Research on Electric Vehicle Charging Station Location Based on Multiple Objective Snake Optimizer

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Abstract. In view of the characteristics that the performance of electric vehicle power battery is easily affected by low temperature environment, by taking the influence of low temperature environment on the energy consumption of electric vehicle into account, a bi-objective location model was constructed to minimize the user's generalized travel cost and the total construction cost, and Multiple Objective Snake Optimizer (MOSO) was designed to solve the model. The feasibility of the model and the effectiveness of the algorithm are verified by taking the Central China and the Northeast China as examples, and the influence of the difference of siting strategy and the change of charging demand on siting strategy is explored.

Keywords: charging facility · bi-objective site selection · Multiple Objective Snake Optimizer

1 Introduction

With the acceleration of the modernization of cities, the problems of resource shortage and environmental pollution are becoming increasingly prominent. Since the 18th CPC National Congress, the Ministry of Transport has coordinated efforts to promote energy conservation, emission reduction and environmental protection in transport, and accelerated the green and low-carbon transformation of the sector. The total quantity of new energy vehicles in our country has been increasing year by year, including the increase of electric vehicles. But there is a big gap in the number of electric vehicle charging facilities, and electric vehicle drivers are prone to range anxiety. Therefore, reasonable planning of EV charging stations is of positive significance for reducing drivers' travel costs and popularization of EV.

In recent years, there have been a lot of achievements on the planning of electric vehicle charging stations. Jiang et al. [1] and Xie et al. [2], from the perspective of user charging convenience, built a model that minimized user travel time cost and charging station construction and operation cost. Zhang et al. [3] conducted charge-discharge cycle experiments on square ternary lithium batteries and found that low temperature had a particularly significant impact on energy loss. Wang et al. [4] and Niu et al. [5] proposed that the influence of environmental temperature should be considered in

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predicting EV charging demand. Liu et al. [6] found that ambient temperature would significantly affect the endurance, power consumption and other performance of electric vehicles. Since the charging station location model is a NP-Hard problem, most scholars adopt heuristic algorithm to solve the model. Turk S. et al. [7] proposed a solving model for optimal parameter setting by simulated annealing algorithm. Wu et al. [8] adopted the improved immune clone selection algorithm to solve the site-capacity model with the goal of minimizing the annual total cost of charging stations. Tian et al. [9] adopted the multi-objective particle swarm optimization algorithm to solve the dual-objective programming model considering users' preferences for charging selection.

In summary, the existing literature has laid a solid theoretical foundation for this study. However, few studies have considered the impact of regional environmental temperature differences on the site selection planning strategy of charging stations, and most of the existing literatures have established single-objective models. Based on this, this paper considers the influence of ambient temperature on battery capacity and energy efficiency, proposes a dual-objective location model with minimal generalized travel cost and construction cost, and designs a MOSO to solve the problem.

2 Model Building and Solving

2.1 Model Hypothesis and Symbol Description

(1) All electric vehicles are pure electric vehicles with the same battery capacity;
(2) EV drivers all generate charging demand at the node and take the node generating charging demand as the starting point O(i), select charging station to receive charging service (regardless of the charging differences among charging stations), and continue to drive to destination D(i) after charging;
(3) Each EV with charging demand can only be satisfied by one charging station, and all of them can complete one charging;
(4) The charging stations mentioned in this paper are all fast charging stations with a power of 120kW, and all vehicles leave when fully charged;
(5) Users' driving behavior in the city is rational, that is, they choose the shortest route.

The symbols of variables and parameters in the model are as follows: G, traffic network, G = {N, A}; N, network node set, N = {n|n = 1, 2, …n*}; A, section assembly, A = {a|a = 1, 2, …a*}; J, collection of alternative points of charging station; M_{ij}, rechargeable vehicle assembly; M_{ij}={m|m = 1,2, …m*}; O(i), starting point; D(i),end point; $S_{O(i)}^{E(m)}$, $S_{j}^{E(m)}$ and $S_{D(i)}^{E(m)}$, the state of charge of vehicle m at O(i), j and D(i); $\eta(T)$, battery energy efficiency at ambient temperature T; $\lambda_{\mathrm{loss}}(T)$, attenuation rate of battery capacity at ambient temperature T; Q0, nominal capacity of battery; $Q_{O(i)}^{E(m)}(T)$, maximum battery capacity of vehicle m in O(i); $E_{O(i),j}^{m^{travel}}$ and $E_{j,D(i)}^{m^{travel}}$, driving energy consumption of vehicle m driving from O(i) to j and from j to D(i); $t_{O(i),j}^{m^{travel}}$ and $t_{j,D(i)}^{m^{travel}}$, the driving time of vehicle m from O(i) to j and from j to D(i); $t_{m,j}^{charge}$, the time while vehicle m receives charging service in j; $m_{cp,j}$, number of charging piles in j; $K_{O(i),j}^{m}(T^{*})$ and $K_{j,D(i)}^{m}(T^{*})$, air conditioning energy consumption of vehicle m driving from O(i) to alternative point j and from j to D(i); τ, time value coefficient; θ, Value coefficient of energy consumption; P_{land}, unit price of land; P_{cs}, unit price of charging station construction; P_{cp}, charging pile unit price; P_e, unit price of electricity; c^0_{hr}, annual labor cost per unit charging pile; c^0_m, average annual management cost per unit charging pile; ε, Coefficient of capital recovery. $\delta_{O(i),j}^{ak'_{i,j}}$, $\delta_{j,D(i)}^{ak''_{j,i}}$ and ξ_j are decision variable.

2.2 Charging State Measurement

This paper assumes that energy consumption is related to driving distance and ambient temperature. In order to consider the gradual change of initial charging state of charging vehicle, it is assumed that the initial charging state of EV in all OD pairs follows triangular distribution, and its probability density function [10] is:

$$\mathrm{f}\left[S_{O(i)}^{E(\mathrm{m})}|S_{\min},\ S_{\bmod},\ S_{\max}\right]=\begin{cases}\frac{2[S_{O(i)}^{E(m)}-S_{\min}]}{(S_{\max}-S_{\min})(S_{\bmod}-S_{\min})},\ S_{\min}\le S_{O(i)}^{E(m)}\le S_{\bmod}\\ \frac{2[S_{\max}-S_{O(i)}^{E(m)}]}{(S_{\max}-S_{\min})(S_{\bmod}-S_{\min})},\ S_{\bmod}\le S_{O(i)}^{E(m)}\le S_{\max}\end{cases} \tag{1}$$

where, $S_{\min}$, $S_{\bmod}$ and $S_{\max}$ is the lowest, the mode and the maximum value of the initial charging state of the charging vehicle, with values of 20%, 40% and 60% respectively.

In order to consider the influence of ambient temperature, especially low temperature, on the performance of power batteries, energy efficiency and capacity decay rate [11] are introduced in this paper, and calculated as follows:

$$\eta(T)=-0.007286T^2+4.066T-474.7; \tag{2}$$

$$\ln\lambda_{loss}(T)=1981/T-4.939 \tag{3}$$

Then, under different ambient temperatures, the maximum capacity of battery when the charging demand of the EV is:

$$Q_{O(i)}^{E(m)}(T)=S_{O(i)}^{E(\mathrm{m})}\cdot Q_0\cdot(1-\lambda_{loss}(T)) \tag{4}$$

Then, under different ambient temperatures, the charging states of the electric vehicle when it reaches the alternative point j and the end point D(i) of the charging station are as follows:

$$S_j^{E(m)}=\frac{Q_{O(i)}^{E(m)}(T)-E_{O(i),j}^{m^{travel}}-K_{O(i),j}^m(T^*)}{Q_{O(i)}^{E(m)}(T)} \tag{5}$$

$$S_{D(i)}^{E(m)}=\frac{Q_0\cdot(1-\lambda_{loss}(T))-E_{j,D(i)}^{m^{travel}}-K_{j,D(i)}^m(T^*)}{Q_0\cdot(1-\lambda_{loss}(T))} \tag{6}$$

2.3 Generalized Travel Cost Model for Electric Vehicle Users

The travel cost generated by EV users in the process of travel includes time cost and energy consumption cost. Time cost includes the time value generated by driving and charging behaviors, and energy consumption cost refers to the energy consumption value generated by driving behaviors and the use of air conditioning.

$$\min Z_1 = \tau \cdot t_{total}^{O(i),j,D(i)} + \theta \cdot E_{total}^{D(i),j,D(i)} \tag{7}$$

s.t.

$$\max(t_{m,j}^{\text{wait}}) \le t_{\max}^{wait} \tag{8}$$

$$S_{D(i)}^{E(m)} \ge S_{\min} \tag{9}$$

$$\delta_{O(i),j}^{ak_{i,j}'} + \delta_{j,D(i)}^{ak_{j,i}''} \le 2, \sum_{j=1}^{j*} (\delta_{O(i),j}^{ak_{i,j}'} + \delta_{j,D(i)}^{ak_{j,i}''}) \le 2, \forall a \in A \tag{10}$$

where, constraint (7) is user travel total cost minimization model; constraint (8) indicates that the queuing waiting time is not greater than the maximum waiting time; constraint (9) means that the electric quantity of the electric vehicle when it reaches the destination is not less than the psychological safety threshold of the driver; Constraint (10) means that each vehicle can only get charging service at one charging station.

$$\begin{aligned} t_{total}^{O(i),j,D(i)} &= \sum_{m=1}^{m*}\sum_{j=1}^{j*} (t_{O(i),j}^{m^{travel}} + t_{j,D(i)}^{m^{travel}} + t_{m,j}^{charge}) = \\ &\sum_{m=1}^{m*}\sum_{j=1}^{j*} \left[\begin{array}{c} \sum_{a=1}^{a*} \delta_{O(i),j}^{ak_{i,j}'} \cdot \dfrac{l_a}{\overline{v}_a} + \sum_{a=1}^{a*} \delta_{j,D(i)}^{ak_{j,i}''} \cdot \dfrac{l_a}{\overline{v}_a} + \\ \dfrac{Q_0 \cdot (1 - \lambda_{loss}(T)) \cdot (1 - S_j^{E(m)})}{120 \cdot \eta(T)} \end{array} \right] \end{aligned} \tag{11}$$

$$E_{total}^{O(i),j,D(j)} = \sum_{m=1}^{m*}\sum_{j=1}^{j*} \left[\sum_{a=1}^{a*} \delta_{O(i),j}^{ak_{i,j}'} \cdot E_a + \sum_{a=1}^{a*} \delta_{j,D(i)}^{ak_{j,i}''} \cdot E_a + K^m(T^*) \right] \tag{12}$$

$$K^m(T^*) = \begin{cases} W_{\text{winter}}(T^*) \cdot (\sum_{a=1}^{a*} \delta_{O(i),j}^{ak_{i,j}'} \cdot \dfrac{l_a}{\overline{v}_a} + \sum_{a=1}^{a*} \delta_{j,D(i)}^{ak_{j,i}''} \cdot \dfrac{l_a}{\overline{v}_a}), T^* \le 15°\text{C} \\ 0, \quad 15°\text{C} < T^* < 28°\text{C} \end{cases} \tag{13}$$

where, E_a is the driving energy consumption of road segment a, and $W_{\text{winter}}(T^*)$ is the heating power of air conditioning. The calculation is as follows:

$$E_a = e(\overline{v}_a) \cdot l_a \tag{14}$$

$$W_{\text{winter}}(T*) = \begin{cases} 3.5, 0°\text{C} < T^* < 15°\text{C} \\ -0.2121T^* + 3.5, T* \le 0°\text{C} \end{cases} \tag{15}$$

2.4 Build a Total Cost Model

For investment operators, the optimization goal of the location model is to minimize the average annual total cost of charging facility investment. The total cost of investment construction includes: land cost [12], construction cost, operation and maintenance cost. At the same time, the service radius and service level constraints are proposed to ensure the user's travel satisfaction.

$$\min Z_2 = \varepsilon \cdot [C_{land} + C_{TC} + C_{oper}] \tag{16}$$

s.t.

$$S_{T,\max} \geq m^* \cdot \overline{Q}_E \tag{17}$$

$$m_{cp,j} \in [m_{\min}, m_{\max}] \tag{18}$$

$$\sigma_{O(i),j,D(i)} = \begin{cases} 1, S_j^{E(m)} > 0, S_{D(i)}^{E(m)} > 0 \\ 0, else \end{cases}, \sum_{j=1}^{j*} \sigma_{O(i),j,D(i)} \geq 1, \forall k \in k'_{i,j}, k''_{i,j} \tag{19}$$

$$\delta_{O(i),j}^{ak'_{i,j}} \leq \xi_j \tag{20}$$

where, Constraint (16) is Construction total cost minimization model. Constraint (17) is the capacity constraint of transformer j of the charging station, is the maximum capacity of transformer, m^* is the total number of charging vehicles, and $\overline{Q}_E$ is the average charging demand of vehicles. Constraint (18) is the constraint on the number of charging piles. Constraint (19) is the charging station in any path chosen by the vehicle can ensure that it reaches the charging station or destination before the power consumption reaches 0. Constraint (20) is the constraint on users' charging behavior, indicating that users can charge at point j only when there is a charging station at the alternative point j of the charging station.

$$C_{land} = \sum_{j=1}^{j*} P_{land} \cdot (785 + 60\lceil m_{cp,j}/2 \rceil) \cdot \xi_j; \tag{21}$$

$$C_{TC} = FC + VC = \sum_{j=1}^{j*} P_{\mathrm{cs}} \cdot \xi_j + \sum_{j=1}^{j*} P_{cp} \cdot m_{cp,j} \cdot \xi_j \tag{22}$$

$$\begin{aligned} & C_{oper} = C_e + C_{\mathrm{hr}} + C_m = \\ & P_e \cdot \sum_{j=1}^{j*} AL_{cp} \cdot T_{cp,j} \cdot \xi_j + (c_{hr}^0 + c_m^0) \cdot \sum_{j=1}^{j*} m_{cp,j} \cdot \xi = \\ & P_e \cdot \sum_{j=1}^{j*} \sum_{m=1}^{m^*} \xi_j \cdot 15 \cdot t_{m,j}^{charge} \cdot 365 \cdot \xi_j + (c_{hr}^0 + c_m^0) \cdot \sum_{j=1}^{j*} m_{cp,j} \cdot \xi \end{aligned} \tag{23}$$

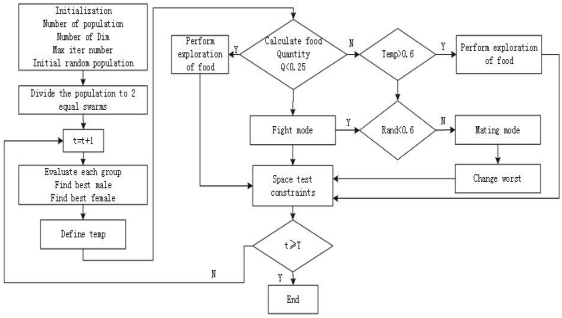


Fig. 1. MOSO flow chart

2.5 Algorithm Solution

Snake Optimizer [13] (Snake Optimizer, SO) was proposed by Fatma A. Hashim and Abdelazim G. Hussien. Compared with other intelligent optimization algorithms, SO has good performance. However, in solving multi-objective problems, SO is easy to converge to the local optimal solution in the non-inferior optimal domain, and the solving speed is slow. Therefore, a Multiple Objective Snake Optimizer (MOSO) based on multi-objective optimization is proposed to improve the disadvantage that SO is prone to fall into local optimality when solving bi-objective models. The specific process of MOSO is shown in Fig. 1.

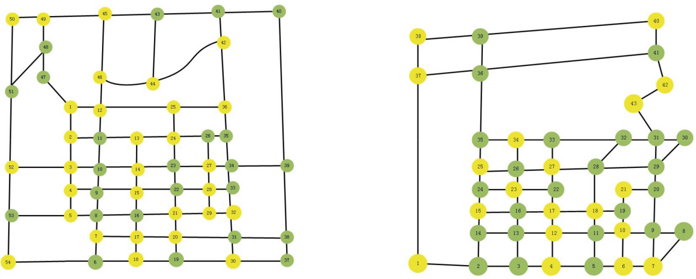
3 Example Analysis

3.1 Network and Parameter Settings

In order to verify the effectiveness of the model and algorithm, a region in Central China and Northeast China is selected as an example respectively. Each road node in the study area is a potential charging station, that is, alternative point of charging station. The road network in the study area is shown in Fig. 2. The yellow circle represents the charging demand points. The parameter Settings in the model are shown in Table 1.

3.2 Result Analysis

According to Fig. 3, it can be seen that the solutions of the results obtained by MOSO algorithm dominate those obtained by SO algorithm, and the distribution of the solutions obtained is significantly more uniform, which proves the effectiveness of MOSO algorithm in solving the bi-objective model. In this paper, fuzzy decision method is used to calculate the optimal compromise solution, as shown in Table 2. Taking Northeast China as an example, among the 20 groups of solutions, the maximum membership value is Plan 6. Based on the above analysis, it can be seen that the relative optimal solutions of Central Plains and Northeast China are Plan 18 and Plan 6 respectively. That is, 10 eV charging stations and 5 eV charging stations shall be built respectively, as shown in Fig. 4.

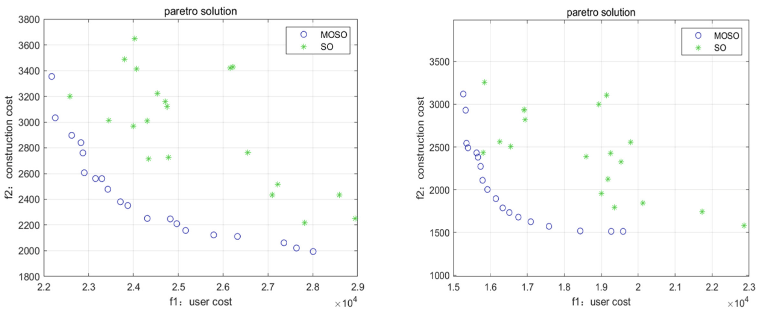


(a) The road network of Central China (b) the road network of Northeast China

Fig. 2. The road network of the study area in the two regions

Table 1. Part parameters of EV charging station location model

Parameter	Digital setting	Parameter	Digital setting
Q_0	41.4kW·h	P_{cs}	$2 * 10^5$ yuan
$e(\overline{v}_a)$	Central China 0.183	P_{cp}	$5 * 10^4$ yuan
	Northeast China 0.181	P_e	0.76yuan/kWh
Θ	0.488yuan/km	m_{min}	3
τ	Central China 26.78yuan/ h	m_{max}	20
	Northeast China 28.9yuan/h	ε	0.14
S_{min}	20%	s	10year

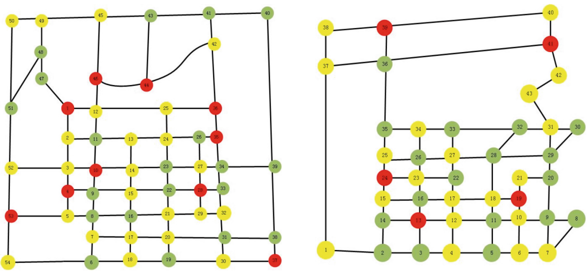


(a) Pareto Frontier in Central China (b) Pareto Frontier in Northeast China

Fig. 3. Pareto frontier map of charging station location by region

Table 2. Pareto solution set and comprehensive index of solution in each region

Area	Number	Z_2	Z_2	μ_1	μ_2	μ
Central China	2	28007.67	1994.02	0.00	1.00	0.50
	…	…				
	18	23709.67	2380.32	0.74	0.72	0.73
	19	23429.37	2477.90	0.79	0.64	0.71
	20	23296.08	2560.34	0.81	0.58	0.70
Northeast China		…	…			
	5	19592.36	1513.36	0.00	1.00	0.50
	6	16335.64	1787.99	0.75	0.83	0.79
	…	…				
	20	15356.24	2544.75	0.98	0.36	0.67



(a) Site selection of Central China (b) Site selection of Northeast China

Fig. 4. Site selection results of two regions

4 Conclusion

In this paper, the influence of ambient temperature on the battery capacity and energy efficiency of electric vehicles is considered, and a bi-objective location model is constructed with the objective of minimizing the generalized travel cost and total construction cost of users. The solution of the model is solved by MOSO, which can provide theoretical reference for the planning and layout of urban public service facilities. The calculation results show that the optimal system can be achieved when 10 eV charging stations are built in the Central Plains and 5 eV charging stations in Northeast China respectively. Through the above calculation and analysis, the following conclusions can be drawn: 1) the performance of MOSO is better than that of SO in solving the bi-objective model; 2) due to regional environmental temperature differences, EV ownership is affected to some extent, so the planning strategies of EV charging stations in the two regions are different.

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