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A multi-objective site selection of electric vehicle charging station based on NSGA-II

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A B S T R A C T

The planning of charging infrastructure is crucial to developing electric vehicles. Planning for charging stations requires considering several variables, including building costs, charging demand, and coverage levels. It might be advantageous to use a multi-objective optimization method based on the NSGA-II. We need to address the current problems in choosing the location of electric vehicle charging stations. Firstly, urban land use is divided into five functional areas, and the TF-IDF algorithm is applied to the division of functional areas. A combined clustering algorithm is proposed to cluster POIs in functional areas into several clusters and determine the cluster centers as charging demand points. We Analyze charging practices and travel patterns of electric car users, fit the charging likelihood of various functional regions, and calculate the charging demand of each charging demand point in the study area. Introduce the NSGA-II algorithm and consider the charging station's progressive coverage to fit the actual area covered by the charging station.Taking the maximization of system benefits and the maximization of the minimum coverage level as the optimization objectives to carry out multi-objective optimization. Finally, we take the charging station planning in the urban area of Hohhot as an example and provide different site selection planning schemes. The planning schemes for different numbers of charging stations are analyzed to obtain a charging station planning scheme that takes into account both objectives.

1. Introduction

With the concept of low carbon and environmental protection, new energy vehicles are gaining attention in people's daily travels as a kind of clean energy transportation. To cut down on pollution, governments have been encouraging the usage of new energy vehicles. Planning for the infrastructure necessary for charging electric vehicles (EVs) has significant effects (Kchaou-Boujelben, 2021). The current development process of charging stations has many serious problems, such as lagging development and unreasonable layout, making it difficult to find a pile during peak charging periods. These problems seriously affect the driving experience of electric vehicle users and cause bottlenecks in their development. To satisfy the enormous demand for charging electric vehicles, allay consumer concerns about mileage, and enhance the efficiency of charging and swapping services. There is an urgent need to develop a scientific and practical charging station deployment plan.

The location of charging stations involves several parties, such as charging station builders, users, and distribution networks, and is a facility siting problem. In terms of optimization objectives, the optimization objectives are different for different planning subjects. From the perspective of electric vehicle users, travel cost (Cao et al., 2021), user satisfaction, and charging convenience (Huang et al., 2015; Xu et al., 2022) are the primary considerations. From the perspective of charging pile operators, site planning objectives include distribution grid load (Huang et al., 2018; Wu et al., 2021) and construction cost (Luo et al., 2020). Also included are greenhouse gas emissions (Zhang et al., 2018) and coupling network expansion (Wang et al., 2018).

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Large scale, multiple constraints, and nonlinearity characterize the charging station siting problem (Li et al., 2022), which makes the problem's solution difficult. Heuristic solution algorithms are mainly used for solving optimization problems in large real-world environments, and such algorithms can give compliant solutions within an acceptable time frame. Heuristics based on genetic algorithms are widely used in charging station siting problems (Kadri et al., 2020; Xie et al., 2018). Multi-objective optimization is used when there are more than two objective functions. The non-dominated ranking genetic algorithm (NSGA-II) is a potent multi-objective genetic algorithm available (Deb et al., 2002). Multiple fields have made extensive use of it to resolve multi-objective optimization issues.

In this paper, we zone the city according to the road network and Separate function areas by combining the Point of Interest data (POI, Point of Interesting) using the TF-IDF (term frequency-inverse document frequency) algorithm. A combined clustering method is applied to the POI data of each functional area to obtain functional area clusters; We obtain the location information of the cluster centers as charging demand points and candidate points for building charging stations. We examine the charging habits of electric cars and forecast the demand for charging. Consider the characteristics of realistic charging infrastructure to meet the demand. Propose an asymptotic coverage model based on service distance. Take maximizing system efficiency and maximizing minimum coverage level as the optimization objectives. A multi-objective siting model for electric vehicle charging stations is established. The coverage model is the foundation of the suggested model. It is evident from the description above that this is an NP-hard problem (ReVelle & Eiselt, 2005). A collection of Pareto solutions are needed for the bi-objective model. The intelligent decision of the charging station siting problem is realized to organize charging stations in the most effective way. Finally, the placement of charging stations in Hohhot's urban area is analyzed as an arithmetic example to provide a siting plan and Check the method model's performance in this paper.

2. Literature Review

Related scholars have taken different approaches to studying several aspects of the charging station sitting problem. One research approach starts with the city's spatial layout and social development. The specific regional layout characteristics are analyzed, and the geographic area theory is applied to plan to charge station locations. (Meng et al., 2020) After identifying a specified number of candidate places and taking into account social aspects, a method for choosing the charging station construction plan with the lowest social cost among all the candidate plans was proposed. (Wu et al., 2017) constructed a triangular intuitionistic fuzzy number (TIFN) based structure for locating electric vehicle charging stations. They established a characteristic index system of siting factors, including economic, social, environmental, planning, and residential community characteristics portraits. However, siting theories such as central location only consider the perspective of facility location and cannot focus on the actual charging demand of EV users. A strategy for choosing appropriate sites for electric car charging stations was proposed by (Ademulegun et al., 2022). The approach allows the selection of key criteria according to any given goals and technical-physical-socio-economic factors for EV charging stations. Assist in the deployment of electric vehicle charging stations for their designated purpose.

Another research approach is to consider the behavioral characteristics of EV users from the charging demand. Estimates of the demand for electric vehicles based on compiled data from national censuses and local statistics yearbooks. (He et al., 2016). The ensemble coverage model, the maximum coverage location model, and the p-median model are compared based on the estimated EV demand. The outcomes demonstrate that the p-median solution outperforms the other two models. (Pan et al., 2020) created a siting model for public charging stations for electric vehicles with the intention of maximizing the current activity of electric car drivers. The charge selection behavior of EV drivers is first simulated. This procedure considers the EV drivers' current activities, the accessibility of home and public charging, range anxiety, and consumption of energy for the remaining portion of the journey. Second, a coverage siting strategy for public charging stations for electric vehicles is suggested with the goal of maximizing the current activities of electric vehicle drivers. (Cao et al., 2021) presented a probability calculating model that thoroughly examines the charging habits of owners to forecast the charging load at the planning site. Based on the results of EV load prediction, they develop a site selection model that aims to minimize user travel costs. A genetic algorithm optimizes charging station locations to obtain a library of charging station locations and capacities.

Analyze various data with the aid of artificial intelligence techniques and big data analysis technologies. The travel pattern was obtained by simulating the charging habits of EV users. (Bai et al., 2019) divided the city into a grid using the one-size cells. The GPS data of vehicles in the grid are used to estimate each grid's charging demand. It is suggested to use the non-dominated ranking genetic algorithm (NSGA-II) that combines linear programming, neighborhood search. They are using travel chain theory and the origin-destination (OD) matrix. (Krol & Sierpinski, 2022) Modeled charging station siting problems using graphs of urban road networks. Download complete road network data for urban areas from OpenStreetMap. Applying a genetic algorithm along with fuzzy logic, pareto front analysis, and fuzzy logic can create a collection of optimal solutions. An actual case study of a medium-sized city in southern Poland is used to illustrate the methodology. To place electric vehicle charging stations as efficiently as possible, (Yi et al., 2022) use data-driven strategies. They created a distinct grid to divide up their research area. Based on trip origin-destination (OD) and social dimension parameters, a modified geographic PageRank (MGPR) model is created to estimate the demand for electric car charging. This model is verified against real-world charging data. (Wang et al., 2019) use artificial intelligence to evaluate the complicated urban EV driving routes and determine the charging station.

The foundation of planning for charging stations is determining charging demand—some basic models in the sitting field deal with charging demand. There are two main categories. One category is the nodal model, which classifies models into four categories based on their objectives: aggregate coverage, maximum coverage, p-center, and p-median problems (Ko et al., 2017). (Janjic et al., 2021) were used for site selection analysis based on p-median. The distance was weighted using the hierarchical analysis (AHP) method. Optimization of construction cost, charging station distance, parking, and distribution network. Another category is the flow model. In order to maximize the quantity of flow captured on the network, (Hodgson, 1990) presented a flow capture location model (FCLM) whose objective is to locate a certain amount of facilities. (Kuby & Lim, 2005) introduced a flow model (FRLM) contemplating the EV range restriction. The model can accommodate EV range constraints. However, there are still limitations in the existing studies on the charging station planning problem: the service radius of charging stations is mainly fixed, which does not match the realistic charging station progressive coverage. The charging station planning problem involves multiple subjects, such as charging station builders, users, and distribution networks. Existing studies only consider the interests of a single subject among many planning subjects and carry out single-objective optimization to plan the lowest cost or capture the most demand, which cannot simultaneously satisfy the interests of multiple subjects. Therefore, we propose an asymptotic coverage model based on service distance. The optimization objectives are to maximize the system benefits and maximize the minimum coverage level. We develop a multi-objective charging station siting model for electric vehicles. The issue in this research is resolved using multi-objective NSGA-II.

2. Data processing and charging requirements analysis

Big data technology has attracted much attention in intelligent transportation and smart cities. The utilization of traffic swipe data, cell phone signaling data, and road network data has emerged as a research approach for analyzing the spatiotemporal characteristics of cities. We have collected urban data such as POI and road network. The machine learning algorithm TF-IDF and combined clustering algorithm constructed the charging station sitting model. Each charging demand point and demand in the study area can be obtained, and its location is considered a candidate point for charging facility construction.

2.1 City Data Collection

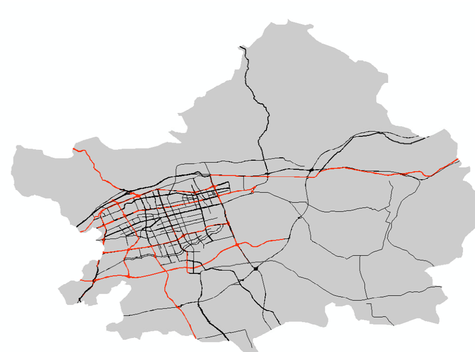
（1）POI Data

POI data includes geographical location (latitude and longitude), name, classification, and other information about geographical objects, which has been applied in several research disciplines. POI data can be obtained from online map service providers. The POI data used in this research is downloaded based on the development API of the coordinate picking service provided by AutoNavi. Amap uses Mars coordinates to encrypt the position, so the POI obtained by this method needs to be converted to the general WGS84 coordinate system according to the source for processing. The acquired POI data are classified into more than ten categories, such as food and beverage, shopping and consumption, and transportation facilities. The POI data in the study area are merged into five major land use categories: commercial, work, public, residential, and leisure areas through the POI category merging method. POI data for urban functional area identification can significantly reduce the subjective factor of manual judgment.

（2）Road Network Data

OpenStreetMap (https://www.openstreetmap.org/) is an open-source, user-participation online mapping project. Its database encompasses global geographic information, including roads, rivers, and lakes. The road network data in the study area is extracted through OSM. Because the original road network data contains all levels of roads in the study area, the data needs to be more concise and can be used indirectly. According to the road levels, the roads above the secondary road level are extracted to simplify the road network data in the study area, as shown in Fig.1.

(a) Original road network in study area



(b)Graded extraction road network

Fig. 1. Hierarchical extraction of road network data

2.2 Data processing methods

2.2.1 City functional area division method

There are usually two urban functional area division methods: kilometer grid division and road network division. Grid division divides the map area into square grids of equal size according to a certain distance (e.g., 5 Km) for analysis and processing of geographic data. This method is easy to handle and convenient to analyze. However, its undifferentiated map division cannot reflect the natural structure and morphology within the study area. To better understand the spatial layout and structure of the city, this study uses the study area road network to divide the city. The road network data obtained from the OSM website were simplified, imported into ArcGIS software, and processed into a single-line road network. We can obtain a functional urban division based on the road network.

TF-IDF is a machine-learning algorithm. The word frequency of a word within a document is used to calculate the word frequency (TF) value. The IDF value is obtained by counting the number of occurrences of the word in all documents. The TF-IDF value is Multiply TF and IDF. As in the following equation. A high TF-IDF score indicates that the term appears more frequently in this text than in other documents, indicating that the word is more essential in this document. This word has a good category classification ability and is suitable for text classification.

$$\begin{aligned} &TF(d,w_i)=\frac{count(d,w_i)}{count(d,*)} \qquad IDF(w_i)=\log\frac{|D|+1}{|\{d:w_i\in d_i\}|+1}+1 \\ &TF\text{-}IDF(w_i)=TF(d,w_i)*IDF(w_i) \end{aligned} \tag{2.1}$$

where d denotes the document; wi denotes the word; count (d, w_i) denotes the frequency of the word w_i occurring in document d; count$(d,*)$ denotes the total number of words occurring in document d; $|D|$ denotes the total word count; $|\{d{:}w_i \in d_i\}|$ denotes the total number of documents containing the word w_i. The formula takes a smoothing approach to avoid errors in the calculation due to the denominator being zero. It can be utilized for urban functional area categorization based on the TF-IDF algorithm concept. Reclassify all the acquired POI data according to the broad category merging method. A label of land use category is added to each POI. Import the POI data into ArcGIS software according to the latitude and longitude information and make spatial connections with the zoning units of the processed OSM road network division. We obtained all the POI data contained within each land unit. In urban functional division, each land unit divided by the OSM road network is regarded as a document, and all documents correspond to all land units. The land use category of POI data in each document is used as a word. The TF-IDF value of all the words in our documents is calculated separately. The POI land use category with the largest TF-IDF in each document is used as the functional area name of the land use unit. After the functional area division of the study area is completed, the land use category with the highest TF-IDF value becomes the functional area type of the land use unit. The functional area type is assigned to all POI data in the land unit. Thus, a CSV file containing POI latitude, longitude, and functional area type is obtained. Different colors are used for each type of functional area according to the functional area type.

2.2.2 Combined clustering method

The POIs contained in each functional area type need to be divided into different functional area clusters. The geographical position of each cluster is determined by the longitude as well as the latitude of its center point. The location information of the functional area clusters is needed for location planning in the charging station siting process. Clustering analysis is a commonly used unsupervised learning algorithm. There are numerous clustering algorithms available, including hierarchical, partitioning, density-based, and grid clustering. K-means is a common partitioning and grouping algorithm. It separates a certain set of data to K clusters, with the number K specified by the user. The basic idea is to compute the distance between every component and each cluster center, then allocate each component to the cluster center that is closest to it. Recalculate the center-of-mass position of all objects after the assignment and iterate until the center-of-mass position no longer changes. K-means evaluates the model by the SSE (Sum of Squared Errors). The smaller the SSE value, the closer the points in each cluster are to their center of mass, and the more effective the clustering effect. DBSCAN is a density-based clustering algorithm. The DBSCAN algorithm requires two parameters, Eps and MinPts. Eps denotes the neighborhood and MinPts denotes the number of samples of points in the neighborhood. If at least MinPts samples in any sample x_i's Eps neighborhood, then x_i is the core object for that sample. If xj is located in the Eps neighborhood of x_i, then x_j is said to be Density-direct by x_i. If there exists a sequence $p_1, p_2... p_m... p_n$, where $p_1 = x_i$, $p_n = x_j$, and pm is pm-1 density-direct, then the sample xi and the sample x_j are said to be density-reachable. DBSCAN defines a cluster as the biggest density-connected sample set created by the density reachability.

The choice of the K-value is crucial to the K-means algorithm. Because the quantity of clusters of geographic locations of charging demand points is unknown, if the distribution of charging demand points is too dispersed, the location of the center of mass obtained by clustering according to the set K-value may be far from the actual location. Because the DBSCAN clustering algorithm aggregates according to the density connected by a set radius, it can automatically cluster the geographic location of charging demand points into several clusters. However, DBSCAN only clusters the data into several clusters but needs help finding the cluster centers. Therefore, this study proposes a combined clustering algorithm based on DBSCAN and K-means, as shown in Fig. 2. First, according to the density-reachable characteristics of DBSCAN, Eps, and MinPts are set, and charging demand point physical location data are divided into numerous groups. The geographic location of the charging demand point contained in each cluster is used as input. The K-value of each cluster is set to 1. The K-means algorithm is used to determine the position of each cluster's centroid.

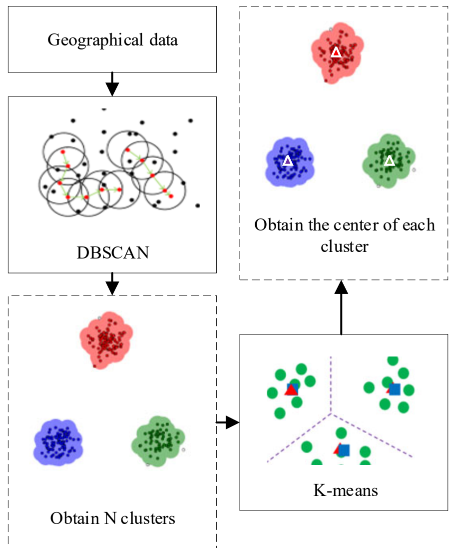


Fig. 2. Combinatorial clustering algorithm

2.3 Charging demand analysis

Planning charging infrastructure begins with an analysis of charging demand in the research region. One of the charging demand analyses is from the charging station side, building a model to forecast the demand for electric vehicle charging using data on traffic flow. This prediction method is only suitable for charging demand in small areas such as highway entrances and exits. The other is from the user side, analyzing the travel patterns of electric vehicle users and establishing a statistical model based on travel characteristics to realize the prediction of charging demand in an extensive range of research areas. Considering users' actual travel charging demand, when users of electric vehicles predict that the remaining power cannot meet the next driving mileage, users will choose to charge. There is a great difference in users' acceptance of remaining power, so a larger number of samples should be selected to analyze the law of it. The lowest acceptable SOC is represented by x. We find the probability of charging demand of EV users corresponding to different x.

The following presumptions are the foundation of this paper. 1. There is a linear relationship between electric vehicle power consumption and driving mileage, and the driving range D of each electric vehicle battery is equal. 2. Each user has only one round-trip travel requirement per day, that is, from one functional area to another functional area. 3. According to the "2022 White Paper on Charging Behavior of Electric Vehicle Users in China" issued by EVCIPA (China Electric Vehicle Charging Infrastructure Promotion Alliance), the weekly charging frequency of electric vehicles is as high as 4.51 times, that is, an average of one charge every 1.55 days. When the user is charging, the remaining power SOCr can be expressed as:

$$SOC_{\mathrm{r}} = 1 - SOC_{\mathrm{t}} = 1 - \frac{E}{S} = 1 - \frac{d_{\mathrm{t}}}{D} = 1 - \frac{2 \times 1.55 \times d_{\mathrm{s}}}{D} \tag{2.2}$$

In the formula, E represents the power consumed before charging; S represents the battery's rated capacity; D represents the mileage of the electric vehicle; *dt* represents the round-trip mileage and *ds* represents the mileage of a single trip. The minimum SOC acceptable to users is different according to the usage habits of each user. The minimum acceptable SOC determines the charging willingness of electric vehicle drivers. The charging demand occurs when the remaining power of electric vehicles is less than the minimum acceptable power. In this way, the relationship between the probability of the user's charging demand and the acceptable minimum SOC (indicated by x) can be obtained:

$$P_c(x) = P(SOC_r \le x) = P\left(1 - \frac{2 \times 1.55 \times d_s}{D} \le x\right) = P\left(d_s \ge \frac{D}{3.1}(1-x)\right) \tag{2.3}$$

Pc(x) in the equation represents the charging demand probability at different minimum acceptable SOCs, and the equation eventually translates to the probability of a single trip ds ≥ D/3.1 (1-x). As the data size increases to a certain number, the frequency of single trip *ds* greater than D/3.1 (1-*x*) can gradually approximate the charging demand probability. We can solve the probability of generating charging demand in each functional area when the range is D. Single trip mileage, and trip purpose data are provided in the National Household Travel Survey 2017. The probability of charging demand is calculated separately for different functional areas of the city (residential, work, public, commercial, and leisure areas). Due to the discrete nature of the data, it is necessary to divide the minimum acceptable SOC at specific intervals to calculate Pc(xi) and finally to obtain the continuous function Pc(xi) using fitting. Observing the distribution of discrete points, the fitting function used in this study is:

$$P_c(x) = a\mathrm{e}^{bx} + c\mathrm{e}^{dx} \tag{2.4}$$

The results and fitted images of each region fit are shown below:

$$\begin{aligned}
&P_{c\text{-public}}(x) = 0.0674079877e^{1580472x} + 8.12932228\times10^{-6}e^{11.3962666x}\\
&P_{c\text{-Residential}}(x) = 0.0173941023e^{2.63686943x} + 1.19407213\times10^{-6}e^{13.4411261x}\\
&P_{c-\text{work}}(x) = 0.0173949934e^{2.40200274x} + 5.78849572\times10^{-6}e^{11.9x39311x}\\
&P_{c\text{-commercial}}(x) = 0.018828681e^{1.72300523x} + 1.16894163\times10^{-6}e^{13.660769x}\\
&P_{c-\text{leasure}}(x) = 9.64004599e^{3.80105067x} + (-9.61723311)e^{3.80105871x}
\end{aligned} \tag{2.5}$$

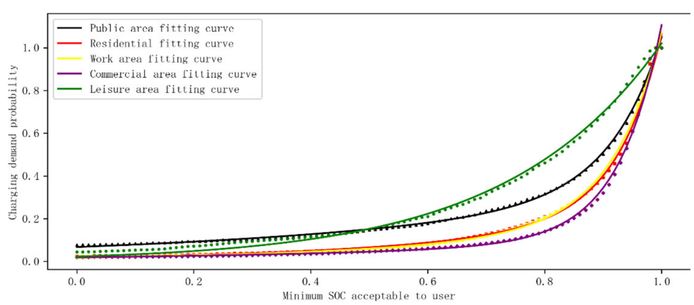


Fig. 3. Regional charging demand probability curves

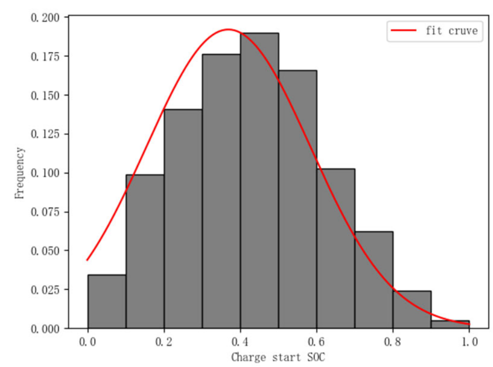


Fig. 4. Charging start SOC distribution map

From Fig. 3, the leisure area has the largest charging demand, and the commercial area has the lowest charging demand. The RMSE (Root Mean Square Error) of the five regional charging demand probability functions after function fitting are 0.01028998, 0.012037, 0.01202038, 0.016444, 0.01722425, and the maximum value of RMSE for the five regions is 0.0017, indicating that the fit is more accurate and can match well to the discrete points. Electric vehicle users have different charging habits, and the timing of charging varies greatly. The minimum acceptable SOC is a subjective concept. The SOC at the beginning of charging can reflect the charging habits and usage psychology of electric vehicle users, so the SOC when electric vehicle users start charging can be used instead of the lowest acceptable SOC. According to the starting charging SOC in Shanghai's new energy vehicle operation data, the division of electric vehicle users' choice of charging in each segment of SOC is obtained. The starting charging SOC is the highest at 40%~50%, nearly 20%, and 90%~100 % lowest, only 0.5%. The statistical results are shown in Figure 4, and it can be observed that it approximately follows a normal distribution. The fitted normal distribution curve indicates that the charging start SOC's probability density function is as follows:

$$f_c(x) = \frac{1}{\sqrt{2\pi}\times0.1946}\mathrm{e}^{-\frac{(x-0.3791)^2}{2\times0.1946^2}} \tag{2.6}$$

In the formula, x represents the SOC at the beginning of charging, which is used to replace the minimum SOC acceptable to the user. Electric vehicles are usually charged when they are parked. As a result, the functional area's charging needs can be determined by the number of electric vehicles parked there. The following formula can be used to express the charging demand for each functional area.

$$N_i = y_i\omega\int_0^1 P_c(x)f_c(x)dx \tag{2.7}$$

In the formula, y_i is the amount of parking attraction in the functional area. (Cheng et al., 2012) proposes an improved model of parking generation rate to calculate y_i. This paper refers to the model provided by the literature to calculate y_i as the following formula.

$$y_i = n_i \frac{a_i R_i}{\rho} \mu \delta \tag{2.8}$$

n_i is the total quantity of POIs in the area. a_i is the amount of parking attracted per unit area. *Ri* is the area of a single POI. the three parameters ρ, μ, and δ represent turnover rate, parking strategy influence rate, and service level influence rate, respectively. ω represents the penetration rate of a city's electric vehicles. The integral of the product of the charging demand probability Pc(x) and the starting charging SOC distribution $f_c(x)$ is the charging probability.

3. Optimization of charging station location based on NSGA-II algorithm

The design of charging stations for electric vehicles is fraught with uncertainty. First, EV users can flexibly choose fast, slow, and power exchange, which is very different from traditional fuel car refueling in terms of period. Second, the massive number of electric vehicles joined to the grid at once will impact the grid's efficient operation. Finally, the development of electric vehicle-related technologies may significantly change electric vehicles' charging time and users' charging habits. The site selection optimization of EV charging stations needs to consider various factors such as urban land use and demand distribution, establish site location models for different optimization objectives and constraints, and coordinate the planning of charging station layout schemes.

3.1 Charging pile progressive coverage model

Previous studies usually regard the coverage of the charging station as a fixed radius, complete coverage within the service radius, and complete non-coverage beyond the coverage. This strict dichotomy based on the service distance is inconsistent with reality. The charging station can also attract a small amount of charging demand outside the service radius. Therefore, a progressive coverage model is proposed. Within the basic coverage radius, the charging station meets the entire demand for charging. Outside the basic coverage radius, the charging station partially covers the charging demand. Beyond the maximum service range of the charging station, the charging station does not cover the charging demand. To define the link between the distance and the charging station coverage level, we create a non-convex and non-concave function. Within the distance range of D1, the coverage level of charging stations is 1. Between D1 and D2, the coverage level is a decreasing function of distance; as shown in Fig. 5, the coverage level is 0 when the distance exceeds D2, which is more similar to the coverage of charging stations in reality.

$$f(d_{ij}) = \begin{cases} 1 & d_n < D1 \\ \frac{1}{2} + \frac{1}{2}\cos\left[\frac{\pi}{D2 - D1}\left(d_n - \frac{D2 + D1}{2}\right) + \frac{\pi}{2}\right] & d_n \in [D1, D2] \\ 0 & d_n > D2 \end{cases} \tag{3.1}$$

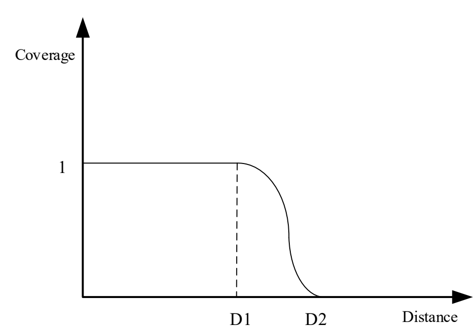


Fig. 5. Progressive coverage curve

3.2 NSGA-II bi-objective optimization

The problem of charging station location planning involves multiple subjects, such as charging station builders, users, and distribution networks, and the interests of multiple subjects are contradictory. Considering only one subject for layout optimization will damage the interests of other subjects, so it is necessary to optimize multiple objectives simultaneously. The location of the charging station is thus a multi-objective planning issue. This study weighs the two objectives of maximizing system benefits and maximizing basic coverage level and solves the multi-objective optimization problem of charging station location.

Following is the objective function:

$$F1 = max\frac{\sum_i\sum_j w_i q_{ij} z_{ij}}{\sum_i\sum_j c_j x_i + \sum_j b_j r_j} \qquad F2 = \max q' \tag{3.2}$$

The following table displays the parameters and their definitions:

Table 1
Parameters and Meaning

Model Parameters	Parameter Meaning
I	Collection of charging demand points $I = \{i \mid 1,\ldots,n\}$
J	Collection of charging facility points $J = \{j \mid j \in I\}$;
w_i	Charging demand for charging demand point *i*
d_{ij}	Euclidean distance from charging demand point *i* to charging facility point *j*
c_j	Cost of new charging facilities at j-point
b_j	Cost of serving a vehicle at a charging facility site
q_{ij}	Coverage level of charging demand point i by charging facility point j
q'	Minimum service level $q' = \min\{q_{ij}z_{ij}\}$, $q_{ij} = f(d_{ij})$

Objective function 1 is to maximize the system benefit, which equals the ratio of facility service benefit to facility construction cost. Objective function 2 is to maximize the basic coverage level. The following constraints need to be met:

$$\begin{aligned} &\sum_i z_{ij} = 1, \forall i \in I && z_{ij} \le x_i, \forall i \in I, j \in J \\ &\sum q_{ij} z_{ij} \ge q', \forall i \in I && \sum_i w_i z_{ij} \le m_j, \forall j \in J \\ &z_{ij} \in \{0,1\}, \forall i \in I, \forall j \in J && x_i \in \{0,1\}, \forall j \in J \end{aligned} \tag{3.3}$$

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a popular multi-objective optimization algorithm. NSGA-II mainly selects individuals by calculating non-dominated sorting and crowding distance to select the optimal set of solutions. Our research uses the NSGA-II to optimize the two objectives of location planning. By default, the charging station is constructed at the charging demand point. Depending on whether the charging demand point is recognized as a construction point for a charging station for genetic coding. If a charging station is built at point *i*, it is encoded as 1; if it is not at point *i*, it is encoded as 0. We obtain a set of binary strings as chromosome codes. Fig. 6 shows the detailed flowchart of the algorithm for NSGA-II.

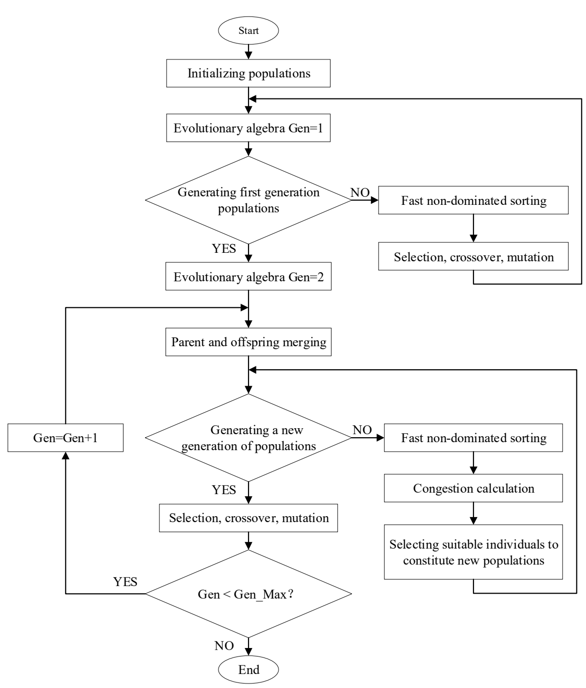


Fig. 6. NSGA-II algorithm flow chart

The algorithm must provide parameters like population size and iterations. The multi-objective optimization algorithm solves all feasible non-dominated optimal solutions for the decision maker. This provides the decision-maker with multiple objective tradeoffs. The pareto front is defined by the corresponding objective function values of all pareto optimal solution sets. Since the two objectives of system effectiveness and coverage level are contradictory and cannot be maximized simultaneously, a bi-objective optimal solution cannot be obtained. Only Pareto optimal solution sets with two balanced optimization objectives can be obtained. The individuals in the Pareto frontier output by the iterative operation are the set of non-dominated optimal solutions.

4. Example analysis

4.1 Functional Area Division

In this study, we use the sitting planning of charging stations in the main city of Hohhot City as an illustration. We collected approximately 90,000 POI data in the study area and downloaded the road network data of the study area from the OSM website. Subsequently, we performed appropriate processing on the acquired data. The graded extracted road network is used to divide the main urban area of Hohhot into 553 study units. The 553 study units are categorized into five urban functional zones of work, commercial, leisure, residential, and public zone according to their TF-IDF maxima by the TF-IDF algorithm. The division of functional areas is shown in Fig. 6.

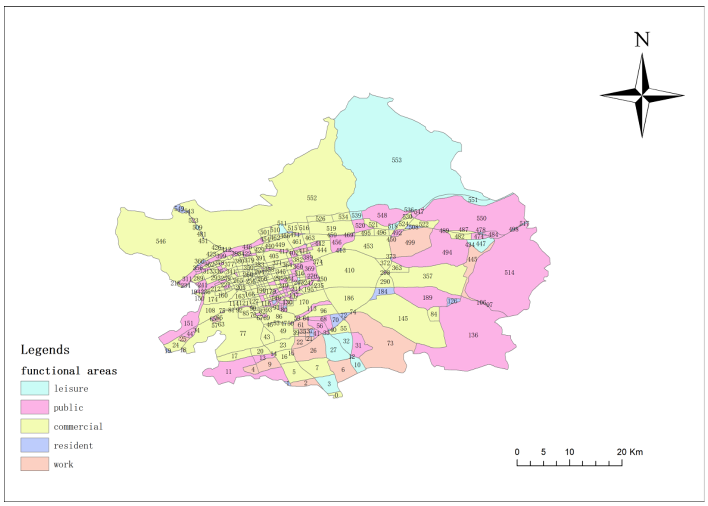


Fig. 7. functional area

Then the POIs within each unit are labeled with the functional zone type. Using the Python module Folium Map, which locates POIs using latitude and longitude information, the POI data is shown. The five functional zones are displayed on the map using different colors, as shown in Fig. 8 for the partial functional zone division of the study area.

Fig. 8. POI functional area distribution

A combinatorial clustering algorithm was used to cluster each type of functional area POI in 553 study units, setting the DBSCAN clustering algorithm parameters as Eps = 1Km and MinPts = 5. The five types of POIs were clustered into 143 clusters, and then each cluster was used as input to specify the number of clusters K = 1 for K-Means clustering. Finally, the coordinates of the centroids of the 143 clusters are obtained to determine the location of the charging demand points. As shown in Fig. 9.

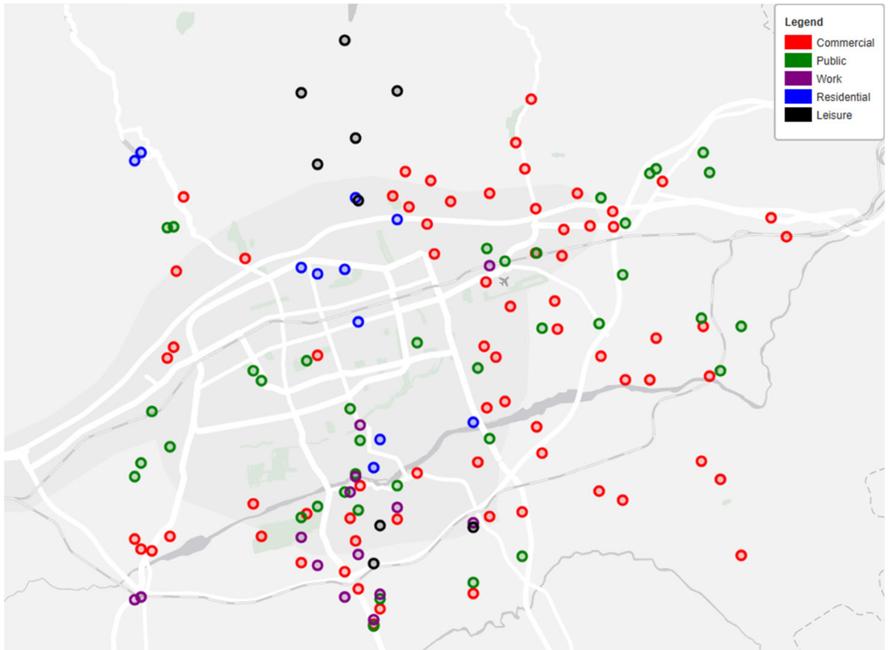


Fig. 9. Charging demand point distribution

4.2 Charging demand analysis

The quantity of POIs at a charging demand point determines the charging demand at that demand point. People generate traffic demand between different POIs. Each POI has a different level of attraction for people and generates different traffic demands. Thus, the charging demand attracted to it is also different. The charging demand can therefore be calculated as the product of the quantity of charging demand attracted by the kind of POI in the functional area at the charging demand point and the number of POIs. According to the parking demand of POI in each functional area, the charging demand of each charging demand site is determined in our study using the charging demand calculation method mentioned above.

Statistics from the Chinese Ministry of Public Security show that 13.1 million new energy vehicles were registered in China by the end of 2022, accounting for 4.10% of the country's total automobile fleet. The construction of charging stations should be moderately advanced given the quick growth of electric vehicles. We set the penetration rate of electric vehicles at 6%. The literature proposes an improved model of parking generation rate, we refer to the model parameters in the Case Study of the literature, and taking into account the real circumstances in our study region. We set the amount of parking spaces per hundred square meters(ai) and the area of a single POI (Ri) in different functional areas as shown in Table2. We set the turnover rate ρ = 1.3, parking strategy impact rate μ = 70%, and service level impact rate δ = 1. For some areas with high charging demand, adjust the parking strategy impact rate and service level impact rate accordingly. The 143 charging demand points' charging demand can be determined. The parameter settings and total charging demand are shown in Table 2.

Table 2
Charging demand by functional area

Functional Area Type	a_i（Parking spaces /100m^2）	R_i (m^2)	Parking demand (million vehicles)	Charging probability	Total charging demand
Work	0.63	75000	10.5	0.05408	341
Public	0.36	45000	14.08	0.13281	7482
Commercial	0.31	35000	21.16	0.04275	3618
Residential	0.85	125000	6.69	0.05762	1542
Leisure	0.23	245000	3.64	0.12534	1827

4.3 NSGA-II charging station multi-objective optimization

Consider the optimization of charging station location under progressive coverage. Combined with the continued driving mileage of electric vehicles under low-power working conditions, the radius of progressive coverage is set to D1 = 4 km (complete coverage) and D2 = 8 km (decreasing coverage with increasing distance). When the service distance is larger than 8 km, it is considered that the charging station cannot cover the charging demand. The set of charging demand points is $I=\{i|1,...,143\}$. The charging station construction point $J=\{j|\, j\in I\}$. Each charging demand point's amount of demand has been calculated. A new charging station is expected to cost 20 million RMB to build. The cost per electric vehicle service is 0.1 million RMB. The latitude and longitude of the two points can be used to determine the distance between the charging facility and the charging demand point.

Initialize the population with a 0-1 binary code for the chromosomes of the individuals, where 1 means build the charging station, and 0 means do not build the charging station. Set the evolutionary generation Max_gen = 500 generations; population size Pop_size = 300; crossover probability cx_prob = 0.8; mutation probability mut_prob = 0.3, and run the NSGA-II algorithm to obtain the Pareto optimal solution set, there are eight solutions in the Pareto frontier, where each solution and its objective value are shown in the following table:

Table 3
Pareto front solution and objectives value

Number of charging stations	System benefits (objective function 1)	Minimum coverage level (objective function 2)	Cost required (million yuan)
49	5.892557081	0.337572707	2440
50	5.84078147	0.358482546	2460
54	5.723788218	0.582873732	2540
56	5.652892679	0.666334055	2580
59	5.516062932	0.700601366	2640
67	5.214891447	0.832140755	2800
68	5.17826915	0.912981734	2820
76	4.900355633	1	2980

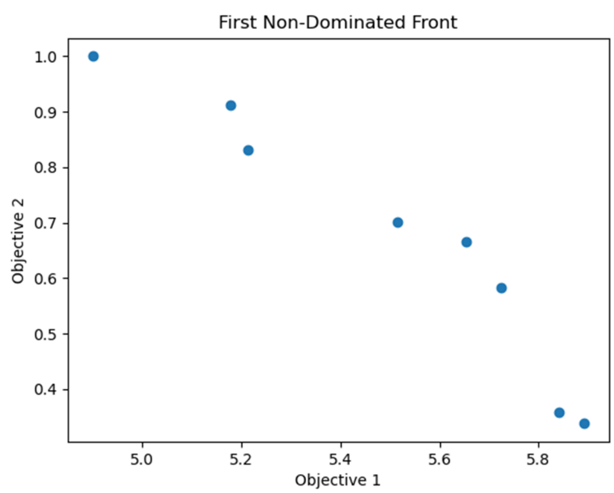


Fig. 10. Pareto optimal solutions

Observing the distribution of the Pareto solution set in Table 3 and Fig. 10, the objective value of the system benefit decreases as the objective value of the minimum coverage level increases. The system benefit can exceed 5.8 when there are 49 and 50 charging stations, but the minimum coverage level is only about 0.3. The minimum coverage level increases when 56 and 59 charging stations are built. When the number of charging stations reaches 67 and 68, the minimum coverage level increases and reaches a higher value of 0.9. When the maximum minimum coverage level reaches 1, the lowest system benefit objective value is 4.9. This indicates that there is a contradiction between these two objectives, and they cannot be optimized at the same time. Therefore, we can only choose to weigh the two objectives to obtain the overall optimum.

4.4 Analysis of charging station planning results

To show the charging station layout of each solution in the collection of Pareto optimum solutions of optimization results in this case. It helps decision makers to weigh the decision options when considering different factors. Some representative solutions are selected to show the charging facility layout scheme. We visualize the distribution of charging stations and charging allocation when 56 and 67 charging stations are selected. When charging stations are 56, the charging stations and their assigned charging demand points are shown in Table 4. The relationship between the location and distribution of constructed charging stations is shown in Fig. 11. The red dot in the figure indicates the location of the charging demand point, the green square indicates the charging station construction point, the purple circle indicates the area where the coverage of the charging station is 1, and the yellow part indicates the area where the coverage level of the charging station decreases with the service distance.

Table 4
Part of the charging demand allocation when building 56 charging stations

Charging station location	Collection of charging demand points served
14	14,28,118,119
29	9,26,27,29,30,32
58	1,19,58,61
69	5,22,23,64,69
94	15,45,46,94,99,104,105,106,110,116
132	67,68,130,132,133

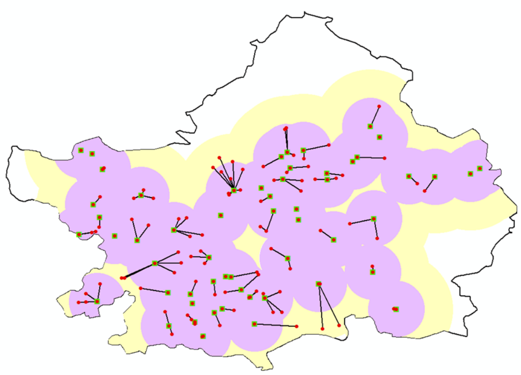


Fig. 11. Distribution when building 56 charging stations

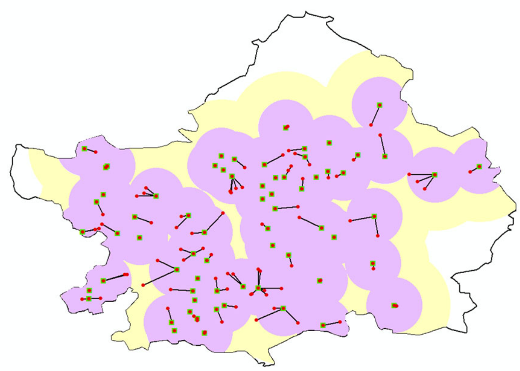


Fig. 12. Distribution when building 67 charging stations

When charging station is 56, The charging stations and their allocated charging demand points are shown in the Table 5. The relationship between the location and allocation of charging stations is shown in Fig. 12.

Table 5
Part of the charging demand allocation when building 67 charging stations

Charging station location	Collection of charging demand points served
20	8,20,67,68,73,117,131,132
43	43,93,122,123
85	84,85,86
99	15,45,46,94,99
119	28,30,32,119
125	100,101,125,134

From the above chart, it is possible to visualize the location of charging facility construction and the distribution of each charging demand point for different planning solutions. The charging station planning scheme can be selected based on the factors considered. If the convenience of charging needs to be ensured and social equity promoted, the option with the largest minimum coverage level and 76 charging stations should be selected. Assuming that system benefits and charging station building costs are taken into account, It is best to choose the planning strategy that will benefit the system the most, and 49 charging stations should be built. However, in most cases, both factors need to be considered together. Therefore, 67 charging stations are selected to be built, and the planning layout is shown in Fig. 12. By choosing this scheme, the target value of system efficiency is reduced by 11.5%, while the target value of minimum coverage level is increased by 59.4%. Also, in Fig. 11, it can be observed that some of the charging stations are built too close to each other. When constructing charging stations, the charging station that is too close can be constructed as a larger-scale charging station. This helps to save costs and improve system efficiency. Based on the above analysis, decision-makers can reasonably plan the charging station layout based on the factors considered.

5. Conclusion

This paper proposes a dividing urban functional zoning method based on POI data and urban road networks, considering the two decision goals of system benefit and minimum coverage level. Focus on charging facilities gradually covering the need for charging. We select the NSGA-II to optimize the charging station sitting layout. We derive and analyze different sitting planning schemes in the Pareto optimal solution, and the conclusions of this paper are as follows. For urban functional zone division, the study area is divided into functional zones of different kinds by TF-IDF algorithm using POI data and road network data. A combined clustering algorithm is proposed to cluster the functional area POIs into 143 functional area clusters. The functional zone division results can be consistent with reality, and the site of the charging demand point is at the center of each cluster of functional zones. The NSGA-II algorithm is introduced, and the progressive coverage of charging stations is considered. The planning of charging stations in Hohhot City is analyzed as an arithmetic example. A site selection scheme for multi-objective planning is derived by setting appropriate algorithm parameters, considering two target values. Different charging station number siting planning schemes are analyzed, and the resulting siting scheme can consider both objectives.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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