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Optimization of Charging-Station Location and Capacity Determination Based on Optical Storage, Charging Integration, and Multi-Strategy Fusion

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Abstract: To reduce electric vehicle carbon dioxide emissions while charging and increase charging pile utilization, this study proposes an optimization method for charging-station location and capacity determination based on multi-strategy fusion that considers the optical-storage charging station. By analyzing the characteristics of vehicle trajectory data, the dwell points that support charging are extracted; the center point of the dwell area is obtained through k-means clustering, indicating the candidate site of a charging station and optical-storage charging station. The process for determining demand points and quantities is described as follows. Set the parking lot as the demand point; select the period with the most vehicle stops, and determine the demand according to the proximity principle. Using the investment cost, user time cost, and total carbon dioxide emissions from charging as the targets, a data-driven co-evolutionary model is established. It is solved using the multi-objective particle swarm optimization algorithm. Further, the analytic hierarchy process is used to determine the optimal location and sizing scheme. Empirical analysis is completed using Beijing taxi track data as an example. The experiments show that after constructing an optical-storage charging station, the number of charging piles can be reduced by improving the charging pile utilization rate, and the investment cost can be effectively controlled. The station is built at a location with a large demand, effectively reducing the carbon dioxide emissions caused by charging and indirectly reducing user time cost.

Keywords: Optical-storage charging station; Co-evolutionary model; k-means clustering; Multi-objective particle swarm optimization; Analytic hierarchy process

1 Introduction

Energy bundling is critical in national development. However, with continuous exploitation of fossil fuels, it has become less common. In addition, the world is experiencing an energy crisis, which has led to increasing prices. Environmental pollution, greenhouse gas (GHG) efficiency, and other issues are becoming an increasing concern. As a result, electric vehicles (EVs) have emerged. Faced with three major challenges of global fossil energy depletion, low energy utilization efficiency, and environmental pollution, China has formulated the "dual carbon" strategic goal of carbon peaking and neutralization. Development of the EV industry has become an important measure for achieving this goal. In development of new EV technology routes, construction and use of charging stations play a vital role. However, construction of EV stations impacts the power grid and generates carbon emissions. To promote new energy and suppress this impact, the "integrated optical storage and charging station" was proposed. Reasonable planning for charging stations and optical-storage charging stations in cities is important in solving environmental and traffic problems. Charging stations improve the utilization rate of photovoltaic resources, reduce EV demand for grid power, and promote low-carbon EV development.

This study comprehensively considers site selection and capacity determination for ordinary and optical-storage charging stations. Charging-station candidate sites and charging demand points were established to improve the utilization rate of charging posts through in-depth mining of vehicle trajectory data. To comprehensively consider other factors and simultaneously minimize the total cost of charging-station investment and operation, user time cost, and system carbon emissions from charging, multi-objective particle swarm optimization (MOPSO) was used to determine the location and capacity of charging stations and optical-storage charging stations. The final location and capacity were determined using the analytic hierarchy process (AHP). The practicality and effectiveness of the method were demonstrated through case analysis and verification. The impact of establishing an optical-storage charging station was analyzed in terms of investment cost, user cost, and carbon dioxide emissions.

The remainder of this paper is organized as follows. Section 2 summarizes previous related research. Section 3 introduces the data acquisition and charging-station siting and sizing methods. The charging-station siting and sizing model is constructed in Section 4. Section 5 presents the empirical analysis. Section 6 presents the conclusions, limitations of the study, and future research directions.

2 Related Research

2.1 Charging-Station Location Optimization Based on Big Data

Optimization of the charging-station location and capacity is restricted by practical factors; thus, researchers have optimized charging-station location using actual data. Huang et al. [1] proposed a location-selection method for EV charging stations based on a high-density urban geographic information system (GIS) and determined the location and capacity of charging stations considering existing charging stations and renewable potential. Pagany et al. [2] investigated charging-station location based on GIS data and determined the demand according to the number of visits by users to potential points of interest (POI) and their stay time to choose the best location. Zhang et al. [3] proposed a hybrid method using a GIS and Bayesian network (BN) to develop a charging-station location scheme. The BN model comprised nine standards. Singapore was used as an example to verify its applicability and effectiveness. Researchers have also studied charging-station location and capacity using vehicle trajectories and user data. Kong et al. [4] used a community network to mine user interest points, vehicle parking lot information mined in a GPS track, and clustering to locate EV charging stations. Yang et al. [5] divided the map into equidistant grids, used mobile location data to extract potential traffic demand locations, including the starting points and destinations of taxi users, and matched them with the map. A grid with large demand indicated a candidate site for a charging station. The experiments showed that this method could accurately locate potential traffic locations with high demand. Liu et al. [6] considered environmental factors and minimized CO_2 emissions in a system using GPS-enabled trajectory data. They proposed an intelligent optimization method based on a data-driven particle swarm optimization to locate charging stations. Zhang and Zhu [7] used taxi GPS data statistics and analysis and the Monte Carlo method to extract the charging demand. They comprehensively considered the construction cost, taxi waiting cost, and impact of a charging station to establish a mathematical model and used a genetic algorithm to solve it. Based on the taxi track data of Fuzhou, Luo et al. [8] extracted taxi stops that could support an EV charging duration greater than 30 min and clustered the stops in non-road areas to obtain the charging-station location area. The rationality of the method was demonstrated through a rationality analysis of charging convenience for the driver and the economy of the charging station. The time distribution of the dwell points was analyzed; the charging-station capacity was determined by the peak dwell points in the charging-station area. Su et al. [9] extracted the distribution characteristics of resident taxi demand points through analysis of taxi track data and urban traffic data, establishing a spatio-temporal distribution prediction model of electric taxi charging demand through simulation. The model was established using the operation cost, taxi arrival time, and waiting time cost as targets to complete site-selection planning for the charging station. Vazifeh et al. [10] optimized the location of EV charging stations by grid-processing urban traffic and determined the spatial distribution of parking times according to the call records of EV users. Based on historical EV ownership, Yan et al. [11] used a BP neural network to predict the time distribution of EVs in the target planning area, determined the spatial distribution of EVs using measured traffic data in the target area, and established a charging-station location and capacity model with charging-station cost and user economic loss as the targets.

2.2 Multi-Objective Charging-Station Location Optimization

In addition to charging-station location and capacity research based on actual data, researchers have used multi-objective location optimization. Liang et al. [12] built a simulation optimization model for location of EV charging stations and configuration of charging piles with the goal of minimizing the total net present value of charging stations and the number of customer churns in the planning period. A two-stage simulation optimization algorithm based on the tabu search algorithm optimized the charging-station location and charging-pile configuration and ensured charging efficiency. Ai et al. [13] established a charging-station location and capacity planning model considering the comprehensive interests of charging-station operators, EV users, and power grid enterprises, proposing a chaos-simulated annealing particle swarm optimization algorithm to solve the problem. Based on the travel chain and Dijkstra's shortest path algorithm, Wang et al. [14] proposed a charging-station location and capacity model that considered the driver travel chain by analyzing the change in the number of vehicles in residential, working, and commercial areas in different periods. With the grid revenue and average user charging distance as objective functions, a fuzzy double-objective optimization method that considered the priority of objectives was proposed to determine the optimal planning scheme for EV charging stations. Considering the economy of operators, driver charging satisfaction, EV power loss, traffic efficiency, and grid security as comprehensive objectives, Kong et al. [15] proposed a two-layer model for location and scale planning of EV charging stations. Dynamic real-time data replaced static statistical data, and a simulation platform was established for location planning of EV charging stations in different cities and regions. Lee et al. [16] comprehensively considered charging demand capability, user convenience, and installation convenience indices and developed a final charging-station location scheme using the charging infrastructure location index (CILI). Xiao et al. [17] optimized the location of charging stations with the goal of minimizing the sum of the annual total cost of charging stations and the annual loss cost of EV users, divided the service scope of each charging station with the goal of minimizing user travel distance to the station, and combined the simulated annealing and Dijkstra algorithms to solve the planning model. Xu et al. [18] established a charging-station location model based on analysis of urban population kernel density with the goal of EV user satisfaction and charging convenience, and optimized the immune algorithm to solve the model. The results showed that compared with the traditional model, the proposed EV charging-station location model better met user needs.

2.3 Charging-Station Optimization Research Based on Environmental Factors

EV charging stations provide electrical energy primarily through thermal power generation. EVs consume electrical energy and indirectly produce carbon dioxide emissions. Thus, some researchers consider environmental factors and renewable energy as influencing factors in charging-station optimization, considering the following: (1) Environmental emissions. Hafez and Bhattacharya [19] established a charging-station location model to minimize the life-cycle cost of the charging station, considered environmental emissions, analyzed the impact of different types of energy generation, and analyzed the charging behavior of plug-in hybrid electric vehicles (PHEVs). Shaaban et al. [20] established a two-level model of mixed-integer nonlinear programming for remote communities with the goal of minimizing investment and operation costs considering greenhouse gas emissions, and determined the location and capacity of distributed generator sets and charging stations. Feng and Ye [21] developed upper- and lower-level models from the perspective of system optimization and user equilibrium, aiming to minimize system-level travel time and greenhouse gas emissions to build a bi-objective, bi-level programming model for location of EV charging stations. The Frank–Wolfe algorithm and NSGA II algorithm were used to solve the problem. Luo and He [22] built a bi-level planning model to determine the location and capacity of EV charging stations with the overall social and economic cost and carbon emissions as the decision-making objectives. They proposed an improved coyote optimization algorithm to solve the planning model, verifying its feasibility and effectiveness. (2) Renewable energy supplies power to the charging station. Ugirumurera and Haas [23] studied a green-planning EV charging system, explained the intermittency of solar power generation based on a three-dimensional Markov chain model, established a mathematical model, and determined the optimal number of solar panels and energy-storage capacity with the goal of minimizing the investment cost and meeting the performance indicators of the charging system. Li and Hu [24] aimed to minimize the operating cost, determine optimal scheduling for charging and discharging of the energy-storage system, and provide the initial state of charge for energy storage during the day. Based on the updated forecast of photovoltaic and charging demand, they proposed a rolling optimization strategy for the optical-storage charging station. Chaudhari et al. [25] proposed a hybrid optimization algorithm for integrated energy-storage management of optical storage and charging aimed at minimizing the cost degradation model of the energy-storage system and the horizontal cost of photovoltaic power generation. Based on the charging station of a photovoltaic (PV) microgrid, Sechillarin et al. [26] considered the mutual benefits of the integrated charging station, public distribution network, EV users, and surrounding buildings, and considered user needs and demands as the basis for evaluating the efficiency of integrated charging stations, related services, and power networks of various sizes. Fathabadi [27] designed a new type of independent charging station powered by a combination of solar and wind energy when a fuel-cell system was present, and analyzed the charging behavior of the PHEV. Yang et al. [28] optimized the number of chargers in an optical-storage charging station based on statistical distribution data of the traffic flow of the intercity expressway network and EV charging decisions after using the charging guidance system, and optimized the optical-storage equipment capacity according to the lighting conditions and load levels at each station. In combination with the time-sharing electricity price, they proposed an energy-exchange strategy for an optical-storage charging station. Zhao et al. [29] proposed a two-stage optical-storage charging station location and capacity determination method based on data-driven distributed robust optimization. The location of charging points was determined using a Monte Carlo simulation method; the location of charging stations was determined using an integer programming model. Considering the charging-station interests and user satisfaction, a data-driven distributed robust optimization constant-capacity model was established. Using risk theory, the distributed robust optimization model was transformed into a mixed-integer linear programming problem, and the number of charging piles and optical-storage capacity in the charging station were optimized. Liu et al. [30] proposed a capacity allocation method for optical-storage equipment that considered demand response and carbon emissions. Based on the charging subsidy price and response time, they established an EV demand-response model. To minimize the annual investment operation cost and carbon emissions of optical-storage charging stations, they established an optimization model for capacity allocation of optical-storage charging stations, considering demand-response operation strategies.

Vehicle trajectory data mining and comprehensive location and capacity determination for charging stations and optical-storage charging stations are less common in the literature. Thus, vehicle trajectory data were used in this study to determine the location and capacity of ordinary charging stations and optical-storage charging stations.

3 Data Acquisition and Location and Capacity Determination Method

3.1 Vehicle Parking-Point Detection

Vehicle track data can be divided into driving track data and parking track data, according to the vehicle driving speed. When the vehicle speed is not zero, the vehicle is in a driving state; otherwise, it is static. The daily speed changes of the vehicles are shown in Figure 1. To minimize the impact on user economy and time efficiency while the vehicle is charging, most drivers charge when the vehicle is stationary. Thus, dwell data were extracted from the vehicle trajectory data and clustered to determine the dense region of vehicle dwell points to obtain a candidate point set for the charging station.

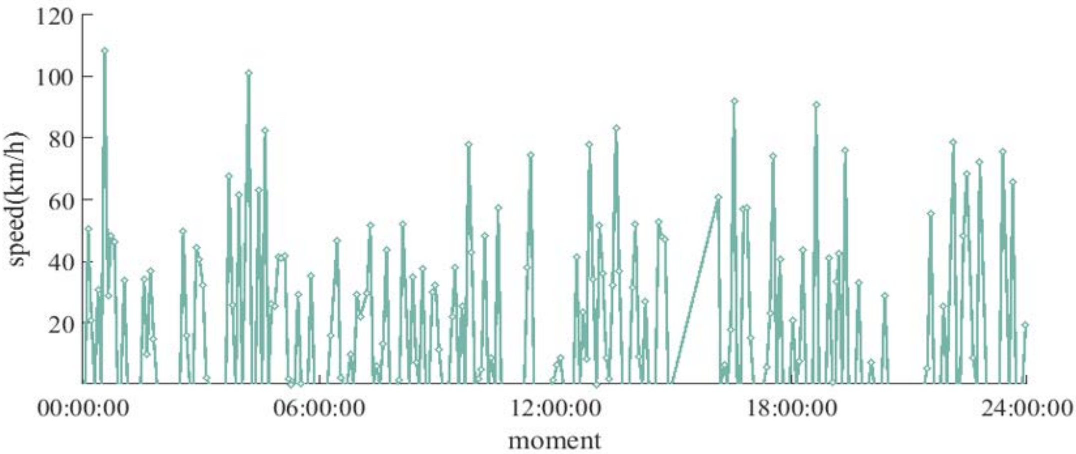

Figure 1. Changes in vehicle speed in one day

According to current battery technology in new energy vehicles, rapid charging of EVs for 30 min restores 80% of the battery capacity. To save time, most car owners choose a fast-charging mode. Thus, the dwell time extracted in this study should be sufficient to support EV charging behavior; that is, the vehicle dwell time should be at least 30 min.

The dwell-point detection method extracts the change time of the vehicle driving state, calculates the dwell time, extracts dwell-point track records with dwell times of at least 30 min, and deletes the other dwell-point records. The detection method for dwell-point extraction is shown in Figure 2.

3.2 Determination of Candidate Charging Stations and Demand Points

To meet the requirements that most EV drivers complete EV charging while parked and effectively improve the utilization rate of charging piles, the candidate charging stations should be located where vehicles often park. Thus, k-means clustering was conducted for all vehicle stops that met the conditions. k-means is defined as: giving the dwell point set $X_{\text{stop}} = \{x_i\}$ for all vehicles to meet the charging requirements, selecting cluster centers (candidate charging station locations) and recording them as $\mu_1^{(0)}, \mu_2^{(0)}, \ldots, \mu_k^{(0)}$. Through continuous iteration, the loss function J converges, as expressed in Eq. (1). Each sample x_i in the dwell-point set is allocated to the nearest candidate charging-station site, as shown in Eq. (2). For each cluster center k, the center of the class is recalculated, as expressed in Eq. (3).

$$J(c, \mu) = \min \sum_{i=1}^{m} \|x_i - \mu_{ci}\|^2 \tag{1}$$

$$C_i^t = \arg\min_k \left\|x_i - \mu_k^t\right\|^2 \tag{2}$$

$$\mu_k^{(t+1)} = \arg\min_{\mu} \sum_{i:C_i^t = k}^{b} \|x_i - \mu\|^2 \tag{3}$$

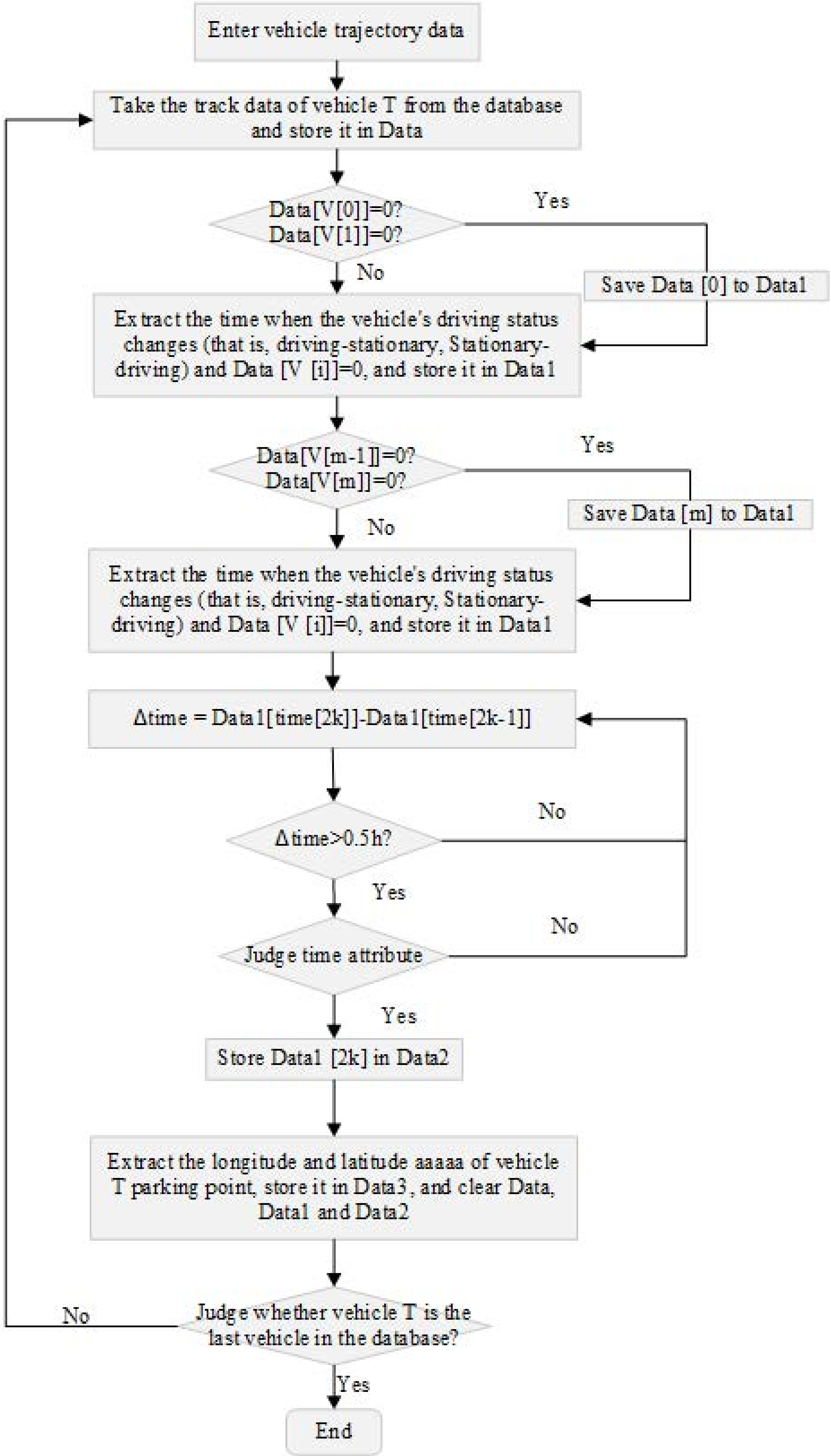

Figure 2. Dwell-point extraction process

For most vehicles, parking spaces include temporary road parking lots, shopping malls, markets, squares, and hospitals. Thus, the period with the most stops was selected as the research period after analyzing the time distribution of vehicle tracks. According to the longitude and latitude distance formula shown in Eq. (4), the vehicle stop point-set

$X_{\text{stop}} = \{x_i\}$ is stored in the demand point set $X_{\text{demand}} = \{x_j\}$ according to the minimum distance $\min_{dis}$, and is recorded in the demand volume for this point.

$$dis = R * \arccos\left[\cos\cos\left(lat_m\right) * \cos\left(lat_n\right) * \cos\cos\ \left(lat_m - lat_n\right) + \sin\sin\left(\text{ lon }_m\right) * \sin\sin\left(\text{ lon }_n\right)\right] \tag{4}$$

where, R represents the Earth's radius, $lat_{m/n}$ represents the longitude of the m stop-point or n demand-point, and $lon_{m/n}$ represents the latitude of the m stop-point or n demand-point.

3.3 Site Selection and Capacity Determination Method

The candidate charging stations were located in an area with dense vehicle parking; the demand point and demand were determined according to the distance between the parking lot and parking-point. The location and capacity determination model were established; MOPSO was used to solve the problem. The final location and capacity determination scheme of the charging station was determined using AHP. The process is illustrated in Figure 3.

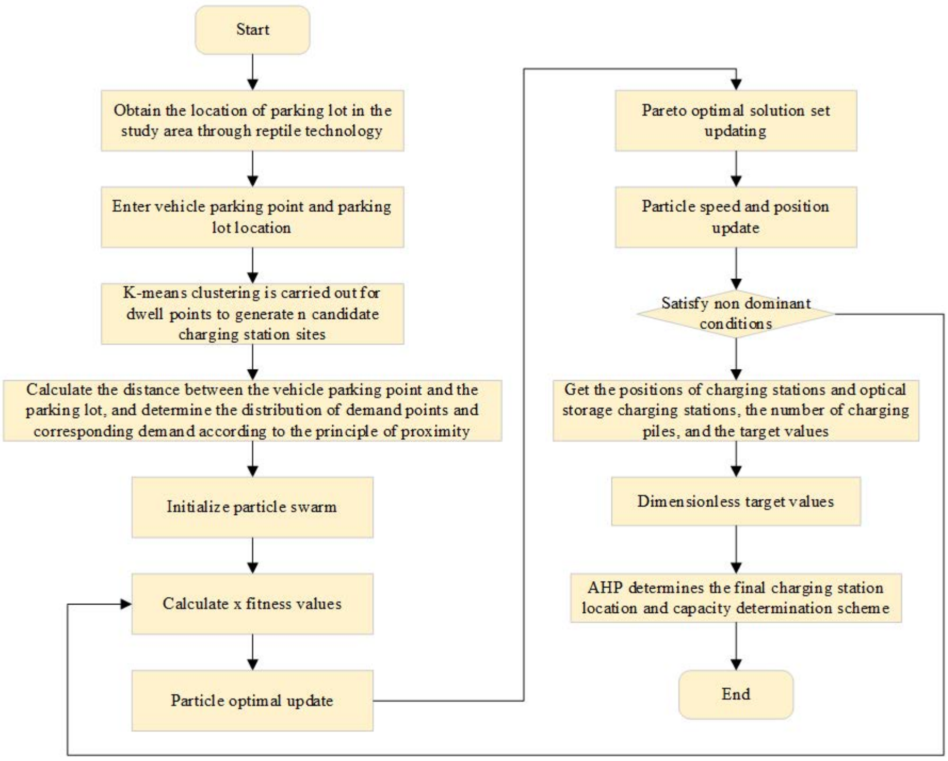

Figure 3. Procedures for site selection and capacity determination for charging stations and optical-storage charging stations

The mathematical expression of MOPSO in this study is presented as follows. Assume that the particle swarm size is M^*N, where the number of particles is M, and the charging station has a total of N candidate sites. Searching in the target space of D dimension, the position of each particle at t time is $\mathrm{n}\left(x_t\right) = \{n\left(x_{t1}\right), n\left(x_{t2}\right), \ldots, n\left(x_{tN}\right)\}$; For $x_{ti} = 1$, ordinary charging stations are built at the candidate charging station site; for $x_{ti} = 0$, the candidate charging station site has storage charging stations; $n\left(x_{ti}\right)$ indicates the scale of the charging station (number of charging posts). The particle velocity is $v_{ti} = \left(v_{t1}, v_{t2}, \ldots, v_{tN}\right)$, where $p_{\text{best}}\left(t\right)$ is the optimal value of a single particle in the search process, and $g_{\text{best}}\left(t\right)$ represents the optimal value of all particles in the search process. The velocity and position of each particle in the particle swarm are given by Eqs. (5) and (6).

$$v_{(t+1)i} = v_{ti} + c_1 * r_1\left(p_{\text{best}}\left(t\right) - n\left(x_{ti}\right)\right) + c_2 * r_2\left(g_{\text{best}}\left(t\right) - n\left(x_{ti}\right)\right) \tag{5}$$

$$\mathrm{n}\left(x_{(t+1)i}\right) = x_{ti} + v_{(t+1)i} \tag{6}$$

where, c_1 and c_2 are the learning factors of particle swarm individuals and social cognition, respectively, also known as acceleration constants; r_1 and r_2 are random numbers uniformly distributed in the range $[0, 1]$.

The multi-objective optimization in this study must optimize three objective functions simultaneously: investment cost, user time cost, and additional CO_2 emissions caused by charging. However, there are contradictions between them, and they cannot be optimized simultaneously. Thus, it is necessary to find a group of balanced charging-station locations and capacities such that the three objective functions are well-balanced.

For any two charging-station locations and capacity determination schemes x_v and x_u solved by the proposed co-evolutionary model, if and only if the three objective functions $f(x)$ all meet $f(x_v) \leq f(x_u)$ and there is one $f(x_v) < f(x_u)$, then x_v governs x_u. x_v is the dominating solution, and x_u is a non-dominating solution. For any feasible charging-station location and capacity, if no other solution dominates, the solution is a Pareto-optimal solution. The Pareto front of the charging-station location and capacity corresponds to the optimal solution for site selection using MOPSO.

4 Model Creation

4.1 Investment Cost

$$\min F_I = \sum_{i=1}^{n} \frac{r*(1+r)^t}{(1+r)^t-1} * [C_{li} * S * (N_{pi} + N_{oi}) + F_p * N_{pi} + F_o + F_s * X_{si}] * X_{bi} \tag{7}$$

where, F_I represents the total investment cost of building charging stations and optical-storage charging stations; C_{li} represents the unit land cost of the area where the i candidate charging station will be built; S refers to the average floor area required by a charging pile to charge an EV; N_{pi} represents the number of charging posts in the i candidate charging station; N_{oi} represents the land area of the remaining facilities of the i candidate charging station (land area of energy storage facilities, roads, etc.); F_p is the cost of one charge point; F_o represents other operating costs of each charging station; F_s represents the cost of solar panels and optical-storage systems required by optical-storage charging stations; X_{si} is a variable from $0-1$. If $X_{si}=1$, the i candidate charging station is an optical-storage charging station; if $X_{si}=0$, the i candidate charging station is an ordinary charging station. r is the depreciation rate; t is the service life of the charging station; X_{bi} is a variable from $0-1$. If $X_{bi}=1$, a charging station is built at the i candidate charging-station location; if $X_{bi}=0$, no charging station is built at the i candidate charging-station location; n represents the total number of candidate charging stations.

4.2 User Time Cost

Each candidate charging station was chosen for the EVs based on the number of available charging piles and the proximity principle. If there were remaining EVs that did not meet the charging demand after the EVs in the j demand point was selected, nearby candidate charging stations were selected to complete charging according to the principle of proximity.

$$\min F_T = F_D + F_W \tag{8}$$

where, F_T represents the cost of user arrival and waiting time, F_D and F_W represent the EV distance cost from the demand point to the candidate charging station and the EV waiting time cost after arriving at the charging station, respectively, expressed as:

$$F_D = \sum_{i=1}^{n}\sum_{j=1}^{m} N_{cj} * C^* f_{ij} * D_{ij} + \sum_{j=1}^{m}\left(1-\sum_{i=1}^{n} f_{ij}\right) * C * \min D_j \tag{9}$$

where, N_{cj} represents the number of EVs to be charged in the j demand point; f_{ij} represents the proportion of the j demand point being met by the i candidate charging station; D_{ij} represents the distance from the j demand point to the i candidate charging station; $\min D_j$ represents the nearest distance from the j demand point to the candidate charging station to be built; m represents the total number of EV demand points; C is the vehicle cost per kilometer.

$$F_W = \sum_{i=1}^{n}\sum_{b=1}^{z} P^* (\mathrm{con}_i - b * nc * N_{pi}) \tag{10}$$

where, P represents the user unit waiting time cost; con_i represents the total number of EVs from different demand points to the i candidate charging station; nc refers to the number of EVs that can be charged by one charging pile at the same time; nc is taken as 2; $b = (\mathrm{con}_i / nc * N_{pi})$, indicating the number of charging batches for all EVs that have reached the jjj candidate charging station.

4.3 Indirect CO_2 Emissions

$$\min F_E = \sum_{i=1}^{n}\sum_{j=1}^{m}[D_{ij} * f_{ij} * N_{cj} + (1 - f_{ij}) * \min D_j * N_{cj}] * q * e * (1 - X_{si}) \tag{11}$$

where, F_E represents the total carbon dioxide emissions of the system; q represents the electricity consumption per kilometer of EV travel; e is the carbon dioxide emissions per kilowatt-hour of electricity produced.

5 Case Study

5.1 Case Study

This study used track data from 4,933 taxis in Beijing from August 1, 2020, to August 10, 2020, with a total of 4,263,030 records. Ideally, a vehicle completes charging with minimal impact on user economic and time efficiency; most drivers chose to complete charging when the vehicle was stationary, which can indirectly improve the utilization efficiency of a charging pile. A total of 36,840 stops with a taxi dwell time of 30 min or more were considered. However, continuous 24-hour data were only available from August 2–7; 24,031 stops remained after deleting stops outside this range, and stops outside of Beijing or with abnormal longitude and latitude, as shown in Figure 4.

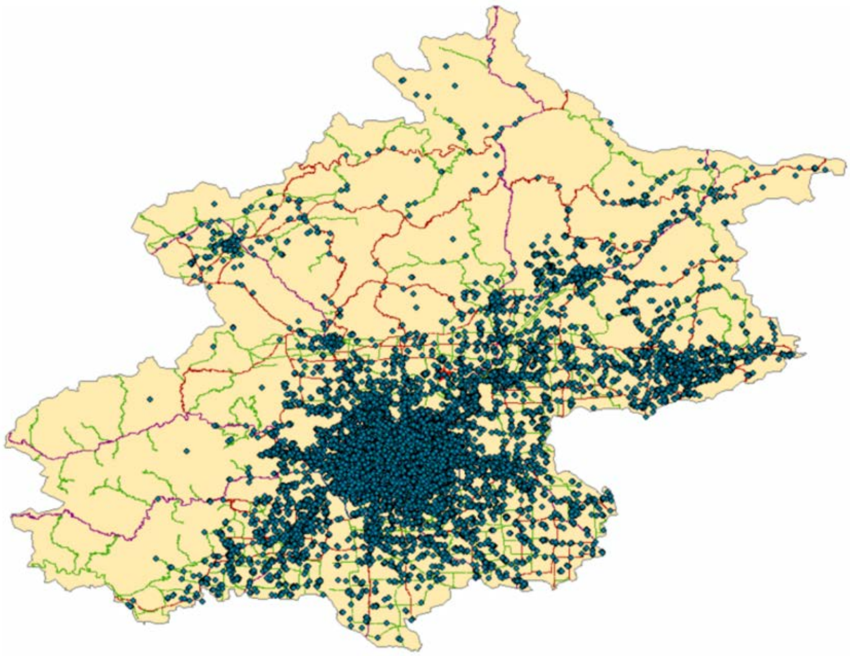

Figure 4. Taxi stops in Beijing

5.2 Determination of Candidate Charging Stations and Taxi Demand Points

Using taxi track data in Beijing from August 2-7, non-operating time was stopped with a taxi dwell time exceeding 30 min. To maximize taxi driver profit, candidate sites for EV charging stations were selected in areas with a high density of taxis. k-means clustering was performed on 24,236 stops to obtain the candidate charging station sites. For convenience in the subsequent analysis, k=10 was selected, as shown in Figure 5.

Most taxis stay in public parking lots during non-operating hours; thus, reptile technology was used to crawl 1,160 temporary parking lots, shopping malls, fairs, squares, and public parking lots at hospitals in Beijing. To consider the constant capacity of each candidate charging station, 24 h was divided into six time periods: 1:00–5:00, 5:00–9:00, 9:00–13:00, 13:00–17:00, 17:00–21:00, and 21:00–1:00 the next day. The charging demand of electric taxis in each period is shown in Figure 6. The period with the highest charging demand for electric taxis (August 2, 9:00–13:00) was selected, as shown in Figure 7. The areas where taxis stay during this period can reflect the areas where EVs are often parked. The distributions of each demand point and demand quantity were obtained by determining the demand points.

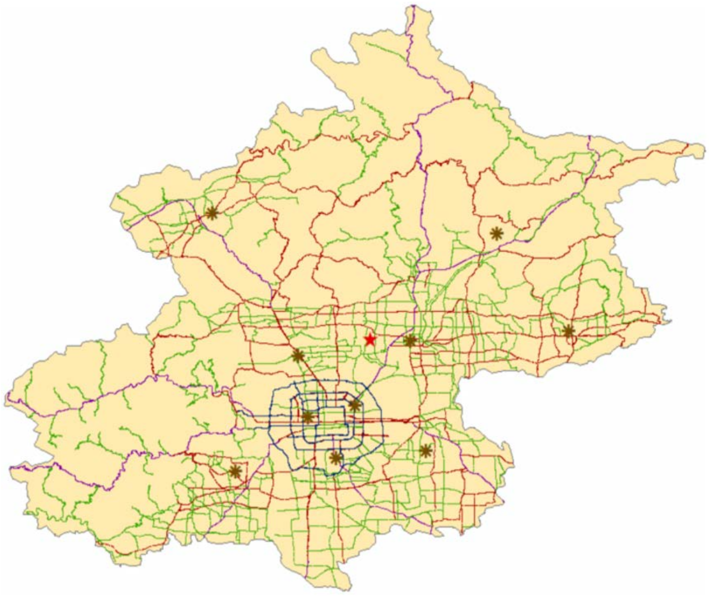

Figure 5. Determining charging-station candidate sites

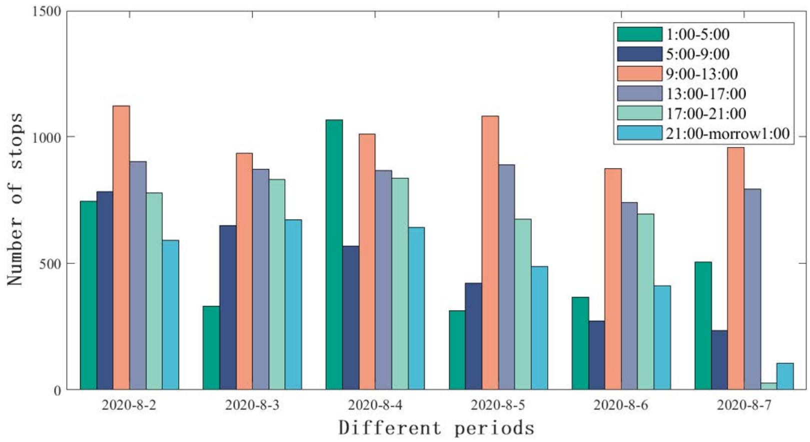

Figure 6. Taxi charging demand in different time periods

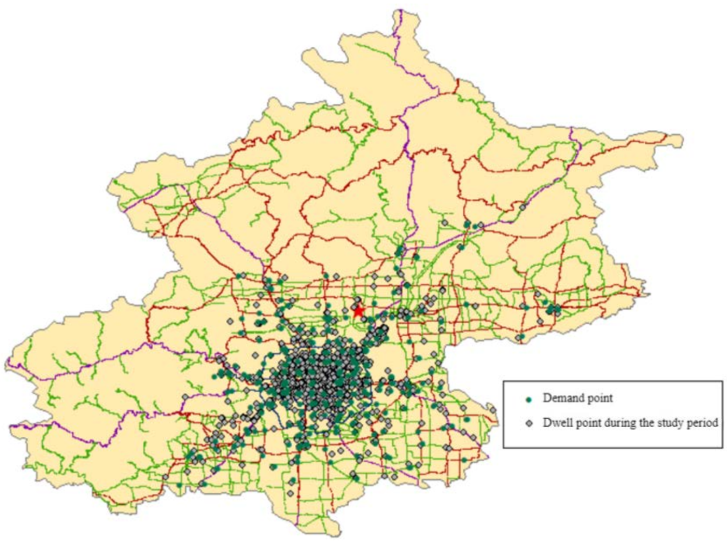

Figure 7. Distribution of stops and demand points in study period

5.3 Model Solution and Results Analysis

To simplify the charging-station location and sizing model, the following assumptions were made:

(1) With current optical-storage charging station energy-storage technology, only a few electric taxis can be charged simultaneously. Thus, it was assumed that the scale of an optical-storage charging station was smaller than that of an ordinary charging station. At this stage, it was not considered that the charging pile in the optical-storage charging station used energy-storage facilities or accessed the grid for charging.

(2) To complete charging, all electric taxis used the principle of proximity and selected charging stations based on their scale.

(3) The remaining EV power was sufficient to reach the charging station.

In this study, MOPSO was used to solve the data-driven co-evolutionary model. The ordinary charging stations are large in scale; the number of charging piles is not more than 50. The number of charging piles in the optical-storage charging station is not more than 10; fast-charging time is 30 min; that is, each taxi is fully charged in 30 min.

Figure 8 shows the relationship between the number of ordinary charging stations, optical-storage charging stations, and investment cost. As the total number of charging stations decreases, the total investment cost decreases. When the number of charging stations in the entire system is the same (e.g., m=10, where m represents the total number of charging stations, m1 represents the number of ordinary charging stations, and m2 represents the number of optical-storage charging stations), with an increase in the number of optical- storage charging stations, the total investment cost exhibits an overall upward trend, including special cases. If the investment cost of charging piles and land is not considered, the more optical storage and charging power stations, the higher is the investment cost, owing to the high cost of photovoltaic power generation and energy-storage facilities. However, because the overall scale of the optical-storage charging stations not connected to the grid is small, some optical-storage charging stations contain fewer charging piles, require fewer photovoltaic panels and energy-storage facilities for power generation, and their overall floor area is small. For example, when m1=2 and m2=8, the maximum investment cost reaches 278,373,093.7 yuan, and the total number of charging stations is 113. When m1=1 and m2=9, although the number of optical-storage charging stations increases, the total number of charging stations is 59, and the investment cost is lower. Thus, even if the cost of photovoltaic power generation and energy-storage equipment is high, the total investment cost can be reduced by improving the utilization efficiency of the charging piles and reducing their number.

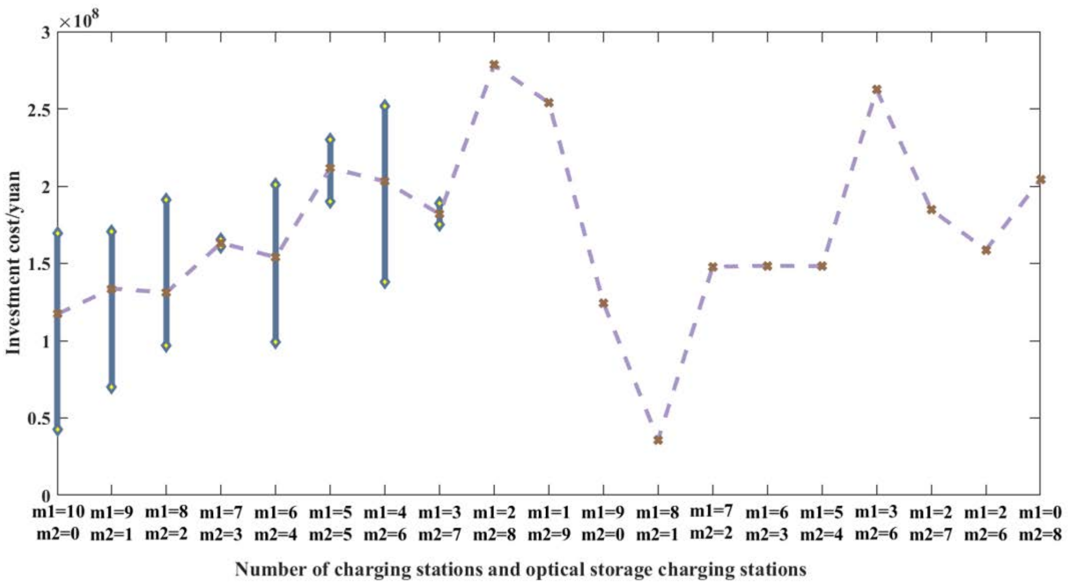

Figure 8. Investment cost for different numbers of charging stations

The relationship between the number of charging stations and time cost and the relationship between the number of charging stations and carbon emissions are shown in Figure 9 and Figure 10, respectively. The time cost is inversely proportional to the number of charging piles in the system. When the total number of charging stations is the same, the number of charging piles in the system decreases, resulting in a constant increase in the user waiting time cost. Due to the small size of optical-storage charging stations, the number of charging piles in the system decreases, and the user time cost increases to a certain extent. However, if the number of charging piles in the system with different site selection and capacity determination schemes is similar and smaller charging stations are built at appropriate locations, the user time cost is lower. With multiple large-scale charging stations in places with large demand (one or two places with large demand can be selected to build large-scale charging stations), many EVs in the system are in a waiting state. At this time, the waiting time cost in the system is far greater than the user arrival time in other conditions, such as m1=3, m2=7. Two fixed-capacity schemes are shown in Table 1 and Table 2. The total number of charging stations is 75. The user time costs are 806,628.966 yuan and 943,694.049 yuan, respectively. Candidate sites 2, 5, 6, and 10 have a small demand. Scheme 1 does not build a large-scale charging station at candidate sites with high demand; Scheme 2 builds a large-scale charging station at candidate sites with high demand. This results in many EVs waiting for a long time, increasing the total user waiting time cost of the system. However, if all candidate sites with low demand are built with oversized charging stations, the arrival time and waiting time of users are increased, and low charging-station utilization may result. As shown in Table 3, this scheme builds oversized charging stations at all four candidate sites with low demand, which creates investment pressure and leads to many users arriving at charging stations from afar, increasing their arrival time. Similarly, building oversized charging stations with high demand increases the user waiting time.

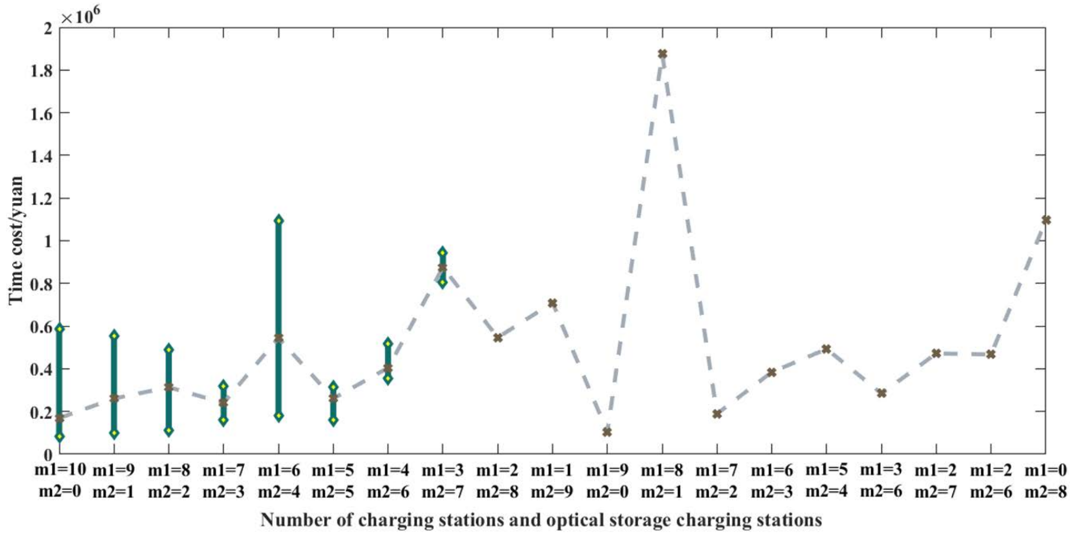

Figure 9. User time cost for different numbers of charging stations

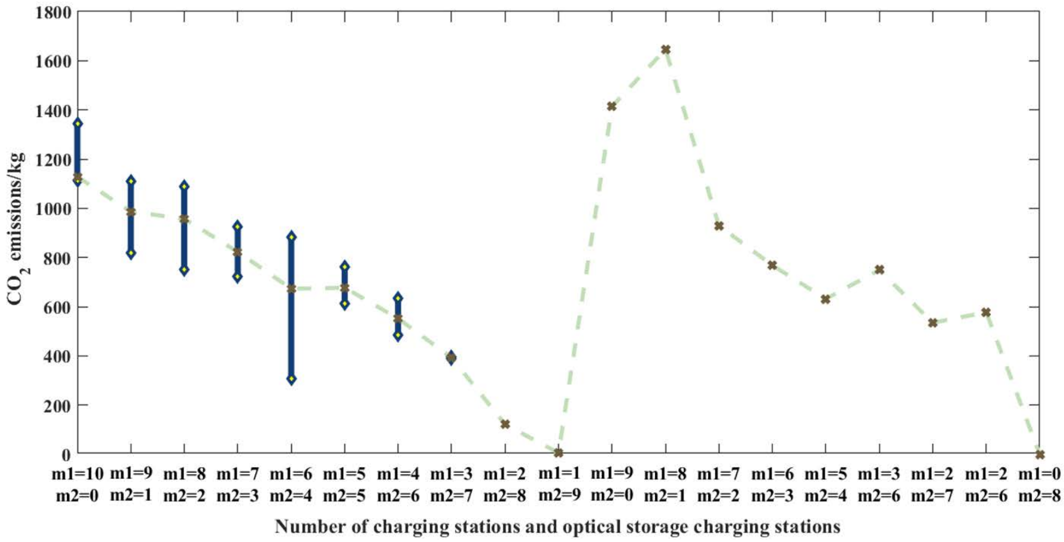

Figure 10. CO_2 emissions caused by charging and driving for different numbers of charging stations

Table 1. Candidate site sizing when m1=3, m2=7, scheme 1

Number of Candidate Sites	1	2	3	4	5	6	7	8	9	10
Charging Pile/Set	7	33	1	2	8	6	6	3	5	4

Table 2. Candidate site sizing when m1=3, m2=7, scheme 2

Number of Candidate Sites	1	2	3	4	5	6	7	8	9	10
Charging Pile/Set	5	5	11	8	1	1	30	4	2	8

Table 3. Over-construction and large-scale charging-station plan

Number of Candidate Sites	1	2	3	4	5	6	7	8	9	10
Charging Pile/Set	10	38	19	2	48	29	9	9	31	30

The carbon dioxide emissions caused by charging in the entire system show an upward trend with a decrease in the total number of charging stations. When the total number of charging stations was the same, with an increase in the number of optical-storage charging stations, CO_2 emissions caused by charging and driving in the system decreased. When the entire system used optical-storage charging stations, the carbon dioxide emissions caused by charging reached zero. Optical-storage charging stations were built in locations with large demand; EV charging at optical-storage charging stations is preferable. Owing to the small scale of optical-storage charging stations, many EVs are not in a waiting state simultaneously. Thus, building an optical-storage charging station at a location with large demand reduces CO_2 emissions in the system caused by charging and driving and indirectly reduces the waiting costs of many EVs.

This study comprehensively considered investment cost, user time cost, and carbon emissions caused by charging and driving. Although construction of an optical-storage charging station was considered, these objectives can be maintained at low levels within a certain range. Considering challenges based on environmental factors, and that charging-station service should be user-oriented, AHP was used to determine the weights of the three objectives, with importance ranked as CO_2 emissions $>$ time cost $>$ investment cost. The weights were 0.6333, 0.2605, and 0.1062, respectively. C.R.=0.0373 < 0.1; thus, the consistency of the judgment matrix was acceptable. The fitness values of all non-inferior solutions were dimensionless, producing the optimal location and capacity determination scheme for ordinary charging stations ($BCS_1 - BCS_n$) and optical-storage charging stations ($GWM_1 - GWM_n$), as shown in Table 4.

Table 4. Optimal location and capacity determination scheme for ordinary and optical-storage charging stations

Charging Station	**Longitude and Latitude** ($^\circ$)	**Number of Charging Posts (set)**	**Charging Station**	**Longitude and Latitude** ($^\circ$)	**Number of Charging Posts (set)**
BCS_1	117.096, 40.1556	7	GWM_5	116.671, 39.8235	3
GWM_1	116.461, 39.9491	9	GWM_6	116.291 40.0868	4
GWM_2	116.106, 39.768	8	GWM_7	116.322 39.9177	1
GWM_3	116.626 40.1289	4	GWM_8	116.404, 39.8044	7
GWM_4	116.883 40.4245	9	GWM_9	116.037 40.4817	7
Total investment cost (yuan/year)				253883942.0	
User time cost in study period (yuan)				709870.7	
CO_2 emissions caused by charging in study period (kg)				5.3	

As shown in Table 4, the system consists of 59 charging stations, one ordinary charging station, and seven charging stations. There are nine optical-storage charging stations and 52 charging stations; thus, the investment cost does not increase with an increase in the number of optical-storage charging stations. Compared to schemes with more charging stations in the system, the user time cost is lower and effectively controlled. GWM_1-GWM_3 and GWM_6-GWM_8 were built in areas with high charging requirements. Thus, most EVs complete charging at optical-storage charging stations, effectively controlling CO_2 emissions caused by charging and indirectly reducing the cost of user waiting time in the system to a certain extent. GWM_4 and GWM_5 were built in low-demand areas. Building small optical-storage charging stations can reduce public resource waste and investment costs, and help reduce CO_2 emissions in the system. To reduce investment costs, regular charging stations were built in areas with low demand to prevent investment pressure caused by construction of optical-storage charging stations. Owing to the large number of optical-storage charging stations in the system and the small number of ordinary charging stations, the user time and investment costs of this scheme are higher than those of other site selection and capacity determination schemes; however, indirect CO_2 emissions are significantly reduced.

6 Conclusion and Future Research

This study proposes an optimization method for determining the location and capacity of charging stations and optical-storage charging stations based on multi-strategy fusion. By mining vehicle trajectory data, the utilization rate of charging posts was improved, and the vehicle dwell time was fully utilized to determine candidate charging stations and demand point sets. In comprehensively considering other factors, a data-driven co-evolutionary model was established with investment cost, user time cost, and CO_2 emissions caused by charging as targets. The final site-selection scheme was determined based on an AHP using a MOPSO solution. Based on track data from taxis in Beijing, the following conclusions were drawn: (1) After constructing optical-storage charging stations, the main investment costs were charging piles, photovoltaic power generation panels, and energy-storage facilities. Thus, the utilization rate of each charging pile improved, the number of charging piles in the system was effectively controlled, and increasing the number of optical-storage charging stations did not produce investment pressure. (2) Optical-storage charging stations should be built at locations with large charging demand to reduce additional CO_2 emissions caused by charging and control the user waiting time cost in the system.

This study used only taxi track data for verification. However, the proposed method is applicable to all types of city vehicles. To facilitate analysis, only ten candidate sites were selected for verification, and only optical-storage charging stations not connected to the power grid were considered, without considering simultaneous power supply from the power grid or energy-storage facilities. Future research will address these limitations.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] P. Huang, Z. J. Ma, L. Z. Xiao, and Y. J. Sun, "Geographic information system-assisted optimal design of renewable powered electric vehicle charging stations in high-density cities," *Appl. Energy*, vol. 255, p. 113855, 2019. https://doi.org/10.1016/j.apenergy.2019.113855

[2] R. Pagany, A. Marquardt, and R. Zink, "Electric charging demand location model—A user-and destination-based locating approach for electric vehicle charging stations," *Sustainability*, vol. 11, no. 8, p. 2301, 2019. https://doi.org/10.3390/su11082301

[3] Y. Zhang, B. K. Teoh, and L. Zhang, "Integrated Bayesian networks with GIS for electric vehicles charging site selection," *J. Clean. Prod.*, vol. 344, p. 131049, 2022. https://doi.org/10.1016/j.jclepro.2022.131049

[4] Y. Kong, J. Wu, M. Xu, and K. Hu, "Charging pile siting recommendations via the fusion of points of interest and vehicle trajectories," *China Commun.*, vol. 14, no. 11, pp. 29–38, 2017. https://doi.org/10.1109/CC.2017.8233648

[5] Z. Z. Yang and Z. Y. Gao, "Location method of electric vehicle charging station based on data driven," *J. Transp. Syst. Eng. Inf. Technol.*, vol. 18, no. 5, pp. 143–150, 2018. https://doi.org/10.16097/j.cnki.1009-6744.2018.05.021

[6] Q. Liu, J. Liu, W. Le, Z. Guo, and Z. He, "Data-driven intelligent location of public charging stations for electric vehicles," *J. Clean. Prod.*, vol. 232, pp. 531–541, 2019. https://doi.org/10.1016/j.jclepro.2019.05.388

[7] Y. Zhang and P. Zhu, "Research on site selection model of special charging stations for taxis," *J. Geo-Inf. Sci.*, vol. 23, no. 5, pp. 802–811, 2021. https://doi.org/10.3778/j.issn.1002-8331.2109-0295

[8] S. J. Luo, F. M. Zou, F. Guo, and L. C. Liao, "Location method for electric taxi charging station based on trajectory data," *J. Comput. Eng. Appl.*, vol. 58, no. 8, p. 273, 2022. https://doi.org/10.3778/j.issn.1002-8331.2109-0295

[9] S. Su, Y. J. Li, Z. R. Jia, J. Yang, M. C. Xia, and Q. F. Chen, "Electric taxi charging station planning based on GPS trajectory mining," *Electr. Power Autom. Equip.*, vol. 42, no. 10, pp. 255–263, 2022. https://doi.org/10.16081/j.epae.202205005

[10] M. M. Vazifeh, H. M. Zhang, P. Santi, and C. Ratti, "Optimizing the deployment of electric vehicle charging stations using pervasive mobility data," *Transp. Res. Part A*, vol. 121, pp. 75–91, 2019. https://doi.org/10.1016/j.tra.2019.01.002

[11] G. G. Yan, H. N. Liu, N. H. Han, S. S. Chen, and D. M. Yu, "An optimization method for location and capacity determination of charging stations considering spatial and temporal distribution of electric vehicles," in *Proceedings of the CSEE*, vol. 41, no. 18, 2021, pp. 6271–6284. https://doi.org/10.13334/j.0258-8013.pcsee.202001

[12] H. Liang, C. Yang, S. Z. Yu, and X. P. Jiang, "Research on electric vehicle siting of charging stations and configuration of charging pile based on simulation optimization method," *Comput. Simul.*, vol. 34, no. 8, pp. 168–172, 2017. https://doi.org/10.16081/j.epae.202207001

[13] X. Ai, Y. Z. Li, K. Y. Wang, and J. J. Hu, "Locating and sizing of electric vehicle charging station based on chaotic simulated annealing particle swarm optimization algorithm," *Electr. Power Autom. Equip.*, vol. 38, no. 9, pp. 9–14, 2018. https://doi.org/10.16081/j.epae.202207001

[14] D. Wang, J. C. Liu, Z. J. Cao, Y. Niu, H. Tang, and J. Y. Liu, "Planning for charging stations of electric vehicles considering drivers' trip chains," in *Proceedings of the CSU-EPSA, Tianjin, China*, vol. 30, no. 6, 2018, pp. 1–9.

[15] W. Kong, Y. Luo, G. Feng, K. Li, and H. Peng, "Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid," *Energy*, vol. 186, p. 115826, 2019. https://doi.org/10.1016/j.energy.2019.07.156

[16] B. H. Lee, S. J. Jung, J. H. Sung, O. K. Kwon, and B. S. Kim, "Selection of charging sites for electric vehicles in the Republic of Korea based on fuzzy analytic hierarchy process," *J. Korean Phys. Soc.*, vol. 79, no. 3, pp. 217–229, 2021. https://doi.org/10.1007/s40042-021-00128-9

[17] B. Xiao and F. Gao, "Optimization method of electric vehicle charging stations' site selection and capacity determination considering charging piles with different capacities," *Electr. Power Autom. Equip.*, vol. 42, no. 10, pp. 157–166, 2022. https://doi.org/10.16081/j.epae.202207001

[18] D. Xu, W. H. Pei, and Q. Zhang, "Optimal planning of electric vehicle charging stations considering user satisfaction and charging convenience," *Energies*, vol. 15, no. 14, p. 5027, 2022. https://doi.org/10.3390/en15145027

[19] O. Hafez and K. Bhattacharya, "Optimal design of electric vehicle charging stations considering various energy resources," *Renew. Energy*, vol. 107, pp. 576–589, 2017. https://doi.org/10.1016/j.renene.2017.01.066

[20] M. F. Shaaban, S. Mohamed, M. Ismail, K. A. Qaraqe, and E. Serpedin, "Joint planning of smart EV charging stations and DGs in eco-friendly remote hybrid microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5819–5830, 2019. https://doi.org/10.1109/TSG.2019.2891900

[21] C. Feng and L. Ye, "Charging station location model for electric vehicle based on bi-level programming," *Comput. Integr. Manuf. Syst.*, vol. 36, no. 8, pp. 139–144, 2019.

[22] J. X. Luo and D. X. He, "Site selection and capacity planning of charging station based on improved coyote optimization algorithm," *Appl. Res. Comput.*, vol. 39, no. 3, pp. 751–757, 2022. https://doi.org/10.19734/j.issn.1001-3695.2021.09.0364

[23] J. Ugirumurera and Z. J. Haas, "Optimal capacity sizing for completely green charging systems for electric vehicles," *IEEE Trans. Transp. Electrification*, vol. 3, no. 3, pp. 565–577, 2017. https://doi.org/10.1109/TTE.2017.2713098

[24] R. X. Li and Z. C. Hu, "Stochastic optimization strategy for daily operation of electric bus charging station with PV and energy storage," *Power Syst. Technol.*, vol. 41, no. 12, pp. 3772–3780, 2017. https://doi.org/10.13335/j.1000-3673.pst.2017.2013

[25] K. Chaudhari, A. Ukil, K. N. Kumar, U. Manandhar, and S. K. Kollimalla, "Hybrid optimization for economic deployment of ESS in PV-integrated EV charging stations," *IEEE Trans. Ind. Informatics*, vol. 14, no. 1, pp. 106–116, 2017. https://doi.org/10.1109/TII.2017.2713481

[26] M. Sechilariu, N. Molines, G. Richard, H. Martell-Flores, F. Locment, and J. Baert, "Electromobility framework study: Infrastructure and urban planning for EV charging station empowered by PV-based microgrid," *IET Electr. Syst. Transp.*, vol. 9, no. 4, pp. 176–185, 2019. https://doi.org/10.1049/iet-est.2019.0032

[27] H. Fathabadi, "Novel stand-alone, completely autonomous and renewable energy based charging station for charging plug-in hybrid electric vehicles (PHEVs)," *Appl. Energy*, vol. 260, p. 114194, 2019. https://doi.org/10.1016/j.apenergy.2019.114194

[28] J. W. Yang, A. Li, and K. Liao, "Capacity planning of light storage charging station for inter-city highways based on charging guidance," *Power Syst. Technol.*, vol. 44, no. 3, pp. 934–943, 2020.

[29] F. Zhao, J. X. Li, and F. Y. Gao, "Siting and sizing of photovoltaic-storage charging stations on highway considering uncertainties," *Electr. Power Autom. Equip.*, vol. 41, no. 8, pp. 111–117, 2021. https://doi.org/10.16081/j.epae.202105007

[30] G. M. Liu, H. Yu, K. Kang, and J. Zhang, "Capacity allocation of PV-storage-charging station considering demand response and carbon emissions," in *Proceedings of the CSU-EPSA, Tianjin, China*, vol. 33, no. 7, 2021, pp. 106–112. https://doi.org/10.19635/j.cnki.csu-epsa.000731