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Location planning of electric vehicle charging station with users' preferences and waiting time: multi-objective bi-level programming model and HNSGA-II algorithm

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ABSTRACT

Interactive users' preferences and waiting time together have great impact on charging station network design of electric vehicles (EVs), but only waiting time was considered in previous studies. To fill this research gap, this paper addresses a location planning problem for EV charging stations, which considers users' preferences and waiting time simultaneously. The problem is formulated as a multi-objective bi-level programming model, the upper level model determines locations and capacity options of charging stations with the objectives of minimising total cost and minimising total service tardiness, and the lower level model determines the allocation of users to stations with the objective of minimising total travel time. A hybrid non-dominated sorting genetic algorithm II (HNSGA-II) with embedded level determination algorithm (LDA) and a partial enumeration algorithm (PEA) are proposed, respectively, to solve the model. Furthermore, managerial analysis is implemented to verify the advantages of considering users' preferences in reducing charging service tardiness and saving cost compared with the mode of no considering users' preferences. And sensitivity analysis is also performed to provide managerial insights for EV charging station location practice. Finally, a real-world case study is conducted to verify the applicability of the proposed approach in solving practical location planning problems.

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Electric vehicles; charging station location planning; multi-objective bi-level optimisation; users' preferences; waiting time; hybrid non-dominated sorting genetic algorithm II

1. Introduction

In recent years, growing concerns about environmental problem and diminishing fossil fuel reserves have made EVs attract attention worldwide. EVs seem to be a potential alternative to tackle environmental and energy challenges in the transport sector (Sassi and Oulamara 2016; Zhen et al. 2019; Jiao et al. 2021). Many governments are promoting the EV option in order to achieve sustainable transportation (Shen et al. 2019; Duman, Taş, and Çatay 2021). However, the low availability of charging infrastructure is the major barrier to the mass adoption of EVs, and queues are arising at many stations in the existing charging network (Huang and Kockelman 2020), especially during charging peak periods. In California, the congestion of EVs at charging stations has been a common phenomenon (Campbell 2018). Moreover, in China, the ratio of vehicle-pile exceeds 2.4:1, far from the international minimum standard ratio of 1.5:1 (Yi et al. 2020), which can cause serious charging queues, especially in regions with high charging demand density. Overall, serious queuing congestion leads to the negative performance of charging stations and greatly reduces peoples' willingness to adopt EVs, which further severely impedes the sustainable transportation and the low-carbon economy. Therefore, at strategic decision level, there is an urgent need for governments to construct more EV charging stations, with the use of an efficient location planning approach which can reduce users' waiting time efficiently. Motivated by this important strategic decision requirement, this paper aims to study the challenging problem: How to optimise location and capacity allocation of EV charging stations with considering users' preferences and waiting time.

The location planning problem of EV charging stations involves location, allocation of users to stations and capacity allocation of charging stations. A distinct feature of our problem is that users make their station choices based on their own preferences. While they are allocated by the decision maker in common facility location-allocation problems. In fact, through the analysis of users' charging behaviour, several determinants influence users' station choices (iResearch 2020), and the top 3 of them include charging rate, distance and charging price. There-

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fore, users have their own preferences when choosing charging stations, which may lead to the fact that users' gathering charging at preferred stations and low utilisation rate of charging infrastructure at other stations, i.e. the mismatch between charging infrastructure distribution and charging demand distribution. Due to the above significant impact of users' preferences on charging station construction, it should be considered in the location-allocation decision framework. Furthermore, according to the report International Energy Agengy (2018), there are different charging modes currently: slow charging (alternative current (AC) level 1 charging and AC level 2 charging) and fast charging (direct current (DC) level 3 charging). Since level 1 or 2 charging technologies make users wait 2–8 h to fully charge their EVs (Chung and Kwon 2015), they are not suitable to deal with charging queues during peak periods. Hence, we assume the located charging stations belong to the level 3 fast charging type. Moreover, for the top 3 of determinants, the differences of charging speed and charging price among different stations can be ignored due to the same charging service type, thereby distance (equivalent to travel time in the model) becomes a primal factor representing users' preferences in this paper.

As is known, users choose stations according to their travel time, without knowing the situation of queuing waiting at corresponding stations in advance. If users do not expect a long waiting time after arriving a station and turn to other stations, there will be a second travel time consumption accompanied by unknown waiting time, which should be avoided as much as possible through the location design of EV charging stations. Furthermore, due to the separation of users' allocation decision and location-allocation decision for charging stations, it is challenging to deal with users' waiting time at stations through location and capacity allocation of EV charging stations in advance, let alone restrict users' average waiting time. Some previous studies discussed facility location problem with client waiting time (Marianov, Rı´os, and Icaza 2008; Zhang, Berman, and Verter 2009; Zhang et al. 2010); however, these studies do not involve the issue of restricted waiting time which still needs to be addressed further. To ensure the service performance of charging stations, users' waiting time at stations should be restricted to an acceptable range and restricted waiting time is also another distinct feature of the problem. Bae and Kwasinski (2012), Yang et al. (2017) used the *M/M/s* queue model to formulate the EV charging dynamics, similar to these studies, we assume that each station behaves as an *M/M/s* queue system. In fact, there are charging peak hours daily in China (iRsearch 2020), and serious queues occur during charging peak periods, so we focus on reducing and restricting users' waiting time during these peak periods. Furthermore, more stations to be located and larger allocated station capacity levels together bring smaller users' travel time and waiting time. That is, better service quality of charging stations means a higher construction cost. Therefore, two objectives are considered: minimising total cost and minimising total service tardiness, and the Pareto set associated with these objectives should be explored systematically.

The location planning for EV charging stations belongs to the class of refuelling facility location problems. Currently, there are two mainstream modelling approaches: node-serving (Xi, Sioshansi, and Marano 2013; Zhu et al. 2016) and path-flow-capturing (Kuby and Lim 2005; Wu and Sioshansi 2017). While flow-capturing models are based on demands from Origin-Destination (O-D) flow, they are more suitable for dealing with long distance travel. While we study the location planning of charging stations in a certain region instead of a highway network, and queues arise at these locations due to the gathering charging demands during peak hours. Therefore, similar to existing studies, we assume charging demands are produced at specific spatial locations (i.e. nodes) like business communities with the features of small area and concentrated vehicles. Moreover, considering the booming trend of EVs in the future (International Energy Agengy 2018), all potential charging demand should be covered to avoid more serious charging queues in the future. Further, there is an implicit coverage radius for each charging station (Liu, Wen, and Ledwich 2013), which makes a station only cover users' demand within its coverage radius. And it conforms the practical operation of charging stations. Therefore, the station coverage for potential charging demand should be based on coverage radius. In this paper, we assume all stations to be located have the same coverage radius due to the homogeneity of station charging services.

Based on the aforementioned issues, we aim to address a location planning problem for charging stations with users' preferences and waiting time. We propose a method based on *M/M/s* queuing model and maximum waiting time, to link users' allocation decision and charging station location-capacity allocation decision, which are in separation essentially. In the location design of charging stations, the adoption of this method makes users' average waiting time restricted to a certain range, which is not addressed in previous studies. The proposed problem is formulated as a MOBLP model. We prove the proposed model is NP-hard. And multiple objectives and the high non-linearity structure greatly increase the complexity of the model. For solving this complex model efficiently, we propose a HNSGA-II algorithm with embedded LDA algorithm and solution space reduction mechanism. Numerical experiments are implemented on instances to verify the validity of the proposed HNSGA-II algorithm and to show the trade-off between total cost and total service tardiness. Managerial analysis is conducted to verify the advantages of the location mode of considering users' preferences compared with the mode without considering users' preferences. And sensitivity analysis is performed to illustrate the impact of significant parameters and generate useful managerial insights for EV charging station location practice. Finally, a real-world case study is conducted based on Beijing EV charging station location problems to test the proposed location planning approach.

The remainder of this paper is organised as follows. In section 2, we review the related literature. We introduce the location planning problem for charging stations with users' preferences and waiting time, and formulate a MOBLP model for the proposed problem in section 3. In section 4, we propose a heuristic solution algorithm and a partial enumeration algorithm respectively. Next, we discuss our findings from computational experiments and analysis in section 5 and conclude the paper in section 6.

2. Literature review

2.1. Location planning for EV charging stations

Facility location problem has always been a very important issue in strategic logistics design of the production research field (Shi et al. 2019; Pérez-Gosende, Mula, and Díaz-Madroñero 2021). And refuelling station location problem is an important branch of the extensively studied facility location problems, among which EV charging station location planning problem attracts much attention in recent years. So far, many literature has discussed location planning of EV charging stations (Shen et al. 2019). According to modelling approaches, these literature can be further divided into two categories: node-serving and path-flow-capturing.

Path-flow-capturing models assume that the refuelling demands are from vehicle flows in the road network, and these models have been applied in many related studies. Kuby and Lim (2005) extended flow-capturing models to optimal location of refuelling facilities for alternative-fuel vehicles (AFV), considering the limited mileage of vehicles. Other recent research mainly includes the following four aspects. (1) Stochastic flow-capturing location for charging stations (Wu and Sioshansi 2017). Wu and Sioshansi (2017) further considered the stochasticity of the flow and developed a stochastic flow-capturing model to optimise the location of fast charging stations with uncertain EV flows. (2) Multi-period location optimisation of charging stations (Chung and Kwon 2015; Zhang, Kang, and Kwon 2017). Chung and Kwon (2015) formulated a multi-period optimisation model based on a flow-refuelling location model for strategic location planning of charging stations. Zhang, Kang, and Kwon (2017) studied a multi-period capacitated flow-refuelling location problem for EVs, and they proposed an optimisation model to determine the optimal locations of chargers as well as the number of charging modules at each station over multiple time periods. (3) Location optimisation of charging stations considering different behaviour factors (Dong et al. 2016; He, Yin, and Zhou 2015). He, Yin, and Zhou (2015) explored optimally locating public charging stations for EVs in a road network considering drivers' spontaneous adjustments and interactions of travel and recharging decisions. Dong et al. (2016) studied the location problem of fast charging stations on a road freeway considering spatial and temporal transportation behaviours using a flow-capturing based median model. (4) Optimal location for charging stations with queue (Hosseini and MirHassani 2015). Hosseini and MirHassani (2015) studied the optimal location of EV recharging stations with queue using flow demand modelling approach. As can be seen from above, the existing research based on Path-flow-capturing models focuses on location design of charging stations in a road network and only addresses charging demand produced by vehicle flows driving on the route like freeway. As discussed in the Introduction, the concerned charging demand is produced at specific spatial locations (i.e. nodes), and the Path-flow-capturing approaches mentioned above are inappropriate to address our problem apparently.

Another type of research for charging station location planning is based on node-serving models in which charging demand is treated as being generated at specific spatial locations (nodes). Compared with the studies on path-flow-serving, the studies on node-serving are relatively limited. The related research mainly includes the following four aspects: (1) location planning of charging stations based on simulation–optimisation approach (Xi, Sioshansi, and Marano 2013). Xi, Sioshansi, and Marano (2013) developed a simulation–optimisation model of locating EV chargers to maximise their use by privately owned EVs and achieved some results like overall service levels of stations are less sensitive to the optimisation strategy under the application of the proposed model. (2) Location design of charging stations based on coverage model considering the reachability of stations (Frade et al. 2011; Zhu et al. 2016; Gagarin and Corcoran 2018). Zhu et al. (2016) studied the charging station location problem considering PEV commuters' destinations and tolerable distance, proposing a model to simultaneously determine locations of charging stations and the number of chargers installed in each charging station. Frade et al. (2011) studied the location problem of EV charging stations and introduced a maximal covering model to maximise the covered demand within an acceptable level of service and to determine the number and capacity of the stations. Gagarin and Corcoran (2018) proposed multiple domination models for the problem of locating charging stations in road networks, which is solved by the heuristic optimisation algorithm based on k-dominating set. (3) Location design of charging stations using queuing theory (Zhu et al. 2017; Yang, Dong, and Liang 2017; Xiao et al. 2020). Zhu et al. (2017) studied location planning of EV charging stations based on queuing theory, proposing a location planning model to determine locations and capacities of charging stations. Yang, Dong, and Liang (2017) presented a data-driven optimisation-based approach to determine locations of charging stations and charger allocation in each station. Xiao et al. (2020) considered the charging queuing behaviour with finite queue length and further established an optimisation model to decide locations and capacities of EV charging infrastructure. (4) Multi-objective location optimisation of charging stations using cell-based approach (Bai, Chin, and Zhou 2019). Bai, Chin, and Zhou (2019) proposed a method cell-based approach to estimate the potential charging demand of each cell in the divided city area and established a multi-objective optimisation model to determine locations, capacity allocation and service type for EV charging stations. As can be seen from above, previous studies focus on location and capacity allocation of EV charging stations, but there is little research considering users' waiting time. Further, after integrating users' preferences and waiting time into EV charging station location planning, the problem becomes very complicated and difficult to solve. And previous studies do not incorporate the above two issues simultaneously. Nevertheless, it still has to be addressed urgently with great difficulty. Moreover, the models in most research are single-objective, and their objectives are either to minimise total cost or maximise service coverage, there is very little research discussing the trade-off of different objectives.

2.2. Facility location with customer preferences

Our paper also relates to the stream of literature on facility location with customer preferences. Due to the consideration of customer preferences, customers can freely choose their preferred facilities for the allocation of customers to facilities, which is a distinct feature of this kind of literature (Lee and Lee 2012; Camacho-Vallejo, Cordero-Franco, and González-Ramírez 2014; Casas-Ramírez et al. 2017; Díaz et al. 2017; Calvete et al. 2020).

The related studies mainly include the following two aspects: (1) study on different variants of facility location problem with customer preferences (Lee and Lee 2012; Casas-Ramírez et al. 2017) and (2) research on solution approaches of facility location problem with customer preferences (Camacho-Vallejo, Cordero-Franco, and González-Ramírez 2014; Díaz et al. 2017; Calvete et al. 2020). In the first area, some researchers proposed variants of facility location problem with customer preferences. For example, Lee and Lee (2012) studied a facility location and capacity allocation problem considering customer preference and the required minimum number of customers for opening a facility. Casas-Ramírez et al. (2017) proposed a bi-level maximal covering location problem (MCLP), considering customers' preferences and already existing firms in the same market. In the second area, many studies aim to propose solution approaches for different versions of facility location problem with customer preferences. For example, Díaz et al. (2017) designed a greedy randomised adaptive search procedure (GRASP) and a hybrid GRASP-Tabu heuristic, respectively, for the maximal covering location problem with customer preference ordering which is proposed in Casas-Ramírez et al. (2017). Camacho-Vallejo, Cordero-Franco, and González-Ramírez (2014) proposed an evolutionary algorithm based on the Stackelberg's game equilibrium to solve the bi-level uncapacitated facility location problem with customer preferences. More recently, Calvete et al. (2020) further proposed a matheuristic based on an evolutionary algorithm framework to solve the bi-level capacitated facility location problem with customer preferences which is a natural extension of the problem studied in Camacho-Vallejo, Cordero-Franco, and González-Ramírez (2014).

As can be seen from above, the related studies focus on the location of general class of facilities like plants, warehouses and firms, without considering waiting time of customers. And most of these studies are based on the maximal covering location problem (MCLP) introduced by Church and Davis (1992), in which facilities are located to maximise covered customer demand instead of covering all potential charging demand. However, EV charging station belongs to the class of refuelling facility which is different from the above general facilities in terms of service type and construction requirements. And serious queues at stations with users' preferences must be addressed and all potential charging demand needs to be covered through the location design of EV charging stations. There is almost no research related to location planning of EV charging stations which can cover all potential demand, with incorporating users' preferences and waiting time. It is therefore of great interest to study location planning problem of EV charging stations with users' preferences and waiting time, and the above literature has laid a solid foundation for this research.

2.3. Non-dominated sorting genetic algorithm II

Our research problem essentially belongs to a multi-objective optimisation problem with highly nonlinear structure and bi-level attribute, solving it to obtain Pareto-optimal solutions is difficult. Therefore, efficient meta-heuristic methods are needed to solve it. NSGA-II is a well-known multi-objective meta-heuristic evolutionary algorithm proposed by Deb et al. (2002). It has been widely applied to solve multi-objective optimisation problems in different areas, such as production scheduling optimisation (Rabiee, Zandieh, and Ramezani 2012; Han et al. 2013), household e-waste collection facility location (Shi et al. 2019), public facility location (Doerner, Gutjahr, and Nolz 2008), maintenance optimisation for electromechanical products (Su and Liu 2019), configuration selection for reconfigurable manufacturing system (Goyal, Jain, and Jain 2012) and scheduling of cloud manufacturing systems (Vahedi-Nouri et al. 2021). Most of these studies show that NSGA-II outperforms other algorithms in terms of solution quality and even computational efficiency, especially for facility location problems. So we adopt and improve the NSGA-II to solve the proposed problem.

Unlike these literature on the applications of NSGA-II, we particularly propose HNSGA-II algorithm that is customised to our problem to solve the complex structured formulation efficiently and accurately. In specific, we propose a level determination algorithm (LDA) based on the property of the model and numerical search mechanism to address the difficulty of charging station capacity allocation decision incurred by the strong interaction between users' preferences and waiting time. The LDA paly an important role in determining capacity allocation of charging stations which cannot be achieved by the existing algorithms. And it is appropriately embedded in the overall NSGA-II framework and becomes a key part of HNSGA-II. Furthermore, we make full use of the property of the model to propose a novel solution space reduction strategy, which can reduce the generation and evolutionary space of chromosomes efficiently. Combined with the proposed gene repair strategy, it can be employed to ensure the good performance of the HNSGA-II in terms of convergence and solution quality.

3. Problem statement and formulation

3.1. Problem statement

We consider a station location decision maker who determines locations, capacity options of EV charging stations in a region. And the decision maker focuses on the following two objectives: minimising total cost and minimising total service tardiness.

To construct charging stations, land, charging infrastructure and other supporting devices are needed. Considering high price of charging infrastructure and huge cost of land acquisition (Huang and Kockelman 2020), from the perspective of saving cost, minimising total cost is a major goal for EV charging station decision maker. Furthermore, in China, there are peak hours for EV fast charging every day (iResearch 2020), and each charging peak period lasts about 2–3 h and almost coincides with daily rush hours. During such a peak period, many users may need to spend a lot of time queuing at charging stations for a charge. In addition, the trip from a location where one user has a charging demand to a charging station also leads to time consumption. Actually, the sum of travel time and waiting time is essentially equivalent to a valueless delay before a charge, if it exceeds the expected delay time accepted by users, the extra time is regarded as service tardiness. And the larger total service tardiness, the worse service quality of the charging station network. Therefore, minimising total service tardiness is also an important objective in EV charging station construction. However, these two objectives are actually in conflict, requiring the decision maker to make trade-offs based on his decision preferences and actual construction practice.

It should also be noted that, when there are charging stations of more than one in the EV charging station network, users can freely choose their most preferred charging stations. Furthermore, as mentioned in the Introduction, distance (equivalent to travel time in the model) is a primal factor representing users' preferences, which provide a common criterion for users to choose charging stations. Hence, users' allocation decision can be regarded as being done by a unified decision maker who uses this criterion. And the common objective of users is not completely aligned with the objectives of the decision maker. Users often choose their preferred stations to minimise their travel time without knowing the waiting time that they will face. While the decision maker wants to minimise total cost and service tardiness, users' station preferences can result in large total cost and service tardiness with considering restricted waiting time. Therefore, the decision maker must take into account users' allocation while making his location planning decisions. In a word, the charging station decision maker and users are two stakeholders who aim to achieve their own objectives, which shows the general characteristics of the bi-level programming. The resulted problem is essentially a multi-objective bi-level programming (MOBLP) problem.

The complete framework of the bi-level decision-making with different objectives is illustrated in Figure 1. The complete decision process is as follows: firstly, the

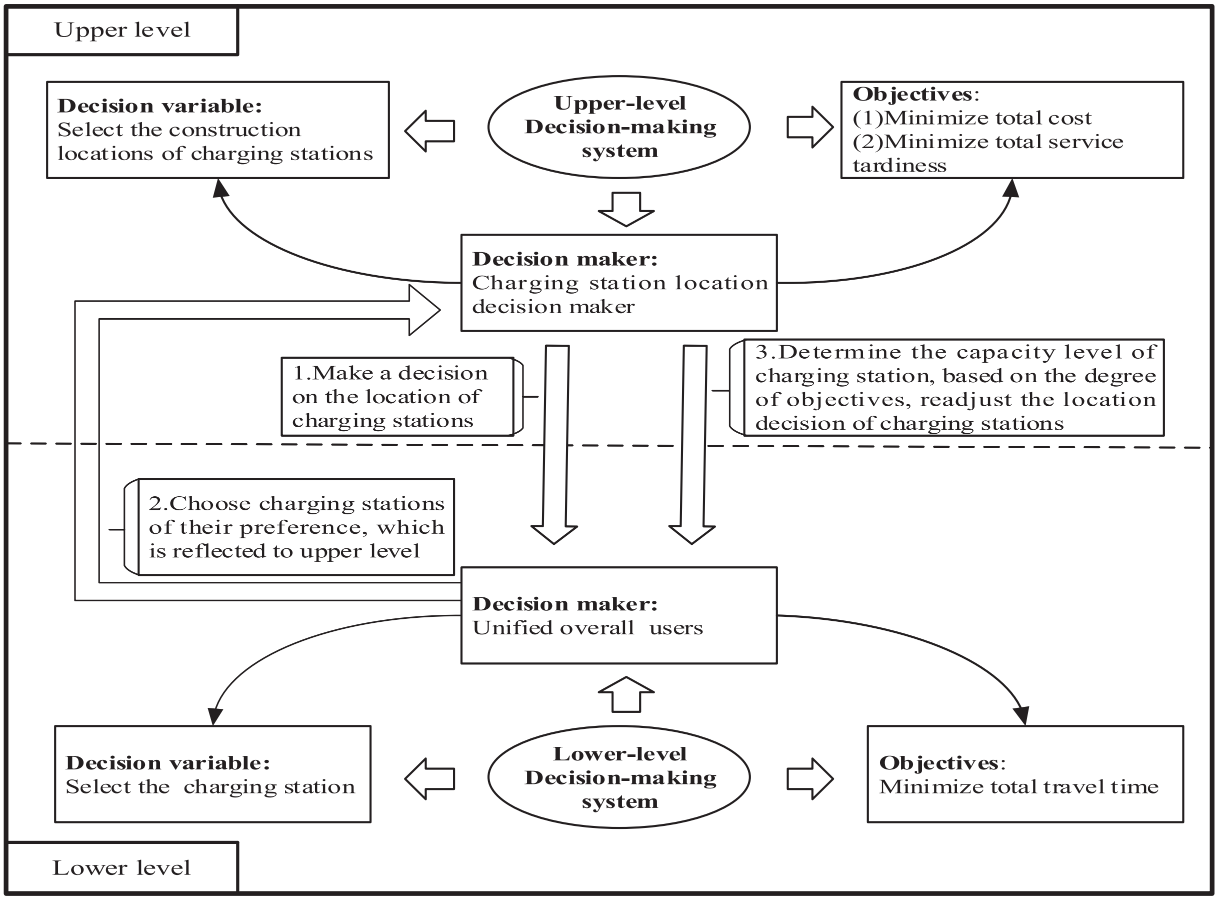


Figure 1. The overall structure of EV charging station location planning.

charging station decision maker at the upper level makes a location decision to determine locations of EV charging stations; secondly, given the selected locations of charging stations, users at lower level are allocated to their most preferred charging stations which can minimise their total travel time; thirdly, the decision maker at the upper level determines the capacity allocation of charging stations according to users' allocation, then readjust the location decision of charging stations based on the achievement degree of his two objectives. The three decision steps in Figure 1 are cycled in a certain order until a balance state is reached.

3.2. Problem formulation

In this section, we first state the assumptions related to the proposed problem and describe the notations used in the model. Then, a MOBLP model for location planning of EV charging stations will be proposed.

3.2.1. Assumptions and notations

The system is represented as a network $G = (N, A)$, where N represents the set of nodes and A denotes the set of arcs. And the nodes represent both demand nodes and candidate construction locations for EV charging stations. We give the assumptions of the model and summarise the key notations.

Based on the characteristics of the problem proposed in this paper, we make the following assumptions:

- We assume fixed construction costs for candidate locations are different, which is a common assumption in the related literature (Nie and Ghamami 2013; Xiao et al. 2020). Further, purchase and installation costs of unit charging pile for candidate locations are also different due to distinct costs of unit construction area required for each charging pile at these locations and different installation conditions (Nie and Ghamami 2013).
- All users have the same station preference, as mentioned in the Introduction, they prefer to choose a station minimising their travel time.
- The travel time of EV users is proportional to their travel distance.
- Each potential charging station location is set with an upper limit of construction level due to the limited land and electrical load.

Table 1. Description of notations for the model.

Notation	Description
Indexes and sets	
i	Index of a demand node, $i \in I$
j	Index of a candidate location for constructing an EV charging station, $i \in J$
N_i	Set of candidate locations within the coverage radius CO of node i, i.e. $N_i = \{j \mid d_{ij} \leq CO\}$
Parameters	
d_{ij}	Travel distance from a demand node i to a candidate station location j
t_{ij}	Average travel time from a demand node i to a candidate station location j
f_j	Fixed construction cost of a charging station at candidate location j
p_j	The cost of installing a charging pile at candidate location j
Q_j	The maximum capacity units a charging station can provide at candidate location j
a	The number of charging piles per capacity unit, which is the minimum level of a charging station capacity option
v	Average driving speed of EVs in the considered region
CO	Coverage radius of charging stations
r_i	Potential charging demand at node i, it is measured by the number of EVs
pr	Daily charging probability for each EV during rush hour
t_e	Expected delay time of users before charging their vehicles
w_{max}	Maximum waiting time accepted by users at a charging station
t_s	Average charging time required for each EV
t_c	Peak charging period for EVs, which coincides with daily rush hour
n	The number of demand nodes or candidate locations, i.e. $n = \lvert I \rvert = \lvert J \rvert$
Auxiliary variables	
w_j	Average waiting time of users at charging station j
E_j	The number of EVs accessing charging station j during a daily peak period
h_j	The number of charging piles required at charging station j under the limit of maximum waiting time w_{max}
Decision variables	
x_j	Equals to one if a charging station is established in location j and zero otherwise
s_j	Capacity units of charging piles installed at station j, s_j can be 0,1,2, … ,Q_j, which represents scale level of charging station j
y_{ij}	Equals to one if users at location i are allocated to the charging station at location j and zero otherwise

- The distribution of EVs is considered in region or city sense.
- Each charging pile can be only used to charge at most an EV at each moment (International Energy Agengy 2018).
- All charging stations to be constructed have the same service radius.

We further summarise the notations related to our model in Table 1.

3.2.2. Location planning model for EV charging stations

The arrival process of EVs at a charging station has certain randomness, which can be assumed to follow the Poisson process (Bae and Kwasinski 2012). Then, each charging station behaves as an *M/M/s* queue system. In general, serious queuing congestion at each charging station is most likely to occur during rush hours. Therefore, we focus on the treatment of users' waiting time during these periods. In order to ensure service performance of charging stations, we set an upper limit of waiting time to restrict average waiting time of users at a charging station. When the number of EVs accessing a certain charging station is fixed, the average waiting time of users at this station decreases with the increase in capacity units of installed charging piles. We allocate capacity units of charging piles to charging stations based on the criterion of maximum waiting time.

The formulas for the average waiting time of users at charging station j are as follows:

$$w_j = \frac{s_j a {\rho_j}^{s_j a+1} P_0}{\lambda_j((s_j a)!)(s_j a - \rho_j)^2} \tag{1}$$

$$P_0 = \left[\sum_{k=0}^{s_j a-1} \frac{{\rho_j}^k}{k!} + \frac{s_j a {\rho_j}^{s_j a}}{(s_j a)!(s_j a - \rho_j)} \right]^{-1} \tag{2}$$

P_0 is the probability of no EV at a charging station. The $\rho_j = \lambda_j/\mu$ is the service density of charging piles at the charging station j. The arrival rate of EVs at the charging station$j$ is $\lambda_j = E_j pr/t_c$, where $E_j = \sum_{i \in I} r_i y_{ij}$ represents the number of EVs accessing the charging station j during period t_c. The average charging service rate of charging piles is $\mu = 1/t_s$. It should be noted that the precondition for Equation (1) and Equation (2) is $\rho_j/s_j a < 1$.

Let h_j be a specific integer variable that can take any non-negative integer value, and we use it to replace $s_j a$. Furthermore, we set the upper limit of waiting time w_{max} for each charging station, and let w_j equals to w_{max}, then, the least number of charging piles h_j required at the charging station j can be given by solving the following equation:

$$w_{max} = \frac{h_j {\rho_j}^{h_j+1} P_0}{\lambda_j h_j!(h_j - \rho_j)^2} \tag{3}$$

Note that Equation (3) has a highly nonlinear structure, we convert it to an equation in function form. Let $G(E_j, h_j)$ replace the right-hand side of Equation (3), then Equation (3) can be rewritten as the following expression:

$$G(E_j, h_j) = w_{\max} \tag{4}$$

When E_j is determined, that is, it takes a fixed non-zero value, $h_j$can be replaced by the following function:

$$h_j = G^{-1}(E_j, w_{max}) \tag{5}$$

However, it is virtually impossible to obtain the closed-form solution of inverse function (5) due to its combinatorial complexity and non-linearity. And fortunately, some numerical search methods like bisection method provide effective tools for obtaining its numerical solution. Based on this idea, we develop a heuristic procedure to solve it.

Then the proposed location planning problem of EV charging station with users' preference and waiting time can be ultimately formulated as the following multi-objective bi-level programming (MOBLP) model:

Upper level model:

$$\min Z_1 = \sum_{j\in J} f_j x_j + \sum_{j\in J} s_j a p_j \tag{6}$$

$$\min Z_2 = \sum_{i\in I}\sum_{j\in J} \mathrm{Max}[(t_{ij} + w_j - t_e), 0] r_i y_{ij} \tag{7}$$

$s.t.$ (1), (2)

$$\sum_{j\in N_i} x_j \geq 1 \quad \forall i \in I \tag{8}$$

$$\rho_j / s_j a < 1 \quad \forall j \in \{u | h_u \neq 0\} \tag{9}$$

$$h_j = \begin{cases} 0 & E_j = 0 \\ G^{-1}(E_j, w_{max}) & E_j > 0 \end{cases} \quad \forall j \in J \tag{10}$$

$$E_j = \sum_{i\in I} r_i y_{ij} \quad \forall j \in J \tag{11}$$

$$s_j = \begin{cases} 0 & h_j = 0 \\ \left\lceil \frac{h_j}{a} \right\rceil & 0 < \frac{h_j}{a} \leq Q_j \\ Q_j & \frac{h_j}{a} > Q_j \end{cases} \quad \forall j \in J \tag{12}$$

$$x_j \in \{0, 1\},\ s_j \in N \quad \forall j \in J \tag{13}$$

Where for given $\{x_j\}$, $\{y_{ij}\}$ is the optimal solution of the lower level model:

Lower level model:

$$\min Z_3 = \sum_{i\in I}\sum_{j\in J} y_{ij} t_{ij} \tag{14}$$

$S.t.$

$$\sum_{j\in N_i} y_{ij} = 1 \quad \forall i \in I \tag{15}$$

$$\sum_{j\in J\setminus N_i} y_{ij} = 0 \quad \forall i \in I \tag{16}$$

$$y_{ij} \leq x_j \quad \forall i \in I, j \in J \tag{17}$$

$$y_{ij} \in \{0, 1\}, \quad \forall i \in I, j \in J \tag{18}$$

For the upper level model, objective (6) is to minimise total construction cost consisting of fixed construction cost and variable cost of installing charging piles. Objective (7) is to minimise the total service tardiness of users. Constraint (8) ensures that every demand node is covered by at least one charging station. Constraint (9) guarantees the utilisation rate of each charging station is less than one, which is the precondition for formula (1) and formula (2). Constraint (10) presents the relationship between variablesh_j, E_j and parameter w_{max}. Constraint (11) states the formula for calculating E_j. Constraint (12) represents the piecewise function used to determine the capacity units s_j of the charging station j. Constraint (13) declares the value ranges of decision variables.

For the lower level model, objective (14) is to minimise total travel time of users. Constraint (15) ensures that users at a demand location can only be allocated to one charging station that can cover them. Constraint (16) guarantees that users cannot be allocated to any charging station that cannot cover them. Constraint (17) ensures that users cannot be allocated to location j unless a charging station is constructed there. Constraint (18) states that the binary nature of decision variables.

Based on the characteristics of the proposed problem and the formulated MOBLP model, we give important proposition and properties as follows.

Proposition 3.1: *The proposed location planning problem of EV charging stations is NP-hard.*

Proof See the Appendix.

Property 3.1: Let $x_1, x_2, \cdots, x_{|J|}$ be a solution of upper level model, and $x_j \in \{0, 1\}, \forall j \in J$. It must not be a feasible solution of the proposed MOBLP model when $\sum_{j\in J} x_j < \xi$, and ξ is obtained by solving the following set covering problem:

$$\min \xi = \sum_{j\in J} x_j \tag{22a}$$

$s.t.$

$$\sum_{j\in N_i} x_j \geq 1 \quad \forall i \in I \tag{22b}$$

$$x_j \in \{0, 1\} \quad \forall j \in J \tag{22c}$$

Proof See the Appendix.

Property 3.2: Let $x_1, x_2, \cdots, x_{|J|}$ be a solution of upper level model, and $x_j \in \{0, 1\}, \forall j \in J$. It is a feasible and acceptable solution of the proposed model only when $\sum_{j\in J} x_j \geq \xi$ and $Q_j > \frac{1}{a}\max(\rho_j, h_j), \forall j \in \{j | x_j \neq 0\}$.

Proof See the Appendix.

Property 3.1 and Property 3.2 provide efficient method for identifying feasibility and quality of solutions, we can use this method to delete infeasible solutions and identify poor quality solutions, which can reduce the solution space and ensure search efficiency of the algorithm. Base on this method, we specifically design a heuristic approach to solve the problem effectively, in addition, a partial enumeration algorithm (PEA) is also proposed as the benchmark to obtain the Pareto-optimal solutions.

4. Solution approach

It has been proven that the proposed problem is NP-hard. There is no polynomial algorithm for solving it. Hence, it is necessary to design an effective algorithm to solve it efficiently. And the non-dominated sorting genetic algorithm II (NSGA-II) can effectively solve complex multi-objective optimisation problems (Ransikarbum and Mason 2021). Until now, it has been extensively applied to solve a wide variety of problems and shows well solution performance. Therefore, based on the NSGA-II, we design a hybrid non-dominated sorting genetic algorithm (HNSGA-II) for solving the proposed problem.

We first propose a LDA algorithm based on Property 3.2 and binary search mechanism, then we incorporate it into the NSGA-II algorithm framework and propose a HNSGA-II algorithm with solution space reducing mechanism. In addition, based on the LDA and Property 3.1, we also design a benchmark algorithm named PEA to exactly obtain Pareto-optimal solutions of the proposed problem. And it is used to verify the validity and advantages of the proposed HNSGA-II algorithm.

4.1. Level determination algorithm

We design a level determination algorithm based on Property 3.2 and numerical search mechanism to determine the capacity allocation of charging stations. We also give the deviation degree between required capacity units and capacity upper limit for a station, which can indicate the feasibility of location solution given by the decision maker.

Let DF_j indicate whether the required capacity level $RE_j$of the charging station j exceeds its capacity limit Q_j, i.e. DF_j equals to RE_j minus Q_j if RE_j is greater than Q_j and zero otherwise. Let $wtime(E_j, \cdot)$ represent the average waiting time function which corresponds to Equations (1) and (2). Let lb and ub denote the upper bound and the lower bound for the capacity level of a charging station, respectively, and the notation zx represents an intermediate variable during algorithm iterations. The detailed pseudocode of LDA is shown in Figure 2 and the bisection algorithm shown in Figure 3 can be regarded as its sub-algorithm. The LDA aims to address non-linearity of constraints and search capacity levels of charging stations efficiently. And it will be incorporated into the following HNSGA-II algorithm and PEA algorithm, respectively.

In terms of the computational complexity, given the input of capacity limit Q_j for one charging station j, the embedded bisection algorithm shown in Figure 3 takes a time complexity of no more than $O(\log_2(Q_j))$. As mentioned in the problem formulation, we have $h_j = G^{-1}(E_j, w_{max})$, where h_j is the number of charging piles required at the charging station j under the limit of maximum waiting time w_{max} and E_j is the number of EVs accessing the charging station j. When $h_j > Q_j$, the time complexity of the LDA is at most $O(h_j - Q_j)$. When $h_j \le Q_j$, the time complexity of LDA is that of the embedded bisection algorithm, that is, $O(\log_2(Q_j))$. Therefore, we can conclude that the overall complexity of the algorithm is $O(\max((h_j - Q_j), \log_2(Q_j))$. Note that w_{max} and Q_j are the key factors affecting the performance of the LDA. In general, larger w_{max} and smaller Q_j incur lower computational complexity of the algorithm. Furthermore, for most of the practical cases, $(h_j - Q_j) \le \log_2(Q_j)$, so the computational complexity of the LDA is no more than $O(\log_2(Q_j))$ (where $Q_{max} = \max_{j \in J} Q_j$).

4.2. Hybrid non-dominated sorting genetic algorithm II

The proposed problem is a very complex NP-hard problem, it is very difficult to search Pareto solutions using the NSGA-II directly, while Property 3.1 of the model provide an efficient strategy for reducing solution space in advance. We use this strategy to improve the NSGA-II algorithm, and further propose a hybrid non-dominated sorting genetic algorithm II (HNSGA-II) combining with the LDA.

The ideas of the proposed HNSGA-II include (1) the NSGA-II is used as global search mechanism, (2) an efficient gene repair strategy is proposed to repair infeasible chromosomes, (3) the strategy of reducing solution space is proposed to enhance the search efficiency, (4) the location decision variables are decoded as chromosomes which can be manipulated by genetic operators and (5) the decision variables of users' allocation can be determined by allocating users to their most preferred stations, and the capacity allocation decision variables can be obtained by using the LDA. The details of the HNSGA-II are introduced as follows.

(1) Chromosome encoding and genetic operators

We use 0-1 encoding for the decision variable x_j to generate all chromosomes in the initial population. Each chromosome has n gene bits, where 1 indicates that a

Inputs:
E_j: the number of EVs accessing station j;
Q_j: the maximum construction level of charging station j;
pr: daily charging probability for each EV;
Output: s_j: the construction level of charging station j; DF_j;

Initialize t_c, t_s, a, w_{max}, $lb \leftarrow 1$, $ub \leftarrow Q_j$
Set $\mu \leftarrow 1/t_s$, $\lambda_j \leftarrow E_j pr/t_c$, $\rho_j \leftarrow \lambda_j/\mu$
If $\rho_j/(Q_j \cdot a) \geq 1$, then
    Set $s_j \leftarrow Q_j$, $RE_j \leftarrow Q_j$
    While $\rho_j/(RE_j a) \geq 1$, do
        Set $RE_j \leftarrow RE_j + 1$
    End while
    While $wtime(E_j, RE_j) > w_{max}$, do
        Set $RE_j \leftarrow RE_j + 1$
    End while
    Set $DF_j \leftarrow RE_j - Q_j$
Else
    Set $RE_j \leftarrow Q_j$
    If $wtime(E_j, RE_j) > w_{max}$, then
        Set $s_j \leftarrow RE_j$
        While $wtime(E_j, RE_j) > w_{max}$, do
            Set $RE_j \leftarrow RE_j + 1$
        End while
        Set $DF_j \leftarrow RE_j - Q_j$
    Else
        Set $s_j \leftarrow$ Calculating the construction level by using bisection algorithm in Fig. 3
        Set $RE_j \leftarrow s_j$, $DF_j \leftarrow 0$
    End if
End if

Figure 2. The level determination algorithm.

Initialize $lb \leftarrow 1$, $ub \leftarrow Q_j$
If $\rho_j/a < 1$ and $wtime(E_j, Q_j) \leq w_{max}$, then
    Set $s_j \leftarrow 1$
Else
    While $(ub - lb) > 1$, do
        Set $zx \leftarrow$ round up the value of $(ub + lb)/2$
        If $\rho_j/(zx \cdot a) \geq 1$, then
            Set $lb \leftarrow zx$
        Else if $wtime(E_j, zx) \leq w_{max}$, then
            Set $ub \leftarrow zx$
        Else
            Set $lb \leftarrow zx$
        End if
    End while
    Set $s_j \leftarrow ub$
End if

Figure 3. The general scheme of bisection algorithm.

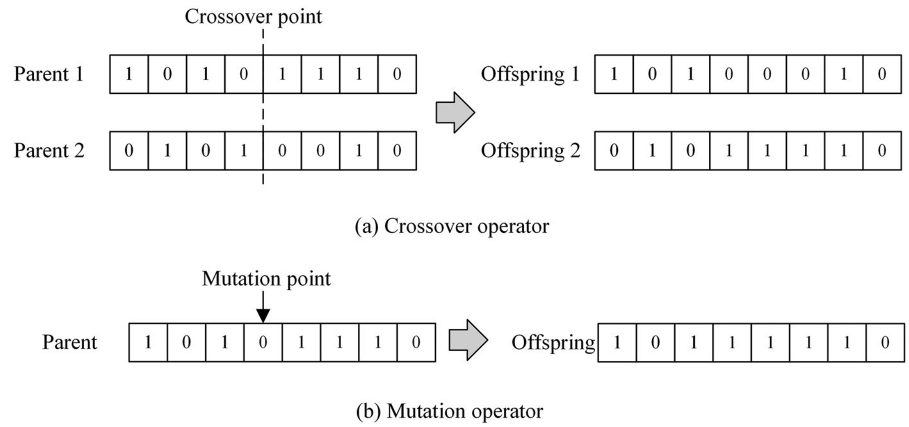


Figure 4. Crossover operator and mutation operator.

charging station is located at the corresponding candidate location, and 0 otherwise. In the proposed HNSGA-II algorithm, binary tournaments are used to select chromosomes and fast non-dominated sorting approach is used to obtain non-dominated solutions. Single-point crossover and bitwise mutation are performed, respectively. Figure 4 illustrates crossover operator and mutation operator.

(2) Gene repair strategy

Both initially generated chromosomes and crossed or mutated chromosomes may not satisfy constraint (8) which ensures all charging demand can be covered. Therefore, we propose a gene repair strategy to ensure the feasibility of chromosomes. And this strategy is presented as follows: we first count the number of gene bits with value 1 in a chromosome. If this number is less than ξ, then switch some values of gene bits from 0 to 1, i.e. increase the number of gene bits with value 1 so that it is greater than or equal to ξ, and then check whether the repaired chromosome can satisfy constraint (8). If not, randomly select several gene bits with zero values and switch their values to one, and repeat this operation until all potential charging demand can be covered.

(3) Solution space reduction strategy

As mentioned in Property 3.1, the value of ξ can be obtained by solving the set covering problem $(22a - 22c)$, then in the iteration process of the proposed HNSGA-II algorithm, we only need to generate and address such chromosomes whose number of gene bits with value 1 is greater than or equal to ξ. Therefore, the solution space needs to be searched will be reduced to a certain extent, which can improve algorithm performance significantly.

(4) The procedures of the HNSGA-II

Let i be the Pareto front level and F_i be the Pareto set at level i. And $|F_i|$ denotes the number of individuals in Pareto front of level i. The detailed procedures of the proposed HNSGA-II are as follows:

Step 1: Initialise some parameters: the number of generations $maxgen$, population size U, crossover probability p_c and mutation probability p_m. Set the value of ξ by solving the sub-problem $(22a - 22c)$ using CPLEX solver.
Step 2: Randomly generate initial population P_0, in which the number of gene bits with value 1 per chromosome is greater than or equal to ξ. Gene repair operator is performed on every chromosome in the population P_0. Set $t = 1$, $P_t = P_0$.
Step 3: Evaluate fitness of the population P_t.
Step 3.1: Solve the lower level model by allocating users to their nearest charging stations, and decision variable y_{ij} can be obtained and variable E_j can be determined further.
Step 3.2: Determine capacity level of each located charging station and obtain the value of each variable $DF_j (j \in J)$ with the use of the LDA algorithm. If $DF_j > 0$, then set a symbol to indicate that the corresponding chromosome is not acceptable.
Step 3.3: Calculate two objective values of the upper level model.
Step 4: Apply the selection, crossover, mutation and gene repair operators on the population P_t to generate a new population Q_t.
Step 5: Evaluate fitness of the population Q_t using the same approach as step 3.
Step 6: Combine the population P_t and Q_t to form R_t, $R_t = P_t \cup Q_t$.
Step 7: Implement the fast non-dominated sorting approach on the population R_t to form P_{t+1}.

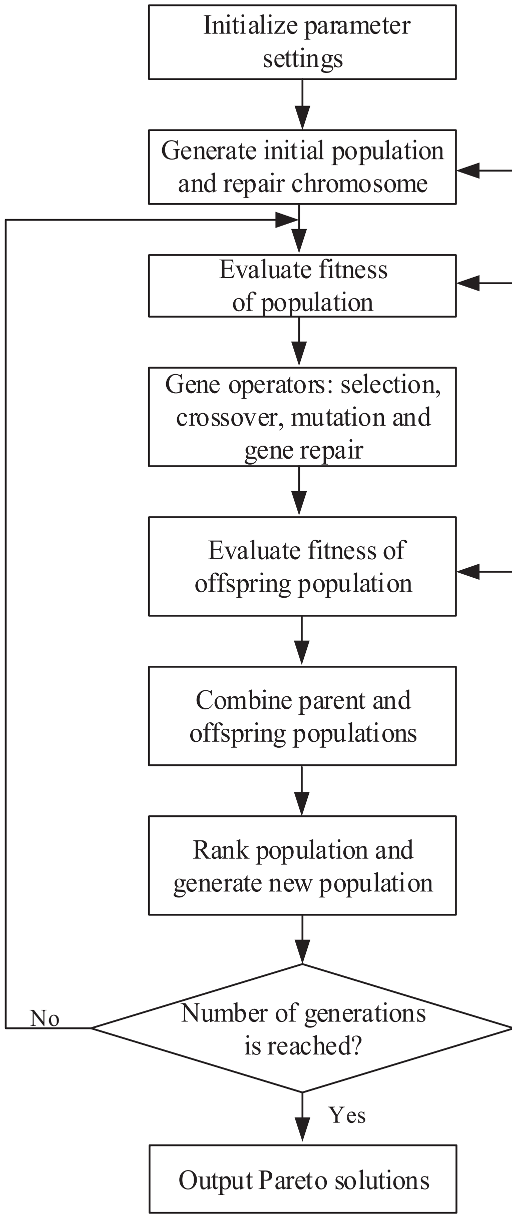


Figure 5. Flow chart of the HNSGA-II.

Step 8: Set $t = t + 1$, if $t \leq maxgen$, go to step 3. Otherwise, obtain the first Pareto front F_1 of P_t. Return F_1, the algorithm is terminated.

The flow chart of the HNSGA-II is illustrated in Figure 5. The overall computational complexity of the HNSGA-II algorithm is $O(2(U^2))$ (where U is the population size), which follows the related conclusion on the NSGA-II proposed by Deb et al. (2002). During the evolutionary process of HNSGA-II, the complexity of the LDA algorithm part is at most $O(U|J|(\log_2(Q_{max})))$ (where $Q_{max} = \max_{j \in J} Q_j$), which is governed by the overall computational complexity $O(2(U^2))$ for our research context. In particular, for the proposed HNSGA-II, population size U is the key factor affecting the performance, smaller U brings faster convergence of the algorithm. For super large-sized instance, the complexity of the LDA algorithm part becomes $O(U|J|(\log_2(Q_{max})))$. In addition to population size U, $|J|$ and Q_{max} are also the key factors affecting the performance of HNSGA-II.

4.3. Partial enumeration algorithm

It is noted that all potential location solutions of charging stations can be enumerated through exhaustive enumeration mechanism. However, it is intractable computationally to enumerate all possible location options. While Property 3.1 and Property 3.2 together provide a criterion which can be used to discard some infeasible solutions in advance and reduce the entire enumeration space, identify and delete unacceptable solutions during the enumeration process. Furthermore, we only need to apply the fast non-dominated sorting approach on the set of all remained feasible solutions, and finally obtain non-dominated solution set without enumerating all possible solutions. On this basis, we design a benchmark algorithm named partial enumeration algorithm (PEA) to solve the proposed problem and verify the validity of the proposed HNSGA-II algorithm.

The procedures of the proposed partial enumeration algorithm are as follows:

Step 1: Obtain the value of ξ by solving the sub-problem (22a − 22c) using CPLEX solver. Enumerate possible solutions satisfying the condition that the number of located charging stations are more than or equal to ξ. Then integrate these solutions to form set SEQ.

Step 2: For each solution in SEQ, check whether it can ensure all potential demand is covered, if not, then eliminate it; otherwise retain it. Finally, all retained solutions are combined to form set RS.

Step 3: For each solution in RS, obtain users' allocation result, then determine the capacity allocation of located stations and further calculate objective values of the upper level model. Then identify whether this solution is acceptable in terms of users' average waiting time. If not unacceptable, it is attached with a special symbol.

Step 4: Implement the fast non-dominated sorting approach on RS to form the Pareto-optimal set FG.

Step 5: If all solutions in FG are attached with the special symbol, then there is no acceptable solution for the proposed problem and the algorithm ends. Otherwise return FG and the algorithm ends.

In terms of the computational complexity, the generation and filtering part of enumerated solutions in PEA algorithm takes a time complexity of no more than $O(2^{|J|} - d(\xi, |J|))$, where $d(\xi, |J|) = C^0_{|J|} + C^1_{|J|} + C^2_{|J|} + \ldots + C^{\xi-1}_{|J|} = \sum_{l=0}^{\xi-1} C^l_{|J|}$. As for the level determination part in PEA, its time complexity is at most $O((2^{|J|} - d(\xi, |J|))|J|(\log_2(Q_{max})))$. Moreover, the fast non-dominated sorting part in PEA takes a time complexity of no more than $O(2(2^{|J|} - d(\xi, |J|))^2)$, which governs the complexity of the generation and filtering part $O(2^{|J|} - d(\xi, |J|))$ and the complexity of the level determination part $O((2^{|J|} - d(\xi, |J|))|J|(\log_2(Q_{max})))$. Therefore, we can conclude that the overall complexity of PEA is $O(2(2^{|J|} - d(\xi, |J|))^2)$. Similarly, the time complexity of the exhaustive enumeration method is $O(2(2^{|J|})^2)$, which is larger than that of PEA. Given the value of $|J|$, the complexity of PEA is determined by the value of ξ. And the larger ξ brings better performance of the PEA. And given the value of ξ, the smaller $|J|$ incurs better performance of the PEA. In short, $|J|$ and ξ are the key factors affecting the performance.

Actually, PEA can obtain exact Pareto-optimal solutions in an efficient manner, due to the following reasons. First, only those the solutions satisfying Property 3.1 need to be enumerated, because the solution that cannot satisfy Property 3.1 is definitely an infeasible solution that does not satisfy the demand cover constraint (8) of the model. Moreover, Pareto-optimal solutions must be feasible, and one infeasible solution cannot be Pareto-optimal. Therefore, the application of Property 3.1 in PEA reduces the enumeration space without discarding any feasible solution that can be Pareto-optimal, which greatly enhance the enumeration efficiency while preserving all possible Pareto-optimal solutions. Second, Property 3.2 can be used in PEA to delete poor or unacceptable solutions which lead to excessive waiting time because of the capacity limits of some open locations. Those unacceptable solutions have very poor quality, they may be infeasible because of the violation of the utilisation rate constraint (9). Furthermore, those unacceptable solutions can be dominated by other solutions easily due to their poor performance in terms of users' waiting time. After adopting Property 3.2 to further discard these unacceptable solutions, the exact Pareto-optimal solutions can be obtained ultimately by implementing the fast non-dominated sorting approach on the set of all remained feasible solutions. Furthermore, from the view point of computational complexity, PEA has lower time complexity compared with the common exhaustive enumeration method, which also verifies the efficiency in getting exact Pareto-optimal solutions.

5. Computational experiments and analysis

In this section, some instances are generated based on the practical operation of EV charging station network in Beijing, China. Computational experiments are conducted on these instances to illustrate the computational results, verify the effectiveness of the proposed algorithm and reveal useful managerial insights. All of the algorithms are implemented using MATLAB R2015a and the solver CPLEX 12.5 with default settings. All experiments are performed on a PC with an Intel Core i5 processor (2.2 GHz) and 8 GB memory.

5.1. Data generation and parameter settings

Beijing is one of the leading cities in promoting EVs and developing related supporting facilities in China. Based on the practical operation of EV charging station network and charging demand distribution in Beijing, several research instances are generated accordingly. Specifically, instances are randomly generated based on two major parameters of the model: the number of nodes n and the range of node coordinates, which are listed in columns 3 and 4 of Table 2. The size and distribution of charging demand are measured by these two parameters, respectively, which largely determine the complexity of the proposed problem.

Instances of six different sizes are generated in this research. For each instance, referring to the practical charging station operation in Beijing, the fixed construction cost $f_j$for candidate location j is randomly generated from uniform distribution $U(80, 120) \times 10^4 yuan$, the cost of installing a charging pile at a location p_j is generated randomly from uniform distribution $U(12, 15) \times 10^4 yuan$. And the amount of charging demand at a demand location r_i is randomly chosen from uniform distribution $U(50, 300)$. The maximum capacity units that a charging station can provide Q_j at location j is randomly generated from $U(4, 7)$, which conforms practical size determined by available land and electrical load in Beijing. In addition, other model parameters are set as follows. The average speed of EVs v is originally set as 40 km/h, and travel time of users can be adjusted through scaling it. Original expected delay time of users before starting a charge t_e is 0.11 h. We assume a daily charging peak period lasts 2 h, each EV user has a charging demand with a certain probability pr every day, and we set original $pr = 0.2$. The average charging time of EVs at each station t_s is originally set as 0.5 h. The number of charging piles per capacity unit is 5. Moreover, there are three options for coverage radius of charging stations in each instance, that is, $CO \in \{5, 7.5, 10\}$. The maximum waiting time accepted by users at a charging station is originally set as $w_{max} = 10$ min.

Table 2. The information of instances.

No.	Instances	n	The range of node coordinates
1	CL10	10	[15 km,15 km]
2	CL15	15	[20 km,20 km]
3	CL20	20	[25 km,25 km]
4	CL30	30	[40 km,40 km]
5	CL40	40	[50 km,50 km]
6	CL50	50	[50 km,50 km]

Table 3. Parameter settings in the proposed HNSGA-II algorithm.

Parameters	Potential value	Final value
Maximum generations	[20, 100]	100
Population size	[20, 150]	100
Crossover probability	(0, 1]	0.9
Mutation probability	(0, 1]	0.5

In terms of parameter settings of the algorithms, for the proposed HNSGA-II, we used trial and error method to set suitable values of its main algorithmic parameters. The trial and error method has been widely used for tuning parameter values of meta-heuristics (Manatkar et al. 2015; Dou et al. 2020). It is adopted by means of incremental method, i.e. change the values of one parameter while keeping all other parameters of the heuristic as constant. There are 4 main parameters that need to be tuned, i.e. the number of maximum generations, population size, crossover probability and mutation probability. After some adjustment experiments, these parameters are set. The potential values and the finally recommended values of main parameters are shown in Table 3. And the detailed differences with different settings see Tables A1–A4 in the Appendix.

In addition, we also employed multi-objective particle swarm optimisation (MOPSO) algorithm (Coello, Pulido, and Lechuga 2004; Jolai, Tavakkoli-Moghaddam, and Taghipour 2012; Abbassi et al. 2021) and multi-objective genetic algorithm (MOGA) (Zhou, Min, and Gen 2003; Rabiee, Zandieh, and Ramezani 2012) which are two popular multi-objective evolutionary algorithms, to further evaluate the performance of the designed HNSGA-II. For the MOPSO, we followed the general settings (Dou et al. 2020) in setting its main parameters' values, where the inertia weight ω, acceleration parameters c_1 and c_2 are set to be 0.9, 2 and 2, respectively. Moreover, for the purpose of fair comparison, both the population sizes and the maximum generations of HNSGA-II for all instances are identical with those of MOPSO and MOGA. Besides, we also used the same method of tuning parameter values as HNSGA-II, to set crossover probability, mutation probability of MOGA to 0.9, 0.4, respectively.

5.2. Computational results

Computational results of instances are obtained through running the proposed algorithm. And for the purpose of illustration without loss of generality, we only

Table 4. The non-dominated solutions for instance CL10 with different *CO*.

No.	*CO*/km	Objective 1 $Z_1/10^4$ yuan	Objective 2 Z_2/h	Capacity allocation results (location, the construction level)	Number of stations
1	5.0	2026.20	3.23	(3,6)(5,4)(6,7)(8,1)(10,5)	5
2		2182.73	0.00	(2,4)(3,6)(5,4)(6,4)(8,1)(10,5)	6
3	7.5	1915.03	52.65	(1,5)(2,5)(3,6)(4,6)	4
4		1975.25	7.32	(1,5)(3,6)(6,7)(10,5)	4
5		1965.98	48.56	(2,5)(3,6)(4,6)(5,4)(8,1)	5
6		2026.20	3.23	(3,6)(5,4)(6,7)(8,1)(10,5)	5
7		2182.73	0.00	(2,4)(3,6)(5,4)(6,4)(8,1)(10,5)	6
8	10.0	1915.03	52.65	(1,5)(2,5)(3,6)(4,6)	4
9		1975.25	7.32	(1,5)(3,6)(6,7)(10,5)	4
10		1862.28	56.85	(2,5) (3,6) (4,6) (5,5)	4
11		1853.05	140.36	(2,5) (4,5) (5,7) (6,5)	4
12		1922.50	11.53	(3,6) (5,5) (6,7) (10,5)	4
13		2026.20	3.23	(3,6)(5,4)(6,7)(8,1)(10,5)	5
14		2182.73	0.00	(2,4)(3,6)(5,4)(6,4)(8,1)(10,5)	6

show the computational results of PEA on instance CL10 with three options of coverage radius *CO*, since the HNSGA-II and other instances have similar results.

Table 4 shows the non-dominated solutions of instance CL10 with three value options of *CO*. It can be seen in Table 4 that, with the increase of coverage radius *CO*, the number of solutions in the Pareto front increases accordingly. In addition, the average number of located stations for the Pareto set with $CO = 5$ is 5.5, which is larger than 4.8 in Pareto set with $CO = 7.5$ and 4.43 in Pareto set with $CO = 10$. With the increase of CO, the average value of total construction cost Z_1 in the Pareto set (2104.47, 2013.04 and 1962.43 for Pareto sets with $CO = 5, 7.5, 10$) decreases and the average value of total service tardiness Z_2 (1.62, 22.35, 33.85 for Pareto sets with $CO = 5, 7.5, 10$) increases gradually. Overall, larger coverage radius *CO* results in less number of stations needed to cover charging demand. Due to economies of scale brought by a smaller number of charging stations with centralised capacity allocation, total construction cost required is reduced. However, it takes more time for a user to access a charging station and complete charge, which leads to larger total service tardiness. On the contrary, the solution with larger cost and smaller service tardiness has a larger number of charging stations with decentralised capacity allocation.

The results in Table 4 indicate that the decision maker needs to make trade-offs between total cost and total service tardiness, so as to design a satisfied charging station network. Furthermore, marginal analysis for Pareto fronts is also very important to help decision maker make the most cost-effective decision. In particular, through marginal analysis, the decision maker can find the value range of total service tardiness with low marginal cost. According to the value range, decision maker can choose a solution from the Pareto front, to ensure the service quality of stations as much as possible without increasing total cost significantly.

5.3. Algorithm performance

Computational experiments are conducted to verify the validity and advantages of the proposed HNSGA-II in comparison with PEA, MOPSO and MOGA. Furthermore, three value options of *CO* are considered for each instance, so that there are 18 computational instances in total. For each of small- and medium-sized instances (CL10, CL15 and CL20), 10 independent runs are performed for HNSGA-II, MOPSO and MOGA. And for each of larger-sized instances, five independent runs are performed for HNSGA-II, MOPSO and MOGA.

Seven widely used performance indicators are used to evaluate the proposed HNSGA-II algorithm comprehensively: the number of Pareto solutions, the ratio of Pareto-optimal solutions, IGD (inverted generational distance), HV (hyper volume) and computational time, convergence metrics $\bar{\gamma}$ and σ_γ (Deb et al. 2002). Where IGD is the average of the closest Euclidean distance between each point of the true Pareto front and the Pareto front obtained by the algorithm, which gives a clear idea about diversity and convergence. And the algorithm with minimum value of IGD brings best performance. The ratio of Pareto-optimal solutions refers to the proportion of the Pareto-optimal solutions in the Pareto front obtained by the algorithm, and the algorithm with larger ratio (maximum value: 1) is more efficient. Moreover, HV refers to volume covered by the Pareto front set obtained by the algorithm relative to a given reference point (the selection of reference point follows the reference Beume et al. 2009, the point (0,0) is selected as the reference point). In general, the algorithm with large HV is suitable, which is usually suitable for the multi-objective optimisation with the maximisation form of the model objectives.

Table 5. Comparison results among HNSGA-II, PEA, MOPSO and MOGA.

		The number of Pareto solutions				The ratio of Pareto-optimal solutions				IGD				HV (10^4)			
Instances	*CO*	PEA	HNSGA-II	MOPSO	MOGA	PEA	HNSGA-II	MOPSO	MOGA	PEA	HNSGA-II	MOPSO	MOGA	PEA	HNSGA-II	MOPSO	MOGA
CL10	5	2	2	2	2	1	1	1	1	0	0	0	0	0.655	0.655	0.655	0.655
	7.5	5	4.9	4.9	4.7	1	0.980	0.980	0.940	0	1.022	0.845	2.890	10.353	12.078	10.332	10.175
	10	7	6.9	6.7	6.3	1	0.986	0.957	0.900	0	0.730	1.791	0.900	26.403	26.401	26.338	20.187
CL15	5	29	28.2	25.3	25.2	1	0.969	0.848	0.855	0	1.629	7.275	6.870	39.011	38.059	35.699	35.192
	7.5	31	29.8	22.7	28.6	1	0.958	0.571	0.919	0	0.834	7.148	1.833	34.886	34.539	34.886	32.216
	10	34	33.6	20.8	31	1	0.953	0.441	0.871	0	0.623	10.871	2.375	45.010	44.025	45.087	41.966
CL20	5	10	9.9	9.2	8.1	1	0.990	0.880	0.570	0	0.439	3.910	33.542	29.433	29.433	30.955	17.290
	7.5	12	11.9	12.9	11.1	1	0.992	0.567	0.867	0	2.936	10.015	12.260	35.701	35.698	33.216	30.601
	10	12	11.9	12.7	11.4	1	0.975	0.533	0.800	0	8.808	12.519	10.774	35.701	35.695	36.643	33.942
CL30	5	–	18	14	18	–	0.908	0.479	0.758	–	6.617	21.283	21.591	–	41.923	49.021	42.158
	7.5	–	43	20	41.2	–	0.847	0.027	0.825	–	4.050	42.219	3.529	–	55.919	82.922	56.146
	10	–	53.4	20.4	49.4	–	0.834	0.018	0.696	–	2.503	64.686	6.223	–	97.351	128.486	97.809
CL40	5	–	18.6	9	18.6	–	1	0	0.72	–	0	80.005	6.388	–	24.963	24.386	24.917
	7.5	–	45.2	19.8	36.4	–	0.961	0	0.252	–	0.537	94.394	25.452	–	115.382	101.920	94.495
	10	–	45.6	21.2	38	–	0.778	0	0.482	–	4.111	87.213	9.991	–	133.012	169.948	126.488
CL50	5	–	36.4	15.8	40	–	0.901	0	0.429	–	0.755	78.575	15.542	–	86.195	148.784	88.423
	7.5	–	56.4	16	58.6	–	0.786	0.003	0.264	–	3.033	136.450	28.273	–	169.440	212.846	140.610
	10	–	50.4	17.8	46.8	–	0.879	0.007	0.131	–	9.532	157.542	57.021	–	213.730	259.078	149.326

Table 6. Comparison results among HNSGA-II, PEA, MOPSO and MOGA.

		Computational time (s)				$\bar{\gamma}$				σ_γ			
Instances	*CO*	PEA	HNSGA-II	MOPSO	MOGA	PEA	HNSGA-II	MOPSO	MOGA	PEA	HNSGA-II	MOPSO	MOGA
		1.15	35.64	54.32	38.86	0	0	0	0	0	0	0	0
	7.5	3.26	34.92	41.71	35.23	0	2.942	0	0	0	173.100	0	0
	10	4.23	32.50	39.85	33.44	0	0	0	0	0	0	0	0
CL15	5	25.88	64.51	81.02	71.69	0	0.076	0.238	0.304	0	1.153	7.543	4.611
	7.5	153.09	53.25	70.03	62.04	0	0	4.550	0.155	0	0	71.420	6.463
	10	226.93	51.38	65.43	54.91	0	0.064	7.419	0.718	0	0.648	115.388	11.672
CL20	5	1520.61	79.53	117.44	100.88	0	0.439	4.060	11.036	0	17.342	108.754	297.249
	7.5	17044.81	81.29	86.20	85.13	0	0	8.752	1.457	0	0	142.924	42.050
	10	46866.28	77.57	77.38	84.97	0	0	10.675	4.976	0	0	249.597	97.836
CL30	5	–	167.18	212.16	179.55	–	1.273	7.400	7.460	–	34.727	123.496	393.264
	7.5	–	167.35	169.86	154.74	–	0.956	34.840	0.496	–	13.268	2164.134	6.614
	10	–	154.81	149.98	148.65	–	1.044	48.948	2.843	–	19.264	2819.740	52.236
CL40	5	–	211.82	263.48	190.67	–	0	57.385	6.787	–	0	4383.640	115.142
	7.5	–	186.11	219.66	179.45	–	0.728	124.244	18.002	–	16.031	30329.400	407.443
	10	–	188.75	226.41	170.15	–	1.225	139.519	3.445	–	62.307	37550.600	51.162
CL50	5	–	289.73	302.45	231.48	–	0.366	185.163	14.746	–	2.234	62115.600	258.984
	7.5	–	226.37	271.67	222.80	–	0.751	208.396	23.012	–	5.931	69458.080	3394.860
	10	–	253.37	244.75	211.60	–	1.345	223.479	26.352	–	27.578	79684.920	1616.836

But this rule for identifying the algorithm performance may be not suitable for the case with the minimisation form of objectives of the model, especially when there is large relative difference in the number of Pareto solutions among different algorithms. So HV is used in combination with other indicators to evaluate the performance of the algorithm. While metrics $\bar{\gamma}$ and σ_γ measure mean and variance of minimum Euclidean distance between each solution in the Pareto set and certain solutions in the Pareto-optimal front, respectively. The smaller the values of these two metrics, the better the convergence of the algorithm.

Tables 5 and 6 together provide the comparative results among the four algorithms. Noting that the symbol – represents that the algorithm could not find the Pareto front within a certain amount of time (15 h). As shown in Table 5, PEA can find the true Pareto-optimal solutions only for small and medium-sized instances within 15 h. And for larger-sized instances, PEA cannot find any Pareto solution. Hence, we approximate the true Pareto-optimal front for large-sized instances by implementing non-dominated sorting operation on the union of non-dominated solutions obtained by all considered meta-heuristic algorithms, to evaluate the values of indicators like the ratio of Pareto-optimal solutions, IGD for the 3 meta-heuristic algorithms.

According to the two indicators: the number of Pareto solutions and the ratio of Pareto-optimal solutions, the HNSGA-II has the best performance among the 3 meta-heuristic algorithms, and the indicators' values of HNSGA-II are closet to those of PEA in comparison with MOPSO and MOGA for small and medium-sized instances. Further, MOGA outperform MOPSO, because it has the larger values of the two indicators for about 78% instances.

The HV metric values in Table 5 indicate that there is no significant difference between the 4 algorithms for small and medium-sized instances and further the HNSGA-II has slight advantage with the values of HV closest to those of PEA in comparison with MOPSO and MOGA. For larger-scale instances, MOPSO has the largest values of HV for most cases but with the lowest number of Pareto solutions, which makes it inferior with considering the minimisation form of the model objectives. While the HNSGA-II also has slight superiority in terms of HV for most of large-scale cases compared with MOGA. According to IGD columns, it can be found that the HNSGA-II has lower IGD values for almost all instances compared with MOPSO and MOGA. Furthermore, MOGA outperforms MOPSO in terms of IGD because it has lower values for 72% instances.

Based on the view point of computational time, it can be found from Table 6 that PEA has better performance for small-sized instances because it can find Pareto-optimal solutions within less time compared with the 3 meta-heuristics. As mentioned before, PEA exhausts much more time than HNSGA-II, MOPSO and MOGA for medium-sized instances and even it cannot find any Pareto solution for larger-scale instances within 15 h. While there is no significant difference among the 3 meta-heuristics, and further HNSGA-II has slight advantage in computational time for small- and medium-sized instances because it exhausts less time than MOPSO and MOGA.

The $\bar{\gamma}$ and σ_γ metric values in Table 6 show that HNSGA-II has the best convergence because it has lowest values for most of the instances compared with MOPSO and MOGA. Moreover, MOGA has secondary performance in terms of $\bar{\gamma}$ and σ_γ indicators, but it still outperforms MOPSO for 81% instances.

In summary, PEA is only suitable for solving small-sized problem, and it is computationally inefficient to solve practical problem with large scale. While the HNSGA-II has solution quality very close to that of PEA but with preferred computational efficiency. Among the 3 meta-heuristics, the designed HNSGA-II outperforms MOPSO and MOGA for solving the proposed problem. Therefore, HNSGA-II is used to conduct subsequent experiments of managerial analysis and sensitivity analysis.

5.4. Managerial analysis for the location planning modes

To verify the advantage of considering the users' preferences, we also conduct managerial analysis for the two location planning modes: considering users' preferences (abbreviated as CUP) and no considering the users' preferences (abbreviated as NCUP). In general, if the users' preferences are not considered, we can naturally assume that each user will randomly go to any open charging station within the coverage radius for charging EV with the same probability. And this assumption is reasonable in the case without considering the users' preferences. Therefore, for the CUP mode, the model will be converted from the proposed bi-level programming model to a general multi-objective nonlinear model without the bi-level structure. In addition to removing the lower level model, the main change also involves the determination of E_j, which represents the number of EVs accessing charging station j during a peak period. And the new E_j for the NCUP mode is as follows:

$$E_j = \sum_{i \in I} r_i \frac{x_j}{\sum_{j \in N_i} x_j} \quad \forall j \in J \tag{23}$$

And the complete mathematical model for the NCUP mode see the Appendix.

For the purpose of illustration without loss of generalisation, the analysis is done on medium-sized instances CL20 and CL30 with 3 options of CO by our HNSGA-II since the other instances have very similar results. Moreover, due to the real users' preferences, the objective values of Pareto solutions under the NCUP mode need to be re-evaluated by using the evaluation approach for the CUP mode. After re-evaluating, the transformed Pareto solutions of the NCUP mode are compared with those of the CUP mode to implement managerial analysis under unified standards.

Figure 6 illustrates comparison results of the two location planning modes for instance CL20. We can observe that most of Pareto solutions for the NCUP mode have extremely large charging service tardiness. We normally define these Pareto solutions with large total service tardiness (more than 150 h) as abnormal solutions. It can be found that the ratio of abnormal solutions for the NCUP mode increase with the increase of coverage radius CO, and all Pareto solutions for the NCUP mode are all abnormal solutions when $CO = 10$. The increase of the ratio is due to the fact that users have more and more choices in randomly accessing charging stations within the coverage radius as the coverage radius increases. This fact will make more and more people gather at the preferred charging stations with considering users preferences, thereby incurring extremely large charging service tardiness. While none of the Pareto solutions for the CUP mode is abnormal for any option of CO. Furthermore, after removing abnormal solutions, the remained Pareto solutions for the NCP mode are absolutely dominated by the Pareto solutions for the CUP

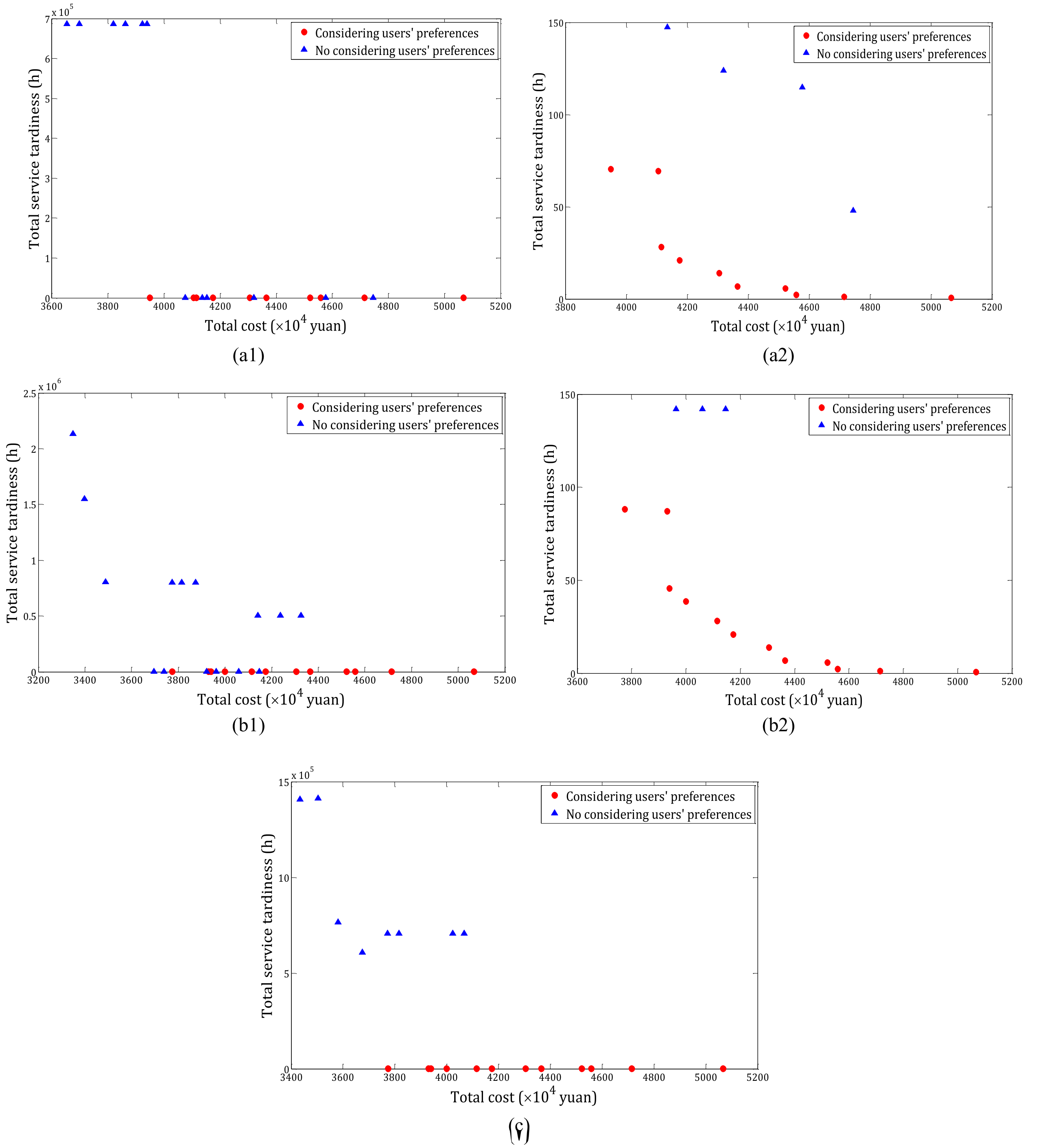


Figure 6. Comparison results of the two location planning modes for instance CL20. (a1) Comparison with abnormal solutions for $CO = 5$. (a2) Comparison after removing abnormal solutions for $CO = 5$. (b1) Comparison with abnormal solutions for $CO = 7.5$ (b2) Comparison after removing abnormal solutions for $CO = 7.5$. (c) Comparison for $CO = 10$.

mode, which is shown in Figure 6(a2) and (b2). The CUP mode has superiority in the reduction of users' charging service tardiness and cost savings compared with the NCUP mode.

Figure 7 also shows similar comparison results. Because instance CL30 has larger size than instance CL20, users have more potential choices of charging stations. Hence, when CO increases to 7.5, all Pareto solutions for the NCUP mode are already abnormal solutions. Similarly, none of the Pareto solutions for the CUP mode is abnormal for any option of CO. Moreover, Figure 7(a2) illustrates that the remained Pareto solutions for the NCP mode are apparently dominated by the Pareto solutions for the CUP mode. The comparison results shown in

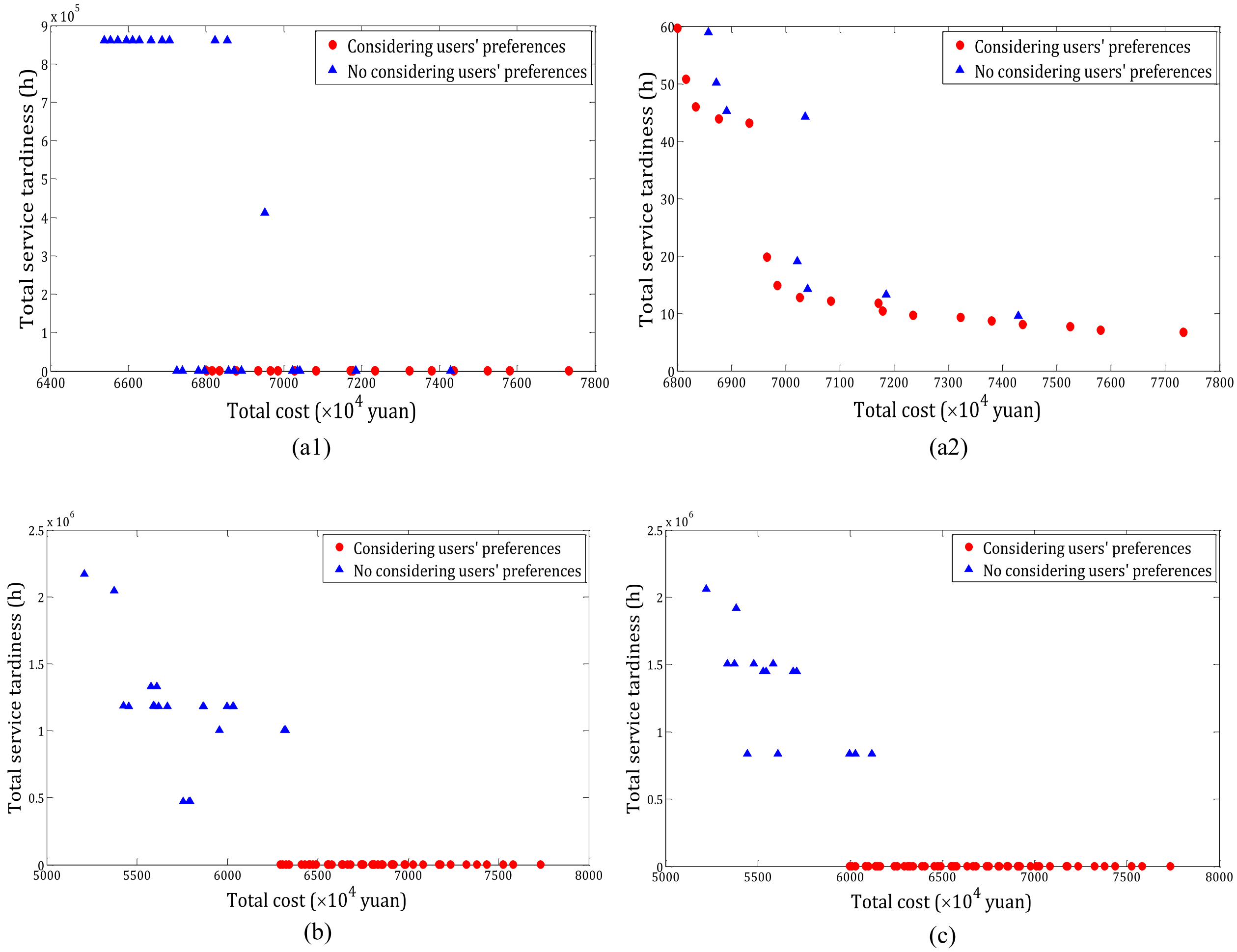


Figure 7. Comparison results of the two location planning modes for instance CL30. (a1) Comparison with abnormal solutions for $CO = 5$ (a2) Comparison after removing abnormal solutions for $CO = 5$. Comparison for $CO = 7.5$. (c) Comparison for $CO = 10$.

Figure 7 verify the advantages of considering users' preferences again.

According to the above managerial analysis, we can conclude that considering the users' preferences has significant advantages in reducing charging service tardiness and saving cost compared with no considering users' preferences. And the CUP mode play an important role in location practice of EV charging stations.

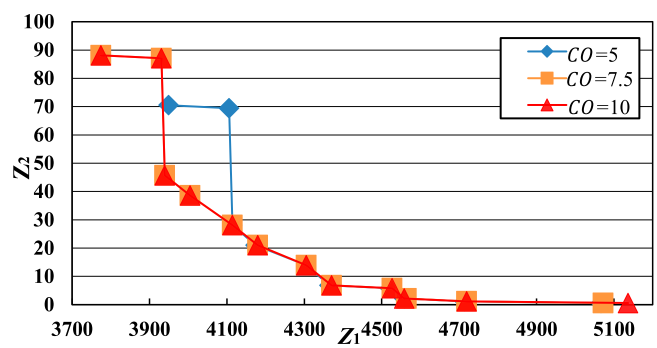


Figure 8. The effect of coverage radius on the Pareto sets.

5.5. Sensitivity analysis

In this section, we will discuss how Pareto front vary with some significant parameters: coverage radius CO, fixed construction cost f_j, expected delay time t_e, travel time t_{ij}, maximum waiting time w_{max} and EV charging probability pr. Sensitivity experiments are performed on these parameters to provide decision-making support for the decision maker. We perform our sensitivity experiments based on the medium-size instance CL20.

(1) The effect of coverage radius

We consider three value options of coverage radius CO: $CO = 5$, 7.5, 10. As shown in Figure 8, there are differences between the Pareto set with $CO = 5$ and the other two Pareto sets, the number of solutions in the Pareto set with $CO = 5$ is smaller than that in the other two Pareto sets and the worst value for objective two in the Pareto set with $CO = 5$ is also smaller

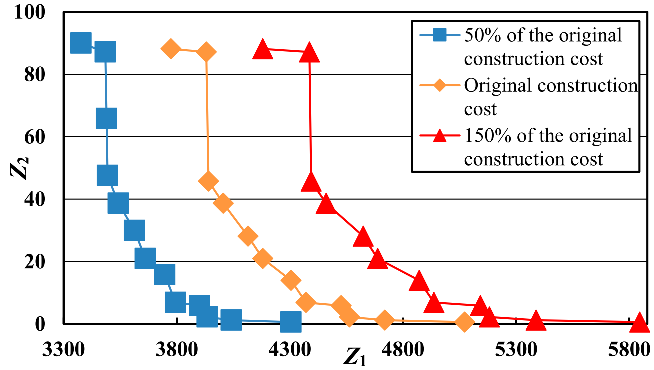


Figure 9. The effect of fixed construction cost on the Pareto sets.

than those in the others. While there are almost no differences among the 2 Pareto sets which correspond to $CO = 7.5$ and $CO = 10$, respectively. Overall, larger CO relaxes the set coverage constraint, which leads to a larger feasible solution space of the proposed problem and further a Pareto set with more potential non-dominated solutions. But this relaxation effect is relatively limited. As a result, the sensitivity of coverage radius CO is relatively low and its influence on the Pareto set is limited.

(2) The effect of fixed construction cost

We perform sensitivity analysis to fixed construction cost by considering the following 3 scenarios: original fixed construction cost, reducing original fixed construction cost by 50% and increasing original fixed construction cost by 50%. From Figure 9, It can be seen that there are significant differences among three Pareto sets under the above three scenarios. All the three Pareto sets can give almost the same best value and worst value for objective 2 Z_2, but the average value of objective 1 Z_1 in each Pareto set increases with the increase of fixed construction cost. Therefore, we can conclude that the increase of fixed construction cost leads to larger total cost but has almost no effect on service quality, which shows the fixed construction cost is a cost parameter with high sensitivity.

(3) Sensitivity to the expected delay time

For sensitivity analysis to the expected delay time, we also consider 3 cases: original expected delay time, reducing the original expected delay time by 40% and increasing the original expected delay time by 40%. From Figure 10, we can find that the values of the best and the worst Z_2 improve with the increase of expected delay time, and the average value of Z_2 in the Pareto set decreases as the expected delay time increases. Given the same service tardiness Z_2, such as 20 h, the total cost in the Pareto set increases largely as the expected delay time increases. In addition, the number of solutions in the Pareto set decreases with increasing expected delay time, which means less decision choices for the decision maker. Hence, the enhancement of users' acceptance to delay time can reduce total service tardiness and reduce total cost with reducing decision space.

(4) Sensitivity to users' travel time

We adjust users' travel time by varying driving speed of EVs which is highly dependent on actual traffic situation. Similarly, we also consider 3 cases of travel time setting: original travel time, reducing the original travel time by 20%, increasing the original travel time by 20%. The increase of users' travel time means the decrease of EV average speed, which indicates worse traffic conditions. From Figure 11, we can find that the values of both the worst Z_2 and the worst Z_1 exacerbate with the increase of users' travel time. Given the same Z_1 (such as 4000 $\times 10^4$ yuan) or Z_2(such as 20 h), the value of corresponding Z_2 or Z_1 increase with users' travel time. Therefore, it can be concluded that the worse traffic conditions have negative effects on both total cost and service quality.

(5) The effect of the maximum waiting time

We also study the effect of the maximum waiting time because it largely determines service quality of charging stations. In the related sensitivity experiments, we set 3 cases of the maximum waiting time: original maximum waiting time, reducing the original waiting time by 50%, increasing the original waiting time by 50%. It can be seen in Figure 12 that, with the increase of the maximum waiting time, the values of the best and worst Z_2 in the Pareto set increase and the values of both the best Z_1 and the worst Z_1 decrease to a certain extent. In addition, as the maximum waiting time increases, the average value of

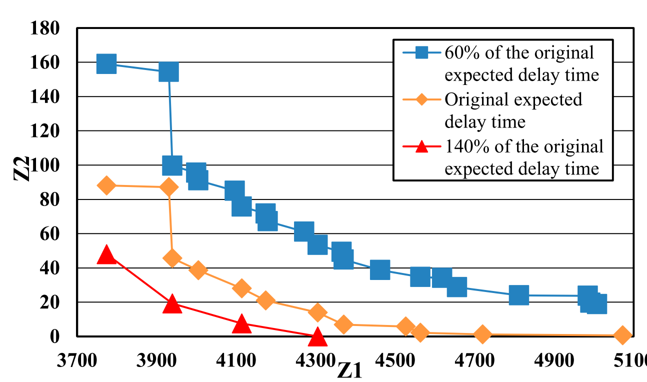


Figure 10. The effect of expected delay time on the Pareto set.

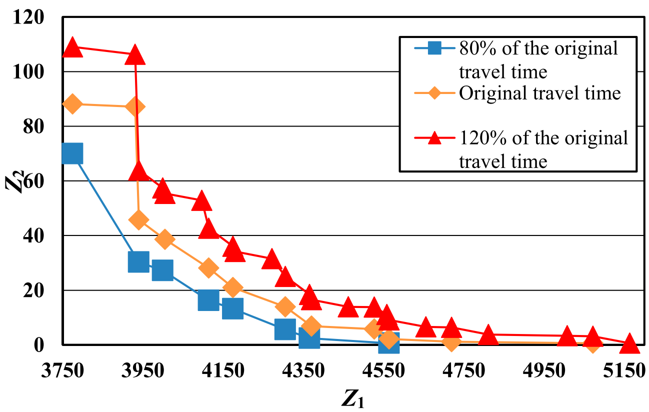


Figure 11. The effect of user travel time on the Pareto sets.

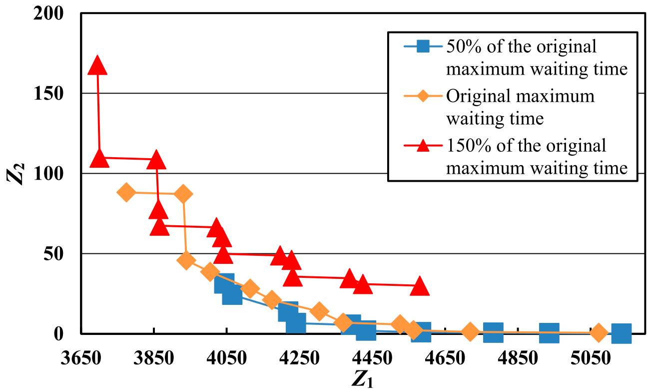


Figure 12. The sensitivity analysis for the maximum waiting time.

total cost Z_1 in the Pareto set reduces and total service tardiness Z_2 increases largely. Therefore, the increase in maximum waiting time reduces cost needed to cover all charging demand but worsens service quality.

(6) Sensitivity to EV charging probability

In the sensitivity analysis to EV charging probability, we also consider 3 cases: original EV charging probability,

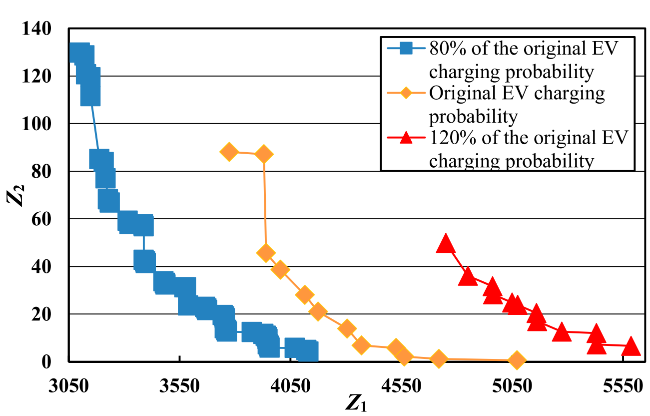


Figure 13. The sensitivity analysis for EV charging probability.

80% of the original EV charging probability and 120% of the original EV charging probability. As Figure 13 illustrates, both the average value of Z_2 and the worst value of Z_2 improve with the increase of EV charging probability. However, the average value of Z_1 in the Pareto set increases with the EV charging probability. And in particular, with the same Z_2, the corresponding cost Z_1 in the Pareto set increases with the EV charging probability. The rise of EV charging probability means the increase of charging demand. So we can conclude that the increase of charging demand requires more total cost but improves service quality, which indicates more invest means are encouraged in the construction of charging stations, considering the increasing adoption of EVs in the following years.

5.6. Real-world case study

To test our proposed location planning approach, a real-world case study is conducted based on Beijing EV charging station location problems. In this case, 186 candidate station locations are selected within the downtown area of Beijing, which is shown as Figure 14. In specific, we first use web crawler technique to capture the data of the longitudes and latitudes of potential places for constructing charging stations, such as the existing EV charging stations, parks, parking lots and shopping malls in this area. Then we further filter out inappropriate locations according to the requirement to available land and electrical load, and the remaining sites are considered as the final candidate locations. The distribution of candidate locations or demand nodes is shown in Figure 14, which is obtained via using Baidu map API. Furthermore, users' charging demand within the study area is assigned to their closest candidate location, then the charging demand related to each candidate location is aggregated accordingly. The thermodynamic diagram of potential charging demand is shown in Figure 15.

In this case study, the coverage radius of EV charging station is set to 5 km. And the values of other major parameters like the average speed of EVs follow the default settings listed in section 5.1. In terms of the parameter settings of the algorithm, the parameters of the hybrid NSGA-II are set in accordance with the previous computational experiments. Given the input data, the results of the design of EV charging stations network can be obtained using the proposed model and method. The obtained Pareto set with 8 Pareto solutions is shown in Figure 16.

The Pareto solution set in Figure 16 also illustrates the trade-off between total cost and total service tardiness, which provide decision flexibility for the decision maker.

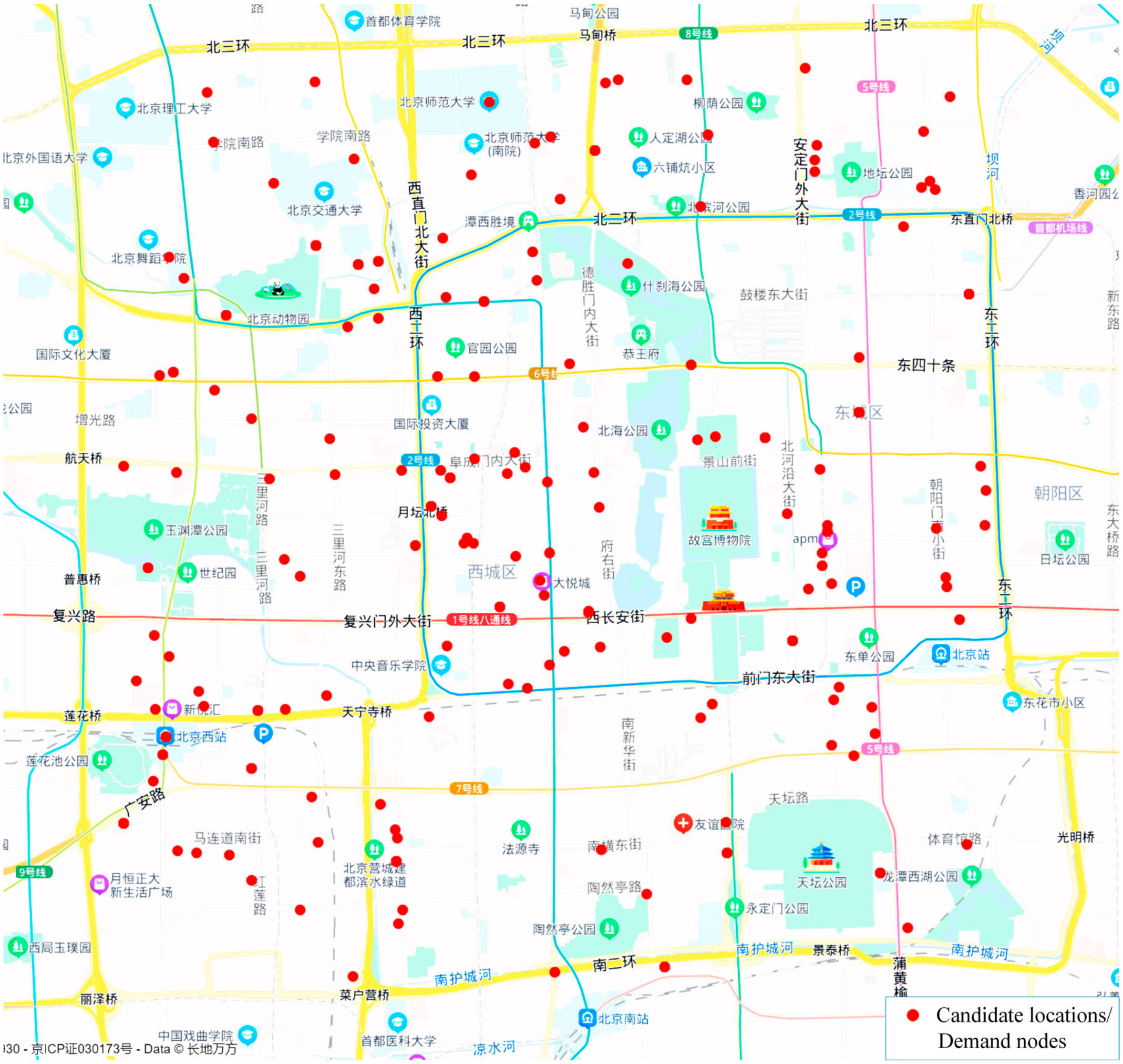


Figure 14. The distribution of candidate locations or demand nodes.

Where the Pareto solution with lowest cost and highest tardiness locates 59 charging stations, and another one with lowest tardiness and highest cost locates 56 charging stations. Hence there is relative small difference between these Pareto solutions in terms of the number of located charging stations, which is due to the relatively small solution region incurred by the small service radius of charging station and the limited capacity of candidate locations under the large size charging demand. Furthermore, according to the tardiness objective values of these Pareto solutions, they can be divided into two categories: one with high service tardiness (more than 60 h) and another one with low service tardiness (less than 30 h). For the purpose of illustration, we choose one from each category of Pareto solutions to show. In particular, we visualise the comparison between the solution with lowest service tardiness and highest cost (abbreviated as SLTHC) and the solution with lowest cost and highest service tardiness (abbreviated as SLCHT) using Baidu map API.

Figure 17 illustrates the comparison between the Pareto solutions SLTHC and SLCHT. In both Figure 17(a,b), the distribution of charging stations coincides with that of the charging demand shown in Figure 15. And the area with high density demand tends to have larger number of charging stations. Moreover, it can be found that there are relatively small differences between these two Pareto solutions on the whole. While the Pareto solution SLTHC has slightly larger number of charging stations with decentralised capacity allocation and the Pareto solution SLTHC has the opposite. It verifies again that the optimisation of cost objective results in

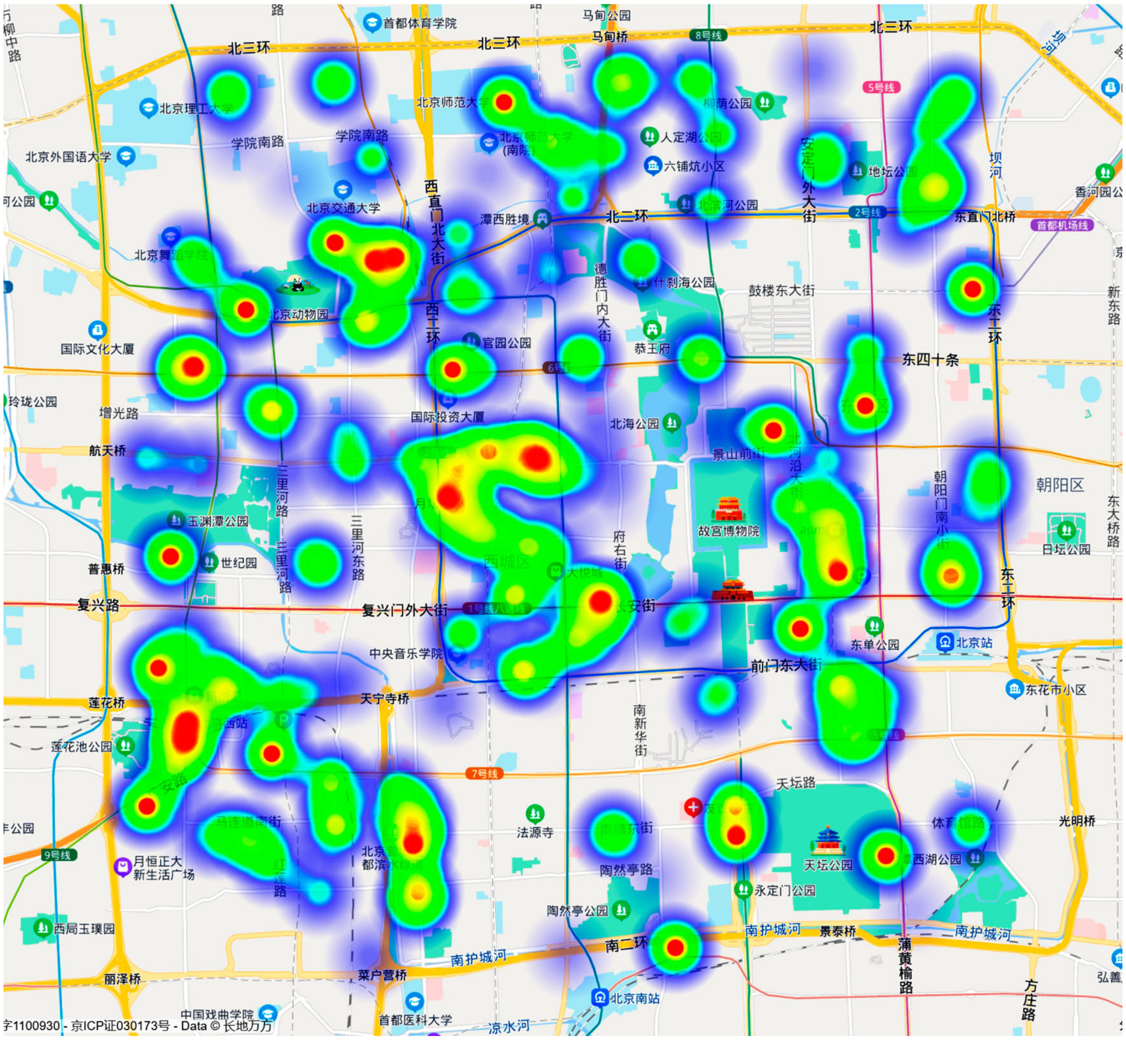


Figure 15. A thermodynamic diagram of the distribution of potential charging demand.

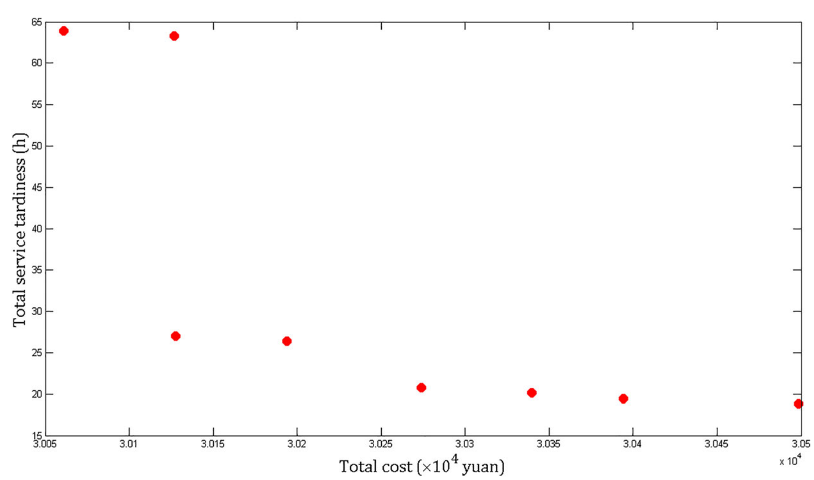
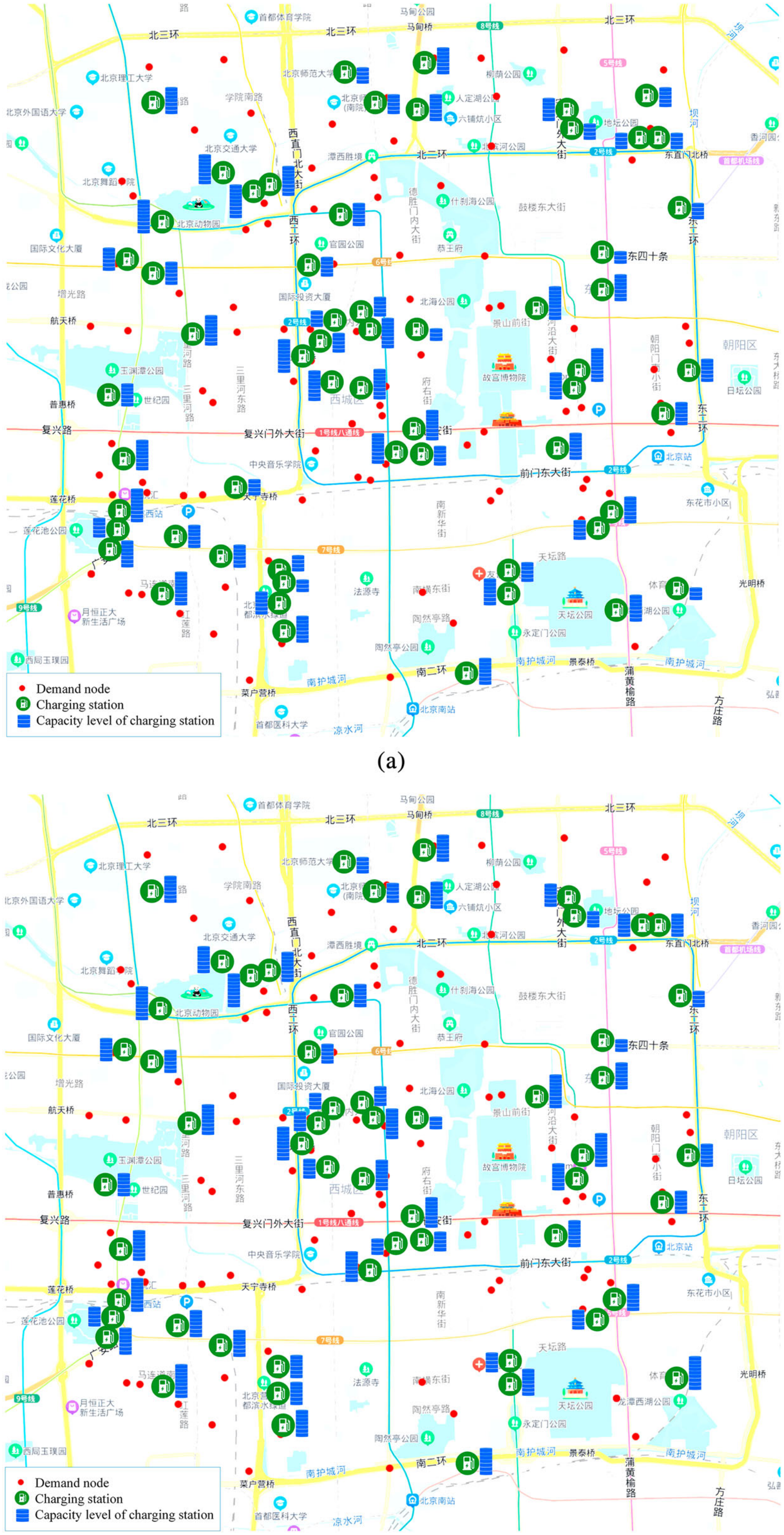


Figure 16. The Pareto set of the case.



(a)

(b)

Figure 17. The comparison between the Pareto solutions SLTHC and SLCHT. (a) The illustration of the Pareto solution with lowest service tardiness and highest cost. (b) The illustration of Pareto solution with lowest cost and highest service tardiness.

a centralised charging station network and the optimisation of service quality objective results in a decentralised charging station network.

In summary, our proposed approach can effectively solve the large size problem from the real-world, providing flexible decision references for the decision maker with the optimisation of total cost and service quality. It could be promisingly applied for the location practice of EV charging stations.

5.7. Managerial suggestions and application strategies

Based on the above results and analysis related to the proposed problem, we propose some management suggestions and application strategies to provide decision support and guidelines for decision makers.

The specific recommendations and strategies are as follows: (1) decision makers must take into account users' preference and waiting time while making his location planning decisions, because considering users' preference has significant advantages in reducing charging service tardiness and saving cost compared with the mode of no considering users' preferences. (2) The decision makers can make the most cost-effective location planning decision through marginal analysis of the Pareto front. That is, decision makers can choose a solution from the Pareto set using the marginal analysis, to ensure the service quality of stations as much as possible without increasing total cost significantly. (3) According to the trade-off relationship between cost and service tardiness, decision makers can also choose a satisfied solution from the Pareto set using weighted average method. That is, the decision maker first rank the solutions in the Pareto set in terms of the weighted average value of two normalised objectives, noting that weights of the two objectives are allocated based on his decision considerations, and then adopt the solution with the highest ranking to design a satisfied EV charging station network. (4) The changes of several parameters studied in section 5.5 have impact on cost and service quality of EV charging stations, so the decision maker must determine suitable values of these parameters before making decisions. In particular, in response to the expanding charging demand in the following years, and the achievement of better service quality as well as the economies of scale for charging station construction, it is necessary that the values of the expected delay time and maximum waiting time should be set slightly less than the original settings in section 5.1, and the values of EV charging probability should be set larger than the original setting. The above suggestions and strategies could be useful to help decision makers to apply the proposed location planning approach in construction practice of EV charging stations.

6. Conclusions

This paper studies a location planning problem of EV charging stations with considering users' preferences and waiting time. A multi-objective bi-level programming model is proposed to determine locations and capacity allocation of charging stations and explore the trade-off between total cost and service quality. As it is a NP-hard problem, a HNSGA-II algorithm is proposed with comparison to PEA, MOPSO and MOGA. The comparison results show that the designed HNSGA-II outperforms other considered algorithms. In addition, the computational results show that the optimisation of cost objective results in a centralised charging station network and the optimisation of service quality objective results in a decentralised charging station network. Furthermore, managerial analysis shows that the location mode of considering users' preferences has significant advantages in the reduction of charging service tardiness and cost savings. Through sensitivity analysis, some managerial insights are presented for location planning of EV charging stations in practice. Finally, the case study based on the EV charging station location problems in Beijing, China, shows that the proposed approach can effectively solve the large size problem from the real-world, providing flexible decision references for the decision maker with the optimisation of total cost and service quality.

Major managerial insights derived from experiments and analysis are concluded as follows. (1) Due to the significant advantages of considering users' preferences in reducing service tardiness and saving cost, users' preferences should be considered emphatically in location practice of EV charging stations. (2) To reduce users' waiting time, the decision makers should choose a smaller maximum waiting time to ensure service performance of charging stations within the budget. (3) The government/operator could try to enhance users' acceptance to delay time through conducting charging price discount related to waiting time (i.e. the longer a customer waits, the stronger the price discount he/she receives), or building supporting facilities like convenience stores and common rooms, so that the impact of charging queue can be alleviated largely and more cost savings can be obtained. (4) To reduce users' service tardiness under limited budget, the decision makers could consider a smaller coverage radius while making location planning decisions through the proposed approach. (5) It will be beneficial for the government/operator to exploit the economies of scales on constructing a charging station, so as to obtain more cost savings with ensured service quality. (6) The decision makers should balance the total cost and service quality to ensure decision effect.

The major shortcomings of this paper include the following two aspects: (1) all users have the same and single station preference of minimising travel time, and in practice, users' preference is stochastic and comprehensive. (2) Potential charging demand at each location is constant, actually, we can obtain realistic demand distribution using the demand estimation method as shown in references like Bai, Chin, and Zhou (2019). Meanwhile, future research interests include (1) it can be interesting and challenging to account for more preference factors in the model (such as users' waiting time and the attraction of charging stations (nearby convenience stores and other supporting facilities) to users, etc.), which will make the overall problem more complicated. (2) Designing more efficient solution algorithm also naturally becomes a research focus for future work. (3) Extending this research to further address location planning for multiple types of charging infrastructures including EV battery swapping stations. (4) It may be more practical to build charging stations over multi-period horizon than within a short period of time (Chung and Kwon 2015), therefore, multi-period location optimisation for EV charging stations with users' preferences and waiting time will also be an interesting research topic in future work.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, [X H], upon reasonable request.

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Appendix

Proposition A.1: *The proposed location planning problem of EV charging stations is NP-hard.*

Proof: We proof it by showing it can be reduced to a location set covering problem, which is a NP-complete problem proven by Karp (1972), and combing with the computational complexity of bi-level linear programming (Ben-Ayed and Blair 1990). If set $p_j = 0$, $t_e = +\infty$, $Q_j = +\infty$, then, $Z_1 = \sum_{j\in J} f_j x_j$, $Z_2 = \sum_{i\in I}\sum_{j\in J}\{\mathrm{Max}[-\infty, 0]\} r_i y_{ij} \equiv 0$. And we can convert the proposed problem to the following problem:

$$\min \sum_{j\in J} f_j x_j \tag{19}$$

s.t.

$$\sum_{j\in N_i} x_j \geq 1 \quad \forall i \in I \tag{20}$$

$$x_j \in \{0, 1\}, \quad \forall j \in J \tag{21}$$

Noting that the solution of the converted lower level model (which remains unchanged) does not contribute to the goal of the entire transformed model, so it is ignored here. Clearly, the above transformed problem is a linear programming problem called location set covering problem (LSCP), and it is a well-known NP-complete problem. Also, the related transformation operations can be done in polynomial time. On this basis, Ben-Ayed and Blair (1990) have proved that solving a simple bi-level linear programming is NP-hard, and multiple objective attributes of the proposed problem and high non-linearity structure in both the objectives and several constraints further increases the complexity of the established bi-level programming model greatly, therefore, the location planning problem of EV charging stations proposed in this research is NP-hard. ■

Property A.1: Let $x_1, x_2, \cdots, x_{|J|}$ be a solution of upper level model, and $x_j \in \{0, 1\}, \forall j \in J$. It must not be a feasible solution of the proposed MOBLP model when $\sum_{j\in J} x_j < \xi$, and ξ is obtained by solving the following set covering problem:

$$\min \xi = \sum_{j\epsilon J} x_j \tag{22a}$$

s.t.

$$\sum_{j\in N_i} x_j \geq 1 \quad \forall i \in I \tag{22b}$$

$$x_j \in \{0, 1\} \quad \forall j \in J \tag{22c}$$

Proof: We prove it by contradiction. Assuming $x_1, x_2, \cdots, x_{|J|}$ is a feasible solution such that $\sum_{j\in J} x_j < \xi$, so this solution satisfies the constraints (8) and (13) of the model, which exactly constitute the constraint set of the above set covering model, therefore, $x_1, x_2, \cdots, x_{|J|}$ is also a feasible solution of the above problem (22a)–(22c). Since ξ is the optimal objective function value of the model (22a)–(22c), considering the solution $x_1, x_2, \cdots, x_{|J|}$, we have the result $\sum_{j\in J} x_j \geq \xi$, which contradicts the assumption $\sum_{j\in J} x_j < \xi$. Therefore, we complete the proof of Property 3.1. ■

Table A1. The difference with different values for maximum generations.

Maximum generations	The ratio of Pareto-optimal solutions	IGD	HV	Computational time (s)
20	0.3	31.204	32.207	16.682
50	0.692	20.933	33.948	36.424
70	0.875	6.821	35.673	52.818
100	**0.992**	**2.936**	**35.698**	81.289

Table A2. The difference with different values for population size.

Population size	The ratio of Pareto-optimal solutions	IGD	HV	Computational time (s)
20	0.158	52.897	33.311	16.433
50	0.758	19.296	35.075	39.496
70	0.775	17.877	35.769	52.63
100	**0.992**	**2.936**	**35.698**	81.289
150	0.983	5.872	35.696	108.045

Table A3. The difference with different values for crossover probability.

Crossover probability	The ratio of Pareto-optimal solutions	IGD	HV	Computational time (s)
0.1	0.55	29.77	30.399	83.593
0.3	0.658	21.506	35.011	93.418
0.5	0.75	16.657	35.072	78.562
0.7	0.975	6.225	35.631	83.13
0.9	**0.992**	**2.936**	**35.698**	81.289
1	0.95	17.616	35.688	78.873

Property A.2: Let $x_1, x_2, \cdots, x_{|J|}$ be a solution of upper level model, and $x_j \in \{0, 1\}, \forall j \in J$. It is a feasible and acceptable solution of the proposed model only when $\sum_{j\in J} x_j \geq \xi$ and $Q_j > \frac{1}{a}\max(\rho_j, h_j), \forall j \in \{j | x_j \neq 0\}$.

Proof: Property 3.2 can be gotten by the Equations (9)–(10), (12) and Property 3.1. Clearly, Property 3.1 is a necessary condition such that $x_1, x_2, \cdots, x_{|J|}$ is a feasible solution. On this basis, in order to ensure the feasibility of it, it also needs to satisfy the constraint (9), $\rho_j / s_j a < 1, \forall j \in \{j | h_j \neq 0\}$, which is equivalent to $s_j > \rho_j / a$, $\forall j \in \{j | h_j \neq 0\}$. Noting that $h_j \neq 0$ means that $E_j > 0$, i.e. $\exists\ i \in I, y_{ij} = 1$, due to the constraint (17),$y_{ij} \leq x_j$, we have $x_j \neq 0$. So the above inequality $s_j > \rho_j / a, \forall j \in \{j | h_j \neq 0\}$ can be further expressed as $s_j > \rho_j / a, \forall j \in \{j | x_j \neq 0\}$. In addition, given the solution $x_1, x_2, \cdots, x_{|J|}$, the value of each s_j can be obtained through constraints (10) and (12). And Q_j denotes the maximum allowable value of s_j, only

Table A4. The difference with different values for mutation probability.

Mutation probability	The ratio of Pareto-optimal solutions	IGD	HV	Computational time (s)
0.05	0.608	24.768	27.956	76.629
0.25	0.842	11.518	34.006	78.83
0.5	**0.992**	**2.936**	**35.698**	81.289
0.75	0.975	8.808	35.694	75.06
1	0.975	8.808	35.694	77.045

when $\frac{h_j}{a} < Q_j$, the value of s_j can be taken such that the average waiting time w_j of users at charging station j ($j \in \{j|x_j \neq 0\}$) does not exceed w_{max}, that is, the waiting time w_j can be accepted by corresponding users and the corresponding solution can be accepted by decision maker. Therefore, combining the above two inequalities, we have $Q_j > \frac{1}{a}\max(\rho_j, h_j)$, $\forall j \in \{j|x_j \neq 0\}$. The proof of Property 3.2 is completed. ■

The model for the location planning mode of no considering the users' preferences:

$$\min Z_1 = \sum_{j\in J} f_j x_j + \sum_{j\in J} s_j a p_j \tag{6}$$

$$\min Z_2 = \sum_{i\in I}\sum_{j\in J} \mathrm{Max}[(t_{ij} + w_j - t_e), 0] r_i y_{ij} \tag{7}$$

$s.t.$ (1), (2)

$$\sum_{j\in N_i} x_j \geq 1 \quad \forall i \in I \tag{8}$$

$$\rho_j / s_j a < 1 \quad \forall j \in \{u|h_u \neq 0\} \tag{9}$$

$$h_j = \begin{cases} 0 & E_j = 0 \\ G^{-1}(E_j, w_{max}) & E_j > 0 \end{cases} \quad \forall j \in J \tag{10}$$

$$E_j = \frac{\sum_{i\in I} r_i x_j}{\sum_{j\in J} x_j} \quad \forall j \in J \tag{23}$$

$$s_j = \begin{cases} 0 & h_j = 0 \\ \left\lceil \frac{h_j}{a} \right\rceil & 0 < \frac{h_j}{a} \leq Q_j \\ Q_j & \frac{h_j}{a} > Q_j \end{cases} \quad \forall j \in J \tag{12}$$

$$x_j \in \{0, 1\}, \quad s_j \in N \forall j \in J \tag{13}$$