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Design and Development of High-Power and Extreme Fast Charging Pile Layout Based on Multi-Objective Optimization

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Abstract

With the rapid increase in electric vehicle (EV) ownership, the strategic planning and layout of charging infrastructure have become essential to encourage EV adoption. This study introduces a comprehensive multi-objective optimization method for selecting locations and designing layouts for high-power and extreme fast charging stations. By thoroughly accounting for user charging demands, economic expenses, and traffic conditions, a multi-objective optimization mathematical model is created aiming to minimize user time and costs while maximizing service capacity and user satisfaction. The model combines queuing theory, network topology analysis, and genetic algorithms to simultaneously handle discrete variables related to station placement, continuous variables for charging pile setup, and complex constraints. Using Panyu District in Guangzhou as a case study, a simulation model with 20,000 electric vehicles and 20 high-power and extreme fast charging stations is developed, focusing on the optimal arrangement of 120 kW, 240 kW, and 480 kW charging piles. The simulation results demonstrate that the optimized charging station layout scheme (13 units of 120 kW, 6 units of 240 kW, and 1 unit of 480 kW) lowers overall costs by 6.74%, reduces user charging waiting time from 1.54 h to 0.65 h, improves user satisfaction by 8.1%, and cuts the peak-to-valley difference in charging load from 900 kW to 450 kW. This work offers both theoretical insights and practical recommendations for the effective planning of electric vehicle charging infrastructure.

Keywords: multi-objective optimization; extreme fast charging; charging station location; user satisfaction

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1. Introduction

In engineering practice, numerous challenges encompass multiple conflicting and impactful objectives. Multi-objective optimization problems, which seek to optimize several objectives concurrently within a specified domain, are frequently encountered. Such problems are characterized by the necessity to address more than one objective simultaneously. The process of selecting sites and constructing electric vehicle charging stations can similarly be formulated as a multi-objective optimization problem for analytical and solution purposes [1].

The rapid expansion of electric vehicle adoption has intensified the need for the development of charging infrastructure. The planning and establishment of charging stations require careful consideration of multiple factors, such as power demand, transportation accessibility, service duration, charging availability, and utilization efficiency. To prevent mismatches—where charging stations are underutilized due to a lack of vehicles or vehicles face shortages of charging facilities—it is imperative to optimize the spatial distribution and construction strategy by integrating these diverse criteria to identify an optimal configuration. This methodology ensures that the deployment of charging stations aligns with market requirements while maintaining economic feasibility [2]. Consequently, the application of multi-objective optimization frameworks to the site selection and layout design of electric vehicle charging stations presents substantial practical significance [3,4].

Extensive research has been conducted by scholars both domestically and internationally on the issue of site selection for electric vehicle power supply networks. Current studies predominantly emphasize single-factor decision-making approaches, primarily focusing on traffic efficiency and cost control [5,6]. Even when a multi-objective optimization problem is converted into a single-objective optimization function through weighted summation, it is not necessary to optimize each individual component separately for its maximum value. This is because all components are aligned in the same direction, have similar magnitudes, and do not conflict with each other. As a result, they can be directly combined into a single scalar objective without needing trade-offs or compromises [7]. Nidhi [8] defined a single-objective total cost function that includes both discrete and continuous variables, presenting an innovative multi-server queuing model that incorporates fault and admission control. The model is validated through algorithmic optimization and a case study involving an electric vehicle charging station with four standard charging piles and two additional piles. To optimize charging infrastructure resources, Campañ [9] applied a column generation algorithm to solve a single-objective mixed-integer linear programming problem aimed at minimizing transportation costs while forecasting the maximum number of vehicles that can use various charging stations within a specified timeframe. Yang [10] adopts a single-objective static non-cooperative Stackelberg game model to analyze the interests of the government, operators, and consumers from cost and benefit perspectives. Using Beijing as a case study, the model's effectiveness is confirmed, and the optimal subsidy rate and charging service fee are determined. Single-objective optimization targets the improvement of one objective function, resulting in a unique global optimal solution that can be directly compared in terms of quality. However, multi-objective optimization problems are prevalent and hold significant importance in various real-world applications, particularly in engineering. These practical problems are often characterized by their complexity and difficulty, thereby constituting a prominent focus of research. In practical scenarios, optimization tasks typically involve multiple objectives. Generally, the sub-objectives within multi-objective optimization problems are conflicting, such that the enhancement of one sub-objective may result in the deterioration of one or more others. Consequently, it is infeasible to attain the optimal values for all sub-objectives simultaneously. Instead, it is necessary to seek a balance and trade-offs to optimize each sub-objective to the greatest extent possible. A fundamental distinction between multi-objective and single-objective optimization problems lies in the nature of their solutions: while single-objective problems yield a unique optimal solution, multi-objective problems produce a set of optimal solutions, referred to as Pareto optimal solutions. Each member of this set is identified as a Pareto optimal or non-inferior solution [11].

In recent years, researchers have studied how to optimize the placement and design of charging stations by considering multiple influencing factors and complex constraints simultaneously, achieving significant results. Ferraz [12] created a comprehensive planning framework for electric vehicle charging infrastructure from the perspective of system operators, accounting for both grid performance and user service quality. A novel variable pricing strategy for slow charging was proposed to dynamically set prices, effectively encouraging users to opt for slow charging while keeping costs close to those of fast charging. However, Gifford [13] discovered that the marginal effect of new public chargers on electric vehicle adoption at the county level varies depending on income. DC fast charging has a much stronger impact on adoption than slow charging. Fast charging particularly benefits lower-income groups, while slow charging mainly serves higher-income groups. Therefore, prioritizing fast charging deployment in low-income areas rather than slow charging can lead to more equitable adoption outcomes. Mehouachi [14] proposed a simplified decision-making method based on selection criteria to tackle the challenge of choosing among multiple objectives and developed a mathematical model for charging station site selection that incorporates photovoltaic systems. For empirical research, thirty-one parking lots and eight gas stations in densely populated areas of Tunis City, Tunisia's capital, were selected as points of interest. Lin [15] identified wind and photovoltaic power as the main energy sources, with thermal power as a supplementary source. A four-objective Pareto optimal balance was achieved using a combination of the ε—constraint method and the Non-dominated Sorting Genetic Algorithm—II (NSGA—II). Adetunji [11] employed six objective functions to balance technical, economic, and environmental benefits, focusing on optimizing the placement of charging stations equipped with fifty fixed 11 kW charging piles on the distribution network busbar. While applicable to regions dominated by slow charging, the methodologies of these studies are ill-suited for the deployment of ultra-fast charging infrastructure in highway service areas or dense urban centers. Zhao [16] integrated four competing goals—operator economic benefits, user experience, economic viability, and social benefits—into an optimization framework. By applying real data from 24 towns in Shanghai's Pudong New Area to validate this multi-objective optimization model, it was discovered that maintaining revenue around 2300 yuan reduces the waiting probability to zero. Alikhani [2] demonstrated that vehicle-to-grid (V2G) technology can reduce costs by more than 100% (resulting in net profit) and cut emissions by 146–165%, indicating that EVs not only compensate for their own emissions but also supply clean alternative energy to the power grid. Bajaj [17] incorporated V2G as a decision variable within three layers of multi-objective functions, ensuring that the revenue EV users gain from V2G surpasses the implicit costs caused by frequent charging and discharging, which accelerate battery degradation. Vehicles equipped with V2G must adhere to ISO 15118-20 standards [18] for AC charging, categorized as Level 2 AC charging (3.7–22 kW), which differs from DC fast charging (50–350 kW). AC slow-charging V2G is currently the only practical technical solution for large-scale intelligent charging optimization, commonly used for residential overnight and workplace daytime charging scenarios.

This study explores the challenge of balancing multi-objectives related to user experience and operational efficiency by simultaneously optimizing seven interconnected goals: route planning, charging duration, waiting time, user charging expenses, station construction costs, user satisfaction, and return on investment. The aim is to find the shortest travel routes to improve space utilization, though this often conflicts with cost-saving efforts. Reducing charging time and energy consumption to boost time efficiency usually leads to higher expenses. Decreasing waiting times to maintain service quality often requires greater investment in infrastructure. Lowering user charging fees can reduce operator profits, while minimizing construction costs can compromise service quality. Improving user satisfaction generally involves increased spending and recovery of investment costs. This paper introduces a collaborative optimization method and a balanced decision-making framework to manage these conflicting objectives.

The key contributions of this work are as follows. First, analyzing the construction model of electric vehicle fast charging stations by considering multiple influencing factors through multi-objective optimization theory. A simulation optimization model is developed by combining this theory with a genetic algorithm. Second, the study utilizes experimental statistical data as input for the optimization calculation, incorporates real-world charging station construction cases, and proposes diverse, personalized charging strategies for both users and operators based on daily charging behaviors. These strategies aim to boost user satisfaction, lower operational costs, and achieve an optimal overall planning and design scheme for charging stations. Third, the paper validates the simulation model's accuracy by comparing its results with actual operational data, demonstrating its effectiveness in improving charging station utilization and maximizing social benefits. Overall, this research offers both theoretical insights and practical guidance for the scientific development and efficient management of electric vehicle fast charging stations.

2. Construction of Multi-Objective Optimization Theoretical Model

The issue of the layout and placement of charging stations addressed in this study involves a variety of factors, including the quantity of charging units, the number of electric vehicles, the locations of charging stations, the geographic locations of charging stations, and the related construction and operational expenditures. A comprehensive methodology is necessary to accommodate the composite variable demand, which consists of numerous charging demand points within the service area; continuous variables represented by the spatial coordinates of charging station locations; and the discrete variables corresponding to the number of charging units allocated to serve vehicles [19,20]. Given the necessity to satisfy multiple demand objectives simultaneously, the resulting model is inherently complex. Therefore, it is essential to consider the requirements of multiple target variables in an integrated manner to identify the optimal solution.

The principal factors influencing the layout and site selection of charging stations are as follows:

(1) User Charging Requirements: This factor is paramount in determining charging station locations, encompassing aspects such as charging capacity, power output, and charging duration [21]. Charging software applications developed by Guangzhou Greater Bay Technology Co., Ltd. must identify appropriate charging stations and their locations based on these user needs. The objective of optimizing charging station placement is to recommend sites that balance the distance between users and stations while facilitating a reasonable planned route. Furthermore, the analysis should estimate both the user's charging costs and the construction costs associated with the charging stations.

(2) Economic Considerations: In planning the construction of charging stations, it is critical to carefully evaluate construction costs to ensure the stations remain economically viable during operation [14]. When selecting locations for charging station deployment, a comprehensive assessment of land costs, construction expenses, operating fees, user charging costs, and environmental benefits is essential.

(3) Transportation Factors: Traffic conditions surrounding potential sites significantly influence the planning and construction of charging stations. Firstly, it is important to consider both the traffic density and the charging demand of electric vehicles [22]. Traffic density refers to the number of vehicles present per unit length of road at a given time. Higher traffic density in a specific area indicates a greater number of electric vehicles, thereby increasing the demand for charging. Consequently, the planning and construction of charging stations must adequately address the charging needs of electric vehicles in the area. Secondly, the convenience of transportation access to the charging station and the time required for users to reach it should also be taken into account [23].

To facilitate a more in-depth analysis of the optimization model for the selection of charging station locations, the following assumptions are established to streamline the computational process:

(1) The vehicle travel routes are abstracted into a network topology model [24], wherein the locations of each charging demand point and potential charging station are identified and annotated on the topology map.
(2) Factors contributing to road congestion during electric vehicles' transit to charging stations are generally disregarded or omitted from consideration [25].
(3) It is assumed that users do not experience difficulties in route selection and consistently choose the optimal driving path.
(4) Throughout the charging process, the vehicle's battery pack is maintained in an optimal charging state, enabling the application of an optimal charging strategy to regulate charging and accurately estimate charging duration [26].
(5) It is presumed that all charging stations satisfy the charging requirements [27,28], allowing vehicles to depart immediately upon full charge or even earlier, thereby not occupying the charging station beyond necessity.
(6) Although various energy storage devices have demonstrated promising fast-charging performance—such as zinc-ion hybrid supercapacitors for solar electric vehicles [29] and Ah-class sodium-ion full cells with hard carbon anodes capable of charging at 6.5C in roughly 9 min [30]—this study focuses solely on the fast-charging requirements of automotive-grade lithium-ion batteries for analytical simplicity, excluding non-lithium chemistries and factors associated with slow charging [31].

Figure 1 presents a simulation topology model derived from the road network of a prototypical Central Business District (CBD) commercial area within an urban environment. This model serves to estimate the charging demand at various parking lot charging stations under varying proportions of electric vehicle penetration. The CBD road network typifies a contemporary commercial shopping center and public transportation hub, encompassing commercial office spaces, cultural and entertainment facilities, and upscale residential zones. The simplified simulation topology comprises 4 starting points, 3 destination points, 17 intersections, 6 parking lots, and 50 road segments. The figure depicts the connectivity among intersections and the adjacency relationships of road segments. This topological traffic data is integrated into the shortest path calculation algorithm employed in the analysis.

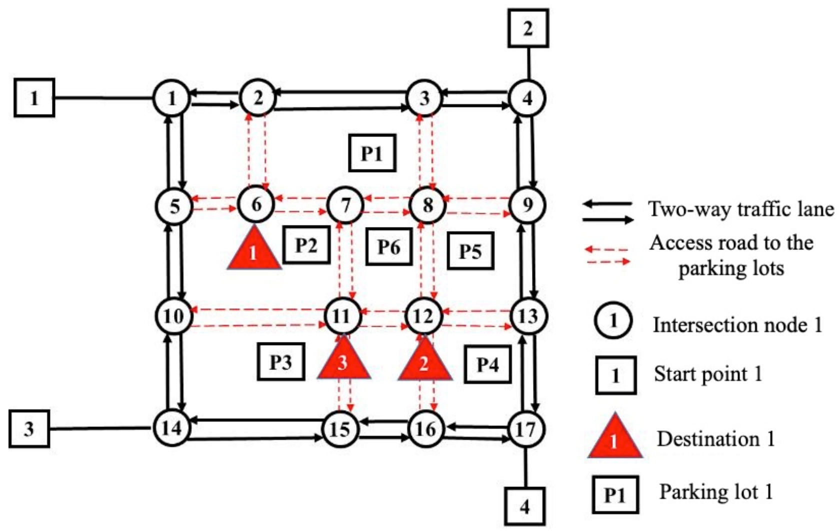

Figure 1. Topology diagram of simulated regional road network.

2.1. Construction of the Objective Function

The objective function developed in this study aims to minimize both temporal and financial costs associated with electric vehicle charging. The temporal cost is further subdivided into queuing time cost (Cost1) and transfer time cost (Cost2). Queuing time cost refers to the duration elapsed between the moment electric vehicles request charging services and their arrival at charging stations, whereas transfer time cost pertains to the travel time incurred when moving from one charging station to another.

The charging time for electric vehicles is computed using the following formula:

$$T_{charg} = \frac{(100 - SOC)}{100} T_{full} \tag{1}$$

Here, T_{charg} represents the charging time of the electric vehicle in hours (h), T_{full} denotes the standard duration required to charge the electric vehicle's battery from zero to full capacity in hours (h), and SOC indicates the real-time state of charge of the electric vehicle's power battery at the commencement of charging as a dimensionless percentage (%).

For vehicles utilizing fast charging, once the battery reaches full capacity, a prompt is issued instructing the user to vacate the charging station. Upon the user's decision to terminate charging and depart, the number of required charging piles decreases by one.

$$N(P_k) = N(P_{k-1}) - 1 \tag{2}$$

Conversely, if the vehicle's SOC surpasses the upper threshold, SOC_max, charging ceases, and the vehicle leaves the charging station, thereby increasing the number of available charging stations by one. In this context, P_k represents the peak load demand of different charging stations during the same period. $N(P_k)$ represents the required number of charging piles, while $N(S_k)$ denotes the number of currently available charging piles.

$$N(S_k) = N(S_{k-1}) + 1 \tag{3}$$

Considering the travel route requirements, the sufficiency of the electric vehicle's remaining battery to reach the subsequent station is assessed. If the remaining charge is inadequate, priority is given to charging at the nearest station. Conversely, if the travel requirements are satisfied, preference is accorded to charging stations proximal to the destination, provided that the residual battery capacity at the destination charging station exceeds 3%.

Assuming full transparency of charging station information, the time required for an electric vehicle to reach a target charging station is calculated by dividing the shortest distance between the vehicle and the charging station by the average vehicle speed.

$$T^{ij}_{transfer} = \frac{60 \times L_{ij}}{1000 \times V_0} \tag{4}$$

The variable L_{ij} is the shortest distance between the i-th vehicle and the j-th charging station in meters (m), V_0 is the average vehicle speed in kilometers per hour (km/h), and $T^{ij}_{transfer}$ is the time it takes for the vehicle to reach the target charging station in minutes (min).

A multi-objective function is thus established to optimize the mathematical model governing the operation of charging stations:

$$F_{cost} = \sum_{k=1}^{n} N_k C_k \frac{d(1+d)^s}{(1+d)^s - 1} \tag{5}$$

$$\mathrm{N}(\mathrm{P_k}) = \sum_{k=1}^{n} \mathrm{N_k} \tag{6}$$

$$\mathrm{Count} \leq \sum_{j=1}^{m} \frac{\mathrm{tp_j}}{\mathrm{C_{pj}}} \tag{7}$$

$$\mathrm{P_{peak}} \leq \sum_{k=1}^{n} \mathrm{P_k N_k} \tag{8}$$

$$\mathrm{dis}_{ij}^{u} \leq \mathrm{R}_j^{s} \tag{9}$$

In the formula above, the objective function F_{cost} is designed to identify the minimum value in yuan per year (CNY/year). The variable N_k represents the quantity of Class k charging stations, while C_k represents the unit cost associated with Class k charging stations in yuan (CNY). d represents the discount rate as a dimensionless decimal, and s denotes the service life of electric vehicles in years (yr). The parameter Count corresponds to the number of charging demands from electric vehicles. tp_j represents the charging demand of charging stations, while C_{pj} represents the designed charging capacity of each charging station. The variable P_{peak} signifies the peak load demand of charging stations over a single day, whereas P_k represents the peak load demand across different charging stations within the same period. The index n specifies the type of charging station, R_j^s defines the service radius of a charging station, and dis_{ij}^u measures the distance between the electric vehicle and a charging station.

The optimized objective function is reformulated as follows:

$$\mathrm{F_{min\_cost}} = \mathrm{N_1} \times \mathrm{C_1} + \mathrm{N_2} \times \mathrm{C_2} + \mathrm{N_3} \times \mathrm{C_3} \tag{10}$$

$$\mathrm{N_1} + \mathrm{N_2} + \mathrm{N_3} \leq \mathrm{N}(\mathrm{P_3}) \tag{11}$$

$$\begin{cases} \mathrm{BN_1} - \mathrm{AN_2} \leq 0 \\ \mathrm{CN_2} - \mathrm{AN_3} \leq 0 \\ \mathrm{CN_2} - \mathrm{BN_3} \leq 0 \end{cases} \tag{12}$$

The proportions of various charging parking durations are calculated, assuming that the probabilities for durations A, B, and C are 0.3, 0.4, and 0.3, respectively.

$$\begin{cases} -\mathrm{p_1 N_1} \leq -\mathrm{P_1} \\ -\mathrm{p_2 N_2} \leq -\mathrm{P_2} \\ -\mathrm{p_3 N_3} \leq -\mathrm{P_3} \end{cases} \tag{13}$$

The variable $p_k (k = 1, 2, 3)$ is the charging power of Class k charging station.

2.2. Model Solution Approach

Given that the primary goal of the function is cost minimization under multi-objective constraints, empirical data concerning charging stations, electric vehicle charging demands, daily travel distances, relevant assumptions, environmental parameters, and predefined variable settings are incorporated into the simulation model. The simulation is subsequently executed, and the outcomes are evaluated against the established constraint values. If these constraints are satisfied, the optimal solution to the objective function is determined. The results are then assessed to verify compliance with minimum charging time and cost criteria. Upon fulfillment of all conditions, the optimal solution is obtained through an iterative process. The simulation workflow is depicted in Figure 2.

To reduce the computational complexity inherent in the model, it is assumed that electric vehicles maintain a constant velocity en route to the charging station, unaffected by traffic congestion [20]. Although actual road conditions are more complex and subject to numerous uncertainties, the model presumes that the results are independent of traffic variability. Furthermore, the model assumes that the number of charging stations adequately meets the charging demands of electric vehicles. In practice scenarios, this assumption is constrained by factors such as service duration, the availability of service vehicles, and the capacity of the charging station infrastructure. Nonetheless, these constraints are considered not to influence the overall site selection process for charging stations.

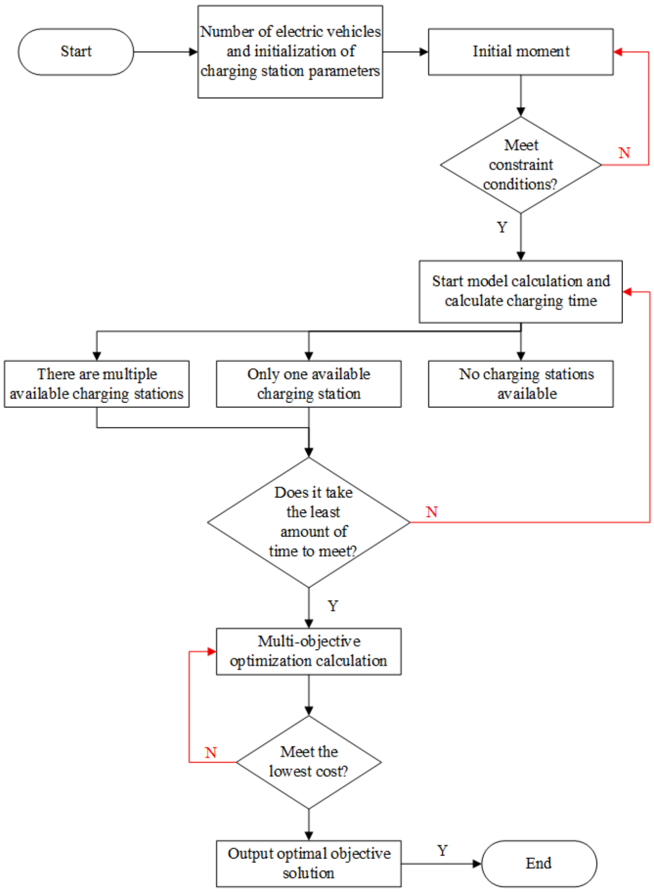

Figure 2. Multi-objective optimization framework for charging station site selection: simulation calculation flowchart.

3. Simulation Analysis of Multi-Objective Optimization for Charging Station Site Selection in a Designated Urban or Regional Context

The spatial distribution and quantity of gasoline stations have been extensively examined, with electric vehicle charging stations increasingly recognized as a complementary infrastructure within the automotive energy network. The planning of charging stations can draw upon the established framework of gas station deployment, primarily guided by the following considerations:

(1) The spatial arrangement of gasoline stations also indirectly reflects vehicular travel behaviors and mobility patterns.
(2) The number of gasoline stations correlates directly with factors such as geographic area, population density, vehicle ownership rates, and prevailing transportation preferences, thereby serving as an objective indicator of regional vehicle ownership levels.
(3) In accordance with pertinent national regulations, the service radius of urban gasoline stations should not be less than 0.9 km, and the minimum inter-station distance should be no less than 1.8 km. The coverage characteristics of gasoline stations are broadly analogous to those of electric charging stations.

The multi-objective optimization model developed herein focuses on fast charging stations within a specific locale, incorporating a range of influential variables, including vehicle operational data, battery energy parameters, SOC metrics, charging pile capacity, charging rates, time-dependent electricity pricing, and queue waiting dynamics. By integrating considerations such as infrastructure construction costs, queue scheduling optimization, and user waiting tolerance thresholds, the model seeks to determine an optimal configuration.

Within this framework, discrete parking and charging intervals are consolidated into aggregated parking event sequences, with individual charging stations serving as the fundamental unit of analysis. It is posited that, over the course of a month, all parking and charging events at a given fast charging stations are temporally ordered; a charging queue emerges whenever the number of available charging points is insufficient to satisfy the instantaneous charging demand of arriving vehicles. Employing queuing theory facilitates a rigorous examination of the interplay between demand characteristics—both in type and volume—and the service capacity of the charging infrastructure. This approach enables precise estimation and evaluation of the demand levels and associated costs for charging stations.

Queuing theory encompasses service system analysis, models vehicle arrivals, and charging service processes, yielding critical performance indicators such as the number of vehicles serviced, queue lengths, waiting times, and utilization rates of charging stations. Through enhancements to the service system design and customer flow optimization, the charging infrastructure can not only meet user demand effectively but also achieve improved economic and operational efficiency in alignment with defined performance criteria.

When creating a queuing model for a charging system, the following criteria should be satisfied:

1. It is assumed that every electric vehicle arriving at the charging station needs to be charged.
2. The arrival times of electric vehicles are considered, including scenarios where multiple electric vehicles arrive simultaneously and wait for charging.
3. The queuing rule for charging operates as follows: upon arrival at the charging station, if there are available charging points, the vehicle will be charged immediately without waiting. However, if no charging points are available, the vehicle's charging request is denied. In this situation, the vehicle may park at the station but cannot receive charging services until the previous user finishes charging and leaves, after which it can begin charging.
4. The service provider installs different types of charging stations within the facility, ensuring that slow charging stations and fast charging stations are kept separate.
5. The output process is designed so that the charging service only ends after the vehicle has completed charging and departed from the charging station following the start of the charging session.
6. During a service cycle, the output metrics of the queuing charging system include the total number of vehicles requiring charging services (AC), the total number of vehicles that receive charging services (TR), the total amount of electricity delivered to vehicles receiving charging services (CE), and the total time that charging stations are occupied (TC).

The formula for the model's calculation is as follows:

$$\mathrm{CE_i} = \min\left\{\frac{100-\mathrm{SOC_i}}{100} \times \mathrm{E}, \mathrm{PT_i} \times \mathrm{CV}\right\} \tag{14}$$

$$\mathrm{CE} = \sum_{\mathrm{i}=1}^{\mathrm{AC}} \mathrm{CE_i} \tag{15}$$

$$\mathrm{TC_i} = \mathrm{PT_i} \tag{16}$$

$$\mathrm{TC} = \sum\nolimits_{i=1}^{AC} \mathrm{TC_i} \tag{17}$$

In the formula, i denotes the current vehicle receiving charging services. $\mathrm{SOC_i}$ refers to the SOC value when the i-th vehicle is at the start of charging, while E represents the total energy capacity of the vehicle's battery pack in kilowatt-hours (kWh). $\mathrm{PT_i}$ is the parking duration of the i-th vehicle at the charging station in hours (h). CV stands for the charging rate of the charging station in kilowatts (kW). AC indicates the total number of vehicles being charged at the charging station. $\mathrm{CE_i}$ is the amount of energy the i-th vehicle gains during charging in kilowatt-hours (kWh), and CE is the total energy delivered to all vehicles at the station. $\mathrm{TC_i}$ represents the time the i-th vehicle occupies the charging station for charging in hours (h), and TC is the total occupancy time of the station.

The overall charging time includes two main parts: the time needed to replenish energy used during travel and the time required to recharge the remaining battery capacity as requested by the user. When the amount of energy to be charged is known, the charging duration depends on the distance between the electric vehicle and the charging station, as well as the charging power. Moreover, if the electric vehicle arrives while other vehicles are still charging, it must wait until the previous vehicle finishes, which adds to the waiting time.

The total charging time for electric vehicles mainly consists of three components: travel time to the charging station, waiting time before charging begins, and the actual charging time. Completing the charging process sooner reduces the overall charging duration.

The cost of charging electric vehicles primarily includes expenses related to power consumption during travel and the charging fees. The total cost of charging electric vehicles encompasses both monetary costs and time-related costs.

The comprehensive multi-objective optimization for selecting electric vehicle charging sites and planning charging strategies aims to identify the best solution that meets multiple goals simultaneously, based on user needs and the computational methods of the integrated optimization model.

The key scenarios considered in multi-objective optimization solutions are as follows:

1. The charging route is the shortest. This is the most traditional approach to designing, scheduling, and managing charging stations. Navigation and charging apps recommend the nearest charging station to users, minimizing the electric vehicles' energy consumption during travel. This strategy only requires geographic location data of both electric vehicles and charging stations to make recommendations.
2. This scheduling mode focuses on minimizing the total charging time for electric vehicles. It calculates the shortest possible charging duration as the control objective, taking into account factors such as the user's travel time to the charging station, the time needed to recharge, and any wait time, thereby reducing the overall time cost for the user.
3. This scheduling approach aims to minimize the waiting time for electric vehicle charging. It seeks to manage the queuing system at charging stations effectively, reduce charging wait times, and maximize user satisfaction. This is also the most efficient charging management method for charging stations.
4. This scheduling strategy is based on minimizing the lowest comprehensive cost of electric vehicle charging. It strives to lower the total charging expenses while maintaining high levels of user satisfaction.

The cost objective function is:

$$\mathrm{CP} = \sum\nolimits_{\tau=0}^{24} \sum\nolimits_{i=1}^{N_{EV}(\tau)} \sum\nolimits_{j=1}^{m} \mathrm{CP_{ij}}(\tau)$$

$$\tau \in [0,24], i \in [1, N_{EV}(\tau)], j \in [1, m] \tag{18}$$

The time cost objective function is:

$$TC = \sum_{t=0}^{24} \sum_{i=1}^{N_{EV}(\tau)} \sum_{j=1}^{m} TC_{ij}(\tau)$$
$$\tau \in [0,24], i \in [1, N_{EV}(\tau)], j \in [1, m] \tag{19}$$

$CP_{ij}(\tau)$ represents the cost of choosing a charging station j for an electric vehicle i at time τ in yuan (CNY), given the electricity price j(t) under a particular scheduling strategy. $TC_{ij}(\tau)$ denotes the time cost for an electric vehicle i to select a charging station j for charging under the same strategy.

The simulation parameters are set as follows: The SOC for electric vehicles requiring charging is limited to between 0% and 50%; vehicles with a remaining charge outside this range are excluded. The data source is sourced from big data statistics on electric vehicle charging. The remaining charge of each vehicle is determined based on the power needed to reach the nearest charging station, establishing a minimum threshold. If the remaining charge falls outside this range, a random value is assigned. The simulation runs over a 24-h period with scheduling updates every hour. Charging electricity prices are calculated according to the power grid's peak and off-peak pricing strategy. The simulation does not account for the load conditions of individual charging piles but assumes that each charging pile can serve only one electric vehicle at a time, thus avoiding any overloading scenarios.

The user's total cost function is defined as follows:

$$W_{ij}(\tau) = \lambda_1 \frac{CP_{ij}(\tau)}{\min CP_{ij}(\tau)} + \lambda_2 \frac{TC_{ij}(\tau)}{\min TC_{ij}(\tau)} + \lambda_3 \frac{CC}{\min CC} \tag{20}$$

$$\begin{cases} \tau \in [0,24], i \in [1, N_{EV}(\tau)], j \in [1, m] \\ \lambda_1 + \lambda_2 + \lambda_3 = 1 \end{cases}$$

In the formula above, λ_1, λ_2, and λ_3 represent the dimensionless weighting factors assigned to various costs.

The ultimate optimization goals for the charging station location model are shown in Equation (21).

$$F(M_j) = \min\left[F_1(M_j), F_2^{-1}(M_j), F_3^{-1}(M_j), F_4^{-1}(M_j), F_5^{-1}(M_j), F_6(M_j), F_7(M_j)\right]^T W_j^T \tag{21}$$

$$\begin{cases} g_j(X) \le 0; j = 1, 2, \ldots, m \\ 0 \le x_i \le 24, \quad i = 1, 2, \ldots, N \end{cases} \tag{22}$$

$$W_j = \sum_{i=1}^{N_{EV}(\tau)} W_{ij} \tag{23}$$

In this context, F_1 denotes the plan with the shortest charging route in kilometers (km), F_2 the plan with the shortest charging duration in hours (h), F_3 the plan with the shortest charging waiting time in hours (h), F_4 the plan with the lowest charging cost in yuan (CNY), F_5 the plan with the lowest construction cost in yuan (CNY), and F_6 represents user satisfaction as a dimensionless index, which is determined by combining the user's charging time cost and overall cost. The lower these costs are, the higher the user satisfaction. F_7 corresponds to the plan that achieves the fastest recovery of investment costs as a dimensionless rate. Specifically, F_1 and F_2 are calculated using Equations (18) and (19), respectively; F_3 is derived from Equation (15); F_4 from Equation (17); F_5 is based directly on the construction cost of the charging station; F_6 is computed using Equation (20); and

F_7 reflects the investment cost scenario aimed at the quickest return on investment, taking into account the inflow, outflow, net present value, and cumulative net present value of the charging station. $X = [x_1\ x_2 \ldots x_N]^T$ denotes the optimization calculation vector; the gain value of the computational vector used in the optimization is represented by x_i, and $g_j(X)$ represents the constraint functions. The optimization objective function emphasizes the service-oriented principle of charging stations, aiming to maximize service benefits. Since both the objective function and constraints involve interval numbers, interval theory is employed to transform and solve these interval-based calculations. The objective function integrates both performance and robustness measures. Within the model's computations, the constraints include uncertain demand deviation parameter denoted as U_i. When $U_i = 0$, there is no uncertain demand (meaning no demand points deviate from the target demand value), and the computational load matches the target demand value. When $U_i = n$, up to n demand points may simultaneously deviate from the target demand. By adjusting the variation of these uncertain parameters, the entire computation process is directed toward orderly convergence, avoiding computational stagnation and progressively approaching the optimal target value.

4. Multi-Objective Optimization Simulation

Prior to developing a simulation calculation model, this study first examines the power load conditions of the charging station and the demand for fast-charging units using historical statistical data. Utilizing the planned capacity of a charging station to be constructed in Panyu District, Guangzhou, along with the charging needs of current electric vehicles in the market, preliminary design calculations are performed. These findings help to narrow down the scope of the multi-objective planning model.

The genetic algorithm used in this study is a random optimization search algorithm that draws inspiration from the evolutionary laws of the biological world, as well as from phenomena such as genetics, mutation, natural selection, and hybridization in biological evolution. The genetic algorithm has inherent implicit parallelism and better global optimization ability. It adopts a probabilistic optimization algorithm to automatically obtain and guide the optimization search space and adaptively adjust the search direction. The genetic algorithm is targeted at the fitness function. Research has shown that genetic algorithms can achieve fast convergence, reasonable optimization results, good robustness, and good computational sensitivity for the fitness function.

Genetic algorithms cannot directly handle the parameters of the problem space and can only handle individuals represented in gene form. Therefore, when using genetic algorithms, the first step is to convert the parameter form of the optimization problem solution into a gene-encoded form and input it into the computational model. The genetic algorithm requires selecting chromosomes with high fitness for replication. Through genetic operators such as selection, crossover, and mutation, a new group of chromosomes that are more adaptable to the environment is generated, forming a new population. Through generations of continuous reproduction and evolution, the offspring population is more adaptable to the environment than the previous population. The optimal individual in the final population is encoded as the optimal solution or an approximate optimal solution of the problem. The fitness function of the genetic algorithm in this project is the objective function. In order to ensure the reliability of the simulation calculation results, the simulation is conducted three times in a row to optimize the average value of the objective as the optimization result, in order to reduce the volatility of the single simulation calculation results.

This study uses MATLAB (R2024b) to package optimization algorithms into a function, with input parameters being statistically obtained data from existing fast charging stations

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and output parameters being optimization target values. The genetic algorithm toolbox in MATLAB is used for optimization and solution.

Based on the number and distribution data of electric vehicles obtained from the target area, it is assumed there are 20,000 electric vehicles with an average driving range of 500 km and a battery capacity of 75 kWh, with a maximum requirement of 1000 charging piles. The distribution of these charging piles is as follows: 60% are 120 kW fast chargers, 35% are 240 kW fast chargers, and 5% are 480 kW fast chargers.

The correlation between electricity consumption and charging prices is derived from statistical data, as illustrated in Figure 3.

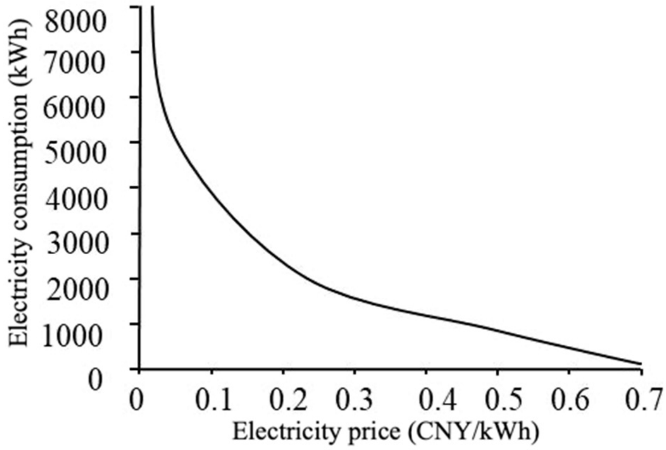

Figure 3. Relationship between electricity consumption and price.

This paper focuses on the main commercial areas in Panyu District, Guangzhou, China, as the focus of the simulation. It incorporates a previously developed charging demand simulation model for case analysis to calculate and optimize the layout of charging piles.

Figure 4 displays the distribution map of all charging stations in Panyu District, including both existing and planned facilities. This project analyzes the layout requirements and optimization outcomes of the charging stations within the simulation model to identify the optimal construction plan. To simplify the calculations, the study focuses solely on building supercharging stations, specifically those with charging power exceeding 480 kW.

According to 2022 statistical data, Panyu District, Guangzhou City, covers an area of 529.94 square kilometers and has a permanent population of 1.8278 million people. Currently, there are 86 gas stations in the district. Based on the current proportion of electric vehicles and the usage heat map within the jurisdiction, the demand for 20 rapid charging stations has been estimated using a modeling approach.

After normalization, the simulation results reveal that under various charging scheduling strategies, the number of charging piles relative to the charging demand and service capacity of electric vehicles stabilizes once it exceeds 200, as shown in Figure 5. Therefore, for service providers with limited budgets, simply increasing the number of charging piles does not necessarily lead to improved electric vehicle service levels when factors such as construction costs, operational pressures, and profit recovery are taken into account. As a result, the subsequent simulation model caps the maximum number of fast charging piles at 200, which significantly reduces calculational complexity without compromising the overall assessment of the charging service quality.

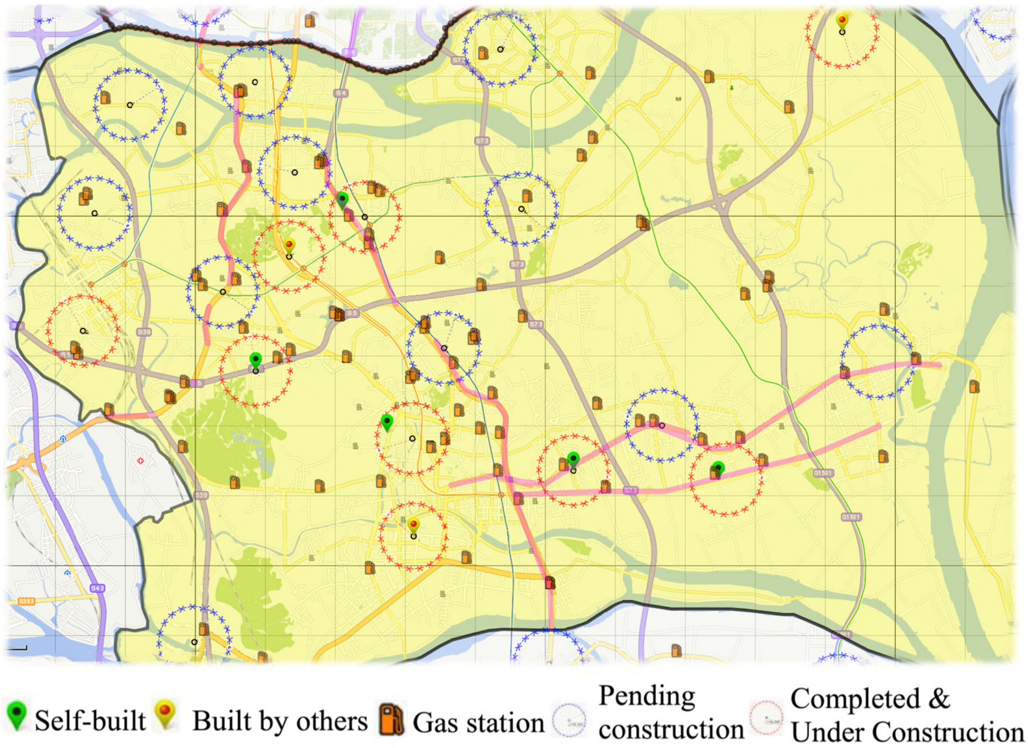

Figure 4. Distribution map of supercharging stations in Panyu District, Guangzhou City.

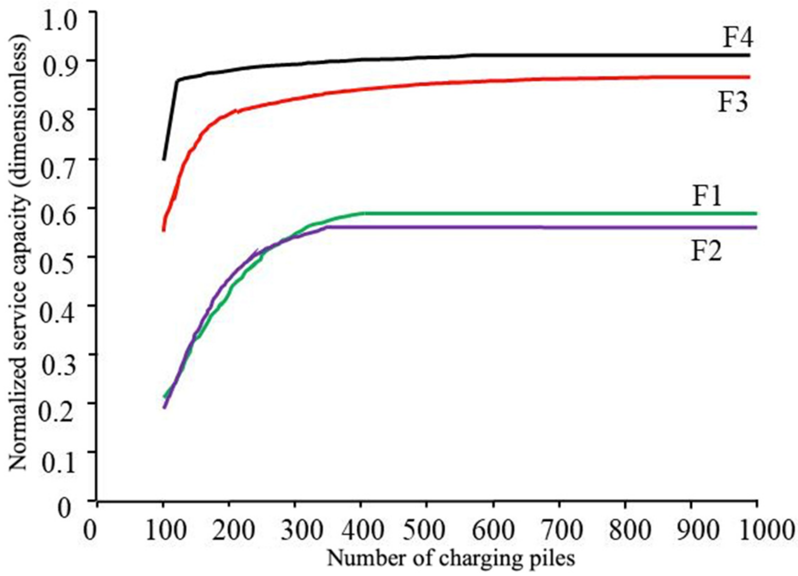

Figure 5. Relationship diagram between the number of charging piles and normalization.

The daily unordered charging power load rate and the variance of the cost weight coefficient for each charging station are derived from real statistical data from a fast charging station. These values should be used as inputs in the calculation model to more accurately represent the actual operating conditions of fast charging stations.

Figure 6 shows that both the cost weight coefficient of charging stations and the variance in the number of charging vehicles have a substantial impact. A higher variance suggests less efficient allocation of charging stations and lower utilization rates. To enhance utilization, the cost weight coefficient is uniformly set to 0.1 when calculating the comprehensive cost of charging electric vehicles at each station. This method enables a thorough evaluation of the influence of various factors.

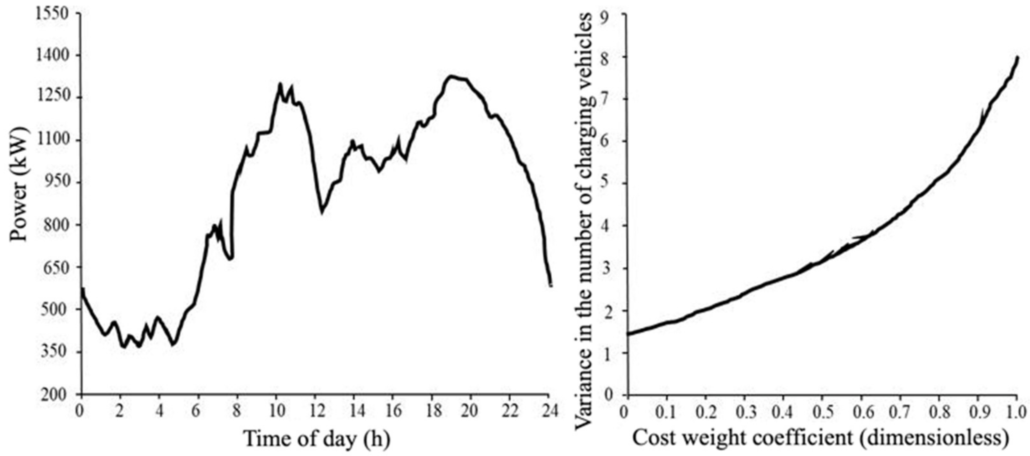

Figure 6. Power and variance versus cost weight coefficient of charging stations' expenses.

5. Calculation Results

This study analyzes and calculates the power requirements for a charging station planned for a specific area of Panyu District, Guangzhou. The facility will include 20 charging units. Based on the statistics of electric vehicle usage and operation nearby, approximately 600 electric vehicles operate within the service area, with pure electric driving ranges between 300 km and 700 km. Battery capacities range from 45 kWh to 100 kWh, and some vehicles support fast charging at 4C rates. Assuming the distribution fully meets charging demand, the study optimizes the configuration of fast charging stations with capacities of 120 kW, 240 kW, and 480 kW to fulfill vehicle charging needs. Considering charging power load, service level, and user costs under various management and operational modes, the study comprehensively selects the optimal resource allocation and management plan to ensure the most efficient operation of the charging station. Prior to optimization, the commercial operation charging mode is set as on-demand charging with a fixed service fee. The anticipated construction and operational costs are presented in Table 1 below.

Table 1. The anticipated construction costs of fast charging stations ($\times 10^4$ Yuan).

Item	Construction Cost	Equipment Cost			Labor Cost	Equipment Maintenance Cost	Total
		120 kW (Unit)	240 kW (Unit)	480 kW (Unit)			
	1100	1.9	5	13	30	30	2400

For ease of simulation modeling and calculation, when the uniform variance value of the optimization function is set to 1, the model's solution corresponds to the optimal solution. Conversely, when the uniform variance value is 0, the model's solution represents the worst-case solution. The initial uniform variance value is set at 0. The overall satisfaction level of the multi-objective function is required to be above 0.7, service efficiency must exceed 0.95, the paralysis probability is set at 0.08, and operating costs are limited to less than 5 million. The daily operating cost is set at 10,000 yuan per day. The population size is 1000, the memory capacity is 500, and the number of iterations is set to 200. The crossover probability is 0.6, the mutation probability is 0.4, and the diversity evaluation parameter is 0.95. The entire iterative calculation process is carried out using the system's built-in genetic algorithm.

From the convergence characteristic curve of the calculation process, it is clear that the optimization procedure achieves stable convergence and reaches the optimal solution in approximately 70 iterations, as shown in Figure 7. The results of the site selection for electric vehicle charging stations indicate that 20 charging stations are sufficient to meet the charging demands of electric vehicles within the jurisdiction. The distribution results are marked by the circled positions in Figure 4, where red circles represent existing charging stations and blue circles indicate locations where new charging stations need to be built.

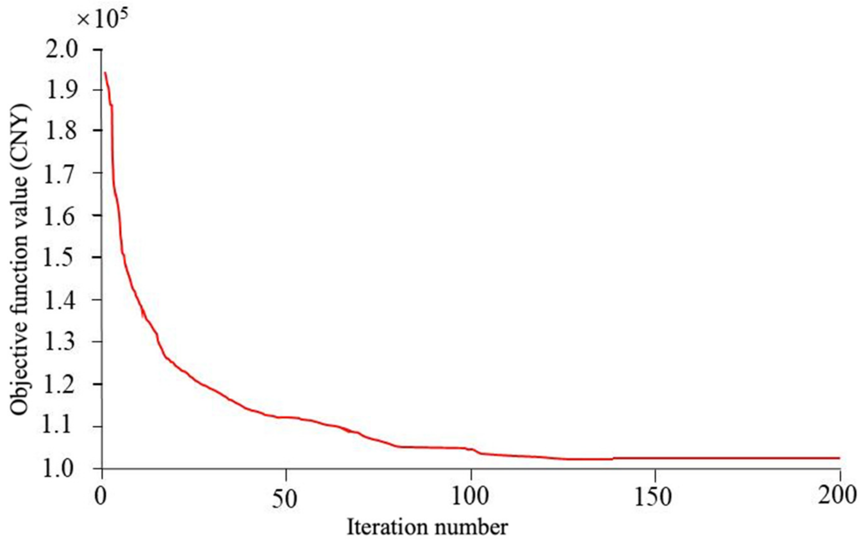

Figure 7. Cost iterative curve of the objective function.

Figure 8 illustrates the distribution of electric vehicles equipped with fast charging stations, as determined by the optimization calculations. The four different colors in the figure represent various scheduling and management modes of the charging stations.

In the traditional scheduling model, electric vehicles are scattered, and the conventional scheduling method only considers driving distance when assigning charging stations. It overlooks users' time costs and the operational impact on charging stations, resulting in poor time efficiency and a lack of systematic regulation. At certain times, too many electric vehicles wait to be charged, leading to low service levels, poor user experience, and numerous complaints. For example, at charging stations 5, 10, and 15, more than eight vehicles often wait simultaneously, significantly degrading service quality and causing many user complaints. Long queues substantially increase users' waiting time and can easily overload charging stations, complicating vehicle distribution and intensifying the operational strain on charging station equipment.

After improving the scheduling approach, the number of electric vehicles waiting to charge dropped significantly. As shown in the figure above, when only one charging station is available, there can be up to six vehicles waiting. This optimization enhances the user experience, lowers the cost related to charging wait times, and greatly reduces the charging load on the station.

Figure 9 presents a comparison between the charging station's load simulation results under a traditional 24-h charging schedule and those after implementing an optimized charging pricing strategy. The figure reveals that the optimized charging strategy decreases the load during peak hours while significantly increasing it during off-peak hours. This change happens because, following the introduction of the scheduled charging feature, many electric vehicles shift their charging to off-peak periods. As a result, the charging power load exhibits fewer extreme fluctuations, with numerous charging sessions concentrated in the early morning. Peak-hour loads are significantly lower, even though the overall average charging load has risen. Prior to optimization, the difference between peak and off-peak charging power was approximately 900 kW; after optimization, this gap narrowed to roughly 450 kW. This demonstrates a notable improvement in charging service efficiency, allowing the station to accommodate many more vehicles. Overall, this marks a significant performance enhancement.

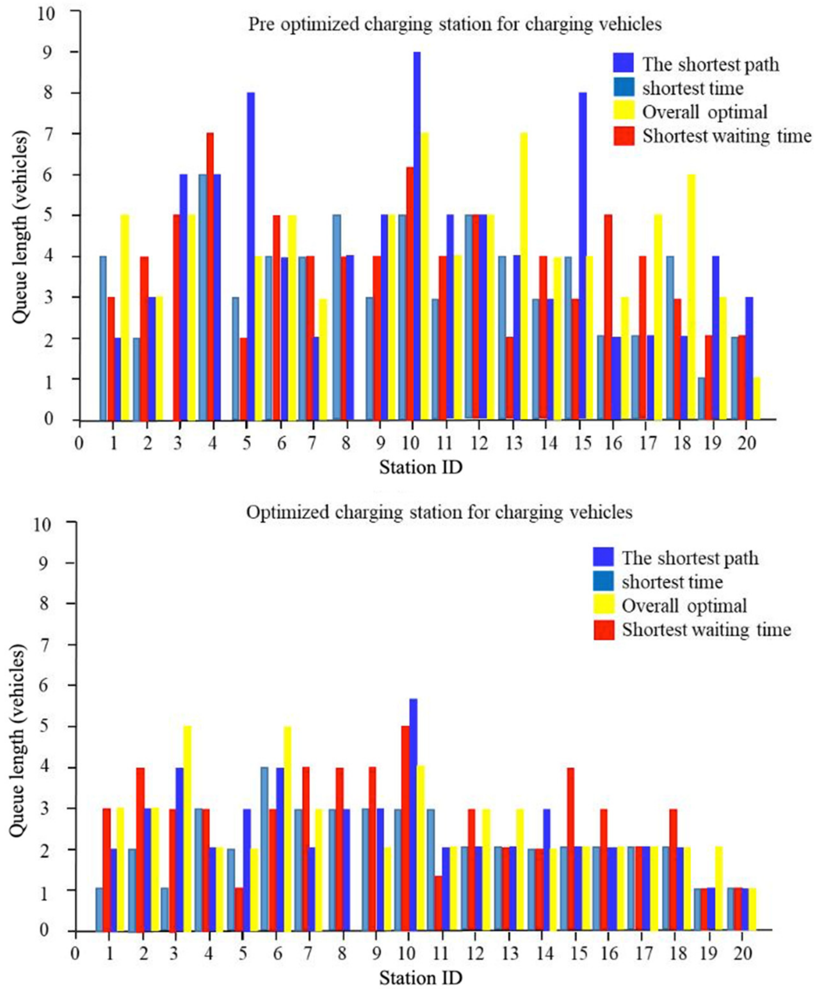

Figure 8. Pre-optimized and optimized charging stations for charging vehicles.

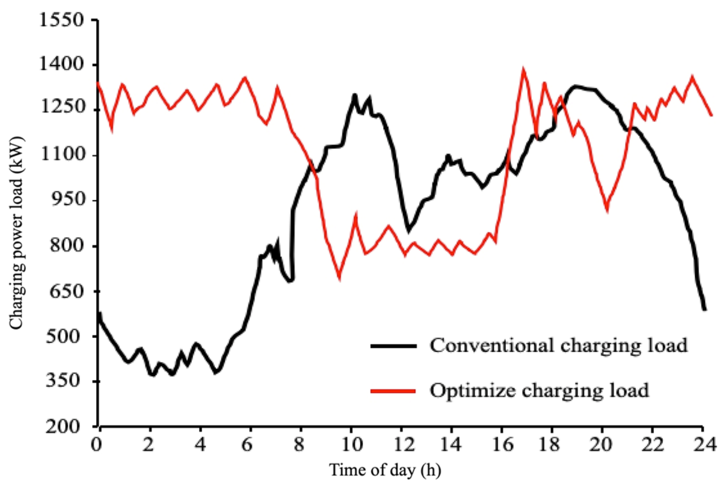

Figure 9. Charging load graph after optimizing the charging strategy.

Following multi-objective global optimization calculations, the best combination of charging stations was identified, as detailed in Table 2. Data shows that over 68.4% of electric vehicles in Panyu District are older models with peak charging power under 120 kW. Around 31.2% of electric vehicles have charging capacities above 120 kW, while fewer than 1% support fast charging at 480 kW. This distribution results from the backward compatibility of 480 kW and 240 kW fast charging stations. Taking into account factors such as queue wait times, charging and operating costs, equipment maintenance, and labor expenses, a comprehensive analysis was conducted. The optimal charging station setup, shown in Table 2, was determined accordingly. All subsequent calculations are based on this charging station configuration.

Table 2. Calculation results for the optimal configuration of charging stations.

Item	120 kW	240 kW	480 kW	Total
number	13	6	1	20

Table 3 presents a comparison between the results obtained after the global optimization calculation and those before optimization. The data show that the model's performance has significantly improved following global optimization. Labor costs have slightly decreased due to reduced waiting times and a modest drop in labor-related expenses. However, equipment maintenance costs have risen, which is an unavoidable result of longer operating hours and less downtime. Service efficiency has improved markedly while the likelihood of system failure has remained largely unchanged. Paralytic efficiency reflects the probability of a charging station being paralyzed. Operating costs have stayed stable with minimal fluctuations. User satisfaction has increased by 8.1%, reflecting a substantial improvement. Charging wait times have been cut from 1.54 h to 0.65 h, and the addition of supercharging stations has greatly boosted charging efficiency and shortened wait times. By optimizing charging strategies during off-peak hours, users' charging expenses have also been significantly reduced, with an average saving of 7 yuan per vehicle, leading to considerable cost savings. Overall, the total cost reduction is notable, amounting to 6.74%. These outcomes are very positive for the development and operation of charging stations and for reducing user expenses.

Table 3. Comparison of calculation results before and after optimization.

Item	Labor Cost (Yuan)	Equipment Maintenance Cost (Yuan)	Benefit	Paralytic Efficiency	Operating Costs (Yuan)	Overall Satisfaction	Charging Waiting Time (h)	User Charging Cost (Yuan)	Comprehensive Cost (Yuan)
Before optimization	366,754.22	314,675.13	0.922	0.0712	20.37	71.3%	1.54	29.4	38,4376.55
After optimization	354,322.15	335,966.47	0.956	0.0852	22.46	79.4%	0.65	22.2	358,478.47

6. Conclusions

This paper focuses on selecting sites and optimizing the layout of high-power and extreme fast charging stations for electric vehicles by creating a multi-objective optimization model that combines user costs, service efficiency, operational economics, and grid load balancing. The model is validated through simulations using Panyu District in Guangzhou as a real-world example. The main findings of the study are as follows:

(1) Effectiveness of the multi-objective optimization method: Unlike traditional single-objective optimization or empirical layout approaches, the model developed here balances multiple goals simultaneously, such as user time costs, economic expenses, service quality, and operational efficiency. This prevents the common problem of getting stuck in local optima seen in single-indicator optimization. Using genetic algorithms, the model reaches a global optimal solution after approximately 70 iterations, demonstrating its efficiency and stability in handling complex constraints.

(2) Charging station configuration optimization: Considering the technical features of electric vehicles in Panyu District, the optimal setup uses a hierarchical structure

mainly composed of 120 kW chargers, supplemented by 240 kW chargers, and backed up by 480 kW chargers in a ratio of 13:6:1. This configuration satisfies the charging needs of most users while balancing equipment investment costs and allowing for future technology upgrades, thus avoiding resource waste from indiscriminately pursuing higher power levels.

(3) Benefits of optimized scheduling strategies: By applying time-of-use electricity pricing and smart scheduling, user waiting times for charging are cut by 57.8% (from 1.54 h to 0.65 h). The average charging cost per vehicle drops by 7.2 yuan, and user satisfaction rises by 8.1 percentage points. Importantly, the peak-to-valley difference in charging load is reduced by half—from 900 kW to 450 kW—effectively easing grid stress and improving the overall utilization of charging infrastructure.

(4) Reference guidelines for high-power and extreme fast charging station layouts: Based on Panyu District's scale (529.94 square kilometers with a permanent population of 1.8278 million), the study suggests establishing 20 high-power and extreme fast charging stations, each covering a service radius of approximately 0.9 km, to complement the existing gas station network. This density indicator can serve as a planning benchmark for similar urban areas.

A limitation of this research is the assumption of constant vehicle travel speeds, without accounting for traffic congestion effects. Future studies could incorporate real-time traffic data and dynamic demand forecasting to develop more sophisticated dynamic optimization models.

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