribution becomes more dispersed, with relatively balanced loads across residential, work, and commercial zones—likely reflecting users' lunchtime travel patterns.

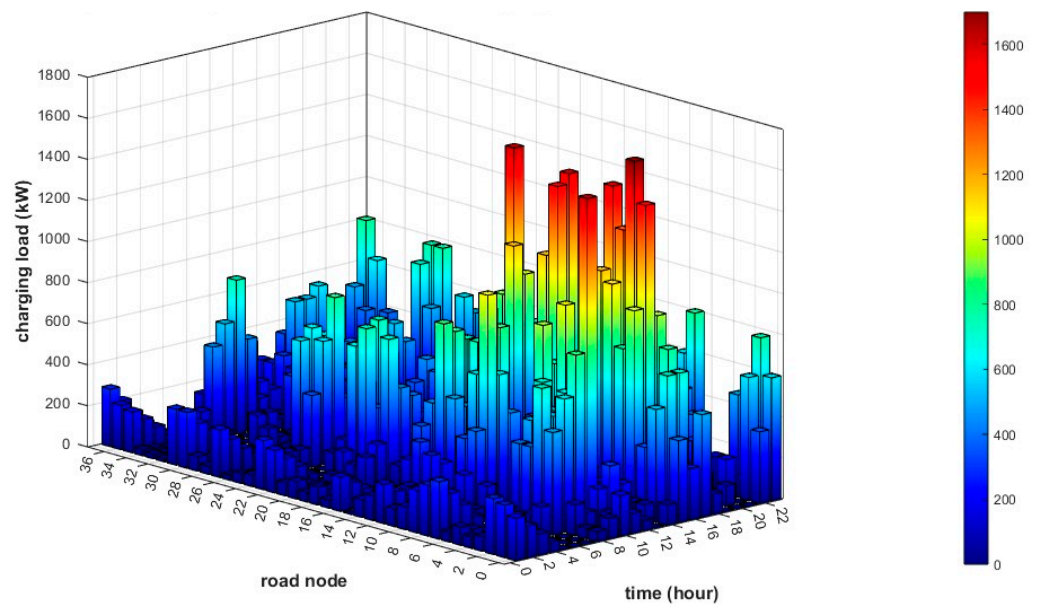


Figure 6. Spatiotemporal distribution map of EV charging load.

Overall, EV users typically depart from residential areas in the morning and travel toward work, commercial, and other functional zones, increasing demand in those areas. After work, vehicle flows shift toward commercial zones for leisure activities before returning to residential areas, resulting in elevated load levels during the evening and nighttime periods.

Table 3. Cost comparison.

	Station Cost (10 ⁴ CNY/year)	Charging Cost (10 ⁴ CNY/day)	Time Cost (10 ⁴ CNY/day)
Case 1	141.66	7.14	5.58
Case 2	141.66	6.67	5.30
Case 3	141.66	7.97	4.79
Case 4	151.14	7.98	4.70

From the perspective of economic cost, as shown in Table 3, Case 1 serves as the benchmark scenario. Due to the preset station locations and capacities aligned strictly with functional zones, both user charging cost and overall system cost remain relatively high,

reflecting inefficiencies in the initial layout and capacity design. In Case 2, updating charging station locations through cluster analysis leads to a noticeable reduction in total charging cost by 6.6%. This improvement arises from better spatial matching between charging demand and station locations, which reduces unnecessary travel distance and energy consumption. However, as service areas and station capacities remain unchanged, the cost reduction potential is limited. In Case 3, although the weighted Voronoi-based service area division significantly improves spatial allocation efficiency, the total charging cost increases. This increase is attributed to users being redirected to less congested but more distant stations, which raises travel distance and electricity consumption. Nevertheless, the higher charging cost is accompanied by substantial operational efficiency gains. Case 4 achieves the most balanced cost performance through joint optimization of station locations and capacities. While the annualized station-side cost increases by approximately 6.7% due to expanded charging capacity, this additional investment supports improved service quality and grid stability. Overall, the moderate increase in infrastructure cost is justified by the significant reductions in user related costs and enhanced system-level performance.

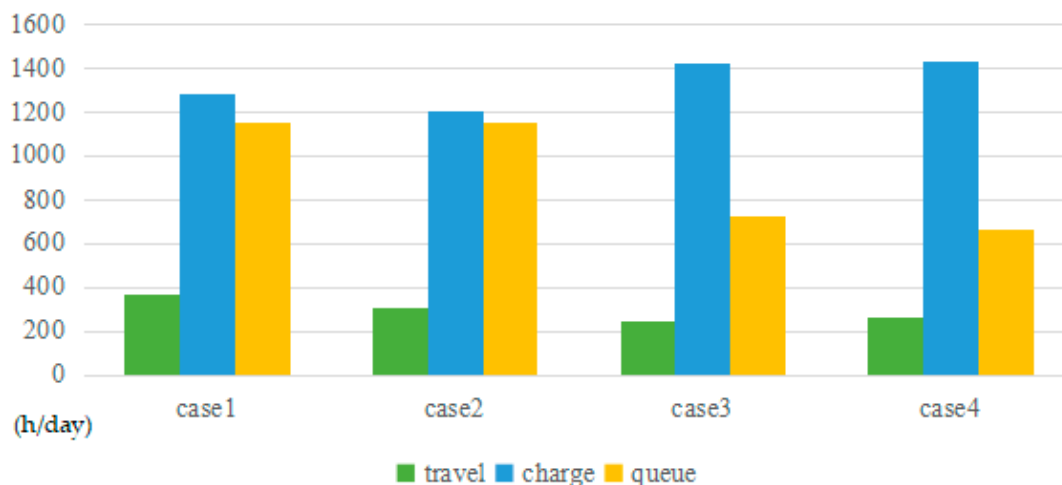


Figure 7. Time composition diagram.

From the perspective of time consumption, as shown in Figure 7. Tables 4 and 5 summarize the time consumption results in the four planning scenarios, providing insight into how different planning strategies affect user time expenditure. In Case 1, where charging stations are preset by functional zones with fixed capacities, the total daily time consumption is the highest (2790.50 h/day). Queuing time accounts for 41.1% of the total, indicating severe congestion caused by the mismatch between charging demand and station capacity. In Case 2, optimizing station locations through clustering reduces travel time by 17.5% compared with Case 1, leading to a moderate decrease in total time consumption. However, queuing time slightly increases both in absolute value and proportion (43.4%), revealing that location optimization alone is insufficient to alleviate congestion when service-area boundaries and station capacities remain unchanged. The increased queue-time proportion in Scenario 2 indicates that location-only optimization may concentrate charging demand at highly attractive sites when capacity is not adjusted accordingly, thereby inducing local congestion. This observation supports the necessity of joint optimization of station location and capacity as adopted in Scenario 3. In real-world operations, dynamic pricing policies (e.g., time-of-use tariffs, congestion-aware pricing, or incentive-based routing) can further alleviate queuing congestion by redistributing charging demand

across stations. Such pricing mechanisms can be incorporated into the proposed framework as an additional operational layer by influencing user station-choice behavior and demand allocation. Case 3 introduces weighted Voronoi-based service area partitioning, which substantially redistributes charging demand among stations. As a result, queuing time is reduced by 36.8% to 724.84 h/day, and its proportion drops to 30.3%, no longer dominating total time expenditure. Travel time is further reduced, while charging time increases due to higher service utilization and longer effective charging durations, reflecting a shift from waiting toward productive charging activities. Case 3 is designed as a service-area optimization scenario based on the weighted Voronoi division. The primary goal is to enhance spatial service balance and mitigate local congestion and queueing effects by redistributing charging demand more evenly across stations. As a result, this scenario prioritizes congestion mitigation and service efficiency improvement over strict economic cost minimization. In Case 4, where station locations and capacities are jointly optimized under road-grid coupling constraints, total daily time consumption is minimized at 2351.21 h/day. Queuing time is further reduced to 662.88 h/day, accounting for only 28.2% of total time. Although travel time slightly increases compared with Case 3, the overall time structure becomes more balanced among travel, charging, and queuing. These results demonstrate that the proposed collaborative optimization strategy achieves the most efficient and rational time allocation outcome by simultaneously addressing spatial allocation, capacity configuration, and congestion mitigation. It should be noted that the optimized deployment may involve a moderate increase in infrastructure investment in certain scenarios. This increase reflects a collaborative planning trade-off to improve service accessibility and congestion mitigation while maintaining grid security, rather than indicating a purely negative profitability outcome.

Table 4. Time consumption.

	Travel Time (h/day)	Charging Time (h/day)	Queuing Time (h/day)
Case 1	365.47	1277.82	1147.21
Case 2	301.46	1198.91	1149.85
Case 3	246.88	1422.68	724.84
Case 4	263.12	1425.21	662.88

Table 5. Time proportion.

	Total Time (h/day)	Travel Time	Charging Time	Queuing Time
Case 1	2790.50	13.1%	45.8%	41.1%
Case 2	2650.22	11.4%	45.2%	43.4%
Case 3	2394.40	10.3%	59.4%	30.3%
Case 4	2351.21	11.2%	60.6%	28.2%

The voltage situation of the 18 nodes in different scenarios are illustrated in Figure 8a–e.

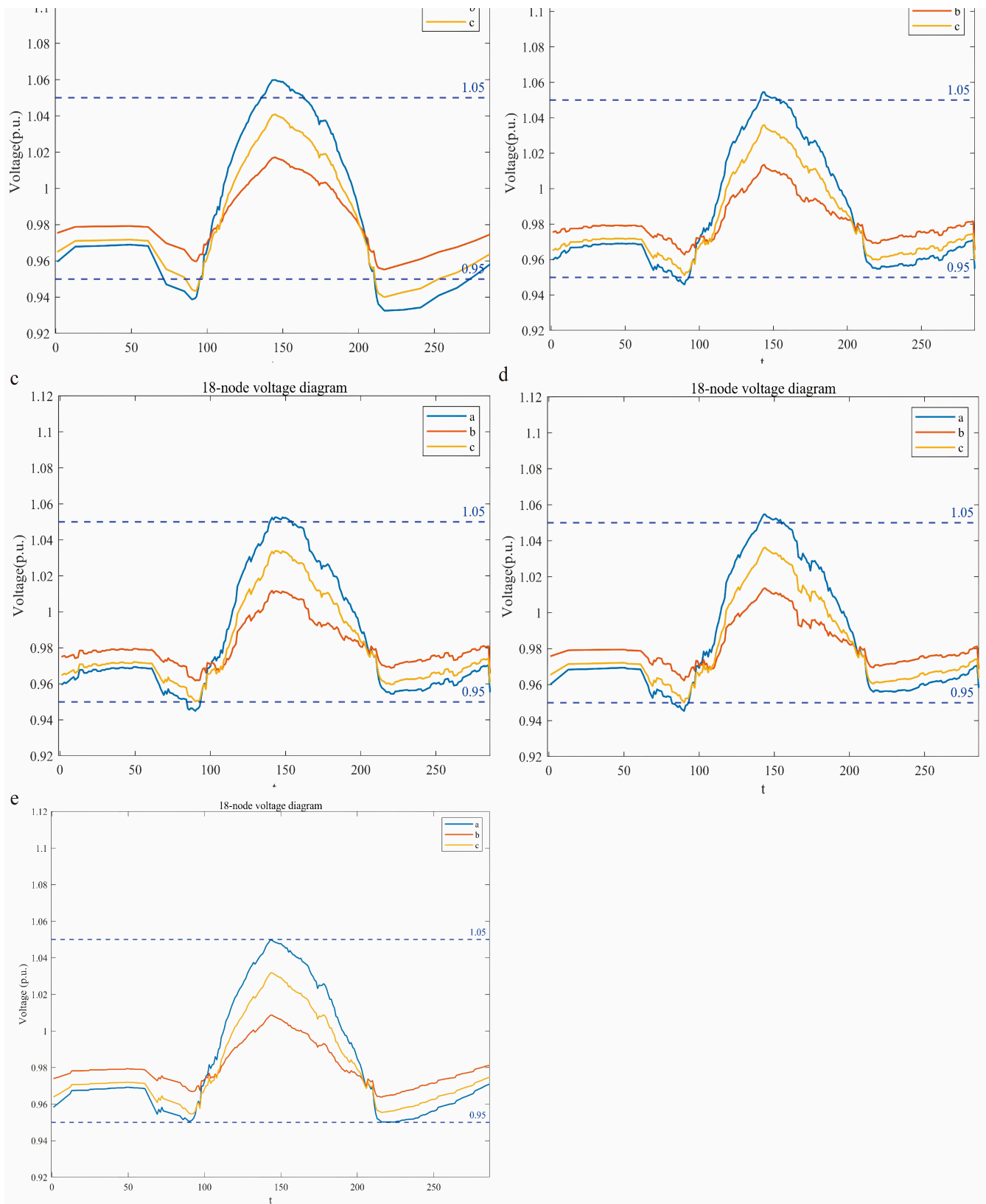


Figure 8. Voltage situation diagram. (a) Voltage diagram of the 18th node in the load flow state without station construction. (b) Voltage diagram of the 18th node in Case 1. (c) Voltage diagram of the 18th node in Case 2. (d) Voltage diagram of the 18th node in Case 3. (e) Voltage diagram of the 18th node in Case 4.

As a comparison, the voltage situation of the 18th node in the power flow network without considering the load injection of the charging station is shown in Figure 8a.

The voltage profiles in Case 1 as shown in Figure 9b reveal inherent weaknesses in the initial configuration. When user charging demand characteristics and voltage quality constraints are not explicitly incorporated into the planning stage, voltage violations are observed, including overvoltage from 12:00 to 13:00 and undervoltage between 07:00 and 08:00. This demonstrates that the preset station layout and capacity design fail to adequately accommodate the operational characteristics of the distribution network.

The voltage profile of the 18th power flow node for Case 2 is shown in Figure 8c. Compared with Case 1, voltage fluctuations become more concentrated, and voltage violations worsen due to the aggregation of loads within certain periods. Therefore, the fundamental problems associated with capacity constraints and voltage quality are not solved in this scenario.

The voltage profile of the 18th power flow node for Case 3 is shown in Figure 8d. As station capacities remain unchanged from previous cases, voltage violations continue to occur during periods of high load injection, indicating unresolved capacity limitations.

The voltage profile of the 18th power flow node for Case 4 is presented in Figure 18e. Compared with the previous three scenarios, this scheme yields significant improvements in voltage stability, effectively mitigating the adverse impacts of EV charging on the distribution network and enhancing power supply reliability.

Case 4 delivers the most significant improvement in voltage performance. By jointly optimizing station locations and capacities under road-grid coupling constraints, charging loads are more evenly distributed across the network and aligned with grid supporting conditions. The voltage profile shows markedly enhanced stability, effectively mitigating the adverse impacts of EV charging on the distribution network and improving overall power supply reliability.

The comparative results indicate that the proposed integrated strategy achieves the most balanced system performance among all scenarios. By jointly optimizing station location, service area partitioning, and capacity allocation under road-grid coupling constraints, the strategy effectively reduces user time cost while alleviating voltage violations. Compared with partial optimization schemes, the coordinated framework enables charging load redistribution based on both traffic accessibility and grid supporting capability. Although station-side investment increases moderately, the resulting improvements in user efficiency and grid operational safety justify the additional cost.

7. Conclusions

This paper presents a collaborative planning methodology for EV charging stations that integrates user demand considerations with distribution-network operational constraints. By constructing static topology models of both the road network and the power grid and incorporating key coupling factors—including dynamic traffic flow, battery energy consumption, charging behavior, and ambient temperature, a dynamic OD prediction method is developed using an improved gravity model combined with the Floyd algorithm. Together with Monte Carlo-based charging load simulation and K-means++ clustering for demand-hotspot identification, a multi-objective optimization model was formulated, targeting three goals: annualized station-side cost, total user cost, and grid voltage deviation.

To address the strong coupling between charging station service areas and capacity configuration, a coordinated optimization framework was designed by integrating a weighted Voronoi diagram with a multi-objective particle swarm optimization algorithm. This approach enables dynamic service area partitioning and global capacity optimization. Comparative analysis across four planning scenarios verifies the effectiveness of the proposed framework: it substantially reduces user travel, charging, and queuing times;

improves voltage stability within the distribution network; and achieves balanced optimization among charging station operators, EV users, and the power grid—all with only a moderate increase in construction investment.

Uncertainties in EV charging demand and traffic conditions may affect planning outcomes in road–grid coupled systems. In this work, stochasticity is introduced through the Monte Carlo-based EV demand generation process, and time-varying travel time is captured by the traffic-dependent speed model. In addition, the deployment decisions are evaluated over the entire scheduling horizon, which mitigates sensitivity to transient or isolated extreme conditions. A systematic robustness assessment (e.g., sensitivity bounds or probabilistic guarantees under parameter uncertainty) is an important extension and will be investigated in future work. This study adopts a simulation-based validation framework due to the limited accessibility of real operational datasets, such as detailed EV charging behavior traces, station-level queueing records, and distribution-network operational measurements, which are often proprietary or privacy-sensitive. While the model parameters are configured based on settings in the literature and practical charging standards, future work will focus on calibrating and validating the proposed planning framework using real-world datasets when they become available.

Despite the demonstrated effectiveness of the proposed framework, several limitations should be acknowledged. First, the proposed methodology is designed as a planning-oriented decision-support tool, focusing on evaluating charging station deployment strategies over a representative planning horizon. It does not aim to model real-time operational control, instantaneous traffic fluctuations, or short-term charging dispatch decisions. Second, the road and power network models were constructed based on static topologies with dynamic attributes embedded through traffic-dependent travel times and stochastic demand generation, which may not fully capture all operational contingencies in highly volatile urban environments. Third, due to limited access to large-scale, high-resolution operational datasets, the framework is validated primarily through simulation-based case studies with parameter settings derived from the literature and practical standards. While these assumptions are common in planning studies, the direct transferability of the results to specific real-world systems may require further calibration using local data. These limitations do not undermine the structural validity of the proposed framework but instead clarify its intended scope and provide directions for future refinement.

This study focuses on establishing and validating a road–grid coupled collaborative planning framework for charging station deployment. While the proposed framework captures key interactions among traffic dynamics, charging demand formation, service-area allocation, and grid voltage constraints, several extensions remain possible. These include the incorporation of richer behavioral models, finer-grained operational data calibration, and systematic uncertainty quantification. Such extensions are valuable but are beyond the scope of the current work, which aims to demonstrate the planning effectiveness and structural advantages of the proposed framework.

Overall, the proposed method enhances the scientific rigor and operational efficiency of charging station planning while strengthening the coordination between transportation and power systems. It offers valuable theoretical support and practical guidance for the rational deployment and integrated development of urban EV charging infrastructure. Future research will further extend this framework toward coordinated charging and discharging strategies for EVs, with the dual objectives of maximizing user benefits and enhancing distribution-network operating quality. By jointly considering vehicle to grid interactions and time-varying station utilization levels, future studies will explore how flexible charging and discharging behaviors can alleviate network stress during peak periods while improving resource utilization during off-peak hours. In addition, incorporating

station-level utilization efficiency into the optimization framework will enable a more balanced allocation of charging resources across time, thereby supporting secure system operation and achieving benefit maximization for users, charging station operators, and the power grid.

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Appendix A

Table A1. Road setting parameters.

	First-Class Road	Second-Class Road
a	1.726	2.076
b	3.15	2.870
n	3	3
ς_1	1.520	1.534
ς_2	−0.004	−0.001
ς_3	2.992×10^{-5}	0
ς_4	0.247	0.210
$C_{ij,0}$	1000	700
$V_{ij,0}$	60	40

Table A2. Model parameters settings.

Road Parameter	
ξ_0	0.18624
ξ_1	0.35886
ξ_2	0.042429
ξ_3	0.0013696
μ_h	5
δ_h	5
μ_c	23
δ_c	6
θ	10%
βSOC_{need}	20%
α	1
$\mu_{SOC_{ini}}$	0.455
$\sigma_{SOC_{ini}}$	0.1

$\mu_{t_s,W}$	7.82
$\sigma_{t_s,W}$	1.5
$\mu_{t_s,B}$	9.46
$\sigma_{t_s,B}$	0.68
r_0	8%
T	25
κ	30%
C_{pile}	2
$C_{land,H}$	0.2
$C_{land,w}$	0.25
$C_{land,B}$	0.3
$C_{land,O}$	0.25
s_{pile}	12.5
ϖ	40%
C_T	0.002
$k_{p,w}$	0.234
$\sigma_{p,w}$	168.784
$\mu_{p,w}$	439.467
$k_{p,B}$	0.644
$\sigma_{p,B}$	45.678
$\mu_{p,B}$	69.568
$k_{p,O}$	0.401
$\sigma_{p,O}$	89.975
$\mu_{p,O}$	178.386

Table A3. Time of use electricity price table..

Time Period (h)	Time-of-Use Electricity Pricing (CNY/kWh)
01:00–08:00	0.8
09:00–10:00	1.2
11:00–13:00	1.6
14:00–17:00	1.2
18:00–21:00	1.6
22:00–24:00	1.2

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