

Article

Coordinated Capacity Planning and Charging Scheduling for Multiple EV Charging Stations Considering Time-of-Use Pricing and Energy Storage

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Abstract

With the rapid growth of electric vehicles (EVs), high charging demand has increased uneven station utilization and pressure on distribution networks. Therefore, this paper proposes a collaborative method for capacity planning and charging scheduling of multiple charging stations (CSs) considering time-of-use (TOU) pricing and energy storage systems (ESSs). A total system cost model is established, including transformer and ESS costs. Secondly, a deep neural network-guided improved sparrow search algorithm (DNN-ISSA) is proposed to optimize the number of chargers and parking spaces by predicting the initial capacity center. Furthermore, a charging scheduling algorithm is proposed to optimize user charging time by introducing a TOU price response function to modify charging probabilities. A case study of 36 CSs in Jinan shows that the proposed method reduces average charging time by 15.7, 15.4, and 15.2 min for 1000, 5000, and 10,000 demand points, while lowering the total system cost from 73.92 to 70.36 million yuan. The convergence value of DNN-ISSA reduces by 15.05%, 21.67%, and 11.61% compared with the improved sparrow search algorithm (ISSA), particle swarm optimization algorithm (PSO), and sparrow-particle swarm optimization algorithm (SSA-PSO), respectively. The proposed method enhances energy utilization, mitigates peak loads, and supports low-carbon EV charging operation.

Keywords: electric vehicle; charging station; queue theory; scheduling optimization; optimization algorithm



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1. Introduction

With the advancement of the “dual-carbon” goals and the rapid development of the new energy vehicle industry, EVs have become an important direction for the low-carbon transformation of urban transportation. However, the rapid growth of EVs has led to a continuous increase in charging demand, resulting in an uneven distribution of charging demand in both time and space [1]. During peak hours, charging congestion, increased queuing time, and reduced charging efficiency are likely to occur in some areas. Meanwhile, concentrated charging may intensify load fluctuations at CSs and impose pressure on the safe and stable operation of distribution networks. In this context, the TOU price mechanism can guide users to shift charging demand to off-peak periods through price signals, while energy storage systems can achieve peak shaving and valley filling by charging during low-price periods and discharging during peak periods [2]. Therefore,

how to coordinately optimize CS capacity planning and charging time scheduling while considering user charging behavior, TOU prices, and energy storage operation has become an important issue in EV charging network planning.

Rational CS siting and sizing are essential for improving charging service capability, reducing construction and operation costs, and alleviating pressure on the power grid. In recent years, many researchers have studied EV CS planning. Ahmad et al. established an integrated model combining CS planning, renewable energy, energy storage management, and parking behavior to reduce energy loss, investment cost, and peak demand [3]. Li et al. studied CS location and capacity under smart charging strategies, and analyzed their effects on grid peak–valley difference, user cost, and carbon emissions [4]. Nareshkumar et al. incorporated queuing waiting constraints into the coordinated planning of CSs and renewable energy sources in a coupled transportation-distribution network [5]. Li et al. established a robust planning model considering demand uncertainty and service quality constraints to alleviate congestion in public charging facilities [6]. More recently, Gan et al. proposed a bi-level planning model for EV charging stations by considering the spatial–temporal distribution characteristics of charging loads under uncertain environments, which further emphasizes the importance of coordinated charging station planning [7].

In the process of CS capacity planning, the arrival of users and the charging service process have obvious randomness. Queuing theory provides an effective method for describing charging congestion and user waiting behavior. Zhao et al. considered fuzzy quality of service, multiple charging options, and queuing reliability in CS capacity planning, thereby improving the robustness of planning results [8]. Wu et al. constructed a two-layer planning model for CS location and capacity determination, reducing the variable scale of the planning problem and improving the utilization rate of public charging facilities [9]. An et al. studied EV charging scheduling by considering real-time traffic conditions and travel distance, aiming to shorten the total charging time of users [10]. Algafri et al. studied the allocation of EVs to CSs in smart cities, comprehensively considering travel distance, traffic conditions, user preferences, CS capacity planning, and response time [11].

With the development of data acquisition technologies, research on charging demand forecasting and charging scheduling based on real-world data has gradually increased. Zhao et al. systematically reviewed the application of reinforcement learning in EV charging scheduling, and pointed out that planned charging scheduling is of great significance for improving user satisfaction, CS revenue, and grid security [12]. Sun et al. proposed a data-driven optimization method for early-stage CS deployment using population, travel, transportation network, and point-of-interest data, thereby improving the rationality of public charging infrastructure planning [13]. Mao et al. developed a charging demand forecasting model combining ensemble learning and deep learning based on real-world CS data from multiple cities, and identified CS operational and time-series features as key factors affecting prediction accuracy [14]. Zhang et al. proposed a graph-based spatio-temporal attention network (G-STAN) based on real-world city-level EV charging data to capture spatio-temporal charging demand features and improve short-term prediction accuracy [15]. Jiang et al. constructed a charging demand forecasting framework based on real-world travel and charging records to characterize multidimensional spatio-temporal correlations among different regions [16].

Time-of-use prices and energy storage systems provide new ideas for reducing peak charging loads, lowering user charging costs, and improving grid-friendly operation. Demand response models considering seasonal electricity prices have also been developed to improve the economic operation of energy systems under time-varying pricing mechanisms [17]. In addition, recent studies have investigated the optimal configuration of PV and ESS to enhance the regulation capability of EVs under orderly power utilization

scenarios, indicating the potential of ESS in improving charging load flexibility [18]. Yang et al. studied the optimization of TOU prices in a deep vehicle-grid integration system, and pointed out that users' charging decisions are affected by price, waiting time, and charger availability [19]. Reasonable TOU prices can effectively shift charging loads. Rehman et al. combined energy storage systems, renewable energy, and ultra-fast CS operation management, showing that energy storage systems can reduce grid peak demand, lower energy costs, and balance user preferences with grid requirements [20]. Zhao et al. established a multi-objective TOU price optimization model based on WGAN-GP, reducing user charging costs and peak–valley load differences by considering users' price response capability [21].

In terms of solution methods, the related problems usually involve multiple stations, multiple variables, integer constraints, and nonlinear constraints. Therefore, intelligent optimization algorithms have been widely applied in this field. Roy et al. combined GIS, multi-criteria decision-making methods, and multi-swarm particle swarm optimization to study CS layout optimization considering spatial accessibility, land use, grid access, and land cost [22]. Zhu et al. proposed a multi-objective dynamic binary particle swarm optimization method for CS location and capacity planning under coordinated spatio-temporal charging demand to improve the solution quality of the combinatorial optimization problem [23]. Mei et al. incorporated distribution network resilience into CS layout planning and solved the model using a method combining Voronoi diagrams and particle swarm optimization [24]. Wang et al. established a multi-objective optimization model considering charger type differentiation, dynamic electricity prices, and queuing delay, and solved the model using simulated annealing, verifying its effectiveness in reducing total system cost [25].

Recent studies have increasingly adopted hybrid optimization methods by combining different metaheuristic strategies or integrating data-driven models with optimization algorithms. Although these methods can improve global search capability, most of them still rely on randomly or chaotically generated initial populations, and the data-driven component is commonly used for charging demand forecasting rather than directly guiding capacity optimization. Beyond studies focusing separately on capacity planning or charging scheduling, integrated planning and scheduling have attracted increasing attention in recent research. These studies jointly consider capacity decisions, resource allocation, idle capacity, and scheduling interactions to improve overall system performance [26]. Moreover, blind search may still occur in high-dimensional integer decision spaces, particularly when the numbers of chargers and parking spaces at multiple CSs are optimized simultaneously.

In summary, existing studies have made considerable progress in CS location and capacity planning, charging scheduling, energy storage operation, and intelligent optimization. However, several limitations remain. First, although integrated capacity planning and charging scheduling have received increasing attention, the coordinated consideration of capacity decisions, user charging behavior, TOU pricing, and ESS operation within a unified framework remains insufficient. Second, existing capacity planning models mainly focus on construction costs and service coverage, while the combined effects of user travel time, queueing time, charging time, and social cost are not adequately characterized. Third, in most data-driven studies, deep learning is primarily used for demand forecasting rather than for constructing optimization-oriented initial solutions. Fourth, existing hybrid metaheuristic methods generally improve search operators but still rely heavily on random or chaotic initialization, which may result in poor initial solution quality, blind search, slow convergence, and local optima in multi-station integer-variable optimization problems.

To further highlight the novelty of the proposed method, Table 1 compares this study with representative EV charging planning and scheduling studies.

Table 1. Comparison with representative EV charging planning and scheduling methods.

Refs.	Method	Main Characteristics	Limitations
[23,27]	Metaheuristics algorithms	Solve nonlinear and mixed-integer optimization problems in EV charging station planning.	Rely mainly on random initialization, which may cause blind search, slow convergence, and local optima.
[24]	Hybrid optimization methods	Improve the search process by combining heuristic algorithms with spatial analysis or other optimization strategies.	Focus mainly on search-operator improvement, while insufficiently using station feature information to guide initialization.
[14,16]	Data-driven EV charging methods	Use real-world charging data and learning models to analyze or forecast EV charging demand.	Serve mainly for demand prediction or behavior analysis, rather than directly guiding the optimization search process.
Proposed method	Proposed DNN-ISSA	Learn the nonlinear mapping between station features and the initial capacity center, and embed the predicted center into ISSA initialization and early-stage search.	Reduce blind search, narrow the search region, and improve convergence speed and solution stability compared with random initialization and operator-level improvement.

To address these limitations, this study develops a coordinated framework for CS capacity planning and charging scheduling. In the capacity-planning stage, DNN-ISSA exploits station-level features to predict the initial capacity center and uses it to guide population initialization and early-stage search, thereby reducing blind exploration and enhancing convergence performance. In the charging scheduling stage, a price-sensitivity coefficient is embedded in the TOU response function to adjust users' charging probabilities and promote load shifting toward lower-price periods. Accordingly, CS capacity decisions, user charging behavior, TOU pricing, and ESS operation are integrated within a unified optimization framework.

The main contributions of this study are summarized as follows:

1. This study develops a collaborative optimization model for the capacity planning of multiple CSs considering TOU pricing and ESS. The model aims to minimize the total system cost by comprehensively considering construction and operation costs, user time costs, transformer costs, and ESS costs. An M/M/s/K queueing model is introduced to describe the stochastic arrival, queueing, and finite-capacity service process of EV users. On this basis, two comparative scenarios with and without ESS are designed to analyze the impact of ESS on CS capacity planning, total system cost, and grid-friendly operation.

2. Based on real-world charging data, charging probabilities across different functional areas and time periods are analyzed, and a charging scheduling algorithm is designed to optimize user charging time. By introducing a TOU price response function to modify users' charging probabilities, the proposed method guides users' charging behavior, thereby reducing charging congestion and improving the utilization efficiency of charging resources.

3. A deep neural network-guided improved sparrow search algorithm (DNN-ISSA) is proposed. Different from conventional hybrid metaheuristic methods that mainly rely on random or chaotic initialization, the DNN learns the nonlinear mapping between station-level features and capacity decisions and predicts an initial capacity center to guide both population initialization and early-stage search. Meanwhile, a golden sine strategy, adaptive Lévy perturbation, constraint repair mechanism, and local neighborhood search

are introduced to improve the convergence speed, solution accuracy, and stability of the algorithm while reducing the risk of falling into local optima.

2. Structure Framework and Models

For the capacity planning of EV charging stations, Section 2 presents the overall structure framework and mathematical models of the proposed method.

2.1. Structure Framework

The overall framework of the proposed CSs capacity planning and charging scheduling is shown in Figure 1. In the capacity planning module, a DNN-ISSA is developed by integrating DNN-based initial capacity center prediction with the ISSA, thereby optimizing the number of chargers and parking spaces. Then, real-world charging data are processed to extract key parameters, such as average arrival rate, peak charging periods, and charging probabilities, providing data support for scheduling optimization. In the charging scheduling module, users' charging probabilities are modified based on the TOU price response mechanism to guide users' charging behavior. The effectiveness of the proposed method in capacity planning, user charging time optimization, and load smoothing is verified through simulation by comparing the average charging time, peak–valley difference, peak–average ratio, and load standard deviation before and after optimization.

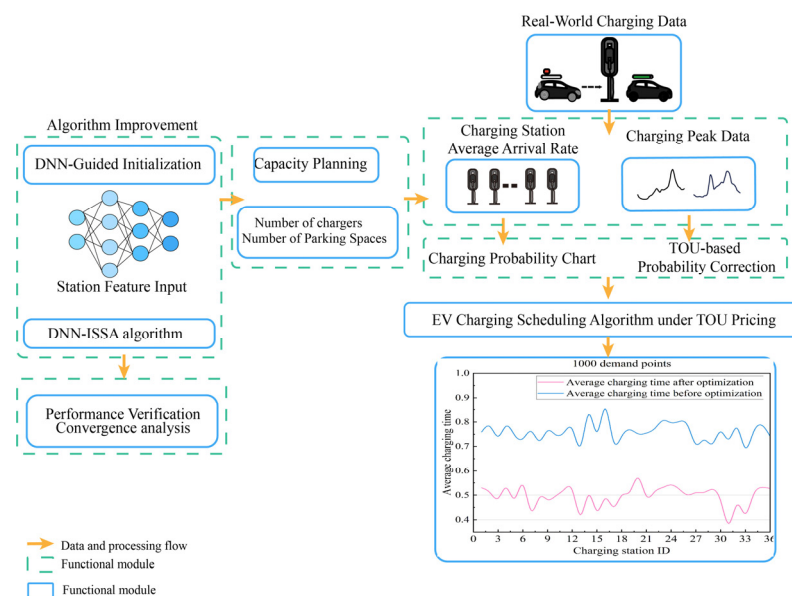


Figure 1. Capacity planning and charging scheduling framework.

2.2. EV Charging Station Capacity Planning Model

We formulate an objective function to minimize the total system cost of the CS system, considering construction and operation costs, user time costs, transformer capacity costs, and ESS costs. Unlike traditional models that only consider the construction cost of chargers or user queuing costs, the proposed model integrates CS capacity planning, user charging time, distribution capacity requirements, and the operational benefits of the energy storage system into a unified optimization framework. The objective function is shown in Equation (1).

$$\min F = \sum_n^N (\varepsilon_1 \cdot C_{1,n} + \varepsilon_2 \cdot C_{user,n} + C_{c,n} + C_{b,n}) \quad (1)$$

where $C_{1,n}$ denotes the construction and operation cost of CSs; $C_{user,n}$ represents the user time cost; ε_1 and ε_2 is the weighting coefficient of CS construction and operation cost and weighting coefficient of user cost, respectively. $C_{b,n}$ is the transformer cost of the CS. And $C_{c,n}$ is the ESS cost of the CS.

2.2.1. Construction and Operation Cost Model

The construction and operation cost model of a CS primarily includes the costs of chargers and land, as well as the station's operational costs, where C_{con} denotes the cost of chargers and land; and $C_{op,n}$ denotes the operation cost, as shown in Equation (2).

$$C_{1,n} = \frac{r_0(1+r_0)^m}{(1+r_0)^m - 1} \cdot C_{con} + C_{op,n} \quad (2)$$

where r_0 denotes the discount rate; and m indicates the depreciable life span of the equipment.

The construction cost of a CS includes the purchase cost of chargers, land cost, and auxiliary facility cost, as shown in Equation (3).

$$C_{con} = W_F + Q_c \cdot Q_u + e \cdot Q_{u,n}^2 + C_{land} \quad (3)$$

where denotes W_F capital construction expenditure of the CS, which covers the essential infrastructure, power distribution components, and auxiliary facilities of the CS; Q_c represents the unit price of each charger; $Q_{u,n}$ denotes the number of chargers for CS n ; e indicates the equivalent coefficient of charger supporting facilities; C_{land} represents the land construction cost.

The land construction cost includes land use cost and parking space construction cost, as shown in Equation (4).

$$C_{land} = C_F + C_{p,u} \quad (4)$$

where C_F represents the land use cost per charger; $C_{p,u}$ represents the parking spaces cost.

The land use cost of the CS covers the land occupied within the station and government subsidies are considered, as shown in Equation (5). Considering the number of parking spaces corresponds to the station's maximum service capacity, its relationship with the maximum system capacity K in the queueing model is shown in Equation (6).

$$C_F = Q_{u,n} \cdot (S_c \cdot P_{land} - S_{sub} \cdot P_{kw}) \quad (5)$$

$$C_{p,u} = K \cdot S_p \cdot P_{land} \quad (6)$$

where S_c represents the area occupied per charger; P_{land} represents the unit price per square meter of land; S_{sub} represents the government subsidy per charger; P_{kw} represents the charging power of the charger; S_p represents the area occupied per parking space.

For convenience of analysis, the operating cost of the CS is shown in Equation (7).

$$C_{op,n} = 0.01 \cdot C_{con} \quad (7)$$

2.2.2. User Cost Model

To quantify users' time costs, we establish a user cost function based on charging time, queueing time, and driving time, as shown in Equation (8).

$$C_{user,n} = \sum_n^N \left(\frac{M}{T_{work}} \cdot T_i^{total} \right) \quad (8)$$

where M is the local residents' average annual income in the region, and T_{work} is the average annual working hours of residents in the region.

The total charging duration of an EV at a CS involves multiple stages. To comprehensively describe this process, the total charging time of an EV, T_i^{total} is defined, and its calculation is shown by Equation (9).

$$T_i^{total} = T_i^c + T_i^q + T_i^{tr} \quad (9)$$

(1) Charging Time Model

First, we formulate a charging time model based on the variation in the battery state of charge (SOC), which fully considers differences in the initial battery energy, as shown in Equation (11).

$$E_i^{eq} = (SOC_i^{\max} - SOC_i^{pr})E_i^r \quad (10)$$

$$T_i^c = \frac{E_i^{eq}}{P_{kw}\mu_{kw}} \quad (11)$$

where T_i^c represents the charging time of the EV; and μ_{kw} represents the charging efficiency, which is influenced by thermal losses during the charging process and battery characteristics. In Equation (10), E_i^r represents the battery capacity of the EV; $SOC_i^{\max}$ represents the maximum state of charge of an EV, the battery reaches its rated full capacity; SOC_i^{pr} represents the remaining state of charge of the EV, defined as the ratio of the remaining energy to the total battery capacity.

(2) Queueing Time Model

In this study, the M/M/s/K queueing theory is employed to construct the queueing time model. Equation (13) and Equation (14) represent the average queue length and average arrival rate, respectively. And their ratio gives the queueing time of EV users, as shown in Equation (12).

$$T_i^q = \frac{L_q}{\lambda_e} \quad (12)$$

$$L_q = \sum_{n=s}^K (n-s)P_n \quad (13)$$

$$\lambda_e = \lambda(1 - P_K) \quad (14)$$

The model for the idle probability of the CS P_0 , the customer loss rate P_n , the average queue length L_q , and the average waiting time L_q can be obtained.

$$P_0 = \begin{cases} \left(\sum_{n=0}^{s-1} \frac{\rho^n}{n!} + \frac{\rho^s(1 - \rho_s^{K-s+1})}{s!(1 - \rho_s)} \right)^{-1} & (\rho \neq 1) \\ \left(\sum_{n=0}^{s-1} \frac{\rho^n}{n!} + \frac{\rho^s(K-s+1)}{s!} \right)^{-1} & (\rho = 1) \end{cases} \quad (15)$$

$$P_n = \begin{cases} \frac{\rho^n}{n!} P_0, 0 \leq n < s \\ \frac{\rho^n}{s!s^{n-s}} P_0, s \leq n \leq K \end{cases} \quad (16)$$

In Equation (15), P_0 represents the probability that there are no EV receiving charging service in the station, whereas P_n in Equation (16) denotes the probability that a customer leaves the CS if the waiting time is excessively long.

To evaluate the service efficiency and load of the CS, the EV charging service intensity ρ is defined, as shown in Equation (17), and Equation (18) is the arrival rate.

$$\rho = \frac{\lambda}{\mu} \quad (17)$$

$$\lambda = \begin{cases} \lambda_{low}, P_s^t = 0 \\ \lambda_{high}, P_s^t = 1 \end{cases} \quad (18)$$

$$\rho_s = \frac{\rho}{s} \quad (19)$$

whereas Equation (19) can be used to evaluate the utilization of the CS. A value close to 1 indicates that the station is heavily loaded, while a relatively small value suggests that the system capacity may be underutilized.

(3) Travel Time Model

Road conditions and traffic congestion are considered through corresponding coefficients, and the remaining battery level of EVs is incorporated, as low battery may reduce speed or require more frequent charging stops, thereby increasing travel time T_i^{tr} . The calculation is shown in Equation (20).

$$T_i^{tr} = \frac{d_{i,s}}{v_{i,s} C_r (1 - SOC_i^{pr})} \alpha_r \quad (20)$$

$$d_{i,s} = |x_s - x_i| + |y_s - y_i| \quad (21)$$

where $d_{i,s}$ stands for the distance an EV user travels from the demand point to the charger, calculated using the Euclidean distance, is calculated by Equation (21). $v_{i,s}$ denotes the travel speed; C_r is the road condition coefficient. Considering that the road network in the study area mainly consists of urban expressways, arterial roads, and ordinary urban streets, C_r is set to 1.35 in this study as an empirical correction coefficient representing typical urban mixed-road conditions. α_r is the traffic congestion coefficient and SOC_i^{pr} represents the remaining battery level.

2.3. Energy Storage and Transformer Cost

We equip the CS with transformers of appropriate capacity to meet the power supply demand when multiple charging piles operate simultaneously, as shown in Equation (22).

$$C_{b,n} = S_b \cdot P_{kw} \frac{Q_{u,n}}{\kappa \cdot \cos \phi \cdot P_T} \quad (22)$$

where S_b is the unit price of each transformer, and P_T denotes the transformer capacity; κ is the transformer load rate; $\cos \phi$ is the power factor;

Considering load fluctuations and TOU pricing, the ESS can reduce electricity purchase costs by charging during off-peak periods and discharging during peak periods. Therefore, we incorporate energy storage benefits into the model and use the net cost to evaluate its economic effect, as shown in (23).

$$C_c = C_{storage} - C_{save} \quad (23)$$

where $C_{storage}$ is the configuration cost of the energy storage system, and C_{save} is the electricity cost savings obtained from energy storage operation.

$$C_{storage} = \frac{r_0(1+r_0)^m}{(1+r_0)^m - 1} \cdot (C_{bat} \cdot E_b + P_b \cdot C_{pcs}) \quad (24)$$

In Equation (24), C_{bat} is the unit capacity cost of the energy storage battery; E_b is the energy storage battery (ESB) capacity; P_b the discharge power of the ESS; and C_{pcs} is the cost of the power conversion system (PCS);

$$C_{save} = 365 \cdot \left(\sum_{t=1}^{24} p_t (L_{load}(t) - L_{opt}(t)) \right) \cdot \Delta t \quad (25)$$

where p_t represents the TOU price at time period t ; $L_{load}(t)$ and $L_{opt}(t)$ represent the CS loads before and after energy storage optimization, respectively; and Δt is the duration of each time interval.

2.4. Constraints

(1) State of Charge (SOC) Constraint

To extend the battery life of EVs and prevent overcharging or overdischarging, the SOC must remain within the predefined limits:

$$SOC_{min} < SOC(t) < SOC_{max} \quad (26)$$

where SOC_{max} denotes the maximum battery SOC, and SOC_{min} denotes the minimum battery SOC.

(2) Energy Balance Constraint

$$SOC_{n,t+1} = SOC_{n,t} + \eta \cdot P_{n,t}^{ch} \cdot \Delta t - \frac{P_{n,t}^{dis}}{\eta} \cdot \Delta t \quad (27)$$

$$P_{n,t}^{ch} P_{n,t}^{dis} = 0 \quad (28)$$

where $SOC_{n,t}$ and $SOC_{n,t+1}$ denote the SOC of the battery at time period t respectively; η denotes the charging efficiency. In Equation (28), $P_{n,t}^{ch}$ and $P_{n,t}^{dis}$ denote the charging and discharging powers of the ESS at CS during time period t , respectively. This complementarity constraint requires at least one of the two variables to be zero, thereby preventing the ESS from charging and discharging simultaneously. The operating state of the ESS is determined according to the TOU price-driven scheduling strategy, and the mutually exclusive state-switching mechanism ensures that the ESS operates in only one of the charging, discharging, or idle states during each time period.

(3) Maximum Charging or Discharging Power Constraint

The charging and discharging power of an EV is limited by its rated power. It is assumed that the EV charging/discharging power remains constant within each time interval Δt .

$$0 < P_{n,t}^{ch} \leq P_{max}^{ch} \quad (29)$$

$$0 < P_{n,t}^{dis} \leq P_{max}^{dis} \quad (30)$$

$$P_{min}^{dis} < P_{kw,t} < P_{max}^{ch} \quad (31)$$

where P_{max}^{ch} denotes the maximum charging power of the energy storage battery, and P_{max}^{dis} and P_{min}^{dis} represent the maximum and minimum discharging power.

(4) Capacity and Distance Constraints

The number of EVs served by each CS should be within its operational capacity, as shown in Equation (32).

$$Q_{u,n} < K \leq 2 \cdot Q_{u,n} \quad (32)$$

The service distance between each demand point and the corresponding CSs should not exceed the maximum allowable service distance, as shown in Equation (33).

$$d_{i,s} \leq D_{\max} \quad (33)$$

where $d_{i,s}$ represents the distance from the demand point to the charger, and $D_{\max}$ is the maximum service distance.

3. DNN-ISSA for Solving CSs Capacity and Parking Spaces Planning

To improve the optimization efficiency and solution quality of CSs capacity planning, this study combines a deep neural network with the improved sparrow search algorithm to develop a DNN-ISSA-based capacity optimization method.

3.1. Principle and Process of DNN-ISSA

ISSA is a swarm intelligence optimization algorithm improved based on SSA [27]. To address the problems of high variable dimensionality, numerous integer constraints, and susceptibility to local optima in the joint optimization of CSs capacity and parking spaces, this study introduces a golden sine strategy, adaptive Lévy perturbation, and a constraint repair mechanism [28]. In addition, the initial capacity center predicted by the DNN is used to guide the population search, thereby improving the quality of the initial solution, narrowing the search range, and accelerating convergence [29].

Figure 2 shows the principle of DNN-ISSA. The DNN takes station features as inputs and predicts the initial capacity center of each CS. The predicted capacity center is then used to guide the initialization and search process of ISSA. Compared with the original ISSA, DNN-ISSA narrows the search range and reduces blind search, enabling the algorithm to approach the optimal solution more efficiently and converge more rapidly.

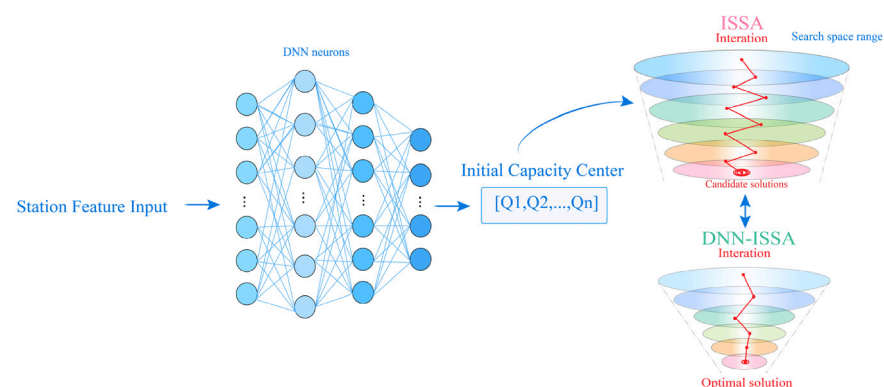


Figure 2. The principle of DNN-ISSA. (The blue arrows indicate the data and optimization flow)

3.2. DNN-ISSA-Optimized Capacity Planning for EV Charging Stations

The iterative process of DNN-ISSA mainly includes the following steps:

Step 1: Initialize the ISSA parameters.

Set the parameters, including the population size pop , the maximum number of iterations $T_{\max}$, the variable dimension dim , the lower and upper bounds lb and ub , the producer ratio PD , and the scout ratio SD . In this study, the number of chargers and parking spaces at each CS are taken as decision variables, and the position of an individual is expressed as:

$$X = [Q_{u,1}, Q_{u,2}, \dots, Q_{u,n}, K_1, K_2, \dots, K_N] \quad (34)$$

Step 2: Train the DNN initialization model.

Step 2-1: Construct the DNN model.

Construct a DNN model to learn the nonlinear mapping between CS features and capacity centers. Considering the input and output dimensions, training stability, and computational efficiency, adopt a two-hidden-layer architecture with 128 and 64 neurons, respectively, based on preliminary experiments, and use ReLU as the activation function [30]. This configuration provides an appropriate balance between prediction accuracy and computational cost. Use the trained DNN to output the initial capacity center of each charging station, thereby providing stable initialization guidance for ISSA.

Step 2-2: Generate DNN training samples.

Step 2-2-1: Extract structural features of CSs.

Construct the input features based on CS coordinates, charging power, the number of peak hours, valley-period arrival rate, peak-period arrival rate, and functional area type.

Step 2-2-2: Predict the target values.

Construct target labels using station-level features, including the average arrival rate, service rate, charging power, number of peak hours, and spatial distribution characteristics. Use the predicted numbers of chargers and parking spaces to guide the initialization and early-stage search process of ISSA.

Step 2-2-3: Augment the training samples.

Add Gaussian perturbations to the original station features to generate multiple sets of perturbed samples. Then recalculate the corresponding labels to form the DNN training set.

Step 2-3: DNN Model Training.

As previously described, the DNN in this study is not used as an independent charging demand prediction model, but as an initialization guidance module for ISSA to predict the initial capacity center of each charging station, namely the initial numbers of chargers and parking spaces. The dataset was divided into training and testing sets at a ratio of 80:20. The Adam optimizer was adopted to train the network parameters, with the learning rate set to 0.001, the batch size set to 32, and the number of training epochs set to 1500.

Step 3: Start the DNN-guided ISSA.

Step 3-1: Generate the initial population.

Generate the initial population using Circle chaotic mapping and opposition-based learning. Then create DNN-guided individuals by adding small random perturbations around the DNN-predicted capacity centers, and incorporate them into the initial population to improve solution quality.

Step 3-2: Calculate individual fitness.

Decode each individual into the number of chargers and parking spaces at each CS, and calculate the total fitness value.

Step 3-3: Update the positions of producers.

Update the discoverer positions using the golden sine strategy, and introduce DNN-predicted capacity centers for mild guidance in the early iterations to guide the population more quickly toward promising solution regions. The guidance form is expressed as:

$$X_i^{t+1} = (1 - \theta) \cdot X_i^{t+1} + \theta \cdot X_{DNN} \quad (35)$$

Step 3-4: Update the positions of joiners based on the current best individual and the global best individual.

Step 3-5: Update the positions of scouts using adaptive Lévy perturbation.

Step 3-6: Boundary checking and constraint repair.

Perform boundary checking, integer processing, and capacity constraint repair for all individuals after each position update.

Step 3-7: Local neighborhood search.

Perform a small-scale discrete neighborhood search on the current best solution at fixed iteration intervals, and further improve the solution quality by slightly adjusting the numbers of chargers and parking spaces.

Step 3-8: Judge the termination condition.

If the maximum number of iterations is reached, the search is terminated; otherwise, the algorithm returns to Step 3-2 and continues the next iteration.

Step 3-9: Output the optimization results.

Output the optimal objective function value, the optimal number of chargers at each CS, and the optimal number of parking spaces.

The flowchart of the overall process is shown in Figure 3. DNN-ISSA combines a DNN with the ISSA to improve the search efficiency and convergence performance of capacity optimization. The DNN is trained based on CSs features and heuristic initial values to learn the nonlinear mapping relationship between station features and the capacity center, and then predicts the initial capacity center of each CS. Compared with the traditional ISSA, the introduction of the DNN can improve the quality of the initial solutions, narrow the search range, and accelerate the convergence speed of the charging scheduling algorithm.

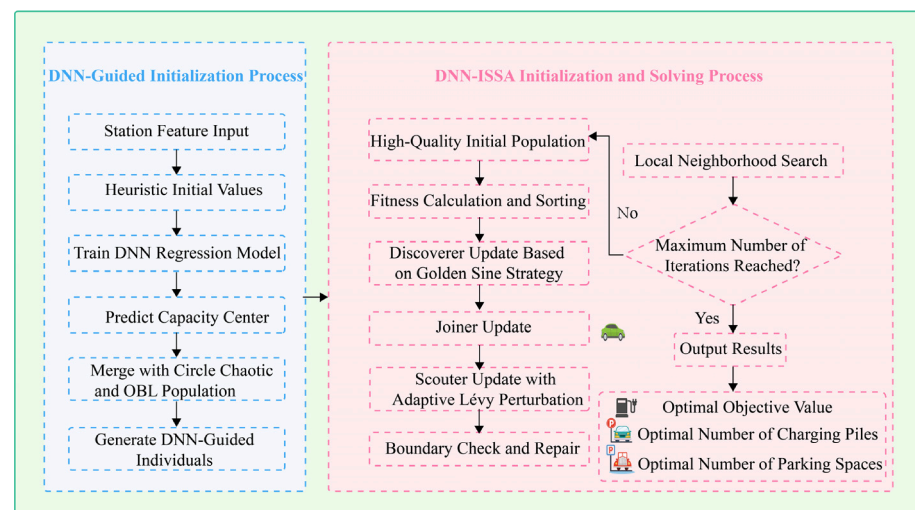


Figure 3. Flowchart of EV charging stations siting plan. (The arrows indicate the direction of process or data flow.)

4. Charging Scheduling Algorithm for EV Charging Time

This section utilizes real-world charging data to analyze EV users' charging behaviors. A charging time scheduling algorithm is then proposed to effectively optimize EV users' charging behavior, thereby improving the utilization efficiency of charging resources.

4.1. Processing of Real-World Charging Behavior Data

CSs located in different functional areas exhibit significant differences in the peak–valley characteristics of charging demand due to heterogeneous usage scenarios. To accurately characterize such spatio-temporal charging behavior patterns, a newly collected dataset covering one full year of commercial operation was provided by a charging service operator [31]. The dataset comprises 72,856 complete charging sessions conducted by 2337 users across 2119 chargers and includes 16 data fields, demonstrating strong representativeness and empirical value.

Charging Probability Analysis

First, the “Location” and “StartTime” were extracted from the dataset, and the charging records were categorized based on various location types. Subsequently, the “StartTime” were divided into 24 hourly intervals.

Based on the visualization analysis, hotspot areas, critical time periods, and dominant demand types can be intuitively identified, providing data support for the design of subsequent scheduling strategies. The charging probability of CSs at different locations across time periods is shown in Figure 4, where the x -axis denotes charging time intervals and the y -axis represents the charging probability. The results indicate pronounced spatio-temporal heterogeneity in charging demand among different functional areas, apartments are dominated by evening demand, companies by commuting period demand, markets and sightseeing by daytime demand, while demand in public parking spaces is more evenly distributed over time.

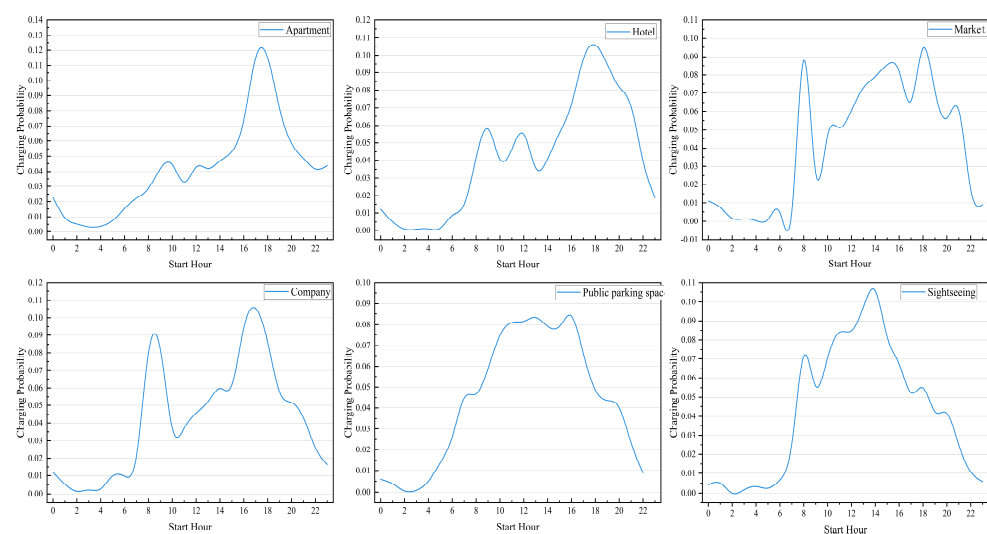


Figure 4. Temporal charging probabilities for CSs at different locations.

The location information of 36 CSs within the region was digitized, with precise coordinates and location types of each station thoroughly recorded. The relevant information is summarized in Table 2. To identify the peak and off-peak charging periods for each station, a threshold was set: time periods with a charging probability greater than 0.08 were defined as peak periods; it indicates that a relatively large number of EVs arrive at the station for charging, representing a high-demand peak; otherwise, the period is considered an off-peak period.

Table 2. Coordinates, location types, and peak charging periods of CSs.

CSs ID	Coordinates	Location Types	Peak Charging Periods
1	1.5, 3.9	Hotel	17, 18, 19, 20
2	1.7, 3.9	Markt	8, 13, 14, 15, 16, 18
3	1.8, 3.6	Apartment	17, 18, 19
4	3.3, 3.7	Public parking space	11, 12, 13, 14, 15, 16, 17
5	3.5, 3.5	Apartment	17, 18, 19
6	4.7, 3.9	Public parking space	11, 12, 13, 14, 15, 16, 17
7	0.6, 2.5	Apartment	17, 18, 19
8	2, 2.5	Company	8, 9, 16, 17, 18
9	1.5, 2.8	Market	8, 13, 14, 15, 16, 18

Table 2. Cont.

CSs ID	Coordinates	Location Types	Peak Charging Periods
10	2.2, 2.1	Sightseeing	8, 10, 11, 12, 13, 14, 15
11	3.3, 2.7	Sightseeing	8, 10, 11, 12, 13, 14, 15
12	3.3, 2.1	Sightseeing	8, 10, 11, 12, 13, 14, 15
13	3.5, 2	Hotel	17, 18, 19, 20
14	3.8, 2	Hotel	17, 18, 19, 20
15	3.4, 1.8	Markt	8, 13, 14, 15, 16, 18
16	2.6, 1.8	Markt	8, 13, 14, 15, 16, 18
17	2.8, 1.7	Hotel	17, 18, 19, 20
18	3.1, 1.4	Hotel	17, 18, 19, 20
19	0.5, 2.3	Markt	8, 13, 14, 15, 16, 18
20	0.7, 2.2	Public parking space	11, 12, 13, 14, 15, 16, 17
21	1.3, 2	Company	8, 9, 16, 17, 18
22	1.2, 1.6	Apartment	17, 18, 19
23	0.7, 1.6	Markt	8, 13, 14, 15, 16, 18
24	0.7, 1.5	Hotel	17, 18, 19, 20
25	0.3, 0.5	Apartment	17, 18, 19
26	3.3, 0.7	Public parking space	11, 12, 13, 14, 15, 16, 17
27	4, 0.6	Company	8, 9, 16, 17, 18
28	3.4, 1.3	Markt	8, 13, 14, 15, 16, 18
29	3.6, 1.4	Hotel	17, 18, 19, 20
30	3.7, 1.2	Hotel	8, 9, 16, 17, 18
31	3.8, 1.1	Company	8, 9, 16, 17, 18
32	3.8, 0.8	Public parking space	11, 12, 13, 14, 15, 16, 17
33	4.3, 2.3	Apartment	17, 18, 19
34	0.7, 3.3	Apartment	17, 18, 19
35	1, 0.6	Company	8, 9, 16, 17, 18
36	2.5, 1.7	Apartment	17, 18, 19

4.2. Charging Time Scheduling Algorithm

This section focuses on the optimization of EV charging time scheduling. Based on the analysis of users' charging probability, we further consider the influence of TOU pricing on the selection of charging periods, and charging load models are established for both the original load scenario and the TOU price-guided scenario. Subsequently, through relevant evaluation indicators, the distribution characteristics of charging loads under different scheduling scenarios are analyzed.

4.2.1. Charging Probability Correction and Load Modeling Based on TOU Pricing

To characterize the impact of TOU pricing on EV users' charging behavior, this paper introduces a TOU price response mechanism based on the original charging probability model and accordingly modifies users' charging selection probabilities in different periods. The five-period TOU pricing scheme of the Shandong power grid was adopted in the case study. The charging probability at time t is shown in Equation (36).

$$P_t^{pro} = \frac{P_m}{H_m}, t \in T_m \quad (36)$$

where P_m denotes the overall charging probability of the m -th type of period; T_m denotes the set of hours included in this type of period; and H_m denotes the number of hours included in this type of period.

Subsequently, the 24 h baseline probabilities are normalized, and an electricity price impact function is introduced to modify users' charging probabilities. Considering that users generally tend to avoid high-price periods and choose low-price periods for charging,

this paper adopts an exponential electricity price response function. The calculation is shown in Equation (37).

$$f(p_t) = e^{-\beta \cdot p_t} \quad (37)$$

where p_t denotes the TOU price at time period t , and β is the price sensitivity coefficient.

Therefore, the charging probability considering TOU pricing can be expressed as in Equation (38).

$$p_t^{TOU} = \frac{P_t^{pro} \cdot e^{-\beta \cdot p_t}}{\sum_{t=1}^{24} P_t^{pro} \cdot e^{-\beta \cdot p_t}} \quad (38)$$

where P_t^{pro} is the original charging probability at time period t .

After obtaining the modified charging probability, this paper introduces load standard deviation peak–valley difference, and peak-to-average ratio three indicators to evaluate the effect of TOU price guidance on smoothing the charging load based on the charging loads under the original scenario and the TOU price-guided scenario.

The peak–valley difference represents the difference between the maximum and minimum loads within a day. The calculation is shown in Equation (39).

$$D_{pv} = P_{\max} - P_{\min} \quad (39)$$

where $P_{\max}$ and $P_{\min}$ denote the maximum and minimum load values during the scheduling period, respectively.

The peak-to-average ratio represents the proportional relationship between the peak load and the average load. The calculation is shown in Equation (40).

$$R_{pa} = \frac{P_{ax}}{P_{avg}} \quad (40)$$

where P_{ax} denotes the peak load, and P_{avg} denotes the average load.

The load standard deviation (Std) represents the degree of dispersion of the load in each period relative to the average load. The calculation is shown in Equation (41).

$$\sigma_p = \sqrt{\frac{1}{24} \cdot \sum_{t=1}^{24} (P_{EV}(t) - P_{avg})^2} \quad (41)$$

where $P_{EV}(t)$ denotes the EV charging load at time period t .

4.2.2. Algorithm Solution Procedure

After completing the modification of charging probabilities and load modeling, this section further presents the specific solution procedure of the optimized charging time scheduling algorithm. This procedure provides a computational basis for the subsequent analysis of the effects of TOU pricing on charging load distribution and users' charging behavior.

Figure 5 shows the simulation process for EV charging scheduling under the guidance of TOU pricing. First, data such as CSs, TOU prices, vehicle parameters, and charging probabilities are input, and the simulation environment is initialized. Then, user demand points are randomly generated according to vehicle charging demand. The charging start time is adjusted based on charging probability and TOU pricing, thereby guiding users' charging behavior.

After multiple simulations, charging load curves under different scenarios are obtained, along with evaluation indicators such as peak–valley difference, standard deviation,

and average total time. These results are used to analyze the impact of TOU pricing on charging load and user behavior.

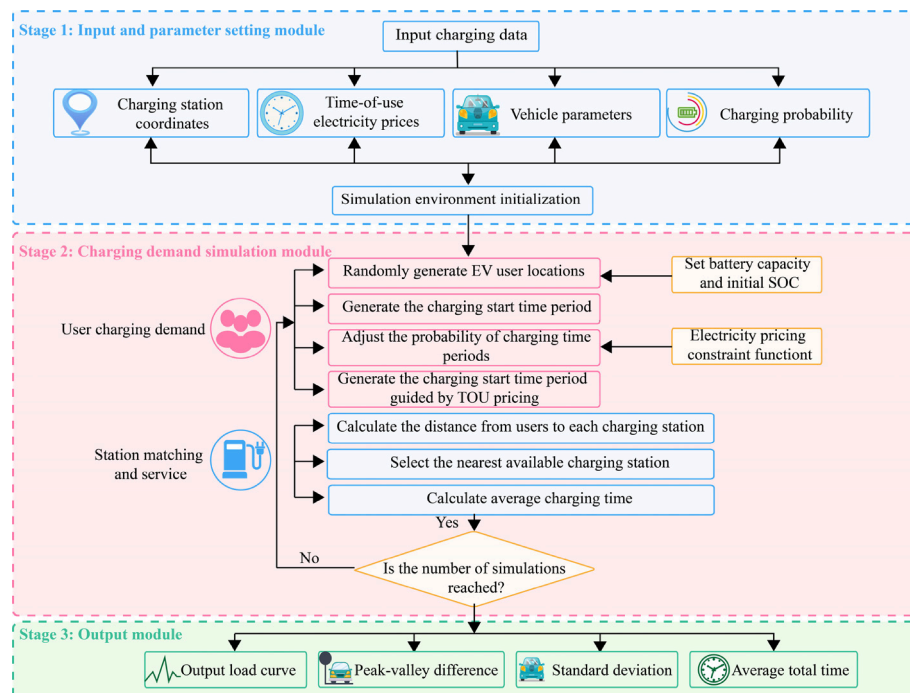


Figure 5. EV charging scheduling algorithm flowchart. (The arrows indicate the direction of data or process flow; different colors distinguish different functional modules).

5. Case Analysis

We selected a typical urban area in Jinan City, Shandong Province, as the research region. The area spans approximately 5 km east–west and 4 km north–south, with a total area of around 20 km². To cover charging behavior under different daily life and commuting scenarios, data from 36 operational CSs in the study area were collected, and the stations were classified into six functional categories: hotels, apartments, companies, markets, public parking spaces, and sightseeing. By analyzing the spatial distribution and functional differences of these scenarios, the influence of urban functions on users' charging choices can be more clearly revealed. The study area, its functional structure, and the spatial layout of CSs are shown in Figure 6.

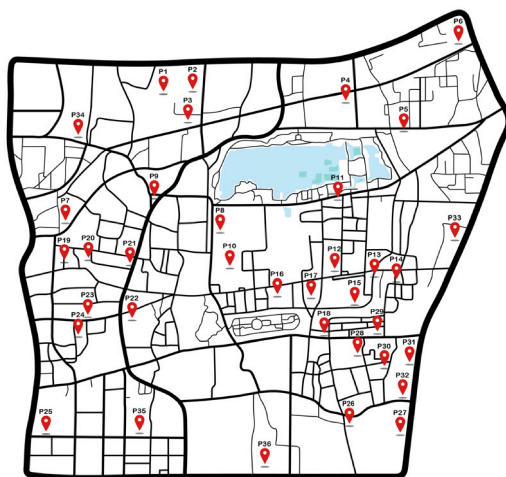


Figure 6. The CS distribution topology. (P1–P36 represent the charging station IDs).

5.1. Simulation Setup and Parameter Settings

In the simulation and analysis corresponding to the model in Section 4, the default parameters and stochastic variable ranges used are detailed in Table 3. The default parameters are used for calculations and performance evaluation under baseline scenarios to ensure consistency of experimental conditions. The ranges of stochastic parameters were set based on actual charging behavior characteristics and system operational constraints, supporting sensitivity analysis and multi-scenario simulations. All algorithms and numerical simulations were implemented in Python 3.10.19 (Python Software Foundation, Wilmington, DE, USA). The figures were generated using OriginPro 2024 (OriginLab Corporation, Northampton, MA, USA).

Table 3. Parameter settings.

Parameters	Meaning	Parameter Type	Value
$SOC_i^{\max}$	Maximum charging SOC	Constant Parameter	0.9
SOC_i^{pr}	Current remaining SOC	Random parameter	(0.2, 0.5)
E_i^r	Battery capacity	Random parameter	(50, 100)
μ_{kw}	Charging efficiency	Constant Parameter	0.9
$v_{i,s}$	Driving speed	Constant Parameter	45 km/h
$D_{\max}$	Maximum tolerable distance	Constant Parameter	1.5 km
C_r	Road condition coefficient	Constant Parameter	1.35
α_r	Congestion coefficient	Constant Parameter	1.25
λ_{high}	Peak arrival rate	Random parameter	(6, 10)
λ_{low}	Off-peak arrival rate	Random parameter	(0, 5)
κ	Transformer load rate	Constant Parameter	0.8
$\cos \phi$	The power factor	Constant Parameter	0.9

The “five-period” TOU pricing system of the Shandong power grid is shown in Table 4. It divides the day into five periods [32]. Differentiated electricity prices are applied across the periods to guide users in optimizing their electricity consumption behavior.

Table 4. TOU price of Shandong power grid.

Period Type	Price (CNY/kWh)	Time
Top-peak period	1.5136	17:00–19:00
Peak period	1.2866	16:00–17:00, 19:00–21:00
Off-peak period	0.7568	0:00–10:00, 15:00–16:00, 21:00–24:00
Valley period	0.2270	10:00–11:00, 14:00–15:00
Deep valley period	0.0757	11:00–14:00

5.2. Simulation Result Analysis

We analyze the simulation results from four aspects: DNN training curves, capacity planning, charging time and load optimization. This analysis verifies the effectiveness of the proposed method in reducing system costs, optimizing CS capacity planning, and improving the distribution of charging load.

5.2.1. Training Results Analysis

Figure 7 shows the changes in training loss and RMSE of the DNN initialization model. It can be observed that the model error decreases rapidly at the early stage of training and then gradually stabilizes. Since the DNN directly predicts the number of chargers and parking spaces in the original capacity scale, the initial random weights may lead to large prediction deviations, resulting in a relatively high initial loss. The enlarged subplots further

show that only slight fluctuations occur after convergence, with no obvious divergence. This indicates that the DNN initialization model has good convergence and stability.

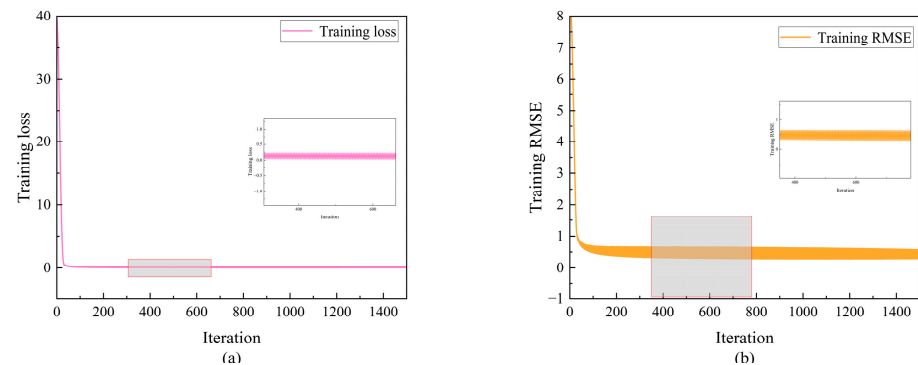


Figure 7. Curves of the DNNs training process: (a) DNNs training loss curves; (b) DNNs training RMSE curves.

5.2.2. Charging Stations Capacity Planning Results

This section analyzes the capacity planning results of CSs. First, the convergence performance and optimization stability of different algorithms are compared to verify the solution advantages of DNN-ISSA. Then, the changes in the number of chargers, the number of parking spaces, and the total system objective value before and after considering ESS are further analyzed.

To verify the solution performance of DNN-ISSA, this study compares it with ISSA, PSO, and SSA-PSO. As shown in Figure 8a, DNN-ISSA achieved a faster convergence speed and a lower final objective value, indicating that DNN-guided initialization can improve the quality of the initial solution and accelerate the optimization process. Figure 7b presents the box plots of the optimization results obtained by different algorithms. DNN-ISSA exhibited the lowest box position, with lower median and mean values than the other algorithms, indicating lower optimization cost. Its narrower box also shows that the results are more concentrated and stable. Compared with ISSA, DNN-ISSA reduced the final objective value by 15.05%.

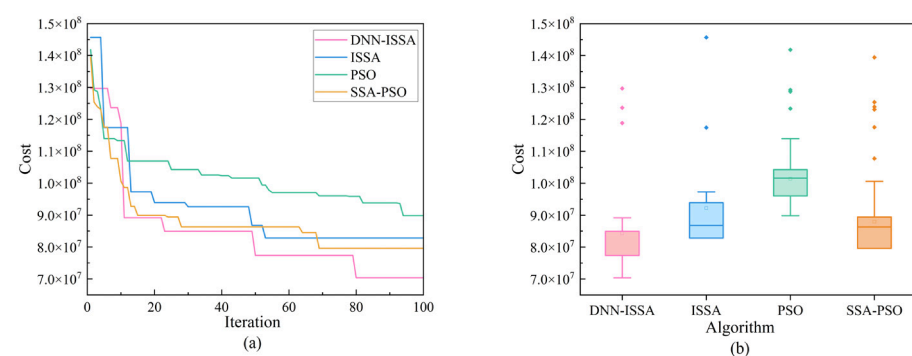


Figure 8. Optimization iteration results of the DNN-ISSA: (a) Curves obtained by compared algorithms, (b) boxplots of the comparison algorithms.

Under identical settings in terms of population size, maximum number of iterations, variable bounds, and objective function, DNN-ISSA and all benchmark algorithms were independently run 20 times. The Friedman test was employed to assess the overall statistical differences among the algorithms, while their computational efficiency was evaluated using the mean running time, standard deviation, and coefficient of variation CV (%). The corresponding results are presented in Figure 9.

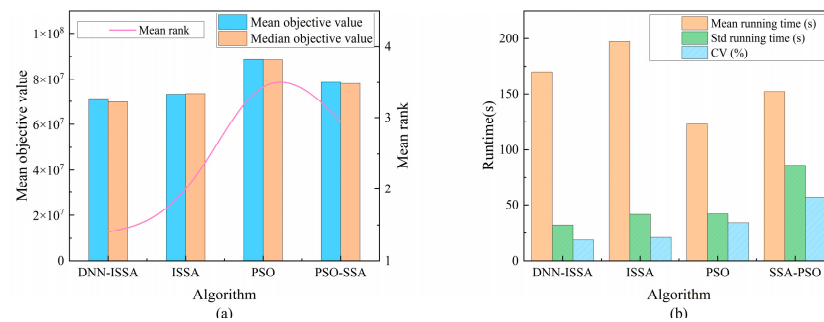


Figure 9. Statistical significance and computational efficiency analysis: (a) Friedman test comparison of different algorithms, (b) runtime comparison of different algorithms.

Figure 9 indicates that DNN-ISSA achieved the lowest mean and median objective values, together with the best Friedman mean rank, demonstrating its superior overall optimization performance. In Figure 9b, PSO achieved the shortest average running time, whereas DNN-ISSA requires moderately more computation due to the incorporation of DNN-guided initialization and additional search strategies. Nevertheless, DNN-ISSA still exhibited a shorter average running time than ISSA and the smallest runtime variation among the compared algorithms, indicating the highest computational stability. Considering its lower objective value and superior mean rank, the additional computational time incurred by DNN-ISSA is acceptable.

As shown in Table 5, after considering ESS, the total number of chargers, total number of parking spaces, and total system cost all decrease, by 5.22%, 10.75%, and 4.82%, respectively. The results indicate that introducing ESS helps optimize CS capacity and reduce the overall system cost.

Table 5. Comparison of configurations with and without ESS.

Indicator	Without ESS	With ESS	Change Rate (%)
Total number of chargers	249	236	5.22
Total number of parking spaces	465	415	10.75
Total cost (CNY)	73,923,755.32	70,360,846.86	4.82
Indicator	Without ESS	With ESS	Change rate (%)

Figure 10 shows that, after introducing the ESS cost model, the ESS can take advantage of TOU price differences by charging during valley periods and discharging during peak periods, thereby reducing the electricity purchase cost of CSs. Meanwhile, this strategy helps relieve load pressure during peak hours and further improves the economic performance of the capacity planning while enhancing power supply reliability.

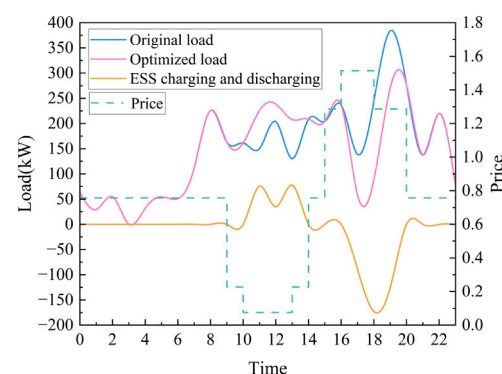


Figure 10. Load optimization results under the ESS.

5.2.3. Charging Time Optimization Results

Based on the optimization results obtained using DNN-ISSA, the optimal capacity planning of CSs within the study area is finally determined, including the number of chargers and parking spaces at each station. To characterize the spatial distribution of EV charging demand within the case study region, we adopt a random generation method for spatial demand points. Simulation experiments are conducted with 1000, 5000, and 10,000 demand points, respectively.

Figure 11 shows that the proposed method reduced the average charging time under the low-, medium-, and high-demand scenarios; the proposed method can effectively guide EV users to avoid charging peak periods and to reasonably select CSs and time slots, thereby significantly reducing overall charging waiting time. Specifically, compared with the unscheduled case, the optimized average charging time is reduced by 15.7 min, 15.4 min, and 15.2 min, respectively. These results further confirm the effectiveness of the charging peak–off-peak identification-based scheduling strategy in improving charging efficiency.

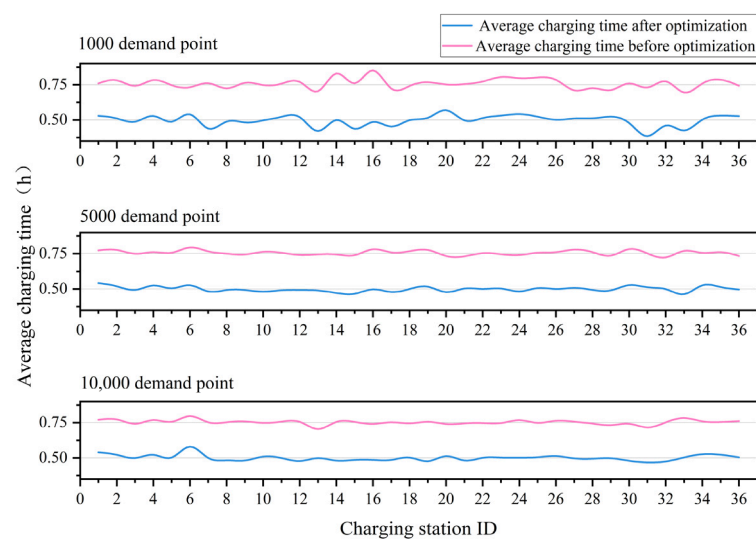


Figure 11. Comparison of charging time for different demand points.

As shown in Table 6, under different demand points, the peak load, peak–valley difference, and peak-to-average ratio in the TOU pricing scenario are generally lower than those in the comparison scenario. This indicates that time-of-use pricing can guide users to charge during off-peak periods, reduce load fluctuations, and improve the charging load distribution.

Table 6. Comparison of load assessment metrics.

Demand Points	Scenario	Peak Load (kW)	Valley Load (kW)	Std (kW)	Peak–Valley Difference (kW)	Peak–Average Ratio
1000	Base	4085.2	497.4	962.5	3587.8	2.1
	TOU	3579.1	741.3	1003.8	2837.9	1.9
5000	Base	21,865.1	4918.9	4909.4	16,946.2	2.3
	TOU	17,688.1	5127.9	4299.8	12,560.2	1.9
10,000	Base	42,319.1	10,614.4	9853.1	31,704.7	2.2
	TOU	38,693.6	10,165.7	8755.9	28,527.8	2.0

5.2.4. Sensitivity Analysis

To further verify the robustness of the proposed model under key parameter variations, a one-factor sensitivity analysis was conducted for the TOU price sensitivity coefficient and ESS capacity.

For the TOU price sensitivity analysis, 5000 demand points were selected as the representative scenario. As shown in Table 7, when $\beta = 0.25$, the load standard deviation, peak–valley difference, and peak–average ratio are relatively low, indicating that a moderate price sensitivity can effectively smooth the charging load. However, when β continues to increase, excessive price response may shift too much charging demand to low-price periods, resulting in new load peaks and larger load fluctuations.

Table 7. Sensitivity analysis results of the TOU price sensitivity coefficient.

Price Sensitivity Coefficient	Std (kW)	Peak–Valley Difference (kW)	Peak–Average Ratio
0	4804.3	14,987.2	2.10
0.25	4285.9	11,675.9	1.78
0.5	4440.7	13,572.1	1.85
0.75	4945.1	14,610.6	2.04
1.0	5837.0	18,952.3	2.34

A sensitivity analysis based on Latin Hypercube Sampling (LHS) was conducted under different ESS capacity levels to evaluate the impact of ESS capacity variation on system economy and load regulation performance.

As shown in Table 8, increasing ESS capacity can reduce the total system cost, but the peak-shaving and valley-filling effect does not continuously improve. When the ESS capacity is within the 100–150% range, the peak–valley difference reaches its optimal value. After the capacity exceeds 150%, the total cost continues to decrease, while the peak–valley difference slightly increases. Therefore, ESS capacity configuration should balance system economy and load smoothing performance.

Table 8. Sensitivity analysis results under different ESS capacity levels.

ESS Capacity Level	Mean Total Cost (CNY)	Std Total Cost (CNY)	Mean Peak–Valley Difference (kW)
0–50%	74,815,572.77	882,696.11	11,187.59
50–100%	71,465,727.25	952,969.6	11,589.51
100–150%	67,944,946.09	1,113,555.58	10,462.61
150–200%	64,873,864.78	969,356.72	10,611.55

6. Conclusions

This paper focuses on the coordinated optimization of EV charging station capacity planning and charging time scheduling. A multi-CS optimization model considering TOU pricing and ESS operation was developed and evaluated using data from 36 CSs in Jinan.

(1) The results show that the proposed DNN-ISSA can effectively improve the solution accuracy and convergence performance of capacity planning optimization. Compared with the traditional ISSA, PSO, and SSA-PSO, the objective function convergence value of DNN-ISSA is reduced by 15.05%, 21.67%, and 11.61%, respectively. This indicates that DNN-guided initialization can improve the quality of the initial population, reduce blind search, and enhance the stability and optimization capability of the algorithm in multiple stations integer-variable optimization problems.

(2) After introducing the ESS costs, the total system costs decrease from 73.9237 million yuan to 70.3608 million yuan. This result indicates that the ESS can utilize the difference in TOU prices by charging during valley periods and discharging during peak periods, thereby reducing the electricity purchase cost of CSs and the total system cost. Meanwhile, the ESS can also alleviate the impact of peak-period charging loads on the distribution network to some extent.

(3) The proposed charging scheduling algorithm based on TOU price response can effectively reduce users' charging time and smooth the charging load. Under the simulation scenarios with 1000, 5000, and 10,000 charging demand points, the average charging time was reduced by 15.7, 15.4, and 15.2 min, respectively, compared with the scenario without scheduling optimization.

In future research, the validation scope will be further expanded by introducing charging station data from different cities and regions and evaluating the proposed method under different urban scales, charging demand characteristics, and TOU pricing schemes. Future work will also further consider fluctuations and uncertainties in charging demand to enhance the robustness, generalizability, and practical applicability of the proposed method.

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