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Optimisation of Electric Vehicle Charging Stations Planning Based on Macro and Micro Perspectives

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ABSTRACT
The growing ownership of electric vehicles in urban areas leads to increasing demand for public charging spaces. With existing charging facilities failing to match the constantly increasing demand for charging, it is necessary to plan for new charging infrastructure. A two-stage approach is proposed for public charging infrastructure planning from both macro and micro perspectives. Firstly, a linear regression model with an exponential elasticity function is used to estimate charging demand, considering comprehensive charging demand factors. Secondly, effective served charging demand (ESCD) is proposed to accurately calculate the charging demand of effective service areas, considering the distance impact factor and competition among neighbouring charging stations. A capacitated maximal service location model (CMSLM) is proposed to optimise the spatial layout of public charging stations by maximizing their ESCD while considering investment budget and charging station capacity limits. CMSLM is solved using sparrow search algorithm from both macro and micro perspectives. The proposed approach is applied to Guangzhou, China, as a case study. Results show that when the investment budget is increased to 5 million CNY, the ESCD of all districts under the macro and micro optimisation perspectives increases by an average of 41.0% and 34.1%, respectively. Optimised charging stations can remedy the spatial imbalance between charging demand and existing charging station distribution, laying the foundation for further construction implementation.

KEYWORDS
electric vehicle; charging demand estimation; charging infrastructure planning; location selection.

Abbreviation	Full name
EV	Electric vehicle
POI	Points of interest
ESCD	Effective served charging demand
CMSLM	Capacitated maximal service location model
SCLM	Set covered location model
MCLM	Maximum cover location model
SSA	Sparrow search algorithm

1. INTRODUCTION

With the growing threat of climate change due to greenhouse gas emissions [1], the transportation sector employs vehicle electrification as a primary method to decrease tailpipe emissions and achieve environmentally friendly transportation [2]. The sales of electric vehicles (EVs) are increasing globally. In 2023, more than one in three new car registrations in China was electric, over one in five in Europe, and one in ten in the United States [3]. The rapid growth in EV adoption has led to a surge in charging demand, and the public charging infrastructure plays a key role in enabling more widespread adoption of EVs [4]. Two major barriers to expanding public charging infrastructure are the underutilisation of inconveniently located charging stations and the insufficient coverage of charging networks in certain regions [5]. Therefore, it is essential to effectively improve coverage and maximise utilisation by optimally locating public charging infrastructure.

In regions where EVs are developing rapidly, considerable charging demand is generated, which is challenging to fulfil. A sufficient and well-distributed public charging infrastructure can be an effective solution to this problem. For instance, Guangzhou, a major automobile production centre in China, is a leading city in vehicle electrification globally. By 2022, Guangzhou's EV fleet ownership reached 540,000 units, representing 4.11% of the country's total. However, the existing charging infrastructure in Guangzhou is unable to meet the current charging demand. Some charging stations are irrationally located, leading to significant practical issues. For example, during peak hours, EV users often face difficulty finding an available charging pile in high-demand areas such as city centres. Conversely, in low-demand areas, there is a surplus of idle piles, resulting in low station utilisation [6]. Difficulty in charging for EV users and low utilisation of charging piles have become significant challenges for the EV industry. The state has enacted policies to facilitate the construction of a high-quality, scientifically optimised and technologically advanced charging infrastructure system [7]. Therefore, a well-founded and practical charging infrastructure planning and construction method is required to solve the aforementioned problems.

The process of public EV charging station planning is typically divided into two main parts: demand estimation and planning methods [5]. One common method for estimating demand is to simulate the energy consumption of EVs in various traffic scenarios by modelling EV battery usage [8]. However, this method can be challenging to scale up for use in large urban environments. To address this issue, several recent studies have utilised data-driven methods to estimate charging demand based on socio-economics (e.g. population density) [5], points of interest (POI) [9] and land use [10]. Charging station planning methods include travel-based, path-based and point-based approaches [11]. The travel-based approach has high data requirements and typically necessitates detailed travel and stay data to ensure model practicality. However, obtaining detailed trip data is challenging due to privacy concerns. The path-based approach considers traffic flow as a dynamic feature, such as flow-capture location model [12] and flow-refuelling location model [13]. This approach assumes that the user completes charging quickly before traveling to the destination, making it feasible only at fast charging stations, where a full charge usually takes only a dozen minutes. However, it is not applicable at slow charging stations where a full charge may take several hours. In contrast, the point-based approach requires less data, such as population density, making it easier to estimate charging station locations and applicable to various regions or countries.

Existing studies on estimating EV charging demand and charging station planning have identified three major gaps that need to be addressed. First, the ability of a charging station to serve the charging demand of the surrounding area is related to the distance between the two, as well as competition from neighbouring charging stations. Existing studies tend to consider only the charging demand that is simply covered by charging stations, which is not sufficiently accurate [5, 14]. Second, some proposed models lack real charging data to verify their validity. These models often use charging event identification to infer the possible charging behaviour of taxis [15, 16], but this data lacks authenticity, and significant differences exist between the behaviour of taxis and private cars. Third, there is a lack of corresponding location optimisation strategies from both macro and micro perspectives. Previous studies have focused on optimizing for minimum cost or maximum benefit, without considering the specific objectives of different stakeholders. The main contributions of this study are as follows:

— Effective Served Charging Demand (ESCD) is proposed to accurately calculate the charging demand within effective service areas. Considering the competition between charging stations, the Voronoi and radial boundary are used to delineate these effective service areas. Additionally, the charging demand within these areas is calculated by accounting for the influence of the distance to the charging stations.

— A two-stage approach is proposed for public EV charging station planning, which consists of a regression model for charging demand estimation and a capacitated maximal service location model (CMSLM) for charging station planning optimisation by maximizing their ESCD, taking into account the constraints of investment budget and charging station capacity from both macro and micro perspectives.
— An optimisation strategy for charging station planning based on sparrow search algorithm (SSA) is proposed. From a macro perspective, the optimisation goal is to maximise ESCD of all charging stations across the region, while from a micro perspective to maximise ESCD of an individual charging station.

The remainder of this article is organised as follows. The next section reviews existing EV charging station demand estimation and planning approaches. Section 3 describes data and variables. Section 4 presents the proposed regression model and location optimisation strategy. Section 5 illustrates the obtained results and analyses differences in optimisation perspectives among different districts. Section 6 presents the conclusions.

2. LITERATURE REVIEW

2.1 Charging demand estimation

One common method for estimating charging demand is to model and simulate the charging demand of individuals and groups of EVs [8]. NetLogo is used to accurately model human behaviour and its impact on load demand resulting from EV charging, using an agent-based approach that considers technical, social and economic parameters. However, these methods are often only applicable to EVs in small areas and difficult to implement in large-scale urban cities. Another category of methods is based on socio-demographic and trajectory data, such as expert recommendations [17, 18], user surveys [19] and taxi trajectories [10, 16]. However, these methods lack real charging usage data for validation, and their reliability is debatable. For instance, EV users may conceal or have biased perceptions of their preferences and habits, meaning that only approximate estimates of user behaviour can be made. Identifying charging events through taxi distance from charging stations and dwell time may differ significantly from actual charging behaviour.

To address the limitations of the aforementioned methods, there has been growing interest in data-driven approaches that identify correlations between charging usage data and external features. While dynamic features may not directly impact the location of new charging stations, they can be valuable in managing peak demand and grid load. The most typical example is the time of day. Charging events at public charging stations usually occur during the day, while private charging station charging tends to happen at night. However, the distribution of charging demand during the day does not affect location optimisation. Static features can reflect long-term stable characteristics near a point or an area and are suitable for planning new charging stations, as the location of charging stations does not change over a short period. These features typically include POI density and type, population density and other factors. A linear regression model was used to relate charging station usage data to POI type and create a heat map of charging demand for the study area [9]. Analysis indicates that POI has a significant impact on charging demand in urban areas. The random forest model was used to model spatial features, including pick-up and pick-down density, population density, land use entropy and road network density [10]. And the Shapley value method showed that all of these features have an impact on the charging demand. A weighted linear integrated model was used to score the demand in the area and identify the areas where gas stations should be built. The scoring criteria included area population, the distance from the fire station, the fault, and so on, and the criteria weights were determined using the analytical hierarchy process and the expert choice app [20].

Previous research investigated the effect of real-time pricing adjustments on charging demand. While real-time data is critical for controlling peak demand and dynamic pricing, it only captures short-term changes and creates privacy concerns, particularly when dealing with location-based data [21]. Long-term historical data, on the other hand, is more suited for charging station planning since station sites do not change over a short period and require insights that represent stable, long-term features [14]. As a result, long-term stable pricing qualities are preferable for charging station planning to short-term price changes, because planning focuses on revenue creation over several years rather than hourly or daily profits.

2.2 Optimisation of charging station planning

The point-based approach is a commonly used method for locating charging stations and has been widely studied. According to [22], this problem is classified as NP-hard, meaning that an exact solution cannot be obtained within a finite amount of time due to the exponential growth of execution time about the problem dimension. Therefore, heuristics are commonly employed to provide approximate solutions within a reasonable computation time. Representative algorithms include genetic algorithm [23] and greedy algorithm [24]. The two main point-based methods for facility location are the Set Covered Location Model (SCLM) [25] and the Maximum Cover Location Model (MCLM) [26]. SCLM aims to minimise the number of facilities while satisfying all customer needs [25]. MCLM aims to maximise demand satisfaction by locating a specific number of facilities. MCLM is a method that sets a distance threshold, similar to SCLM but with the added benefit of allowing for the exclusion of certain demand points when there are insufficient resources to cover all nodes. This feature makes MCLM more realistic. In [27], MCLM is used to locate slow charging stations and compete with fast charging stations located using a traffic capture location model. A two-step approach is proposed for optimally deploying charging points, integrating spatial statistics and MCLM [28]. Additionally, MCLM is employed to quantify the value of locating charging stations at POI, such as schools or stores [9].

In the MCLM, charging station coverage regions typically overlap, neglecting the impact of competition among surrounding charging stations. To more correctly evaluate charging demand for effective service, this study introduces the ESCD, which uses Voronoi and radial boundaries to outline effective service regions while taking into account competition between charging stations. Additionally, this paper proposes an optimisation strategy within the CMSLM to address the needs of various stakeholders with different planning objectives, providing valuable references for the configuration of charging infrastructure.

3. DATA PREPARATION

3.1 Data

Guangzhou was chosen as the research area due to its crucial position as a primary vehicle production centre in China. Multiple datasets from Guangzhou are utilised to extract various variables. A comprehensive description of the data sets is given in *Table 1*.

Table 1 – Description of the data sets

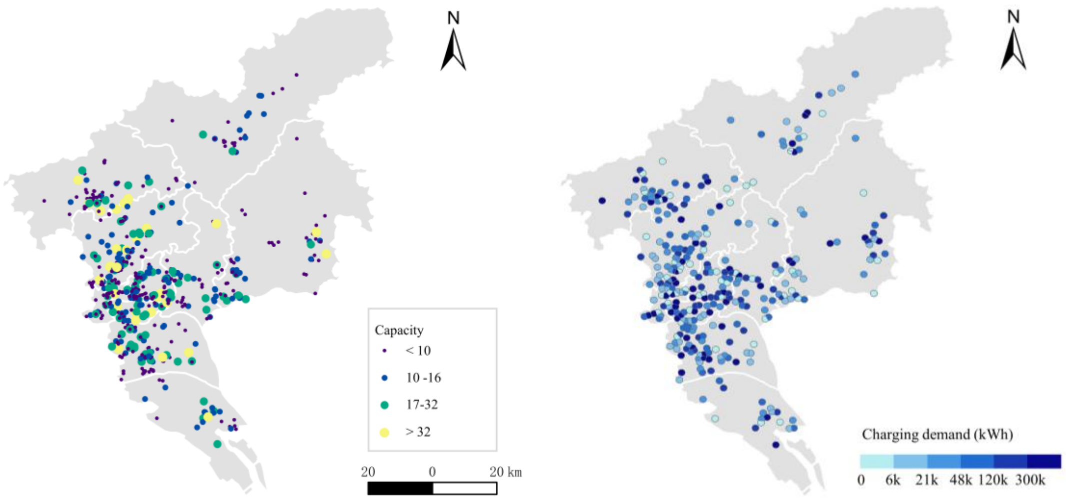
Data set	Data source	Key information	Variable
Charging station data	[29]	ID, longitude, latitude, time, status, power, charging price	charging demand, weighted average charging price
POI data	Amap	POI ID, longitude, latitude, POI type	POI density
Population data	LandScan Global[30]	grid ID, longitude, latitude, population density	population density
Road network data	OpenStreetMap	road ID, longitude, latitude, road type	road network density
Land use data	EULUC-China[31]	area ID, longitude, latitude, land use type	land use entropy

Charging station data is collected from [29]. The data analysed is from 19 June to 18 July 2022. It provides details on 647 commercial charging stations in operation, which collectively have over 7,000 charging piles. POI data is collected from the Amap website. The dataset comprises 246,494 POIs sorted into nine categories, including restaurant, hotel, business, education, health, service, finance, transportation and entertainment. To minimise potential noise, health and service POIs are excluded from further analysis [5], as they do not appear to have any direct association with charging behaviours. Population data is collected from LandScan Global [30] and recorded as square grid data at a one kilometre resolution. Road network data is gathered from OpenStreetMap, encompassing primary road, secondary road, tertiary road, trunk road, motorway and minor road. There are approximately 13,720 road segments in Guangzhou. Land use data is gathered from EULUC-China [31]. It is categorised into five classes, including residential, commercial, industrial, transportation and public management and service.

3.2 Buffer-based variables

Establishing geographical buffers allows for improved summarisation of the features present near the charging stations, including POI and population data. The Voronoi diagram is a prevalent tool for establishing edges between adjacent buffers, preventing any overlapping occurrences [10, 32]. However, applying Voronoi diagrams directly can result in significant variations in the buffer area due to the uneven distribution of charging stations in the area. Nonetheless, it is improbable for distant locations in the region to be impacted by the presence of this charging station. So first, all charging stations are grouped into clusters with a threshold, and the centre of the cluster is the average of the station locations within that cluster. The threshold is determined by hierarchical clustering [10]. Most stations are less than 500 metres away from the closest station and a 500-metre parameter produces a relatively low Gini coefficient (keeping different buffers evenly distributed) while also providing a sufficient number of buffers, therefore 500 metres is chosen as the threshold for clustering. Next, radial boundaries of up to one kilometre were overlaid onto the buffer area of the Voronoi diagram, which is widely regarded as the most acceptable walking distance for most people [33] and is typically used to represent walkable regions when evaluating charging station accessibility [5].

Charging demand. The charging demand of each station is used as the dependent variable and defined as total charging energy consumed in one month. *Figure 1a* exhibits the spatial distribution of the charging stations according to their capacities. The buffers generated with charging demand are illustrated in *Figure 1b*. It is evident that there is an imbalance between the supply and demand for charging infrastructure in Guangzhou.



(a) Capacities of charging stations *(b) Charging demand with buffers*

Figure 1 – The supply and demand for charging infrastructure in Guangzhou

Weighted average charging price (WACP). Previous research has analysed the effect of dynamic pricing on charging station usage, which mainly concentrates on short-term changes. However, when addressing the planning problem, it is crucial to consider the impact of charging pricing on charging station usage over extended periods. Let $\mathcal{T} = \{H, M, L\}$ denote the set of periods, which are peak, flat and valley. The WACP of the i^{th} charging station P_i is defined as follows:

$$P_i = \frac{\sum_{\tau\epsilon\mathcal{T}} \alpha_\tau \sum_t p_i^{\tau,t} t}{\sum_{\tau\epsilon\mathcal{T}} \alpha_\tau T_\tau} \tag{1}$$

where α_τ is the relative significance coefficient of the charging price, $p_i^{\tau,t}$ is the charging price of the i^{th} charging station at time t during the period τ, and T_τ is the time during the period τ.

POI density. POIs are locations of interest to the public and represent destinations frequently visited by drivers, which have a significant effect on the usage of charging stations [5, 9]. Areas with high demand for charging often coincide with high POI density. The POI density of the i^{th} charging station X_i^{POI} can be calculated as follows:

$$X_i^{POI} = \frac{\sum_{k=1}^{K} C_{i,k}}{A_i} \tag{2}$$

where $C_{i,k}$ is the count of the k^{th} POI type in the buffer of the i^{th} charging station, K is the number of POI categories and A_i is buffer area of the i^{th} charging station.

Population density. Population density is highly correlated with the drivers' parking behaviour, which could impact the charging demand [5]. In cases where grids overlap with the buffer, the population is determined by applying the ratio of the overlapping area to the grid area. The population density of the i^{th} charging station X_i^{pop} can be expressed as follows:

$$X_i^{pop} = \frac{\sum_{m=1}^{M} A_{i,m} \cdot d_m}{A_i} \tag{3}$$

where d_m is the population density of the m^{th} population grid, $A_{i,m}$ is the overlapping area of the m^{th} population grid and the buffer of the i^{th} charging station and M is the number of grids.

Road network density. Road network density represents the accessibility and connectivity of the road network [10]. The more accessible the charging station is, the more likely it is to attract more EV owners to the station. The road network density of the ith charging station X_i^{road} is calculated as follows:

$$X_i^{road} = \frac{\sum_{c=1}^{C} l_{i,c}}{A_i} \tag{4}$$

where $l_{i,c}$ is the length of the c^{th} road type in the buffer of the i^{th} charging station, and C is the number of road categories.

Land use entropy. Land use entropy is a widely accepted measure of the average diversity of destinations within a metropolitan area at neighbourhood level [34]. Areas with higher land use entropy may provide drivers with more opportunities for lunch or breaks during charging [10]. The land use entropy of the i^{th} charging station X_i^{land} is defined as follows:

$$X_i^{land} = -[\sum_{n=1}^{N} \eta_{i,n} \cdot ln(\eta_{i,n})]/ln\,(N) \tag{5}$$

where $\eta_{i,n}$ is the percentage of the n^{th} land use type in the buffer of the i^{th} charging station, and N is the number of land use categories. The value of land use entropy is between 0 and 1, and a value closer to 1 indicates a more extensive land use.

Guangzhou is chosen as the research area. $\mathcal{T} = \{H, M, L\}$ is determined based on the period division and electricity price standard in Guangzhou [35], as shown in *Table 2*. Since the charging demand varies greatly across periods, electricity price partially reflects the magnitude of charging demand within the period. During p0eriods of high electricity prices, there is a high demand for charging. The relative significance of charging price can be expressed by the ratio of electricity price over time; the resulting values for α_H, α_M and α_L are 0.56, 0.32 and 0.12, respectively. This outcome is in line with [36], which indicates that, for EVs in China, the proportion of charging time is, respectively, 53%, 32%, and 15% during peak, flat and valley periods.

Table 2 – Period division and electricity prices

Period	**Time range**	**Electricity prices (CNY/kWh)**
Peak	$[10h, 12h) \cup [14h, 19h)$	0.9863
Flat	$[8h, 10h) \cup [12h, 14h) \cup [19h, 0h)$	0.5802
Valley	$[0h, 8h)$	0.2205

The analysis employed five factors that reflect variations in charging price, POI, land use, population and road networks. Due to data constraints, it was not feasible to include further features in the analysis. All of the variables are tested for outliers, and their results are given in *Table 3*. As shown in the table, charging demand, POI density, population density, land use entropy and road network density all vary widely, with extreme high values concentrated in some large business districts and extreme low values found in parks, scenic areas and remote suburbs.

Table 3 – Values of the variables

Variables	Symbol	Units	Min	15%	50%	85%	Max
Dependent variable							
Charging demand	D_i	10^3kWh	0.072	5.689	48.640	330.514	2160.239
Independent variables							
WACP	P_i	CNY/kWh	0.45	0.80	1.02	1.28	1.80
POI density	X_i^{POI}	/km^2	0.31	3.25	125.21	411.29	1021.30
Land use entropy	X_i^{land}	-	0	0.140	0.441	0.677	0.904
Population density	X_i^{pop}	10^3/km^2	0.230	1.847	3.393	5.987	43.638
Road network density	X_i^{road}	km/km^2	0.272	1.869	3.954	6.687	11.270

4. METHODS

4.1 Charging demand estimation

A linear regression with an exponential elasticity function [23] is employed to examine the relationship between charging demand and various independent variables. The exponential elasticity function is used to describe how changes in charge price effect demand, assuming demand reacts exponentially to price fluctuations. The charging demand of the i^{th} charging station D_i is defined as follows:

$$D_i = \exp\left[\xi(P_i - P_0)h\right](\boldsymbol{\beta}\boldsymbol{X}_i + b) \tag{6}$$

where ξ is the price elasticity, P_i is the WACP of the i^{th} charging station, P_0 is an acceptable price for most EV owners, h is the amount of power consumed for a full charge, $\boldsymbol{\beta} = [\beta_1, \beta_2, \beta_3, \beta_4]^T$ is the coefficient vector for the four independent variables, $\boldsymbol{X}_i = [X_i^{POI}, X_i^{pop}, X_i^{land}, X_i^{road}]^T$ is the vector for the standardised independent variables and b is an intercept term. China's charging price generally exhibits low elasticity, typically ranging from -0.15 to -0.1 [37]. Therefore, it is reasonable to use -0.15 for ξ. P_i above P_0 will influence the decision of a few EV owners that they may not charge in the i^{th} charging station [23]. According to [36], the price sensitivity low point is the 15% quantile of the charging price at the charging station; it is reasonable to assume P_0 as the 15% quantile of the WACP, 0.8. In general, the power of L2 commercial charging pile is 7.2 kW, which can fully recharge most long-range battery EVs during an eight-hour charge [38], so that h is 7.2*8 kWh.

The coefficient vector is determined using the least-squares regression method and is illustrated in *Table 4*.

Table 4 – Results of the regression analysis (R^2=0.225)

	Coefficients	t-value	Significance
Constant	-0.0226	-0.760	0.448
POI density	0.1768	2.133	0.034**
Land use entropy	0.0754	1.796	0.074*
Population density	0.1801	2.113	0.036**
Road network density	0.1109	1.307	0.193

**Significant at 0.1 level. **Significant at 0.05 level.*

Charging demand throughout the study area is generated using the regression model as outlined in *Equation 6*. Factors such as WACP, population, road network and POI are taken into account. To achieve this, a given area is segmented into several subareas, the shape and dimensions of which can be customised according to the planner's specifications. A dense grid with a uniform size of 1km ×1km is implemented. The design vector $\hat{\boldsymbol{X}}_s = [\hat{X}_s^{POI}, \hat{X}_s^{pop}, \hat{X}_s^{land}, \hat{X}_s^{road}]^T$ for the s^{th} grid is calculated and inserted into *Equation 7*, the potential charging demand in grid s $\hat{D}_s$ is obtained.

$$\hat{D}_s = \begin{cases} \exp[\xi(\hat{P}_{s,i} - P_0)h]\,(\boldsymbol{\beta}\hat{\boldsymbol{X}}_s + b) & \text{if } y_s = 1 \\ \boldsymbol{\beta}\hat{\boldsymbol{X}}_s + b & \text{else} \end{cases} \tag{7}$$

$$\hat{P}_{s,i} = \frac{\sum_{\tau\epsilon\mathcal{T}} \alpha_\tau \sum_t p_i^{\tau,t} t}{\sum_{\tau\epsilon\mathcal{T}} \alpha_\tau T_\tau} \tag{7a}$$

$$\hat{X}_s^{POI} = \frac{\sum_{k=1}^{K} C_{s,k}}{A_s} \tag{7b}$$

$$\hat{X}_s^{pop} = \frac{\sum_{m=1}^{M} A_{s,m} \cdot d_m}{A_s} \tag{7c}$$

$$\hat{X}_s^{road} = \frac{\sum_{c=1}^{C} l_{s,c}}{A_s} \tag{7d}$$

$$\hat{X}_s^{land} = -[\sum_{n=1}^{N} \eta_{s,n} \cdot \ln(\eta_{s,n})]/\ln(N) \tag{7e}$$

$$y_s = \{0,1\} \tag{7f}$$

$\hat{P}_{s,i}$ is the WACP of charging station i in grid s, $\hat{X}_s^{POI}$, $\hat{X}_s^{pop}$, $\hat{X}_s^{road}$, $\hat{X}_s^{land}$ is the POI density, population density, road network density and land use entropy of the s^{th} grid, respectively. For grid s, $C_{s,k}$ is the count of the k^{th} POI type, A_s is the area, $A_{s,m}$ is its overlapping area with the m^{th} population grid, $l_{s,c}$ is the length of the c^{th} road type and $\eta_{s,n}$ is the percentage of the n^{th} land use type. $y_s = 1$ means that there is a charging station in grid s and $y_s = 0$ means that there is none.

4.2 Charging infrastructure planning optimisation

This section employs the previously generated potential charging demand and a Voronoi diagram created from existing charging stations to determine optimal location selection. First, Voronoi diagram is obtained after adding new charging stations. Next, the ESCD is calculated within the intersection area between the Voronoi region and radial boundary of up to 1 kilometre. Finally, the ESCD by new charging stations is optimised by the SSA.

Effective served charging demand

The boundaries of the areas served by the charging station are illustrated in *Figure 2*. To streamline the computation of these areas, they have been divided into three subregions. This categorisation is based on the location of vertices and the edge opposite the charging station. For the pink region, both vertices are situated at the intersection of the Voronoi boundary and the radial boundary, while the edge opposite the charging station is limited by the Voronoi boundary. The yellow region is similar, but its boundary is defined by the radial limit. In the blue area, the Voronoi boundaries are more restrictive, with one vertex at the intersection of the Voronoi boundary and radial boundary and another at the Voronoi boundary. With this, the effective served charging demand (ESCD) $\hat{Z}_a$ of a charging station is calculated by summing the charging demand of each subregion using *Equations 8 and 9*. When charging station a is closer to the adjacent charging stations, its Voronoi border becomes more restricted, reducing the area that the charging station a may service and thus decreasing the computed ESCD.

$$\hat{Z}_a = \sum_{s\in\Omega_a} f_a(s) \cdot \hat{D}_s \tag{8}$$

$$f_a(s) = \begin{cases} [1 - \frac{\text{dist}((\mu_a, \nu_a), (\mu_s, \nu_s))}{R}]^\beta & \text{if } R - \text{dist}((\mu_a, \nu_a), (\mu_s, \nu_s)) \ge 0 \\ 0 & \text{else} \end{cases} \tag{9}$$

Ω_a represents the area served by charging station a, $\widehat{D}_s$ represents the potential charging demand in grid s and $f_a(s)$ represents the distance impact factor for grid s, which ranges from 0 to 1. The geographic distance dist() between charging station a and grid s is determined using the haversine formula. μ_a, ν_a, μ_s and ν_s are the latitude and longitude coordinates of charging station a and grid s, respectively. β is a hyperparameter and R is the service radius. The distance impact factor decreases as the distance between the charging station and the region it serves increases. If the distance is greater than R, the charging station can no longer provide service, and the impact factor is set to 0. At distances greater than 3,000 feet (0.91 km), the willingness of people to walk from a parking location to an event location is significantly reduced [33]. Thus, R is roughly estimated as 1 kilometre. β is typically set to 2 based on empirical evidence.

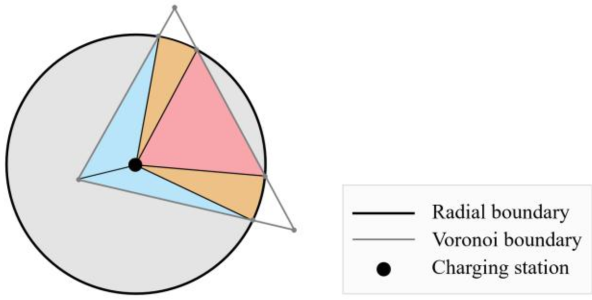


Figure 2 – The limits of the charging station served areas

Regional and individual optimisation

Once ESCD is obtained, the optimal public charging station allocation problem can be addressed by CMSLM. Given the total investment budget, CMSLM optimises the location of charging stations and associated charging piles under the constraint of charging power capacity. Optimisation strategy is presented from both macro and micro perspectives: "regional optimisation" and "individual optimisation". In regional optimisation, the aim is to maximise ESCD across the entire region by summing the charging demand served by all charging stations in the region. This can be interpreted as the government filling gaps in areas with insufficient charging infrastructure while also identifying areas with high potential charging demand and laying out charging infrastructure in advance. The optimisation objective function for region optimisation is represented by *Equation 10*, with the geographic coordinates of the new charging station used as optimisation inputs.

$$\max_{\mu_w,\nu_w} \sum_{e\in E} \hat{Z}_e + \sum_{w\in W} \hat{Z}_w \tag{10}$$

$$\text{s.t.}\ \hat{Z}_a = \sum_{s\in\Omega_a} f_a(s)\cdot \widehat{D}_s \qquad a\in\{E,W\} \tag{10a}$$

$$c\cdot N_a \ge \hat{Z}_a \qquad a\in W \tag{10b}$$

$$N_{min} \le N_a \le N_{max} \qquad a\in W \tag{10c}$$

$$\sum_{a\in W} C_1 + C_2\cdot N_a \le Q \tag{10d}$$

$$N_a \in \mathbb{N} \qquad a\in W \tag{10e}$$

$\hat{Z}_e$ represents the existing charging station's ESCD following the position of the new charging station, and $\hat{Z}_w$ is the new charging station's ESCD. It is important to note that the ESCD for the existing charging station will change as the location of the new charging station changes. E and W are the sets of existing and new charging stations, respectively. c is the capacity of each charging pile for a month. N_a is the number of charging piles for a^{th} station. N_{min} and N_{max} are the upper and lower limits of the number of charging piles for each new charging station, respectively. C_1 and C_2 are the cost of installing a charging station and the equipment cost of a charging pile, respectively. Q is the total investment budget.

Equation 10a is used to update ESCD for both existing and new charging stations. *Equation 10b* guarantees new charging station's charging capacity meets the charging demand. *Equation 10c* ensures the number of charging piles is appropriate for the charging station. *Equation 10d* determines the total budget limit for constructing charging stations and charging piles. *Equation 10e* ensures the number of charging piles is a positive integer.

In individual optimisation, the objective function solely includes the ESCD of the new charging station, which can be interpreted as charging facility construction operators accurately identifying high-demand areas while minimizing competition with surrounding charging facilities and maintaining the attractiveness of their facilities to ensure high revenues. The form of the objective function for individual optimisation is represented in *Equation 11.* The distinction between the two lies in the fact that individual optimisation tends to position new charging stations nearer to existing ones, particularly those with high ESCD, since they are not limited by the constraint of drawing charging demand from existing ones. This is not typically applicable to regional optimisation, as only added service areas can increase the overall charging demand served in the region.

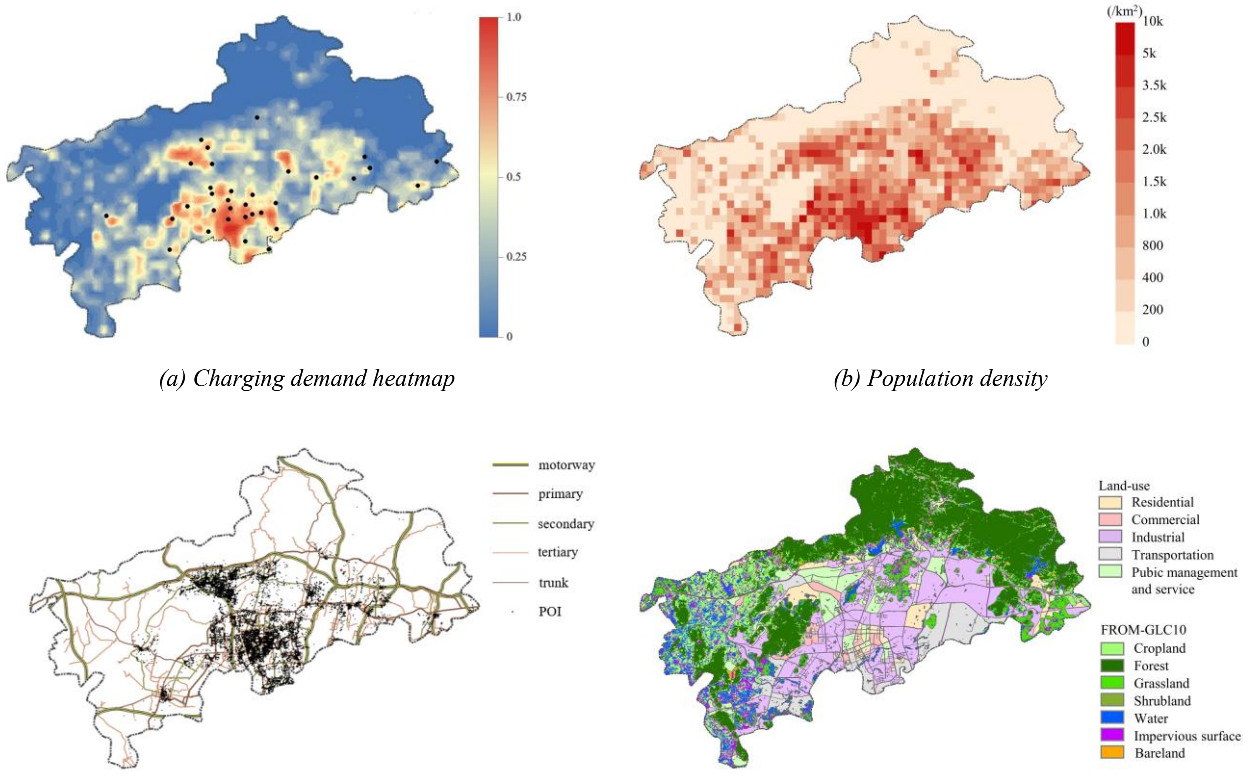
$$\max_{\mu_w, \nu_w} \hat{Z}_w \tag{11}$$

The optimisation problem is non-convex and non-monotonic due to the possibility of multiple global maxima. SSA is a suitable heuristic algorithm for solving these complex optimisation problems, drawing inspiration from the foraging and anti-predation behaviours observed in sparrow populations. The algorithm divides the search group into two distinct parts: the discoverer and the joiner, which divide each other's work to find the optimal value, and at the same time, mimic the real predatory scenarios, and increase the sparrow's danger warning mechanism. Therefore, SSA is advantageous in terms of the searching accuracy, convergence speed, stability and avoidance of local optima.

5. RESULTS AND DISCUSSION

5.1 Regression and heatmap of charging demand

Table 4 displays the results of the regression analysis. The regression followed a linear pattern since the parameters of the exponential term corresponding to the WACP are fixed. All correlations are positive, indicating that POI density, road density, land use entropy and population density have a positive impact on charging demand. The potential charging demand is linearly interpolated to generate more continuous heatmaps. *Figure 3* shows the charging demand heatmap and spatial distribution of POI, road, land use and population density in Huadu district. According to *Figure 3a*, it is clear that the charging stations are primarily concentrated in the central area, where there is a high demand for charging (indicated by the colour red). The surrounding areas also have charging stations, but they are more sparsely distributed and have a relatively lower demand for charging (indicated by the colour yellow). Remote areas are largely devoid of charging stations, corresponding to minimal charging demand (indicated by the colour blue). By examining the spatial distributions of population density, POI density, road network density and land use entropy, we can see that these factors are highly correlated with the distribution of charging demand. Areas with high population density tend to have higher charging demand, as they likely host more electric vehicle users. Similarly, areas with a dense distribution of POIs, such as commercial centres and services, exhibit higher charging demand due to the higher concentration of activities and potential electric vehicle usage. The developed road network in central areas facilitates easy access to charging stations, further increasing the demand. High land use entropy indicates a diverse mix of land uses, which typically attracts more people and, consequently, more electric vehicle charging demand. By combining *Figures 3a–3d*, it becomes evident that charging stations are primarily located in central areas with dense POI distribution, developed road networks, high comprehensive land use, and high population density. In peripheral areas with low POI distribution, low comprehensive land use and low population density, charging stations are distributed along the highway line. This distribution pattern is consistent with the regression results, as all estimated values in the regression are positive. The alignment of these spatial distributions with the regression analysis highlights the importance of these factors in influencing the location and demand for electric vehicle charging stations.



(a) Charging demand heatmap *(b) Population density*

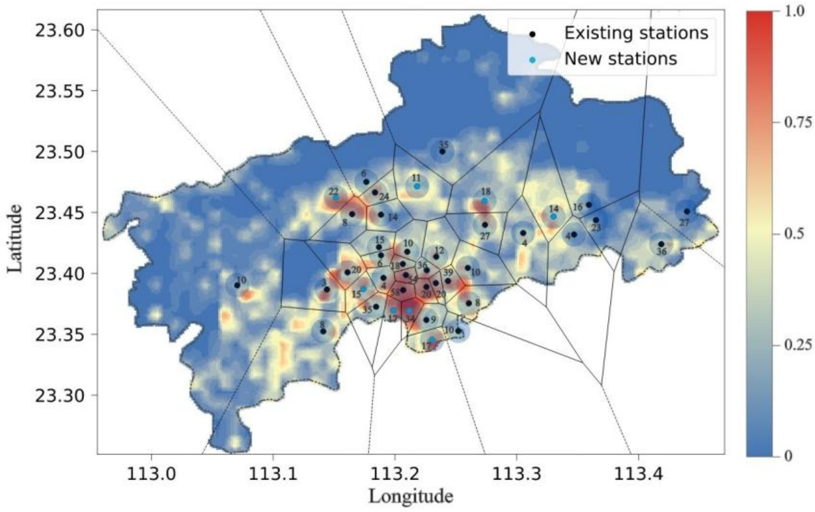
(c) Road network and POI *(d) Land use*

Figure 3 – Charging demand heatmap and spatial distribution of population density, POI, road network and land use in Huadu district. d) is overlaid on 10-m global land cover map (FROM-GLC10) [39].

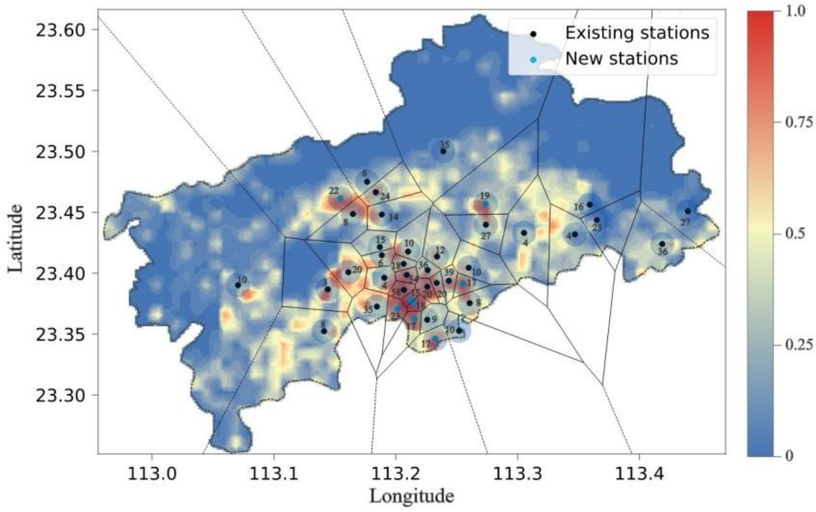
5.2 Optimisation of new charging station planning

Depending on the charging demand heatmap, the positioning of new stations was optimised from two expansion perspectives, as outlined in Section 4.2. Assuming that all public charging stations are freely accessible 24/7, the power of L2 commercial charging pile is generally 7.2 kW [38], and the monthly capacity c is set as 7.2*24*30 kWh. According to the actual deployment of charging stations in Guangzhou, over 95% of existing charging stations have charging piles in the 8–35 range, thus N_{min} is set to 8 and N_{max} is set to 35. The cost of constructing a charging station C_1, including labor and materials, is approximately 40,000 CNY, and the installation cost of a charging pile C_2 is around 18,000 CNY [5]. *Figure 4* illustrates the results of two optimisation perspectives in Huadu district with an investment budget of 3 million CNY. Both optimisation perspectives aim to fill the gaps in highly desirable areas of the city centre, specifically two stations resulting from regional optimisation and four from individual optimisation. The number of charging piles at these four charging stations is similar, suggesting clear competition to divide up the area with the highest charging demand. Another option is to focus on small areas outside the central region with relatively high charging demand, resulting in four stations from regional optimisation and two from individual optimisation. It is evident that newly built stations have a more significant impact on nearby stations under individual optimisation, as it is not limited by the constraint of drawing charging demand from other stations and focuses only on maximizing the ESCD of the additional charging stations. In contrast, the decrease in ESCD of all existing stations due to new stations under regional optimisation is smaller, because its optimisation targets the ESCD of all charging stations in the region, and reducing the ESCD of existing charging stations has no benefit in increasing the overall ESCD level. This behaviour aligns with the previously established optimisation goals, indicating that the earlier objective function is reliable.

Figure 5 displays the changes in the ESCD at each charging station before and after optimisation in Huadu district. The ESCD of all charging stations is more balanced under individual optimisation, resulting in a smaller difference between the highest and lowest ESCD compared to regional optimisation. Combined with *Figure 4*, it can be seen that under individual optimisation, the four charging stations are concentrated in the region with the highest charging demand. This competitive relationship balances them so that the highest ESCD is smaller than under regional optimisation. However, under regional optimisation, the two charging stations adequately satisfy the charging demand in the region with the highest charging demand, so the other charging stations are constructed in regions lacking charging stations. Secondly, the ESCDs of new charging stations under individual optimisation are mostly at the top of the list, while a few ESCDs of new charging stations that are under regional optimisation are in the middle of the range. This suggests that new charging stations under individual optimisation try to locate in high demand areas, while regional optimisation goes more to supplement charging station blank areas, a result that is consistent with both optimisation objectives.

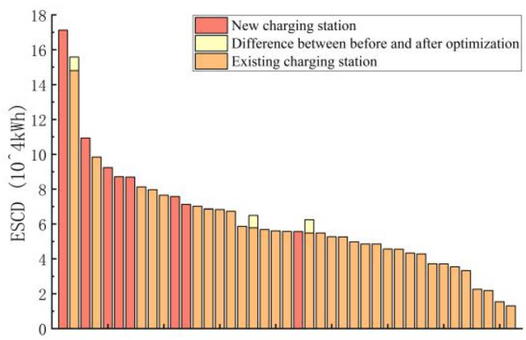


(a) Regional optimisation

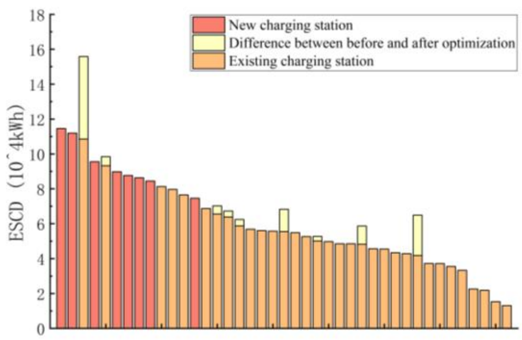


(b) Individual optimisation

Figure 4 – Existing and new stations in Huadu district as decided by the a) regional and b) individual optimisation. The number on each dot indicates the number of charging piles in the station. The shaded area surrounding each station shows the area in which each station can serve for the charging demand.



(a) Regional optimisation

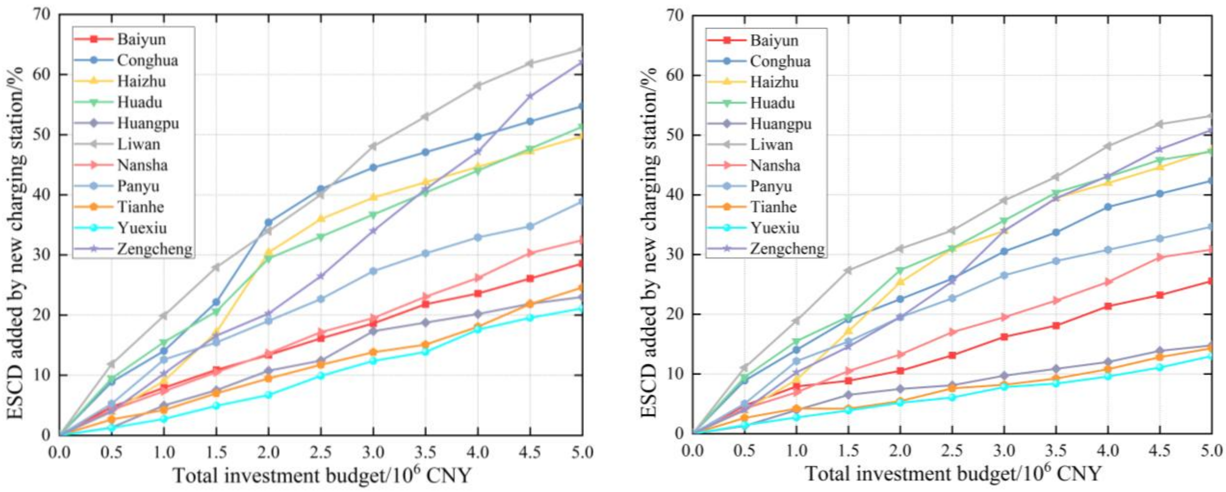


(b) Individual optimisation

Figure 5 – Changes in the ESCD at each charging station before and after optimisation

5.3 City scope

By aggregating the ESCD of the district encompassed by charging stations in each region, the outcomes at the citywide level can be comprehended. *Figure 6* presents the consequences of the changes in ESCD by adding new stations. The results indicate a positive correlation between the ESCD and the total investment budget, though the rate of increase appears to be gradually slowing down. This deceleration suggests that while additional charging stations are still necessary to meet demand, the effectiveness of each new station diminishes as the network expands. The regional optimisation results in a higher improvement level of the ESCD compared to the individual optimisation. On average, after increasing the investment budget to 5 million CNY, the ESCD of all districts under macro and micro optimisation perspectives increases by 41.0% and 34.1%, respectively. This suggests that there is some competition among the charging stations, but it is not too intense. As shown in *Figure 4*, in contrast to regional optimisation, which tends to favour locations situated at a considerable distance from the centre and devoid of charging stations, individual optimisation is more inclined to prioritise competing for the highest-demand areas within the central region. These findings apply to the other 10 administrative districts as well. Additionally, under the same budget conditions, economically underdeveloped administrative districts (e.g. Zengcheng district) tend to exhibit a higher level of ESCD enhancement than their economically developed counterparts (e.g. Tianhe district). This is because the latter have a high level of pre-existing ESCD, and the percentage that can be enhanced with the same budget is relatively low.



(a) Regional optimisation *(b) Individual optimisation*

Figure 6 – Increased ESCD by adding new stations to existing infrastructure using a) regional and b) individual optimisation

The results of the regional optimisation were found to be higher than those of the individual optimisation in improving the ESCD in the study area. Therefore, the former was used to subtract the latter's results, and differences in the ESCD are shown in *Figure 7*. Tianhe and Huangpu districts, which are economically developed, have a high demand for charging infrastructure. However, there is a severe lack of charging stations in these high-demand areas. The individual optimisation has resulted in new charging stations being concentrated in these areas, which does not effectively enhance the ESCD of the entire administrative district when compared to the regional optimisation. Haizhu, Baiyun and Panyu districts, which have a moderate economic level, show little difference between the two optimisation perspectives. This is likely due to the even distribution of charging demand within the district, resulting in less competition between charging infrastructure. As a result, the outcomes of both optimisation perspectives are similar. Economically underdeveloped districts like Conghua and Liwan, have limited charging infrastructure due to insufficient construction in the district. The new stations under individual optimisation are concentrated in the centre, neglecting peripheral areas with high charging demand. Regional optimisation, however, addresses these neglected areas, leading to a more balanced enhancement of ESCD across the district. These findings underscore the importance of considering both economic context and spatial distribution when planning charging station networks to achieve the most effective outcomes.

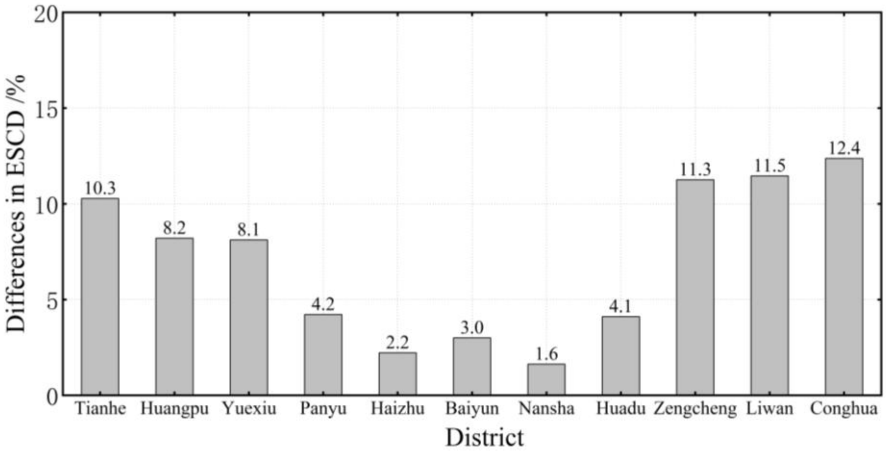


Figure 7 – Differences in the ESCD by regional and individual optimisation. The administrative districts are ranked in descending order based on their GDP in 2022 [40].

6. CONCLUSION

This study presents a two-stage approach for charging demand estimation and new charging station planning optimisation. First, WACP is proposed to measure the long-term stable price attribute of charging stations, and a linear regression with an exponential elasticity function is established to examine the relationship between charging demand and various independent variables. Secondly, an ESCD is proposed to accurately calculate the charging demand of effective service areas, which considers the distance impact factor and competition between neighbouring charging stations. A CMSLM is proposed to optimise the spatial layout of public charging stations by maximizing their ESCD, taking into account the constraints of investment budget and charging station capacity. Then the proposed optimisation strategy based on the SSA provides a reliable solution from both macro and micro perspectives. From a macro perspective, the optimisation goal is to maximise the ESCD of all charging stations across the region, while from a micro perspective to maximise the ESCD of an individual charging station.

The real-world charging data in Guangzhou is used as the case study. A heatmap visualizing the predicted charging demand shows that charging stations are concentrated in central areas with high charging demand, which corresponds to dense POI distribution, developed road networks, high comprehensive land use and high population density. The remaining charging stations are distributed along highways. This distribution is consistent with the regression results and verifies the validity of the regression model. On average, after the investment budget is increased to 5 million CNY, the ESCD of all districts under macro and micro optimisation perspectives increases by 41.0% and 34.1%, respectively. And macro optimisation produces better results than micro optimisation, with a difference in the level of the ESCD increase between the two optimisation perspectives of economically developed Tianhe and Huangpu districts and economically underdeveloped Conghua and Liwan districts ranging from 8.1% to 11.5%. The difference in the ESCD improvement levels at the medium economic level between Haizhu, Baiyun and Panyu districts is 1.6%–4.2%. The obtained results for the placement of new stations, while based on simplified assumptions, can still provide decision-makers with preliminary reference charging station locations.

The proposed charging demand estimation model faces limitations due to the lack of dynamic data such as real-time traffic, weather conditions and grid connection information, which are crucial for accurately forecasting charging demand. For example, real-time traffic data might disclose peak hours and congestion patterns, directly impacting charging station utilisation, whereas weather data could highlight seasonal or daily fluctuations in EV charging behaviour. Additionally, the regression model employed is relatively simple, making it insufficient to fully explain the complex relationships between charging demand and various influencing factors, and some model parameter assumptions can also affect the results. As a result, while new charging stations may be built near the optimal locations suggested by the model, they are unlikely to match these locations exactly. Future research should address these limitations by incorporating the omitted factors and employing more sophisticated models to investigate the deeper correlations between charging demand and influencing factors, which would improve the model's accuracy and reliability.

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王秋璇，邓坤祥，颜江楠，李军

基于宏观和微观视角的电动汽车充电站规划优化

摘要
随着城市地区电动汽车保有量的不断增长，对公共充电空间的需求也日益增加。由于现有充电设施无法满足不断增长的充电需求，因此有必要规划新的充电基础设施。

本文从宏观和微观角度出发，提出了公共充电基础设施规划的两阶段方法。首先，综合考虑充电需求因素，采用指数弹性函数线性回归模型估算充电需求。其次，考虑到距离影响因素和相邻充电站之间的竞争，提出了有效服务充电需求（ESCD），以精确计算有效服务区域的充电需求。在考虑投资预算和充电站容量限制的情况下，提出了一种容量最大服务位置模型（CMSLM），通过最大化充电站的 ESCD 来优化公共充电站的空间布局。CMSLM 采用麻雀搜索算法，从宏观和微观两个角度进行求解。以中国广州为例，应用了所提出的方法。结果表明，当投资预算增加到 500 万人民币时，在宏观和微观优化视角下，各区的 ESCD 平均分别增加了 41.0% 和 34.1%。优化后的充电站可以弥补充电需求与现有充电站分布之间的空间失衡，为进一步的建设实施奠定基础。

关键词
电动汽车;充电需求估计;充电基础设施规划;选址