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Bi-level programming model approach for electric vehicle charging stations considering user charging costs

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ABSTRACT

The rapid development of electric vehicles (EV) has placed greater demands on the planning and construction of public electric vehicle charging stations (EVCS). As EV users are highly autonomous in their charging behavior, the interests of investors and EV users are mutually affected and challenging to balance. Therefore, this paper proposes a bi-level planning model to balance the interests of investors and EV users and optimize global economic costs while improving the service satisfaction of users. The upper-level model aims to optimize the economic cost. In contrast, the lower-level model aims to optimize the service satisfaction of EV users and characterizes the charging satisfaction of EV users through the costs of charging queuing time, distance traveled, desired to charge volume, and actual charging volume, to more accurately reflect the autonomy of EV users. A combination of fast and slow charging piles is also used for planning to meet the needs of different users and improve charging stations' operational efficiency. Finally, a case study is conducted in an area of Beijing to verify that the optimization model has the advantages of low global economic cost, short charging queuing time for users, and high service satisfaction.

1. Introduction

Humanity's social and technological development is closely linked to energy use. In recent years, with the expansion of human society, energy consumption has increased tremendously, thus leading to a series of problems such as global warming and changes in the ecological environment. Therefore, exploring and developing renewable energy sources to gradually replace fossil fuels has become countries' consensus worldwide. Electricity, as a clean energy source, can be obtained directly from various renewable energy sources such as solar, wind, tidal and geothermal energy and is one of the best alternatives to fossil energy. EVs powered by electricity and do not emit polluting gasses have recently received worldwide attention and have been rapidly developed and used. With the rapid growth of EV ownership, the planning and construction of public EVCSs, an essential facility for the promotion and application of EVs, is of great significance to the development of EVs. According to the Guidance on Accelerating the Promotion and Application of New Energy Vehicles issued by the State Council and the Guidelines for the Development of EV Charging Infrastructure (2015–2020) issued by the National Energy Administration of China [1], the construction of charging infrastructure in China is based on the principle of "piles and stations first" and is moderately advanced. Therefore, planning public charging stations for electric vehicles has become an important research direction.

In recent years, researchers worldwide have achieved many results in studying electric vehicle charging stations. The economy is the most crucial factor for the siting and capacity of EVCs. Literature [2] considers the planning and operation cost of charging stations and proposes a mixed-integer nonlinear optimization method to plan EVCs based on the overall economy, a more practical planning method. Based on this, literature [3] uses GIS to consider further the operation cost and service coverage of charging stations and proposes a dual-objective optimization model to solve the user service problem. In addition, since the planning of EVCSs interacts with EV users, the traffic network is also one of the important factors to be considered, and this issue has not been studied in depth in the literature [2,3]. Literature [4] proposes a model for the expansion planning method of the electrified transportation network to address the expansion planning of the transportation network, distribution network, and EVCSs simultaneously. Literature [5,6] proposes a planning method that considers traffic constraints and EV user distribution by analyzing the relationship between traffic flow data, the grid, and the traffic network. Literature [4–6] investigated one or

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two factors involved in the planning of EVCs, respectively, but did not consider multiple factors in an integrated manner. On top of this, literature [7] establishes a simulation platform by considering the numerous factors mentioned above and proposes a more comprehensive and practical planning method by simulating dynamic real-time data for the overall optimization of investors, users, vehicles, traffic, and the grid.

Meanwhile, with the rapid development of technology, a large number of EVs and renewable energy sources, such as wind power and PV, are connected to the grid, which will cause large peak-to-valley fluctuations in the grid and thus affect the stability of the grid operation. However, the above literature does not give sufficient consideration to this problem. In literature [8], an intelligent charging and discharging plan are designed to control the charging behavior of EVs to smooth the load fluctuations. In literature [9], a vehicle-to-grid energy management system is designed to reduce the fluctuations caused by wind power connections to the grid. In literature [10–12], distributed PV and wind power are incorporated into the planning of EVCSs, effectively reducing the operating cost of EVCSs and improving the consumption rate of renewable energy. Literature [13–16] further incorporate energy storage devices into the planning method, which reduces the operating cost of EVCs while increasing the renewable energy consumption rate and improves the stability of grid operation through peak shaving and valley filling. Therefore, reasonably planning and scheduling, adding energy storage, and distributed generation devices are feasible.

EV fast charging technology has also been rapidly developed in recent years, promoting the large-scale application of EVs. The literature [17] provides comprehensive planning of three-level charging posts with different charging rates to improve the operational efficiency of charging stations within limited cost and land. As the research continues, researchers need to consider multiple factors mentioned above, build more complex models and solve them. Literature [18] proposes a mixed integer quadratic constraint programming to coordinate traffic network, distribution network, energy storage system, and fast charging station, and applies a solver to solve the problem, which provides a new idea for the planning problem of charging station. In literature [19], a bi-level planning model is proposed, a bi-level programming model is established by replacing the lower-level model with KKT conditions, and the McCormick relaxation method and the Big M method are used to linearize and solve the bi-level model. A charging-discharging-exchange-storage integrated power station model is established in literature [20] to extend the functionality of charging stations.

However, in practical problems, it is not enough to consider only the return to the investor; the cost of charging arising from the great randomness and autonomy of EV users is also a factor that cannot be ignored but has not been sufficiently considered in the above studies. In a realistic scenario, most EV users are private users who are free to choose whether to use public charging stations or not, as well as the power and the amount of charging per charge. These choices are influenced by the EV user's preferences and factors such as charging queue times, the distance required to travel, and the charging power and price. In terms of long-term planning, these charging costs for EV users affect the overall economic benefits to society and service satisfaction and should therefore be considered an important factor in the planning process. In order to address the gaps mentioned above in the extant literature, a new bi-level planning model is constructed in this paper. The main contributions are as follows.

- A new bi-level planning model is proposed that integrates the interests of both charging station investors and EV users, where the upper model has the global economic return as the optimization objective, and the lower model has the EV user's satisfaction with the charging service (charging cost) as the optimization objective. The global economic cost is optimized while the service satisfaction of the user is improved.
- The time cost, economic cost, and mileage anxiety are considered together to characterize the service satisfaction of EV users. Specifically, the charging queuing time, driving distance, desired charging volume, and actual charging volume are used to reflect the charging cost of EV users and to reflect the autonomy of EV users more accurately, and a combination of fast and slow charging posts are used for planning to meet the needs of different users and grid constraints, to improve the operational efficiency of charging stations and reduce the charging queuing time of EV users.
- The conventional method and the bi-level planning method are solved separately for a region of Beijing, and the effectiveness of the proposed method is verified by comparing factors such as investors' returns, users' charging costs, and queuing times.

2. Problem statement

For this paper, it is assumed that the investment and operation of EVCSs is a public service project and that private charging stations in which EV users are located are not part of the planning. Therefore, the investment and construction of EVCSs need to consider not only the investment and operation costs of charging station investors, but also the impact on grid stability after a large amount of load is connected to the grid, the satisfaction of EV users and the losses generated during the charging behavior need to be taken into account in the EVCSs planning process. In the planning process, there is a certain degree of conflict between the interests of operators and EV users. For operators, it is more cost-effective to increase the utilization of EVCSs and minimize the size and number of EVCSs. On the other hand, EV users want to build more charging facilities to reduce time and power loss.

On the demand side, EV users have significant autonomy and uncertainty and will face the problem of choosing charging stations and how much power they can get from them every time charging demand arises. The planning of EVCSs affects the willingness of EV users to charge, and the amount of charging by users is related to the revenue of EVCSs. On the grid side, large-scale EVs are connected to the grid generating large load fluctuations and impacting power quality and grid stability. It is, therefore, a factor that cannot be ignored in the planning problem of EVCSs. This paper reduces this impact by planning both fast and slow charging posts and limiting the maximum charging power at each planning node [21,22].

Based on the above explanation, a bi-level planning model is proposed in this paper, as shown in Fig 1. The model integrates the interests of the investor and EV users and maximizes the global revenue of the upper-level model while making the queuing time and charging cost of users in the lower-level model the lowest. And the model is solved as a mixed integer nonlinear problem, so the improved PSO algorithm is used to solve it.

3. Mathematical formulation

In this section, the mathematical formulation of the Bi-level model is described.

3.1. Upper model

The upper-level model takes the maximum profit of the investor as the objective function, including charging station revenue, fixed investment cost, land purchase cost, charging pile purchase cost, power distribution cost, safety facility cost, and operation and maintenance costs. The solved planning results are passed to the lower model for further simulation. Its objective function is as follows:

$$\max F = C^{EVc} - C^{Inv} \tag{1}$$

$$C^{Inv} = \sum_{i=1}^{N} \left[\frac{r_0(1+r_0)^{year}}{(1+r_0)^{year}-1} C_{N,i} + C_{O,i} \right] \tag{2}$$

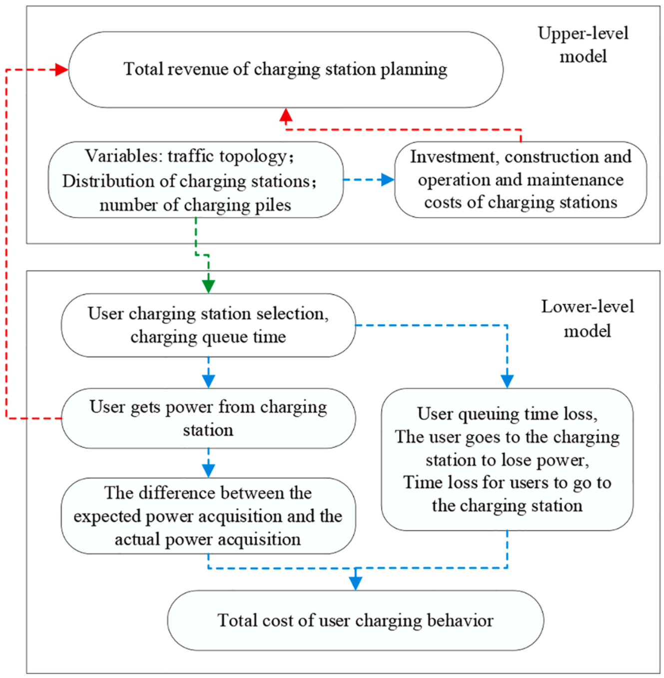

Fig. 1. Bi-level programming model.

Where C^{EVc} is EV users' annual charging fee income, C^{Inv} is annual investment cost, r_0 is the depreciation rate of charging station, N is the number of charging stations planned and constructed, $C_{N,i}$ is the investment cost of charging station construction, $C_{O,i}$ is annual operation and maintenance cost of charging station, *year* is planning service life of the charging station.

The construction investment cost of EVCS can be expressed as follows:

$$C_{N,i} = C_{ty,i} + C_{Np,i} + C_{LA,i} + C_{E,i} \tag{3}$$

Where $C_{ty,t}$ is fixed investment costs for EVCSs, $C_{Np,i}$ is the purchase cost of the charging pile, $C_{LA,i}$ is the land cost of EVCSs, $C_{E,i}$ is additional costs of EVCSs (Includes the cost of transformers, wiring, distribution facilities, and security features).

Since different EV users have different demands for charging rate and charging price, this paper adopts the method of joint planning of slow charging piles and fast charging piles to meet the demands of more users, and since the charging power of slow charging piles is smaller, the load fluctuation generated when connected to the grid on a large scale is also smaller. Therefore, the $C_{Np,i}$ can be expressed as follows:

$$C_{Np,i} = C_{lc}N_{lc,i} + C_{fc}N_{fc,i} \tag{4}$$

Where C_{lc} is the unit price of the slow charging pile, C_{fc} is the unit price of the fast charging pile, $N_{lc,i}$ is the number of the slow charging piles at EVCS, $N_{fc,i}$ is the number of the fast charging piles for EVCS.

The $C_{LA,i}$ mainly includes the cost of the parking space and the charging equipment area, so it is expressed by the parking space footprint m_{EV} and the redundancy ψ_a.

$$C_{LA,i} = (1 + \psi_a)m_{EV} \tag{5}$$

The $C_{E,i}$ and $C_{O,i}$ are related to the operating capacity of the charging station and can be calculated as follows:

$$C_{E,i} = \varphi_e\left(P_{lc}N_{lc,i} + P_{fc}N_{fc,i}\right) \tag{6}$$

$$C_{O,i} = r_T C_{T,i} + T_d T_{year}(a+b)\left(P_{lc}N_{lc,i} + P_{fc}N_{fc,i}\right) \tag{7}$$

Where r_T is transformer operation and maintenance cost proportionality factor T_d is daily operating hours of the charging pile, P_{lc} is the power of slow charging posts, P_{fc} is the power of fast charging posts, a is equipment operation and maintenance cost proportionality factor, b is labor cost proportionality factor.

Since a large number of EVs connected to the grid will generate load fluctuations, to ensure the grid's stable operation, certain constraints need to be made on the number of charging stations and charging power, and the constraints are as follows:

$$N_{\min} \le N \le N_{\max} \tag{8}$$

$$N_{lc\min} \le N_{lc,i} \le N_{lc\max} \tag{9}$$

$$N_{fc\min} \le N_{fc,i} \le N_{fc\max} \tag{10}$$

Where N_{lcmax} and N_{lcmin} are the maximum and minimum planned numbers of slow charging piles in each charging station, respectively, and N_{fcmax} and N_{fcmin} are the maximum and minimum planned numbers of fast charging piles in each charging station, respectively, and their values can be determined according to the specific planning area and the method proposed in the literature [21,22].

The calculation of the maximum and minimum planned number of charging stations N_{max} and N_{min} in the planning area can be expressed as follows:

$$N_{\max} = ceil\left(\frac{SOC_{EV}}{T_d P_{lc} N_{lc\min}}\right) \tag{11}$$

$$N_{\min} = ceil\left(\frac{SOC_{EV}}{T_d P_{fc} N_{fc\max}}\right) \tag{12}$$

$$\sum_{i=1}^{N} T_d\left(P_{lc}N_{lc,i} + P_{fc}N_{fc,i}\right) \ge SOC_{EV} \tag{13}$$

Where *ceil()* is the upward rounding function, SOC_{EV} is the total charging demand of EV users in the planning area in one day, which can be obtained from the load forecast.

3.2. Lower model

Due to the significant autonomy and uncertainty of EV users, the planning of EVCSs affects EV users' willingness to charge, which leads to changes in charging volume or EV users' charging costs. Therefore, it is necessary to simulate the charging behavior of each EV user and track the state of each EV user and EVCS in the simulation of the lower-level model to determine the queuing time and charging cost faced by EV users when they have charging demand. When EV users have charging demand, the optimal choice of EVCSs will be made based on the status and location of EVCSs in the planning area by calculating the required queuing time, travel distance, and expected to obtain power, and a navigation system will be used to guide EV users who have charging demand. The lower-level model solves the charging volume and charging cost for EV users throughout the day and returns the data to the upper-level model for further solutions.

3.2.1. Lower-level model objectives

The lower-level model aims to minimize the charging cost for EV users:

$$\min f = C^{EVl} \tag{14}$$

$$C^{EVl} = T_{year}\sum_{i=1}^{M}\left(C_{me,i} + C_{m,i,t} + C_{w,i,t} + C_{se,i}\right) \tag{15}$$

Where $C_{me,i}$ is the cost of power loss for EV users driving to the target charging station, $C_{m,i,t}$ is the cost of time lost by EV users driving to the target charging station, $C_{w,i,t}$ is the cost of queuing time lost by EV users after driving to a target charging station, $C_{se,i}$ is the equivalent cost of the difference between the expected and actual amounts of charge obtained by EV users at the charging station, M is the total number of charging requests in a day. The $C_{me,i}$, $C_{m,i,t}$, $C_{w,i,t}$, $C_{se,i}$, are calculated as follows:

$$C_{me,i} = \frac{D_{ij}}{L_r} \times C_B \times \eta \times C_{ep,t} \tag{16}$$

Where D_{ij} is the Distance between EV users and the best choice of charging station, L_r is the total EV vehicle range, C_B is the total EV vehicle battery capacity, η is Vehicle charging and discharging efficiency factor, $C_{ep,t}$ is the price of electricity at time t.

$$C_{m,i,t} = \frac{\nu_{EV,i}}{D_{ij}} \times \lambda_{tc} \tag{17}$$

$$C_{w,i,t} = T_{w,i} \times \lambda_{tc} \tag{18}$$

Where $\nu_{EV,i}$ is Vehicle travel speed, λ_{tc} is Time loss equivalence factor, $T_{w,t}$ is the waiting time required for charging.

$$C_{se,i} = C_{ex,i} - C_{ch,i} \tag{19}$$

Where $C_{ex,i}$ is EV user energy access expectations, $C_{ch,i}$ is Actual charging by EV users. The values are derived from statistical data [23].

When EV users have charging demand, if the available charging stations are far away or require a long queuing time, it will greatly affect users' service satisfaction and charging willingness. In addition, the remaining SOC status of EV users also affects the selection of charging stations. When the remaining power of EV users is not enough to drive to the charging station, a penalty cost is introduced with the following constraints.

$$C_{me\min} \le C_{me,i} \le C_{me\max} \tag{20}$$

$$C_{me\max} = \frac{D_{sr}}{L_r} \times C_B \times \eta \times C_{ep\max} \tag{21}$$

$$C_{m\min} \le C_{m,i,t} \le C_{m\max} \tag{22}$$

$$C_{w\min} \le C_{w,i,t} \le C_{w\max} \tag{23}$$

Where D_{ij},$T_{w,i}$,$C_{ch,i}$,$C_{ex,i}$ are obtained by the Dykstra algorithm, the current state of all charging posts, and the following EV user charging behavior model.

3.2.2. Modeling of electric vehicle charging stations

In the planning problem, EVs can be represented in the grid as a probabilistic load model that is affected by the charging behavior of EV users when the charging stations are located in different areas (living areas, commercial areas, industrial areas, etc.) or at different times. It is shown that a variety of probability distributions can describe the charging behavior of EV users, so the Eqs. (24)-(29) is used to model the EVCSs.

The first action time of EV users obeys the positive-terrestrial distribution with μ_0=6.92, σ_0=1.24, and its probability density function is [23]:

$$f(t_0) = \frac{1}{\sigma_0\sqrt{2\pi}}\exp\left[-\frac{(t_0-\mu_0)^2}{2\sigma_0^2}\right] \tag{24}$$

The study shows that the daily mileage of EV users also follows a certain probability distribution with the following probability density function [24]:

$$f_l(l) = \frac{1}{l\sigma_l\sqrt{2\pi}}\exp\left[-\frac{(\ln l-\mu_l)^2}{2\sigma_l^2}\right] \tag{25}$$

where μ_l=11.16, and σ_l=2.7.

User destination dwell time.

In actual planning, the target planning area is related to the traffic flow, EV charging demand, and parking time due to different functional distributions. This paper divides the target planning area into commercial work areas, residential areas, leisure and entertainment areas, and industrial areas. The residence time in different regions obeys a specific probability distribution, where its probability density function is as follows:

The probability density function for the length of time spent in the work area is [25]:

$$\begin{cases} z = \dfrac{pt_i - 438.445}{164.506} \\ f(z) = \dfrac{1}{164.506}\exp\left[-(1-0.234z)^{4.274}\right](1-0.234z)^{4.274} \end{cases} \tag{26}$$

The probability density function for the length of stay in other functional areas is:

$$\begin{cases} z = \dfrac{pt_i - 68.520}{41.761} \\ f(z) = \dfrac{1}{41.761}\exp\left[-(1+0.657z)^{-1.522}\right](1+0.657z)^{-1.522} \end{cases} \tag{27}$$

Initial SOC for EV users

Since the current EV range is long enough to satisfy the travel needs of the average user for several days or even longer, the state of charge (SOC) of EV users at the initial moment of each simulation also obeys a particular probability distribution with the following probability density function [26].

$$f(S_0) = \begin{cases} 4.532S_0^{3.352} & ,0 < S_0 \le 1 \\ 0 & ,\text{otherwise} \end{cases} \tag{28}$$

Minimum SOC preferences and mileage anxiety among EV users

This paper adjusts a minimum charge state preference α for each EV user participating in the simulation. When the charge state of each EV user falls below α during the simulation, the user selects the best charging station and enters the charging state for charging. α obeys a normal distribution with μ_1=0.466 and σ_1=0.179, and its probability density function is [26]:

$$f(\alpha) = \frac{1}{\sigma_1\sqrt{2\pi}}\exp\left[-\frac{(\alpha-\mu_1)^2}{2\sigma_1^2}\right] \tag{29}$$

3.3. Model solving process

The Bi-level programming model in this paper is a mixed-integer non-linear programming (MINLP), so the flowchart shown in Fig. 2 is used to solve it. Whereas the upper model is solved using an improved PSO. The lower-level model simulates the driving and queuing times required for EV users to charge while arising demand by establishing the state variables of each charging post, solving for the optimal path using Dykstra's algorithm, solving for the best charging option, and feeding back the charging revenue of the charging station to the upper-level model. This paper simulates all EV users to obtain the charging station revenue and the total user charging revenue, the specific steps of which are as follows.

Step 1: Initialize simulation starting time t, simulation duration T, and the number of vehicles N; input EV user behavior model; based on upper-level data input, generate charging station location, status, and queuing time; initialize EV vehicle status (such as first travel time Ti, charge status, location, and travel distance).

Step 2: When the EV user with number i has action time Ti = t, go to step 3; otherwise, go to step 5.

Step 3: Determine the EV user's behavior according to Eqs. (24)-(29), update the vehicle location, charge status, and charging status; determine whether a charging demand is generated. If charging demand is generated go to step 4; otherwise, go to step 5.

Step 4: Select the best EVCS and update the EVCS, charging post status, and queuing time according to the EVCS status, queuing time, EVCS maximum service range Dsmax, Dykstra's algorithm, and Eq. (14),

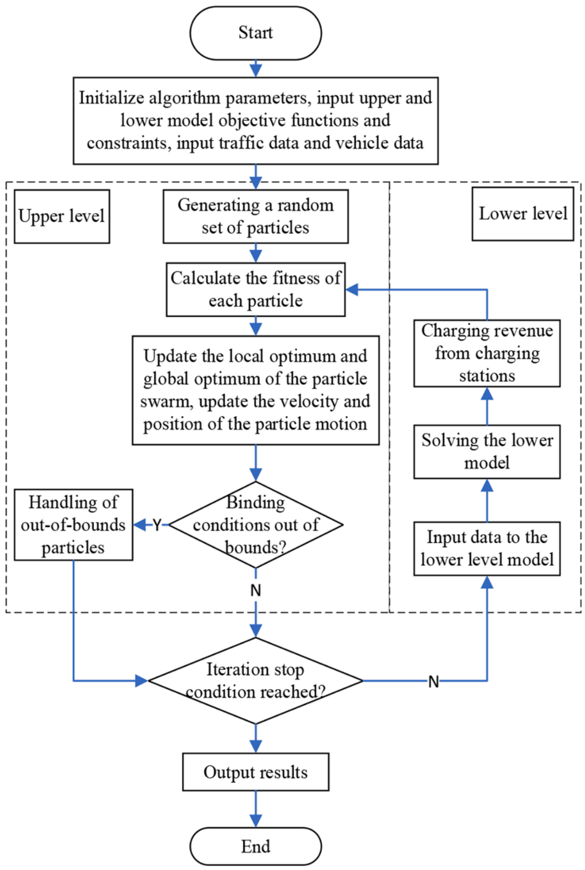

Fig. 2. Bi-level planning model solution flowchart.

update the charging revenue and total user revenue according to Eqs. (13)- (23).

Step 5: $i = i + 1$; if $i \geq N$, go to step 6; otherwise, go to step 2.

Step 6: $t = t + 1$; if $t \geq T$, end the simulation, output the charging revenue and total user revenue, and return the charging revenue to the upper-level of planning; otherwise, take $i = 1$ and return to step 2 until the end condition is met.

4. Case analysis

In this paper, the conventional and bi-level model planning methods are simulated separately for a planning area in Beijing with a 24-hour step time of 15 min to validate the proposed model and solution method, which can be used as a reference for future urban planning of EV systems. A comparison of the two methods is shown in Table 1, and the simulation platform used is MATLAB2018b.

Table 1
Comparison of planning methods.

Factors	Conventional method	Methodology of this paper
Planning model	Single-level planning model	Bi-level planning model
Considerations	Investor returns. Grid operational stability. EV user randomness	Investor returns. EV user randomness. Grid operational stability. EV user charging costs and service satisfaction. EV user charging queue times
System equipment	Fast charging posts. Slow charging posts	Fast charging posts. Slow charging posts
Planning objectives	Economically optimal	Optimal global economy. Optimal cost for EV users
Problem solving	Linear planning	Mixed integer non-linear programming
Case study	An area in Beijing	An area in Beijing

4.1. Basic data

Take an area in Beijing as an example. The planning area spans 11.2 km east-west and 8.6 km north-south, with approximately 91.30km^2 and a total of 84 nodes. The planning area is divided into commercial, residential, recreational, and industrial areas, while the behaviors of EV users in different areas are different. The total number of EVs in the area is set at 10,000, while the paper assumes that EV users have a means of charging in residential areas without using public charging stations. Fig 3

The parameter settings in this paper refer to the guidance on the construction of electric vehicle charging facilities issued by the State Grid Corporation [27], and the specific parameters are shown in Table 2 [1].

4.2. Solution result analysis

While adopting the single-level model, only the investor's maximum income is considered, and the queuing time and driving distance required by EV users when charging needs are not considered. The results are shown in Table 3a and Table 3b.

Table 4a and Table 4b shows the planning results obtained by applying the proposed bi-level planning model, considering both the investor's income and the EV user's loss.

Comparing the two planning results, the bi-level model plans more EVCSs and charging piles in terms of planning locations and numbers, with 52.76% more slow charging piles and 36.84% more fast charging piles, for a total of 50.54% more. Both methods plan more charging facilities in densely populated areas. However, compared to the single-level model, the bi-level model plans more dense charging facilities in densely populated areas and locates some EVCSs closer to less densely populated areas in order to achieve a lower service area. This result is expected, as the conventional approach will reduce the number of charging facilities as much as possible to increase the utilization rate and obtain higher revenue with minimum cost since only the investor's revenue is considered. In contrast, the approach proposed in this paper plans for more charging facilities to reduce the service radius, charging queue time, and power loss, as the charging cost of EV users is more fully considered.

In terms of the combined installation of fast and slow charging piles, the number of fast charging piles only accounts for 12.65% of the total

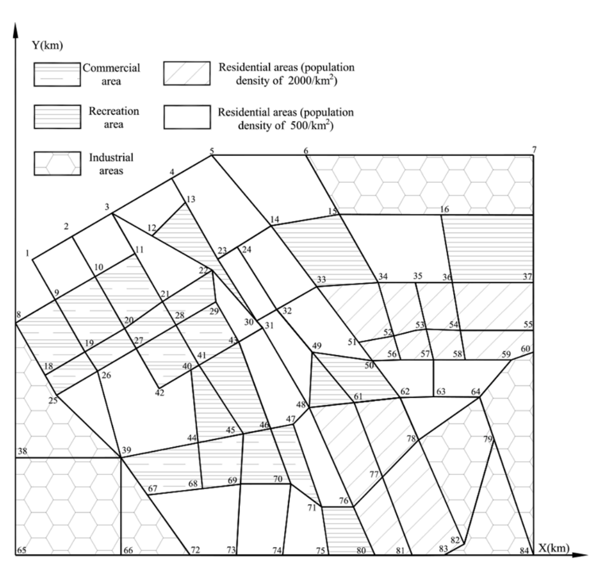

Fig. 3. Map of the planning area.

Table 2
Relevant parameters.

Parameters	Set values	Parameters	Set values
r_0	0.03	*year*	10
C_{Ti}	150 ¥/kW	C_{lc}	30,000 ¥
C_{fc}	80,000 ¥	ψ_a	0.4
a	0.01	b	0.0071
C_{Lai}(Commercial area)	6000 ¥/m^2	C_{Lai}(Residential areas)	2000 ¥ /m^2
C_{Lai}(Other Districts)	3000 ¥/m^2	η(Slow charging)	0.88
η(Fast charging)	0.70	C_B	65 kW•h
v_{EVi}	40 km/h	L_r	300 km
P_{lc}	20 kw	P_{fc}	120 kw
D_{smax}	3 km		

Table 3a
Single-level model planning results.

Parameters	result
Number of charging stations (pcs)	9
Investor's total economic income (10,000 ¥/year)	1508.1
Investor's investment (10,000 ¥/year)	2066.7
Charging revenue of charging station (10,000 ¥/year)	3574.7
Economic loss of EV users (10,000 ¥/year)	1682.9
Average charging queue time for EV users (minutes)	64.54

Table 3b
Single-level model to plan the number of charging posts at each node.

Node number	Slow charging pile (pcs)	Fast charging pile (pcs)
10	28	4
19	26	4
23	30	5
27	48	7
34	12	2
43	20	3
44	43	6
54	14	3
76	14	4

Table 4a
Bi-level model planning results.

Parameters	result
Number of charging stations (pcs)	11
Investor's total economic income (10,000 ¥/year)	1035.1
Investor's investment (10,000 ¥/year)	2459.7
Charging revenue of charging station (10,000 ¥/year)	3494.7
Economic loss of EV users (10,000 ¥/year)	511.02
Average charging queue time for EV users (minutes)	27.81

Table 4b
Bi-level model to plan the number of charging posts at each node.

Node number	Slow charging pile (pcs)	Fast charging pile (pcs)
10	30	4
19	38	5
21	27	4
24	50	7
36	21	3
42	42	6
43	50	8
47	30	4
50	12	2
68	30	5
77	29	4

number of planned charging piles but takes up 31.95% of the charging load, which shows the importance of fast charging piles for the improvement of charging station efficiency. However, due to the high price and operation and maintenance cost of fast charging piles, the charging efficiency and charging the unit price of EV users are also high, so the number of plans should not be excessive.

In terms of investment and revenue, when only the investor's revenue is considered, the single-level model is ¥15.081 millionwhile the bi-level model is ¥10.351 million, but at the same time, the charging cost for EV users decreases from ¥16.829 million to ¥5.1102 million and the average charging queuing time decreases from 60.54 min to 27.81 min. It is worth noting that the annual charging benefits of the bi-level model are lower than those of the single-level model because planning more charging stations will reduce the distance and power required to be driven by EV users when charging demand arises, which reduces energy consumption and has some significance in achieving carbon neutrality. Therefore, in terms of total social benefits, the bi-level model improves the investment by 45.69% and reduces the charging cost of EV users by 69.63%, which is ¥6.99 million higher than the single-level model in terms of total economic benefits.

In terms of charging demand, we made a record of the charging demand during the simulation for 24 h a day, and the results are shown in Fig 4. Since this paper assumes that EV users have a means of charging in their residential areas without the help of public charging stations and only considers the planning and design of public EVCSs, the EV charging demand during the nighttime is relatively at a low point. When 8:00–10:00 and 17:00–21:00 during the daytime, most EV users will travel during this time due to the peak commuting period, and more EV users will choose to charge their EVs after the morning peak and evening peak due to the faster-charging speed of public charging stations compared to home charging posts, so there are two peaks of charging demand during this time. At the same time, the increase in charging demand and the limited number of charging stations and charging piles will lead to peak charging queuing time at this time as well, as shown in Fig 5. In addition, the method proposed in this paper reduces the total electricity demand by 2.23%, a result that is mainly due to the reduced distance that needs to be traveled for charging, which reduces the loss of electricity and has implications for reducing carbon emissions and easing traffic congestion.

In terms of the queuing time required for charging, the average charging queuing time for EV users decreases by 54.06% after the bi-level planning. Comparing the queue times of the two planning methods at each time of day, as shown in Fig 5, it can be seen that when the charging demand is low, the queue times of the two planning methods are similar, mostly between 20–30 min, which is within the acceptable range for EV users. However, when the charging demand reaches its peak, the queuing time of the bi-level plan is significantly lower than the former one, with a reduction of 60%−70%, mainly because more EV users will go to the commercial and industrial areas at

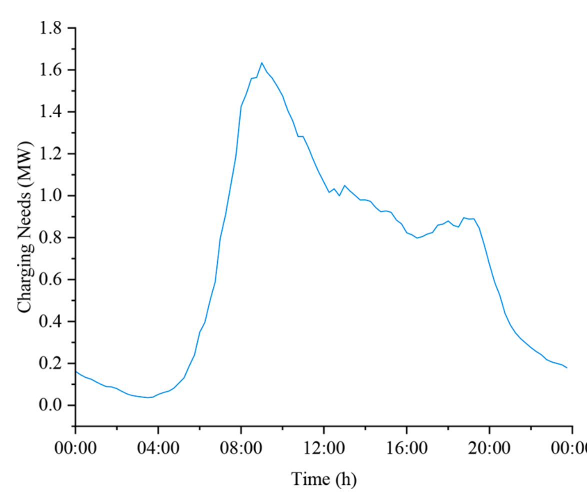

Fig. 4. Charging needs of public charging stations in a day.

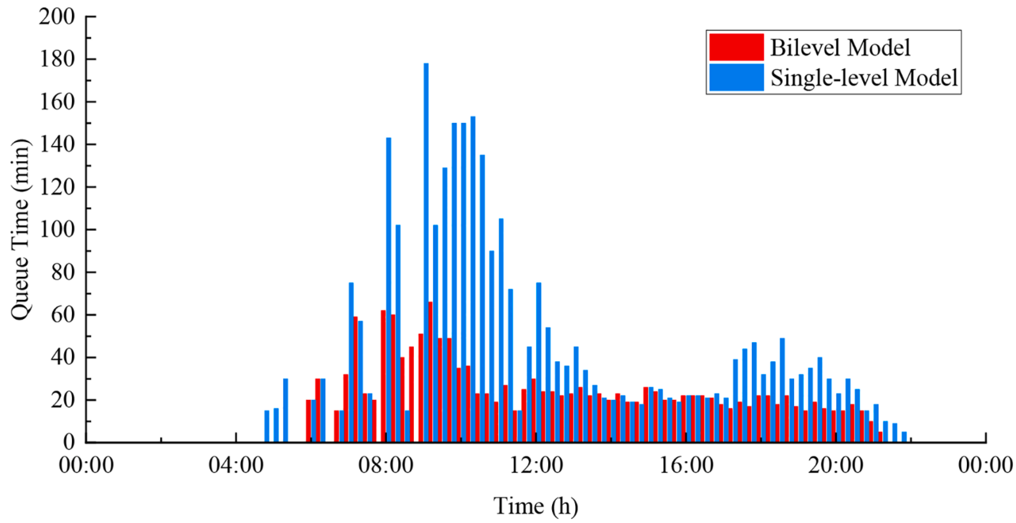

Fig. 5. Charging queue time for two planning methods.

the peak of charging demand, thus generating more charging demand in a certain area. As a result, more charging stations and charging piles are planned in the commercial and industrial areas compared with the single-level plan, which reduces the charging queuing time of EV users during the peak charging period, greatly reduces the charging cost of EV users, and can improve the satisfaction of EV users with the public charging stations to a certain extent.

In summary, a new bi-level planning model is proposed in this paper, in which the return maximization of the investor is considered in the upper-level model. In contrast, the lower-level model simulates the charging behavior of EV users based on the planning of the upper-level model through a probabilistic model, calculates the total amount of user charging and feeds it back to the upper-level model, and then solves it through PSO. The results of this example also verify the validity of the model by appropriately increasing the investment cost of investors to increase the planning quantity of EVCSs and charging piles and appropriately increasing the planning quantity of fast charging piles to reduce the charging cost of EV users better and improve the service satisfaction of users at a smaller cost. Therefore, the bi-level planning model proposed in this paper has certain superiority compared to the single-level model.

5. Conclusion

Due to the autonomy of EV users' charging behavior, their charging costs can significantly affect the global benefits of EV charging station planning. This paper proposes a new bi-level planning model to solve the problem of EVCS siting and capacity setting, considering the autonomy of EV users' behavior and charging costs. The main work and research results of the article are presented below.

- A bi-level planning model has been developed, in which the global economic costs are considered in the upper-level model, and the charging costs of EV users are considered in the lower-level model, to optimize the global economic costs while improving the service satisfaction of users and the model is described in detail.
- Factors such as time cost, economic cost, mileage anxiety, desired to charge volume, and actual charging volume is taken into account to characterize the service satisfaction of EV users and to reflect the autonomy of EV users more accurately. It also adopts a combination of fast and slow charging pile planning methods to improve the operational efficiency of charging stations and reduce EV users' charging queuing time.
- Through a case study of a region in Beijing, it was found that: 1) the bi-level planning approach can improve the global economic benefits of charging station planning; 2) the bi-level planning approach can reduce charging queuing time and charging costs for users; 3) the bi-level planning approach can reduce energy consumption; 4) the use of a combination of fast and slow charging posts can improve the efficiency of charging station operation.

Due to the rapid development of technology, the following suggestions are therefore made for future research: 1) the functions of public charging stations should be complete in the future, with fast charging piles likely to occupy the leading position, requiring more in-depth research; 2) as large-scale electric vehicles are connected to the grid, the impact on the operational stability of the grid can be reduced through reasonable and orderly scheduling and control of the charging and discharging of electric vehicles.

CRediT authorship contribution statement

Jiyong Li: Conceptualization, Methodology. **Chengye Liu:** Writing – review & editing, Software. **Yasai Wang:** Data curation, Formal analysis. **Ran Chen:** Writing – original draft, Writing – review & editing. **Xiaoshuai Xu:** Investigation.

Declaration of Competing Interest

The authors declared that there is no conflict of interest

Data availability

The authors do not have permission to share data.

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