IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 4 February 2024, accepted 19 February 2024, date of publication 23 February 2024, date of current version 1 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3369446

RESEARCH ARTICLE

Research on Location and Capacity of Electric Taxi Charging Station Based on Floating Car Data

LI XIAO WANG[1,2], CHAO MA[3], SHI JUN LU[1,2], AND KANG LI WU[4]
[1]College of Civil Engineering and Architecture, Xinjiang University, Urumqi, Xinjiang 830047, China
[2]Xinjiang Key Laboratory of Building Structure and Earthquake Resistance (XJDX1703), Xinjiang University, Urumqi, Xinjiang 830047, China
[3]College of Business, Xinjiang University, Urumqi, Xinjiang 830047, China
[4]Liangping District Urban Construction Service Center, Chongqing 405200, China

Corresponding author: Li Xiao Wang (xjwanglx@foxmail.com)

ABSTRACT As the electric vehicle industry continues to grow on a large scale, the challenges related to the locating and sizing of charging stations are becoming more apparent. This paper utilizes floating car data from Urumqi, considering factors such as battery SoC, usage time, and the diverse preferences of electric vehicle drivers when making charging decisions. Through this approach, this paper predicts the charging demands of electric vehicles and formulates a model for optimal locating and sizing based on these predicted needs. The research findings indicate that by simulating charging decisions made by electric vehicle drivers, a total of 10,766 charging demands were identified. In comparison, there were 14,759 parking events extracted from the floating car data. This approach reduced redundancy in charging demand predictions compared to directly using the floating car data for extracting parking events. When considering the locating of charging stations, the strategy of exclusively installing fast-charging stations showed better results than the approach involving a mix of fast and slow charging stations. When the decision of locating prioritized minimizing unmet charging demands, it successfully addressed a minimum of 130 additional charging demands. Similarly, when minimizing the idle time for electric taxi drivers was the primary concern, this approach led to a reduction of at least 109 hours in idle time; through a reallocating and sizing adjustment of charging piles within the charging station based on the locating plan, it was possible to meet an additional 83 charging demands. This modification also significantly reduced the average idle time for users, decreasing from an average of 4.26 minutes to 2.63 minutes. Moreover, the charging piles' average usage time increased, going up from 10.31 hours to 10.42 hours, thus improving the overall efficiency of the charging piles. These findings provide valuable insights for the locating and sizing of charging stations tailored to urban electric taxis.

INDEX TERMS Floating car, heterogeneity, location and capacity of charging station, multi-objective planning, NSGA-II.

I. INTRODUCTION

Electric vehicles have gained widespread favor among governments and populations globally due to their energy-saving, environmentally friendly, and low-carbon attributes. With the rapid growth of electric vehicle ownership in China, the expansion of charging piles has significantly lagged behind the surge in electric vehicle numbers. Consequently, electric vehicles are confronted with substantial charging pressures according to [1] and [2]. Thus,the optimization of locating and sizing of charging stations, aimed at achieving a balance between station revenue and user satisfaction, stands as a pressing issue in this field as demonstrated in [3] and [4]. Nonetheless, appropriate locating and sizing require data regarding the distribution and capacity of parking lots, an exploration of the road network and traffic flow within

The associate editor coordinating the review of this manuscript and approving it for publication was Giacomo Fiumara.

the planned regions, and meticulous planning of power grid capacity. The absence of such data frequently results in challenges such as suboptimal layouts and under utilization of resources as mentioned in [5]. The maturation of data collection via floating cars has effectively addressed the data limitations that previously hindered the locating and sizing of charging stations. Maciejewski et al. [6], presents research on large-scale microscopic simulation of taxi services in Berlin and Barcelona based on floating car data collected by local taxi fleets. Therefore, using extensive floating car data can now offer essential data support for developing a more rational and efficient layout of charging stations.

Predicting charging demands plays a decisive role in determining the location and size of charging piles, serving as the foundation for decisions regarding charging stations. In the early stages of research, the trajectory data of electric vehicles were scarce, and researchers relied on relevant statistical data to project charging demands. Jia et al. [7], based on electric vehicle ownership and driving statistics, calculated the overall charging demands for electric vehicles. Similarly, Tian et al. [8], utilizing data from the U.S. National Household Travel Survey (NHTS), considered variables like the onset of charging, daily travel distance, and charging power. They combined these factors with the Monte Carlo method to predict the power needs of charging for both individual and multiple electric vehicles. Sadeghi-Barzani et al. [9], employed an indirect approach by forecasting vehicle ownership to predict charging demands. These studies utilized statistical data such as vehicle ownership, electricity load, regional population figures, and more to estimate the charging demands. While statistical data is readily available, it is worth noting that since charging demands originate from the usage patterns of electric vehicles, predictions solely based on statistical data might not authentically represent the actual charging demands. Other researchers have proposed methods that leverage the traffic flow of road network charging demand prediction. Gao et al. [10], considered energy consumption along road segments as an indicator of charging demand. Wang and Lin [11], used traffic flow at road intersections in combination with variables of energy consumption rate to predict charging demand. He et al. [12], adopted an Origin-Destination (O-D) approach to forecast charging demand within road networks. These methods consider charging demand solely from a spatial perspective, overlooking the impact of factors such as time, battery state of charge, and drivers' decisions on charging demand. This limitation results in less precise predictions of charging demand. Therefore, some researchers have taken a micro-level approach to dynamically simulate travel patterns of electric vehicles for charging demand prediction. Zhao et al. [13], based on the theory of trip chain, achieve a refined simulation of users' behavior patterns. They then analyze the charging demand in different stopping areas based on two charging behaviors. Similarly, Wen et al. [14], also leveraging the theory of trip chain, simulate travel behavior to subsequently compute charging demand for various functional zones. However, in real-world scenarios, the travel destinations of electric vehicles exhibit randomness, leading to a lack of precise spatial information in these methods, resulting in suboptimal charging demand predictions. With a matured technology of floating car data, its accurate spatiotemporal information provides data support for precise predictions of charging demand. Extracting parking events from floating car data, Hua et al. [15], consider them as charging demands, thereby constructing a model for locating and sizing. Methods for predicting charging demand of this nature rarely encompass all three elements-spatial information, spatiotemporal information, and battery SoC-in their predictions simultaneously. Approaches that derive charging demand predictions from the trajectory data of floating cars and incorporate accurate spatiotemporal information represent a future research trend according to [16], [17], and [18], Additionally, the diversity in drivers' charging decisions influences real-world charging demand as demonstrated in [19]. In summary, we can only achieve more precise predictions of charging demand by concurrently considering spatial information, spatiotemporal information, battery SoC, and diversity in driver decisions.

Based on the form of charging demand, classical models for locating models can be categorized into point demand locating and flow demand locating models. Point demand locating traces its roots back to the P-Median model introduced by Hakimi in 1960. In this model, the known parameters include the positions and demands of specific points, the locations of potential facilities, and the number of facilities to be established. The goal is to formulate a locating model that minimizes the sum of distances between each demand point and its corresponding facility as mentioned in [20]. Flow demand locating, on the other hand, finds its origin in the flow-capturing location-allocation model proposed by Hodson in 1990. In this model, the parameters involve traffic flow data for various road segments within a transportation network. The objective is to strategically place multiple facilities to ensure every potential route passes through at least one of these locations, aiming to maximize the coverage of services according to [21]. Point demand locating models assume that electric vehicles charge either at their starting or destination points. In contrast, flow demand locating models assume that charging demand arises while vehicles are in motion during their journey. However, due to the existing technology limitations, the charging time for electric vehicles is relatively long, and drivers typically prefer destination charging over en-route charging as mentioned in [22]. Hence, point demand locating is more suitable for arranging charging piles within urban environments than flow demand locating. In early research, the focus primarily revolved around single optimization objectives. Dong et al. [23], introduced a variant of locating model based on the maximum coverage model. Based on Cai's work, Asamer et al. [24], proposed a decision support system for the locating of charging stations, aiming to minimize the total travel distance, which electric vehicles cannot achieve. In practical scenarios, however, multiple objectives often need to be balanced. Single-objective locating models are inadequate for intricate real-world situations. Subsequent researchers gradually incorporated multiple optimization objectives into their locating models. Mi [25], presented a dual-objective optimal locating strategy that seeks to minimize detour costs while maximizing travel frequency. The aim is to ensure that the limited charging stations in the road network cater to the highest number of demands possible. Chen et al. [26], proposed a multi-objective locating and sizing model for charging stations. Their model encompasses comprehensive optimization goals, including construction and operational expenses of charging stations, charging time, and carbon emissions linked to driving to these stations. Additionally, this model integrates sizing (capacity planning) constraints of charging stations while accounting for carbon emissions. Ficara et al. [27], implemented an agent-based transport model for analyzing traffic in the metropolitan city of Messina (Sicily, Italy). Karaaslan et al. [28], investigated the various factors, both the positive and negative factors associated with electric vehicle adoption and the subsequent effects on pedestrian traffic safety are investigated using an agent-based modeling approach, in which a traffic micro-simulation of a real intersection is simulated in 3D using AnyLogic software. Multi-objective functions are typically chosen from different perspectives, including economic costs of construction and operation [29], users' time costs [30], demand satisfaction [23], travel fulfillment [24], and environmental emission reduction [31]. Optimization models for the layout of charging facilities commonly aim to find optimal solutions from a systemic or user-oriented perspective. From a systemic standpoint, these models are primarily established to minimize the overall construction and operational expenses [32], [33], [34], [35]. This perspective often represents the government or investors in charging piles. While some researchers consider the interests of electric vehicle users alongside the concerns of construction stakeholders, very few studies focus exclusively on the core objective of maximizing the benefits of users. In summary, constructing multi-objective models with an emphasis on the advantages for electric vehicle users aligns more effectively with the evolving mainstream of locating models [36].

Locating a charging station involves defining the types of charging piles to be deployed (such as fast-charging stations or slow-charging stations) and the number of charging units within the station. In the current research, the sizing of charging stations is predominantly determined by eliminating redundant capacity from the total charging demand [37] or by employing queuing theory to establish the sizing of charging units within the station [38], [39], [40]. However, both of these approaches overlook the temporal distribution of charging demand, resulting in relatively short utilization time for the charging piles. Establishing a charging facility network commonly considers multiple types of charging piles, which aligns well with the prevailing characteristics of current networks [24], [41], [42], [43]. Nevertheless, even for operationally-focused vehicles like electric taxis, diverse charging units can cater to their needs during operations. Furthermore, while the cost of a single fast-charging unit ranges from 40,000 to 70,000 yuan, a single slow-charging unit costs only around 3,000 yuan. This substantial cost discrepancy may hold latent optimization potential worthy of exploration.

In light of these considerations, this study extracts parking events from floating car data and employs these events to simulate the charging decisions made by electric taxi drivers. Taking into account the temporal characteristics of charging demand, battery SoC, and the heterogeneous influences on charging decisions arising from factors like station proximity and preferred battery charge levels, the study predicts charging demand. Subsequently, a dual-objective model of locating and sizing is constructed using the results of the charging demand predictions. This model aims to minimize both the unmet charging demands and the idle time in electric taxi drivers (the combined time spent accessing the station and waiting in line). By employing this approach, the study analyzes the optimal locating and sizing of charging stations. Ultimately, this research provides valuable insights into the locating and sizing of charging stations tailored to urban electric taxi services.

II. CHARGING DEMAND ANALYSIS BASED ON FLOATING CAR DATA

Accurately forecasting charging demand stands as a pivotal factor in the locating and sizing of charging stations for electric vehicles. This research, grounded in extensive floating car data containing parking events, takes into account two key facets: the inherent attributes of electric taxis and the diverseness among electric taxi drivers. Through this comprehensive approach, the study simulates the charging decisions made by electric vehicle drivers. In relation to electric vehicles, considerations encompass battery SoC and temporal data. Concerning the individuality of taxi drivers, factors like the maximum acceptable distance to a charging station and the preferred battery charge level are factored in to assess their influence on charging decisions. In effect, this research manages to predict a distribution of charging demand that faithfully mirrors real-world circumstances.

A. EXTRACTING PARKING VENTS

Floating car data (FCD) refers to data collected from moving vehicles, where their information is systematically transmitted to and aggregated by an information processing center. This data is divided into high-frequency and low-frequency categories, distinguished by a time interval of 30 seconds. High-frequency FCD has intervals less than 30 seconds, while low-frequency FCD has intervals exceeding 30 seconds. FCD typically includes details such as the date of collection, time stamps, license plate IDs, vehicle identification number (VIN), geographic coordinates, instantaneous driving speed, and driving direction, among other attributes. The fundamental information encompassed by FCD is illustrated in Table 1.

TABLE 1. The fundamental information encompassed by FCD.

Date	Time	License Plate IDs	Longitude	Latitude	Speed (km/h)	Direction
20170606	113629	XinAN542*	43.823576	87.635237	36	186
20170606	114633	XinAN958*	43.821659	87.634288	54	163

In this study, the initial phase encompassed the preprocessing of floating car data. Employing Matlab, the raw data was structured to extract the daily trip chain for taxi vehicles based on their date and license plate ID. Situations within these trip chains, characterized by consecutive instances of zero instantaneous speed, were identified as parking events. Parking event data with durations surpassing 20 minutes were then isolated and set aside as supplementary data.

B. OTHER RECOMMENDATIONS PARAMETER CHARACTERISTICS OF ELECTRIC TAXIS

In this study, the conversion of gas-powered taxis to electric taxis is postulated. To maintain the operational behaviors of taxi drivers, the charging activities for electric taxis are planned to occur during their parking periods. Since the historical statistics of the battery power of electric taxis in Beijing are complete and valid, and there is no battery power information in Urumqi, there is no relevant statistical data to support the study for the time being, so the study is based on the statistical data of the battery information of electric taxis in the Beijing area, and allocates the battery power information of electric taxis to the parking nodes of the parking time in the parking events.

1) BATTERY SOC

The State of Charge (SoC) in an electric vehicle serves as an indicator of the remaining battery capacity, Battery SoC reflects the remaining capacity of electric vehicle batteries and is expressed as a decimal between 0 and 1. A value closer to 1 signifies a battery with a charge level near 100%, while a value nearer to 0 indicates a nearly depleted battery that requires immediate charging. Novosel et al. [44], modelled the hourly distribution of the energy consumption of EVs and use the calculated loacurves to test their impact on the Croatian energy system. In this study, the methodology introduced by Chen et al. [45], is adopted, utilizing historical data derived from the battery SoC of electric taxis in Beijing. The average battery SoC of multiple electric taxis within each hour over a 24-hour time frame is taken as the representative information for electric taxis during different hours. The distribution of this information is depicted in Figure 1.

2) TEMPORAL INFORMATION

Temporal information has a direct impact on SoC data. Considering the two-hour time difference between Urumqi and Beijing, adjustments were incorporated into the study by projecting the remaining battery SoC two hours ahead. Given the sporadic occurrence of parking events throughout the day and the discrete nature of existing historical data, a transformation was needed to convert the information of battery SoC into a continuous curve that evolves with time. To achieve this, the curve fitting toolbox within Matlab R19b was employed, as illustrated in Figure 2.

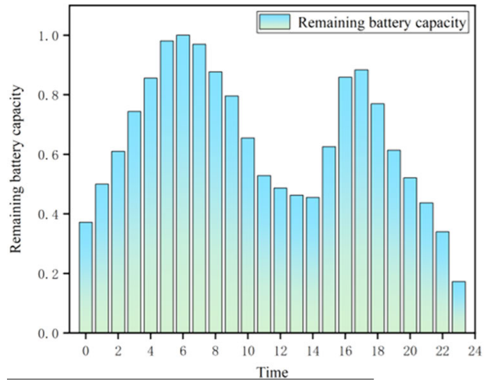

FIGURE 1. The distribution of battery power state over time.

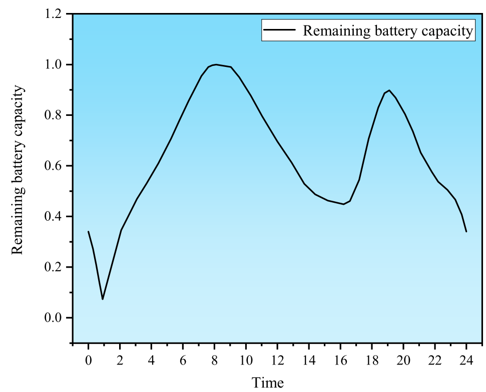

FIGURE 2. The corrected battery power state over time conversion curve.

C. ANALYSIS OF CHARGING BEHAVIOR AMONG ELECTRIC TAXI DRIVERS

This study treats taxi drivers as distinct individuals and introduces two parameters: the maximum acceptable distance to reach a charging station and the preferred battery SoC. These parameters capture the behavior diversity in electric taxi drivers. The maximum acceptable distance to a charging station indicates that each driver will only charge within a certain distance range when the need arises. The preferred battery SoC, termed as the comfortable battery level, represents the electric taxi driver's desire to maintain the battery level above a specific threshold.

1) MAXIMUM ACCEPTABLE DISTANCE TO REACH CHARGING STATIONS

Unlike traditional approaches used in prior studies to capture charging demands at stations, this research introduces the concept of the maximum acceptable distance that electric taxi drivers are willing to travel to access a charging station. This means that the taxi driver takes the point where the parking event occurs as the centre of the circle and the distance to the furthest acceptable visiting charging station, determined by the size of the remaining battery power of the electric vehicle, as the radius, and chooses a charging station by independent decision. In this study, the acceptable distance range for electric taxi drivers to access charging stations is set between 2km and 5km. These boundary values are drawn from the extreme values corresponding to the radius settings of charging station services previously established. The probability distribution of charging station distances is based on the linear satisfaction assumption proposed by Chu's [46].

2) PREFERRED BATTERY SOC

The term "preferred battery SoC" refers to a specific battery charge level that users find personally satisfactory. To draw an analogy from everyday life, consider the preferred battery SoC individuals have for their mobile phones. When the battery SoC drops below this threshold, a need to charge arises. This phenomenon holds true for the charging decisions made by electric taxi drivers as well. In light of this, this study extends this concept to the context of electric taxi drivers. It posits the existence of a certain battery SoC that provides a comfortable experience. When an electric taxi is parked for an extended period (in this study, defined as 20 minutes or longer), if the battery SoC falls below this specified level and available charging piles are unoccupied, electric taxi drivers will have a charging demand.

In this study, the preferred SoC is defined within the range of [60%, 90%], and it follows a normal distribution with a mean of 0.75 and a variance of 0.05. If a randomly generated value falls beyond this range, it is adjusted to the nearest boundary value. The lower limit of 60% is derived from Pan's research as demonstrated in [22], which analyzed the probability distribution of electric vehicle drivers' charging behavior based on different levels of battery SoC. The findings indicate a significant drop in the probability of drivers choosing to charge when their battery SoC exceeds 60%, with probabilities falling to less than 20%. The upper limit of 90% is determined based on Chen's study [47], which recommends maintaining an electric vehicle's battery SoC within the range of [10%, 90%]. Both excessive discharging and overcharging can adversely affect battery longevity.

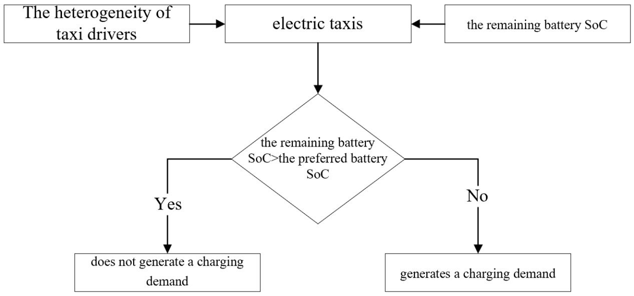

FIGURE 3. **The process of generating charging demand.**

D. CHARGING DEMAND FOR ELECTRIC TAXIS

Based on the time points at which parking events start, values are assigned to electric taxis based on the curve depicting the transformed SoC over time. This process involves assigning SoC values to electric taxis during parking events, considering both the distribution of electric taxi drivers' maximum acceptable distance to charging stations and the distribution function of users' preferred SoC. After data processing, the electric taxis involved in parking events possess information regarding their parking location, duration, battery SoC, as well as the driver's maximum acceptable distance to charging stations and the preferred SoC. Built upon these factors, the assessment of charging demand is carried out.

The data source for this study is floating vehicle data, which captures charging demand through stopping events of the floating vehicles. However, this data alone cannot precisely determine the current state of charge of the vehicle. Therefore, in this study, it is assumed that electric vehicle (EV) drivers generate a charging demand when the remaining battery power of the EV falls below the comfort battery power level. The process of determining charging demand is depicted in Figure 3. In other words, charging demand is triggered when the remaining battery power of the EV is less than the comfort battery power level. Conversely, if the remaining battery power exceeds the comfort battery power level, the EV driver does not generate a charging demand.

III. CONSTRUCTION OF THE LOCATING AND SIZING MODEL FOR CHARGING STATIONS

This study aims to dynamically develop a dual-objective and driver-centric locating model for charging stations, considering a fixed budget. The primary objectives are to minimize both the number of unmet charging demands for electric taxis and the idle time of electric taxi drivers (which includes the time spent visiting charging stations and waiting in queues). Furthermore, the sizing model for charging stations, built upon the locating model, focuses on refining the algorithms for determining the sizing of charging stations. Although the charging reservation system will partially alleviate the charging queuing phenomenon, if the charging station layout is unreasonable and the charging facilities are insufficient, it is the root cause of the queuing phenomenon, therefore the location and capacity model in this study is also applicable to

TABLE 2. Electric taxi related parameters.

Battery capacity	51.2kwh
Fast charge rate	60kw/h
Slow charge rate	7kw/h

the charging station location and capacity under the charging reservation system.

A. ASSUMPTIONS FOR THE CHARGING STATION SITING MODEL

1) CANDIDATE STATIONS

In the current research on the locating of charging stations, the principle is to minimize construction costs while ensuring suitable placement areas. In this study, existing gas stations within the city are considered as potential candidate charging stations.

2) ELECTRIC TAXI

Considering both price and driving range, this study assumes the BYD E5 as the representative electric taxi model. And the specific technical parameters are shown in Table 2.

3) OTHER ASSUMPTIONS

The charging decision is influenced by a variety of factors. To streamline the model and facilitate solution processes, the following assumptions are made:

Assumption 1: Traffic congestion is not taken into account; the average vehicle speed is set at 50 km/h.

Assumption 2: Users have the capability to use a mobile app to access information about the status of all charging piles at charging stations within the research area, enabling direct charging reservations.

Assumption 3: Queuing is only considered for fast charging stations; queues are not considered for slow charging stations.

Assumption 4: If slow charging can restore a preferred battery SoC, drivers prioritize slow charging (due to potential obstacles and inconveniences caused by moving the vehicle during charging).

Assumption 5: If a slow charging station nearby can fulfill the demand, users opt for the closest one.

Assumption 6: When fast charging can meet the demand, users choose the fast charging station with the highest charging capacity.

Assumption7: If both fast and slow chargers can meet the demand, the slow chargers are preferred because the cost of using slow chargers is lower.

Assumption 8: To avoid disrupting taxi operations, the entire charging time is limited to less than or equal to the duration of the parking event.

B. THE SIZING MODEL FOR CHARGING STATIONS

This study aims to develop a dual-objective dynamic locating model while adhering to a fixed construction budget. The primary objectives are twofold: first, to minimize the unmet charging demands of electric taxis, and second, to minimize the idle time experienced by electric taxi drivers. This idle time comprises the duration spent accessing charging stations and waiting in queues. The model is designed with a focus on electric taxi drivers and operates within the constraint of the total number of charging stations. In this context, the objective function (2-1) aims to minimize the number of unmet demands, while the objective function (2-2) aims to minimize the idle time of electric taxi drivers. Constraint (2-3) indicates that the number of charging stations constructed (P) and constraints (2-4) and (2-5) are represented as binary variables (0-1).

$$Min \sum_i f_i \tag{2-1}$$

$$Min \sum_i \sum_j Y_j S_{ij} W_{ij} + \sum_i \sum_j Y_j S_{ij} \frac{D_{ij^{\omega}}}{v} \tag{2-2}$$

$$\sum_j Y_j = P \tag{2-3}$$

$$f_i \in \{0, 1\} \tag{2-4}$$

$$Y_i \in \{0, 1\} \tag{2-5}$$

where i represents the demand point, j represents the candidate station. fi is a binary variable, taking the value of 1 if demand point i is not satisfied and 0 otherwise. Dij is the distance from demand point i to charging station j. Sij is a binary variable, taking the value of 1 if demand point i charges at candidate station j and 0 otherwise. Yi represents a decision, taking the value of 1 if a charging station is established at candidate station j and 0 otherwise. Wij is the waiting time for demand point i at candidate station j. w is the coefficient of detour, set to 1.25. v is the average driving speed, set to 50 km/h.

C. SIZING MODEL OF CHARGING STATIONS

The sizing model builds upon the locating model by focusing on algorithmic improvements. The solving algorithm continues to employ the NSGA-II method, ensuring that each charging station houses a minimum of 3 charging piles. Although the solving procedure remains consistent, the encoding methodology undergoes a transformation. Real number encoding is adopted, with gene values ranging between 0 and 1 as decimals. During the decoding process, these gene values are normalized and utilized to allocate charging piles proportionally. This approach effectively determines the locating and sizing of charging stations.

D. ALGORITHM DESIGN

The algorithm design in this study addresses the optimization of the locating model with dual objectives: minimizing unmet charging demands and idle time for electric taxi drivers. These two objectives are inherently non-commensurable, lacking a unified measurement standard. Hence, the direct application of traditional linear weighting methods to

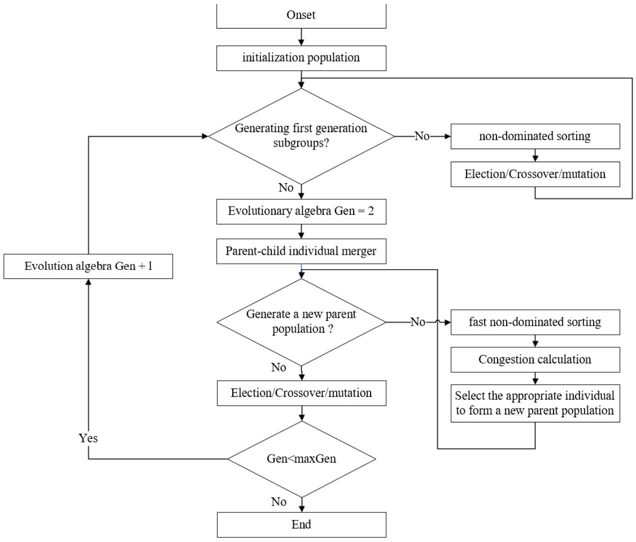

FIGURE 4. The algorithm's workflow.

normalize the objective functions proves challenging. Additionally, considering the extensive scale of the employed floating car data, traditional main objective methods, and layered sequencing techniques suffer from low computational efficiency, repetitive and intricate calculations, and prolonged processing times. The selected algorithm for this study offers several advantages, including high operational efficiency, well-distributed solution sets, strong convergence, and excellent performance in low-dimensional optimization problems. Consequently, this algorithm is the chosen approach for solving the locating model in this research.

The NSGA-II algorithm, also referred to as the Second Generation Non-dominated Sorting Genetic Algorithm, Deb et al. [48], introduced in 2000 as an advanced version built upon the NSGA algorithm. It has gained popularity as one of the most effective multi-objective algorithms. In comparison to the NSGA algorithm, NSGA-II offers superior performance. In this study, distinct models and solutions are developed for different scenarios, and the algorithm's workflow is illustrated in Figure 4.

IV. CASE STUDY ANALYSIS

This study takes Urumqi as the research object for arithmetic analysis based on the above method. First, we obtain the floating car data of gas taxis in Urumqi city, extract the parking events, and use ArcGIS to draw the spatial distribution map of charging demand, on this basis, we model and solve the six working conditions with different ratios of fast charging pile and slow charging pile, and finally obtain the optimal charging station location and capacity model, and the flow of the case study is shown in Figure 5.

A. CHARGING DEMAND PREDICTION

In this study, the floating car data from June 6, 2017, for Urumqi city's gas-powered taxis was utilized (comprising 8,011 taxis on that specific day). All the gas-powered taxis

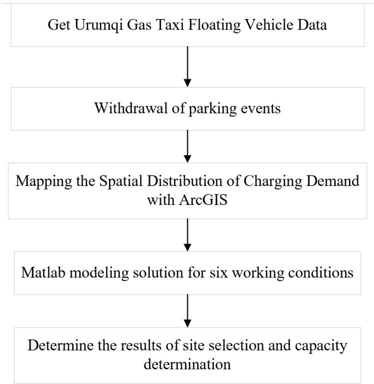

FIGURE 5. Flow chart.

were treated as electric taxis for locating research. Initially, parking events extracted from the floating car data were processed using Python, and the spatial distribution map of charging demands was generated using ArcGIS, as illustrated in Figure 6. The map clearly illustrates that charging demands are predominantly concentrated in Urumqi's four core areas and around the vicinity of the international airport. A total of 14,759 parking events were identified in the floating car data. Based on parking events, battery SoC, time information, and the influence of drivers' heterogeneity on charging decisions are factored in. Thus, a simulation of charging decisions was executed. Consequently, a total of 10,766 charging demands were ascertained, effectively mitigating redundancies in charging demand predictions.

B. LOCATING FOR ELECTRIC TAXI CHARGING STATIONS

1) ANALYSIS OF CANDIDATE STATIONS

In current research on the locating of charging stations, the prevailing principles aim to minimize construction.costs while identifying appropriate locations. In this study, we opted to consider refueling stations as potential candidates for charging stations. Using the Amap platform, we gathered data from 142 refueling stations within Urumqi city, and their spatial distribution is illustrated in Figure 7.

According to national regulations that require a ratio of at least 1:12 between public charging stations and electricvehicles in major cities, such as provincial capitals, on June 6th, 2017, there were a total of 8,011 taxis in the floating car data. This would necessitate the installation of approximately 668 charging stations. Referring to the Code for Design of Electric Vehicle Charging Station (GB50966-2014) as demonstrated in [49], which outlines general guidelines for spatial layout, and considering the average land area occupied by refueling stations, we have determined that each charging station would contain a fixed quantity of 20 charging piles. Consequently, the projected number of charging stations to be established is approximately 34.

The construction cost of a charging station can be divided into fixed costs and variable costs. Fixed costs include the distribution system and monitoring system. Referring to estimates from the Forward-looking Industry Research Institute,

TABLE 3. The arrangement of charging stations and charging piles under various working conditions.

	The number of fast charging piles per charging station	The number of slow charging piles per charging station	Single charging station construction cost (ten thousand yuans)	The Number of charging stations built	Total construction cost ten thousand yuans
Scenario 1	20	0	290	34	9860
Scenario 2	18	2	282	35	9891
Scenario 3	16	4	275	36	9907
Scenario 4	14	6	268	37	9908
Scenario 5	12	8	260	38	9895
Scenario 6	10	10	253	39	9867

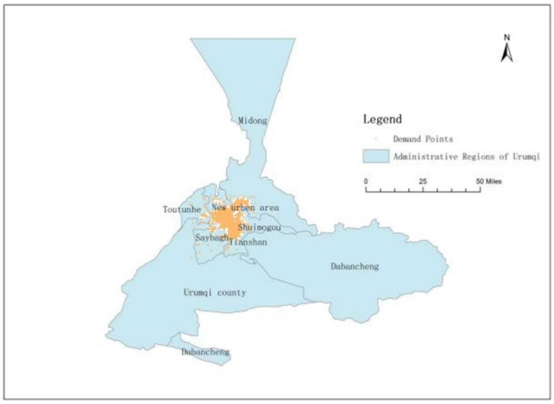

FIGURE 6. The spatial distribution map of charging demands.

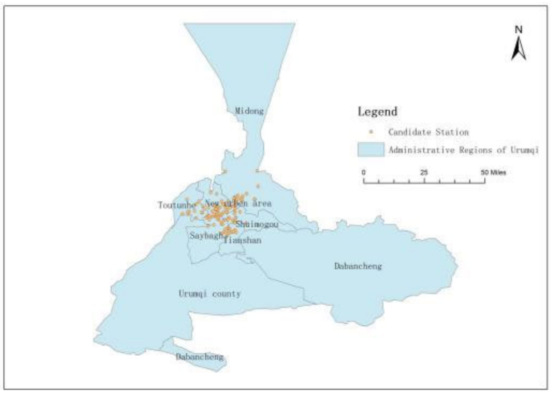

FIGURE 7. The spatial distribution map of potential candidates for charging stations.

the relevant costs are outlined in Table2, resulting in an approximate total fixed cost of 2.1 million yuan for a single charging station according to [50]. Variable costs are directly proportional to the number of charging piles. If the charging demand is entirely fulfilled by fast-charging piles, the overall cost of constructing a charging station would be around 98.6 million yuan. To investigate the optimal proportion between fast-charging and slow-charging piles within the same station, this study assumes a total construction cost of 100 million yuan and performs analysis and solutions for various scenarios, as listed in Table 3.

2) SELECTION OF CANDIDATE STATIONS

In this study, we formulated and solved models for six distinct scenarios. The NSGA-II algorithm was implemented within the Matlab R19b environment, with a crossover probability of 0.8 and a mutation probability of 0.2. The initial population size was set to 200. Using this configuration, we addressed the locating model for electric taxis. After multiple iterations with adjustments, it was determined that for five out of the six scenarios, the convergence of the mean curves for both objective functions was achieved within 100 iterations. However, in the case of Scenario 3, convergence was reached after 160 iterations, and the convergence trends remained consistent across all six scenarios.

Take scenario 1 as an example, where there are 34 charging stations with 20 fast-charging piles each and conducting 100 iterations in the Matlab R19b environment, as depicted in Figure 8. The graph illustrates that both Objective Function 1 (unmet charging demands) and

Objective Function 2 (idle time of electric taxi drivers) show relatively minor fluctuations and gradually converge after around 40 iterations. As the number of iterations increases, Objective Function 1 stabilizes within the range of 1200-1300, while Objective Function 2 stabilizes within the range of 700-800.

The scatter plot for Scenario 1's population is depicted in Figure 9, illustrating a total of 42 solution sets corresponding to 42 distinct layout approaches for charging stations. The objective functions derived for each solution are presented in Table 4. Solution 1 and Solution 42 represent two endpoints of the spectrum. Solution 1's layout scheme minimizes the count of unmet demand points for the 34 fully equipped fast-charging stations, leaving 1243 demand points unfulfilled. However, the value of Objective Function 2 (idle time of electric taxi drivers) reaches a peak at 982.8 hours. Conversely, Solution 42's layout scheme yields the highest count of unmet demand points among all solutions for the 34 full fast-charging stations, with 2285 demand points unaddressed. Nevertheless, its value of Objective Function 2, representing drivers' idle time, is minimized to 578.4 hours. The objective function values of the other solutions fall within the spectrum constructed between these two extreme solutions. For analysis of results, this study selects the extreme solutions for each scenario.

The spatial distribution of charging station layouts for Solution 1 and Solution 42 of Scenario 1 is illustrated in Figures 10 and 11, respectively. In these figures, the horizontal and vertical axes represent the converted planar coordinates of latitude and longitude. Black dots symbolize

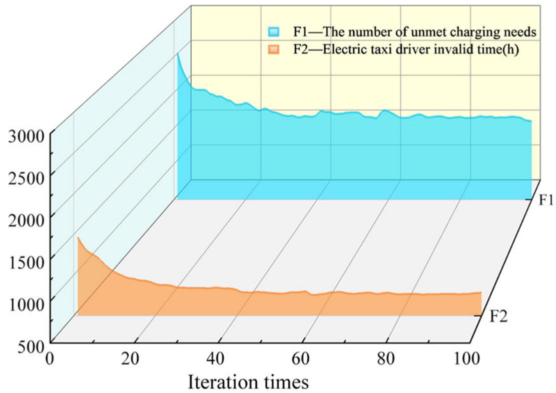

FIGURE 8. The mean value of the objective function of the optimal solution set of condition 1 varies with the number of iterations.

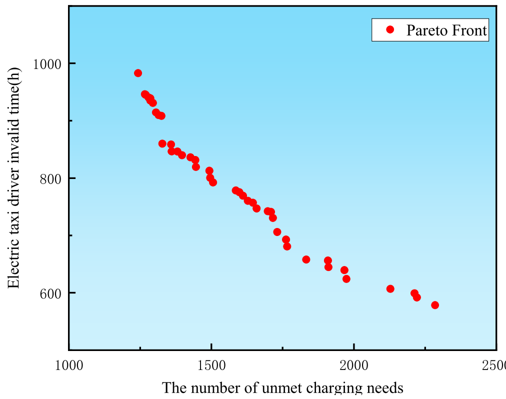

FIGURE 9. The scatter plot for scenario 1's population.

charging demands, blue stars denote candidate charging stations, and red stars indicate the established charging stations at those candidate sites. Solution 1 meets a greater number of charging demands, with relatively larger spacing between charging stations to accommodate more charging needs. Conversely, Solution 42 aims to minimize the time electric taxi drivers spend visiting and queuing at charging stations, resulting in relatively smaller spacing between charging stations. The layout is condensed within central areas of highly-densed demands, leaving regions such as Diwobao International Airport and the Midong District, where charging demands are relatively dense, without a charging station installed.

Extracting Solution 1 from each scenario for comparative analysis, as depicted in Table 5. Objective Function 1, aiming to minimize the number of unmet charging demands, exhibits a fluctuating trend across scenario numbers, with an initial increase, followed by a decrease, and then another increase. This phenomenon stems from the discrepancy between the charging demands captured through the addition of more charging stations and the relatively fewer charging demands addressed by slow charging stations. Regarding Objective Function 1, in contrast to other scenarios, Solution 1 of Scenario 1 caters to at least 130 more charging demands. Solution 1 of Scenario 3 represents the layout with the fewest unmet charging demands among all scenarios featuring slow charging stations. However, it still slightly lags behind the layout of Solution 1 in Scenario 1. Thus, the exclusive utilization of fast charging stations proves more suitable. In comparison to Solutions 2 through 6, Solution 1 of Scenario 1 not only minimizes unmet charging demands but also achieves the shortest idle time for electric taxi drivers.

Comparative analysis was conducted by extracting Solution 42 from each scenario, as presented in Table 6.

In scenarios 1 and 2, where the emphasis is on minimizing unmet charging demands, Scenario 1 exhibited a 109-hour reduction in idle time for electric taxi drivers compared to Scenario 2. This underscores that when the ultimate decision is to simultaneously minimize unmet charging demands and reduce the idle time for electric taxi drivers, the exclusive deployment of fast charging stations is more suitable.

TABLE 4. The calculation results of condition 1.

Serial Number	Objective Function 1	Objective Function 2	Serial Number	Objective Function 1	Objective Function 2
1	1243	982.8005	22	1586	778.4177
2	1267	946.0621	23	1598	775.419
3	1270	944.8776	24	1611	769.2556
4	1280	940.4354	25	1628	760.4281
5	1286	935.0135	26	1646	756.9278
6	1286	938.9647	27	1659	746.9024
7	1295	930.8866	28	1698	742.1868
8	1306	914.4607	29	1709	741.0176
9	1315	909.5803	30	1716	730.3844
10	1325	908.2535	31	1731	706.0706
11	1328	859.8344	32	1762	692.7159
12	1359	858.5581	33	1766	680.654
13	1361	846.4526	34	1833	658.0053
14	1381	846.3598	35	1909	656.2343
15	1397	839.7627	36	1911	644.6407
16	1427	836.0392	37	1967	639.3604
17	1444	831.3082	38	1974	624.135
18	1446	819.2028	39	2128	606.8309
19	1493	812.6739	40	2213	599.2608
20	1496	800.4272	41	2221	591.8516
21	1506	792.2749	42	2285	578.4216

Based on the comparative analysis of endpoint solutions for each scenario, it is evident that whether the focus is on minimizing the count of unmet charging demands or the idle time for electric vehicle drivers, the layout strategy that exclusively utilizes fast charging stations is more advantageous as the ultimate locating decision

C. ELECTRIC TAXI CHARGING SET

Based on the floating car data and the NSGA-II algorithm, we have obtained the layout scheme for electric taxi charging stations in Urumqi. Building on this foundation, we further investigate the initial number of charging piles within each station, which is initially set at an average of 20. However, this setting doesn't accurately reflect the real-world scenario. In areas with high charging demands, charging resources become strained, leading to unmet charging demands. Conversely, in regions with low charging demand, charging piles remain underutilized and inefficient. Taking the layout scheme of Solution 1 in Scenario 1 as an example, the

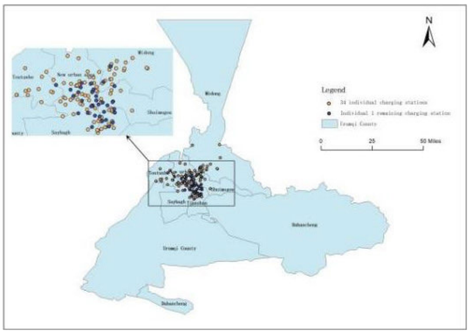

FIGURE 10. The spatial distribution of charging station layouts for solution 1 of scenario 1.

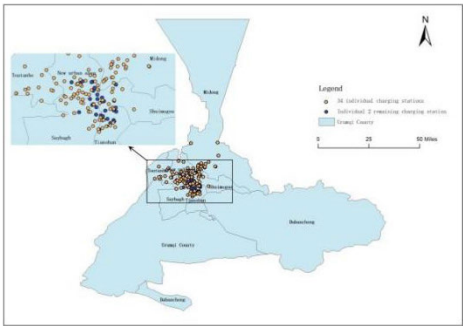

FIGURE 11. The spatial distribution of charging station layouts for solution 42 of Scenario 1.

TABLE 5. The solution of each working condition 1 objective function value.

	Objective Function 1	Objective Function2 (h)
Scenario 1	1243	982.8
Scenario 2	1373	1168.929
Scenario 3	1369	1239.452
Scenario 4	1484	1474.342
Scenario 5	1583	1632.456
Scenario 6	1819	1777.072

utilization of charging piles within Station 1 is depicted in Figure 12, while the utilization of charging piles within Station 14 is shown in Figure 13. In these figures, the horizontal axis represents the time scale, and the vertical axis represents the numbering of charging piles within each station. The length of the small rectangles corresponds to the duration of electric taxi charging, with different colors indicating different charging demands, The number of small rectangles indicates the number of charging demands. In Figure 12, for example, the charging pile numbered 20 within the station fulfills 16 charging demands in a day, whereas in Figure 13,the charging pile numbered 20 within the station serves 7 charging demands throughout the day.

From Figures 12 and 13, it is evident that charging times are concentrated within the time intervals of 0:00 to 6:00 am, 12:00 to 8:00 pm, and 9:00 pm to 0:00. Charging Station 1

TABLE 6. The other endpoint of each working condition solves the objective function value.

	Objective Function 1	Objective Function2 (h)
Scenario 1	2285	578.4216
Scenario 2	2260	687.2192
Scenario 3	2681	674.96
Scenario 4	3098	773.9795
Scenario 5	3201	820.23
Scenario 6	3802	994.7832

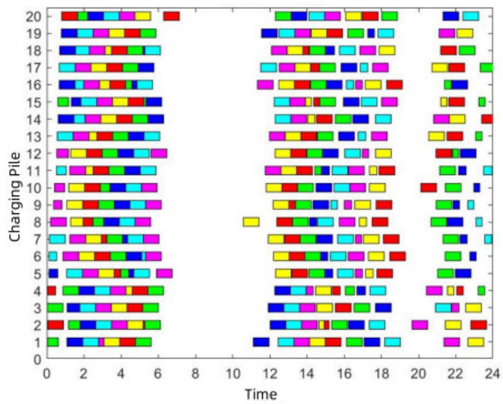

FIGURE 12. The use of charging facilities of charging station numbered 1 in the location scheme of solution 1 of working condition 1.

experiences high demand, with each charging pile being densely occupied. During peak charging hours, there is hardly any idle time, indicating an intense distribution of charging demands near Station 1. On the other hand, at Charging Station 14, during the peak charging hours from 0:00 to 6:00 am, many charging piles remain unused. Additionally, the distribution of fulfilled charging demands from 12:00 to 8:00 pm is relatively sparse. Given this scenario, the study aims to reallocate the layout of charging piles within the selected stations and optimize the sizing of charging stations. The goal is to reduce both the number of unmet demand points and the idle time for electric taxi drivers while simultaneously enhancing the utilization of charging stations.

The reallocation of charging piles within the charging stations is carried out based on the results obtained from Scenario 1, where the locations of the charging stations are already fixed. Taking Solution 1 of Scenario 1 as an illustrative example, the NSGA-II algorithm is applied once again for the optimization process. The fundamental procedure of the algorithm remains unchanged; however, there are modifications in the encoding approach. Real number encoding is employed, with gene values ranging from 0 to 1 represented as decimals. During the decoding process, gene values are normalized, and the distribution of charging

TABLE 7. Charging pile distribution in charging station.

Charging station number	The number of charging piles in the charging station before optimization	The number of charging piles in the optimized charging station	Charging station number	The number of charging piles in the charging station before optimization	The number of charging piles in the optimized charging station
1	20	24	18	20	17
2	20	19	19	20	16
3	20	25	20	20	14
4	20	26	21	20	33
5	20	18	22	20	22
6	20	25	23	20	34
7	20	19	24	20	18
8	20	23	25	20	19
9	20	16	26	20	16
10	20	15	27	20	26
11	20	11	28	20	19
12	20	25	29	20	17
13	20	19	30	20	18
14	20	12	31	20	20
15	20	20	32	20	21
16	20	17	33	20	13
17	20	26	34	20	17

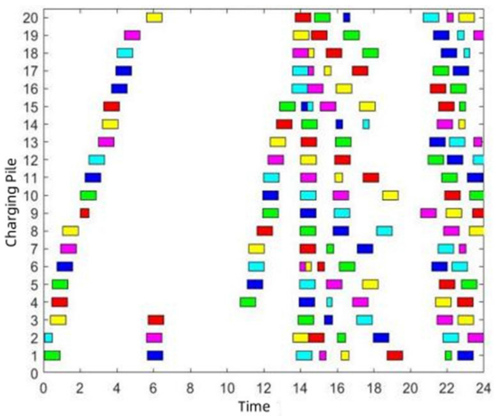

FIGURE 13. The use of charging facilities of charging station numbered 14 in the location scheme of solution 1 of working condition1.

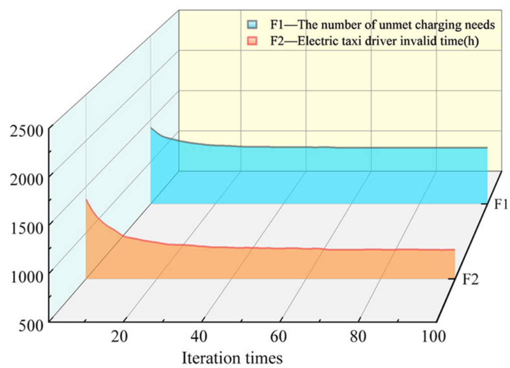

FIGURE 14. The mean value of the objective function of the optimal solution set varies with the number of iterations.

points is determined proportionally. With an initial population of 200 and 100 iterations, both objective functions exhibit minimal fluctuations and converge after approximately 65 iterations. The convergence pattern is visualized in Figure 14, which provides insights into the fact that the average value of objective function 1 (unmet harging demand) hovers around 1170, while the average value of objective function 2 (idle time for electric taxi drivers) centers around 820. The scatter plot depicting the population distribution is presented in Figure 15. The allocation of charging piles for each station is outlined in Table 5. Given that the study utilizes the layout scheme featuring the minimum number of unmet charging demands for sizing, a comparative analysis is conducted against the layout scheme characterized by the minimum unmet charging demand, as highlighted in Table 7.

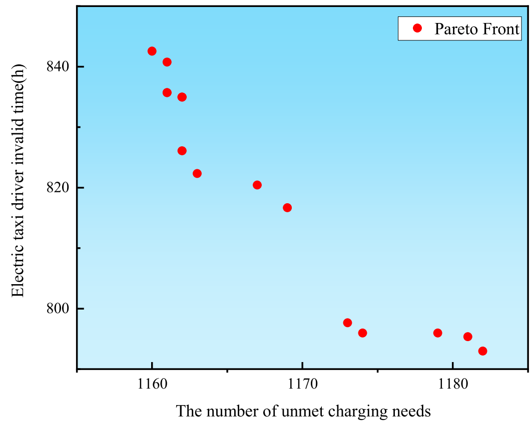

FIGURE 15. The Optimized population scatter plot.

From Table 8, it is evident that the sizing-constrained solution after the reallocation of charging piles can accommodate an additional 83 charging demands while significantly reducing the average idle time for users. This reduction drops from an average of 4.26 minutes to 2.63 minutes. Moreover, the average occupancy time for charging piles increases from 10.31 hours to 10.42 hours. These results underscore the successful achievement of the sizing optimization. This includes reducing unmet charging demands, shortening the time electric taxi drivers spend accessing charging stations and queuing for charging services, and

TABLE 8. **The comparison of results.**

	Results before adjustment	Adjusted results
the unmet charging demands	1243	1160
the average idle time for users(m)	4.26	2.63
the average occupancy time for charging piles(m)	10.31	10.42

simultaneously enhancing the utilization efficiency of charging piles.

V. CONCLUSION

This research is built upon the analysis of parking events extracted from floating car data. It takes into account various factors such as electric vehicles' time information, battery SoC, and the impact of heterogeneity among drivers on charging decisions. This comprehensive approach allows for the prediction of charging demands. Based on these demand predictions, a dual-objective locating and sizing model is constructed for charging stations. The objectives include minimizing both the count of unmet charging demands and the idle time for electric taxi drivers (the sum of time spent accessing the charging station and waiting in queues). The primary conclusions drawn from this analysis are as follows:

(1) In this study, we examine the influence of battery power information, time data, and the inherent diversity among electric vehicle (EV) drivers on charging decisions. We propose a method for predicting charging demand using floating vehicle data, reducing redundancy in charging demand prediction and enhancing its relevance to real-world scenarios.

(2) Our study places a primary focus on maximizing user benefits. We establish a dual-objective model for location and capacity to minimize unsatisfied charging demands and unproductive downtime for electric taxi drivers. This research provides a theoretical foundation for the placement and sizing of electric taxi charging stations within urban areas. Moreover, it offers insights that can facilitate the adoption of electric taxi charging stations in other cities, thus breaking the cycle of the "chicken and egg" dilemma.

(3) It is important to acknowledge the limitations of this study. We have primarily considered a single setting for electric vehicles, and all the EV models used in this study are assumed to be identical. Future research should consider various EV models to provide a more comprehensive analysis.

REFERENCES

[1] H. Wang, Y. Sun, and L. Wang, "Frequency regulation by virtual aggregation of electric vehicles based on consortium blockchain," *Autom. Electr. Power Syst.*, vol. 46, no. 16, pp. 122–131, 2022.

[2] B. Hu, P. Zhang, and E. Huang, "Graph WaveNet based charging load forecasting of electric vehicle," *Autom. Electr. Power Syst.*, vol. 46, no. 16, pp. 207–213, 2022.

[3] E. A. Nanaki and C. J. Koroneos, "Climate change mitigation and deployment of electric vehicles in urban areas," *Renew. Energy*, vol. 99, pp. 1153–1160, Dec. 2016.

[4] X. Sun, Z. Li, X. Wang, and C. Li, "Technology development of electric vehicles: A review," *Energies*, vol. 13, no. 1, p. 90, Dec. 2019.

[5] Y. Zhang, J. Xu, Q. Li, J. Zhou, L. Wang, Z. Zhu, Y. Li, and S. Wang, "An electric vehicle charging station siting and sizing method based on a density peaks clustering algorithm," *Power Syst. Protection Control*, vol. 49, no. 5, pp. 132–139, 2021.

[6] M. Maciejewski and J. Bischoff, "Large-scale microscopic simulation of taxi services," *Proc. Comput. Sci.*, vol. 52, pp. 358–364, Jan. 2015.

[7] L. Jia, Z. Hu, and Y. Song, "An integrated planning of electric vehicle charging facilities for urban area considering different types of charging demands," *Power Syst. Technol.*, vol. 40, no. 9, pp. 2579–2587, 2016.

[8] L. Tian, S. Shi, and Z. Jia, "A statistical model for charging power demand of electric vehicles," *Power Syst. Technol.*, vol. 34, no. 11, pp. 126–130, Nov. 2010.

[9] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," *Appl. Energy*, vol. 125, pp. 289–299, Jul.15, 2014.

[10] Y. Gao, Y. Guo, and T. Li, "Optimal location of urban electric vehicle charging stations using a two-step method," *Electr. Power*, vol. 46, pp. 143–147, Aug. 2013.

[11] Y.-W. Wang and C.-C. Lin, "Locating multiple types of recharging stations for battery-powered electric vehicle transport," *Transp. Res. E, Logistics Transp. Rev.*, vol. 58, pp. 76–87, Nov. 2013.

[12] F. He, D. Wu, Y. Yin, and Y. Guan, "Optimal deployment of public charging stations for plug-in hybrid electric vehicles," *Transp. Res. B, Methodol.*, vol. 47, pp. 87–101, Jan. 2013.

[13] S. Zhao, J. Zhou, Z. Li, and S. Zhang, "EV charging demand analysis based on trip chain theory," *Electr. Power Autom. Equip.*, vol. 37, pp. 105–112, Sep. 2017.

[14] J. Wen, S. Tao, X. Xiangning, C. Luo, and K. Liao, "Analysis on charging demand of EV based on stochastic simulation of trip chain," *Power Syst. Technol.*, vol. 39, no. 6, pp. 1477–1484, 2015.

[15] H. Cai, X. Jia, A. S. F. Chiu, X. Hu, and M. Xu, "Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet," *Transp. Res. D, Transp. Environ.*, vol. 33, pp. 39–46, Dec. 2014.

[16] D. Zhang, J. Jiang, W. Zhang, X. Wang, and Y. Huang, "Optimal configuration of charging spots for electric taxis," *Trans. China Electrotech. Soc.*, vol. 30, no. 18, pp. 181–188, 2015.

[17] Y. Li, J. Luo, C.-Y. Chow, K.-L. Chan, Y. Ding, and F. Zhang, "Growing the charging station network for electric vehicles with trajectory data analytics," in *Proc. IEEE 31st Int. Conf. Data Eng.*, Apr. 2015, pp. 1376–1387.

[18] Q. Liu, J. Liu, W. Le, Z. Guo, and Z. He, "Data-driven intelligent location of public charging stations for electric vehicles," *J. Cleaner Prod.*, vol. 232, pp. 531–541, Sep.20, 2019.

[19] Q. Jiang, "Research on charging facility locations considering user heterogeneity and charging station capacity," Ph.D. dissertation, Nanjing Univ., 2021.

[20] S. L. Hakimi, "Optimum locations of switching centers and the absolute centers and medians of a graph," *Oper. Res.*, vol. 12, no. 3, pp. 450–459, Jun. 1964.

[21] M. J. Hodgson, "A flow-capturing location-allocation model," *Geograph. Anal.*, vol. 22, no. 3, pp. 270–279, Jul. 1990.

[22] L. Pan, "Charging choice behavior based location optimization for EV charging facilities," Ph.D. dissertation, Beijing Jiaotong Univ., 2019.

[23] J. Yang, J. Dong, and L. Hu, "A data-driven optimization-based approach for siting and sizing of electric taxi charging stations," *Transp. Res. C, Emerg. Technol.*, vol. 77, pp. 462–477, Apr. 2017.

[24] J. Asamer, M. Reinthaler, M. Ruthmair, M. Straub, and J. Puchinger, "Optimizing charging station locations for urban taxi providers," *Transp. Res. A, Policy Pract.*, vol. 85, pp. 233–246, Mar. 2016.

[25] Y. Mi, "Bi-objective optimal locations of charging stations for electric vehicles," *J. Harbin Eng. Univ.*, vol. 8, pp. 1264–1268, Jan. 2018.

[26] G. Chen, Z. Mao, J. Li, D. Wang, H. Zhou, and K. Sun, "Multi-objective optimal planning of electric vehicle charging stations considering carbon emission," *Autom. Electr. Power Syst.*, vol. 38, pp. 49–53, 2014.

[27] A. Ficara, M. Fazio, A. Galletta, A. Celesti, and M. Villari, "Large-scale agent-based transport model for the metropolitan city of Messina," in *Proc. IEEE Symp. Comput. Commun. (ISCC)*, Gammarth, Tunisia, Jul. 2023, pp. 1–6, doi: 10.1109/iscc58397.2023.10218196.

[28] E. Karaaslan, M. Noori, J. Lee, L. Wang, O. Tatari, and M. Abdel-Aty, "Modeling the effect of electric vehicle adoption on pedestrian traffic safety: An agent-based approach," *Transp. Res. C, Emerg. Technol.*, vol. 93, pp. 198–210, Aug. 2018.

[29] Q. Luo, W. Tian, and H. Jia, "Location and capacity model of electric vehicle charging station considering commuting demand," *J. Jilin Univ., Eng. Technol. Ed.*, vol. 49, no. 5, pp. 1471–1477, 2019.
[30] T.-Y. Ma and S. Xie, "Optimal fast charging station locations for electric ridesharing with vehicle-charging station assignment," *Transp. Res. D, Transp. Environ.*, vol. 90, Jan. 2021, Art. no. 102682.
[31] W. Tu, Q. Li, Z. Fang, S.-L. Shaw, B. Zhou, and X. Chang, "Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach," *Transp. Res. C, Emerg. Technol.*, vol. 65, pp. 172–189, Apr. 2016.
[32] A. Ip, S. Fong, and E. Liu, "Optimization for allocating BEV recharging stations in urban areas by using hierarchical clustering," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Nov. 2010, pp. 460–465.
[33] Y.-W. Wang and C.-R. Wang, "Locating passenger vehicle refueling stations," *Transp. Res. E, Logistics Transp. Rev.*, vol. 46, no. 5, pp. 791–801, Sep. 2010.
[34] T. D. Chen, K. M. Kockelman, and M. Khan, "The electric vehicle charging station location problem: A parking-based assignment method for Seattle," in *Proc. 92nd Annu. Meeting Transp. Res. Board*, Washington, DC, USA, 2013.
[35] Y. Huang and Y. Zhou, "An optimization framework for workplace charging strategies," *Transp. Res. C, Emerg. Technol.*, vol. 52, pp. 144–155, Mar. 2015.
[36] D. Chen, "Location optimization and recommendation algorithm for electric taxi charging station based on charging behavior," Ph.D. dissertation, Beijing Jiaotong Univ., 2021.
[37] Q. Xu, T. Cai, Y. Liu, L. Yao, and P. Zeng, "Location planning of charging stations for electric vehicles based on drivers' behaviours and travel chain," *Autom. Electr. Power Syst.*, vol. 40, no. 4, pp. 59–65, 2016.
[38] R. Li and H. Su, "Optimal allocation of charging facilities for electric vehicles based on queuing theory," *Autom. Electr. Power Syst.*, vol. 35, no. 14, pp. 58–61, 2011.
[39] X. Sun, K. Liu, and Z. Zuo, "A spatiotemporal location model for locating electric vehicle charging stations," *Prog. Geography*, vol. 31, no. 6, pp. 686–692, 2012.
[40] X. Dong, Y. Mu, L. Yu, X. Jin, H. Jia, and X. Yu, "Freeway FCS planning and correction considering power-flow constraints of distribution network," *Electr. Power Autom. Equip.*, vol. 37, no. 6, pp. 124–131, 2017.
[41] J. Dong, C. Liu, and Z. Lin, "Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data," *Transp. Res. C, Emerg. Technol.*, vol. 38, pp. 44–55, Jan. 2014.
[42] X. Xi, R. Sioshansi, and V. Marano, "Simulation–optimization model for location of a public electric vehicle charging infrastructure," *Transp. Res. D, Transp. Environ.*, vol. 22, pp. 60–69, Jul. 2013.
[43] K. Huang, P. Kanaroglou, and X. Zhang, "The design of electric vehicle charging network," *Transp. Res. D, Transp. Environ.*, vol. 49, pp. 1–17, Jan. 2016.
[44] T. Novosel, L. Perković, M. Ban, H. Keko, T. Pukšec, G. Krajač ić, and N. Duić, "Agent based modelling and energy planning—Utilization of MATSim for transport energy demand modelling," *Energy*, vol. 92, pp. 466–475, Dec. 2015.
[45] L. Chen, W. Zhang, Y. Huang, and D. Zhang, "Research on the charging station service radius of electric taxis," in *Proc. IEEE Conf. Expo Transp. Electrific. Asia–Pacific*, Jun. 2014, pp. 90690Y1–90690Y4.
[46] Y.-J. Chu, L. Ma, and H.-Z. Zhang, "Location-allocation and its algorithm for gradual covering electric vehicle charging stations," *Math. Pract. Theory*, vol. 45, no. 10, pp. 101–106, 2015.
[47] J. Chen, L. Piao, and Q. Ai, "Charging optimization based on improved greedy algorithm for massive EVs," *Electr. Power Autom. Equip.*, vol. 36, p. 10, Jul. 2016.
[48] K. Deb, A. Pratap, and S. Agarwal, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Aug. 2002.
[49] *GB.50966-2014–2014. Code for Design of Electric Vehicle Charging Station*, Ministry Housing Urban-Rural Develop. People's Republic China, 2014.
[50] *2017–2022 China Electric Vehicle Charging Pile Development Status and Development Prospect Forecast 2021*, Prospective Ind. Res. Inst., 2017.

LI XIAO WANG received the Ph.D. degree in traffic engineering major from Nagoya University, Japan, in 2008. In 2009, she returned to China to work with the School of Architectural Engineering, Xinjiang University. She has been engaged in teaching and scientific research in the direction of traffic engineering and traffic planning. As a member of the Young Experts Group of the Academic Committee of the Urban Transportation Planning of the China Urban Planning Society, the Young Experts Group is mainly engaged in the research of intelligent transportation, traffic planning, and traffic travel choice behavior. At the same time, it has a good theoretical basis and practical experience in traffic flow data collection, road characteristic analysis, and urban traffic planning and management. In the past five years, more than 30 academic articles have been published and more than 60 scientific research projects have been presided over, including two national natural science fund projects and one general project of the natural science fund of the autonomous region.

CHAO MA is currently pursuing the degree with the College of Business, Xinjiang University. He is mainly engaged in the research of traffic behavior analysis.

SHI JUN LU received the degree from Wuhan University. He was a Research Assistant with LSGI Department, The Hong Kong Polytechnic University, from September 2016 to February 2017. He joined Xinjiang University, in 2018. Mainly engaged in remote sensing science and technology research.

KANG LI WU is currently pursuing the degree with the School of Architectural Engineering, Xinjiang University. He is with Liangping District Urban Construction Service Center. He is mainly engaged in the research of traffic behavior analysis.