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RESEARCH ARTICLE

Ordered Charging Planning for Electric Vehicle Clusters in Tourist Attractions Based on Improved Moth-Flame Optimization Integrated With Genetic Mechanism

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ABSTRACT This is an optimization problem of ordered charging planning (OCP) for electric vehicle clusters (EVCs) in tourist attractions, and it is an important and difficult problem. In this work, for solving this optimization problem, an improved moth-flame optimization integrated with genetic mechanism (IMFO-G) is proposed. Specifically, based on the moth-flame optimization integrated with genetic mechanism, the adaptive nonlinear decreasing strategies with selection, crossover and mutation probability as well as weight coefficient are designed, and the opposition-based learning is also introduced simultaneously. To verify the effectiveness of proposed IMFO-G, simulation verification of an example of the OCP optimization problem of EVCs in tourist attractions is provided. The simulation results show that the proposed improvement strategies can effectively improve the global optimization performance for IMFO-G, and a more ideal optimization solution of the OCP optimization problem for EVCs in tourist can be obtained.

INDEX TERMS Ordered charging planning, electric vehicle clusters, improved moth-flame optimization, adaptive nonlinear decreasing strategy, opposition-based learning.

I. INTRODUCTION

The vehicle is one of the major means of transportation for people's daily travel. However, the main energy used by traditional vehicles is oil or gas. When such form energy is used, it is not only detrimental to environmental protection, but also consumes a large amount of non-renewable energy such as petroleum [1]. With the rapid progress of the social economy and strong support from relevant policies, electric vehicles (EVs) have been widely used in major cities as never before [2], [3].

Due to a lack of reliability in prediction data for charging load, the disordered charging of EVCs is adopted commonly, which is not conducive to meeting high-quality practical demands [4]. Currently, the ordered charging issue of EVCs has become a hot topic, and it needs to be effectively solved urgently [5]. At present, various novel ordered charging methods and strategies have been proposed. A hierarchical distributed frequency regulation strategy of EVC considering the optimization of demand charging load was proposed [6]. A novel interactive network model of distribution networks

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and electric vehicles was constructed, and a multi-objective orderly charging strategy based on the interactive network model was also designed [7]. An ordered charging approach based on the EVs optimal time-of-use pricing (OTOUP) demand response is proposed [8]. These traditional algorithms can solve the optimization problem of OCP for EVCs. However, it may be difficult to obtain an ideal orderly charging scheme for EVCs using traditional algorithms.

Therefore, intelligent optimization algorithms have received high attention of researchers in relevant fields, and various improved intelligent optimization algorithms have been proposed. An improved particle swarm optimization (PSO) algorithm was proposed to model the orderly charging strategy. However, the effectiveness verification of large-scale example was lack [9]. An improved honey-badger algorithm (IHBA) was proposed to compose the elite OBL, spiral update, and wild dog survival strategies for enhancing the order of the charging of EVs. However, the design is relatively complex, and it depends on the parameters highly [10]. An improved PSO was proposed to obtain an excellent planning solution of electric vehicle charging station layout (EVCSL), and the dynamic adjustment strategy for weight and integration into the two-population genetic mode were proposed to improve the optimization performance for PSO. However, the specific design about OCP optimization problem for EVCs in tourist is missing, and the precision specific solution cannot be obtained [11]. To sum up, improved intelligent optimization algorithms have many advantages, such as computing resource saving, simple configuration, high stability, and high computation efficiency, and they are very popular among researchers. However, these improved intelligent optimization algorithms have not yet achieved the sufficient optimization efficiency.

The moth-flame optimization (MFO) is an efficient one of numerous intelligent optimization algorithms, and it was proposed by S. Mirijalili in 2015 [12]. In recent years, many novel improved moth flame algorithms have been proposed. An efficient chaotic mutative moth-flame-inspired optimizer for global optimization tasks was proposed [13]. An improved immune moth flame algorithm (IIMFA) based on the immune mechanism, Gaussian mutation mechanism, and an opposition-based learning (OBL) strategy was proposed [14]. A modified dynamic opposite learning-based MFO algorithm (m-DMFO) was proposed incorporating a modified dynamic opposite learning (DOL) strategy [15]. An improved moth-flame optimization algorithm based on orthogonal opposition-based learning and a modified position updating mechanism of moths was proposed for global optimization problems [16]. Therefore, the MFO is a good choice for solving the optimization problem of OCP for EVCs. In this work, one proposes a novel improved moth-flame algorithm with efficient strategies for solving the OCP optimization problem of EVCs in tourist attractions, and it is taken as research target.

Based on existing studies on the OCP optimization problem of EVCs passengers and electric vehicle grid (EVG) in tourist attractions, the following summarizes the major contributions and innovations of this paper:

- The mathematical models analyses for the OCP optimization problem of EVCs in tourist attractions: there are many factors to be considered in the actual optimal design of OCP for EVCs, based on an in-depth analysis of several common mathematical models for the OCP optimization problem of EVC, an appropriate and practical mathematical model for the OCP of EVCs with reasonable dual optimization objective function for the OCP optimization problem of EVCs passengers and EVG is constructed.
- The moth-flame optimization and its improved version: on the basis of analyzing the defects of moth-flame optimization, this work presents an improved version combining MFO and genetic algorithm, i.e., improved moth-flame optimization integrated with genetic mechanism (IMFO-G). In addition, to enhance the global optimization ability of the improved version, one introduces the weight coefficient, adaptive nonlinear decreasing strategy with selection, crossover and mutation as well as the OBL.

Compared with improved optimization algorithms with obvious better optimization performance, on the basis of ensuring the preferences of charging users, the planning solution based on the IMFO-G in this work realizes the function of "peak filling and valley filling". As a result, it can effectively balance the load of the power grid and reduce the loss of the power grid, such that the stable, safe and lasting operation of the power grid can be ensured.

The paper is organized as follows. Section II introduces the mathematical model for the OCP optimization problem of EVCs in tourist attractions. Section III illustrates the MFO-G. Section IV provides the simulation verification of an example of the OCP optimization problem of EVCs in tourist attractions. Section V concludes this article.

II. MATHEMATICAL MODELS FOR THE OCP OPTIMIZATION PROBLEM OF EVCS IN TOURIST ATTRACTIONS

Based on the characteristics of the OCP optimization problem of EVCs in tourist attractions, this work provides a appropriate mathematical model with a comprehensive evaluation objective function of charging user preference, the comprehensive evaluation objective function for grid-side, the constraint conditions, and the constraint target model.

A. CHARACTERISTICS OF THE OCP OPTIMIZATION PROBLEM OF EVCS IN TOURIST ATTRACTIONS

In fact, the operation of tourist attractions is facing difficulties in recent years in China. First of all, the isolate policy for containing the spread of the world-wide epidemic situation has a great influence. Secondly, due to the extensive network promotion, people's requirements for the tourism experience quality and the intensity of competition in tourist market are also increasing day by day. In addition, a number of tourist attractions got rich by devious means, and the phenomena seriously reduces tourist experience, so the brand image for whole China's tourism industry has been badly affected. Chinese tourist attractions have their own characteristics, electric vehicle is widely used and has become the most important means for transport of tourist attractions. Thus, the transportation network of EVs is necessary to be constructed. There are two reasons: firstly, compared with other means of transportation, EV has superiorities of environment protection, energy saving, economy, convenience, relaxed wade and large carrying capacity; secondly, most of the tourists have a small amount of money and free time for trip, so that the short-term rental business of EVs has huge market. Now, developing the high-quality electric vehicle traffic network have become the urgent matter for Chinese tourist attractions. For this purpose, five prerequisites should be met in advance. (1) First of all, the EVCs and their drivers employed in the local tourist attraction should have a certain scale, i.e., the total number of vehicles should be greater than or equal to the minimum total number of vehicles set by the tourism authority of current city and the total number of vehicle charging modes (charging modes for different types of vehicles, such as Combo mode, Mennekes mode, tesla mode, Chademo mode, and so on) should be greater than or equal to the minimum total number of vehicle charging types set by the tourism authority of current city. This is a guarantee of profitability for tourist attractions. (2) According to the actual situation of local tourist attractions, a specific location selection and OCP scheme should be given for the charging stations suitable of EVC, which will can save plenty of manpower, time and costs, this is necessary. (3) The construction of related infrastructure, like the construction of control center, charging station control center, various smart charging piles, etc., should be completed. (4) The service system of electric vehicle traffic network should be established, which includes to hire a certain number of various service talents and personnel, establish and improve the transportation regulations of electric vehicles in tourist attractions, and build a certain number of various service institutions (such as various road signs and scenic maps, water stations, rest rooms, first aid stations, fire warning centers, etc.). This is a guarantee of service quality for tourist attractions. (5) All kinds of permits issued are also should be applied for the city tourism administration and other authorities, this is required. If not, especially missing appropriate and practical OCP scheme, the brand effect and profitability for tourist attractions will be discounted.

The electric vehicle traffic network in Chinese tourist attraction is composed of an electric vehicle grid (EVG), a distribution network control center, a charging station control center, various intelligent charging piles and the EVC employed in the local tourist attraction. The specific operating principle for electric vehicle traffic network in Chinese tourist attraction, load power for charging is provided by the EVG; the distribution network control center is used to transmit the load power from the charging station control center to each intelligent charging piles; each intelligent charging pile is used to match vehicles' type, initial battery capacity, and charge according to the charging duration; in addition, each electric vehicle is necessary to be guided for charging according to the appropriate OCP scheme, and the charging time is set by the driver of this charging electric vehicle. The specific electric vehicle traffic network in Chinese tourist attraction is shown in Fig. 1.

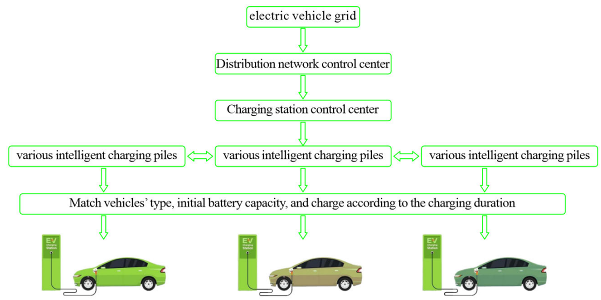

FIGURE 1. Schematic diagram of operating principle for electric vehicle traffic network in Chinese tourist attraction.

For the OCP optimization problem of EVCs in Chinese tourist attractions, charging fee is the first consideration, and time saving is need to be considered as well. For the tourists in tourist attractions, on the one hand, the charging fee is necessary to be saved as much as possible; on the other hand, matching degree on charging time to meet their expectations is also important. In addition, on the grid side of EVG, the most important objective should be to reduce the load fluctuation as much as possible, while also considering network loss.

B. OBJECTIVE FUNCTION OF COMPREHENSIVE EVALUATION OF USER PREFERENCE FOR THE OCP OPTIMIZATION PROBLEM OF EVCS PASSENGERS

The OCP optimization problem of EVCs passengers in tourist attractions should not only consider the saving charging costs as much as possible, but also fully meet the charging demands of EVCs passengers. The charging plan preference matching degree is the ratio of the cumulative sum of charging power matched by 24-hour charging plan and the 24-hour preferred charging plan to the cumulative sum of charging power of 24-hour charging plan, which can quantitatively describe the charging convenience of EVCs passengers. The specific objective function of comprehensive evaluation of charging user preference is as follows:

$$\min Z_1 = \alpha_C \frac{C_{sum}}{C_{sum,max}} + \alpha_p (1 - D_P) \tag{1}$$

$$C_{sum} = \sum_{24}^{t=1} C_t(t) P(t) \tag{2}$$

$$D_P = \frac{\sum_{24}^{t=1} \min\left(P(t), P_p(t)\right)}{\sum_{24}^{t=1} P(t)} \tag{3}$$

where Z_1 is the comprehensive evaluation of user preference, C_{sum} is the cost of recharging, $C_t(t)$ is the charging price of tth hour, $P(t)$ is the charging power of tth hour in the charging plan, D_p is the preference matching degree of charging plan $P_p(t)$ is the charging power of tth hour in the preferred charging plan, $C_{sum,max}$ is the set upper limit of charging fee, and α_C, α_p are the corresponding importance weights of charging cost and charging plan preference matching degree, respectively. Here, $\alpha_C \in (0, 1)$ and $\alpha_p = 1 - \alpha_C$.

C. OBJECTIVE FUNCTION OF GRID-SIDE COMPREHENSIVE EVALUATION FOR THE OCP OPTIMIZATION PROBLEM OF EVG

From the perspective of grid safety and stable operation, the grid side aims to minimize the fluctuation of charging load and grid load, and realize "peak clipping and valley filling". Furthermore, it is to improve the quality of power supply in tourist attractions, and reduce the loss of distribution network lines. For the OCP optimization problem of EVG in tourist attractions, the daily load curve variance and network loss are two particularly important performance indicators in the power grid side. The specific objective function of grid-side comprehensive evaluation is as follows:

$$\min\ Z_2 = \alpha_L \frac{L_{var}}{L_{var,max}} + \alpha_{NL}\frac{NL}{NL_{max}} \tag{4}$$

$$L_{var} = Var(L(1), \cdots, L(24)) \tag{5}$$

$$NL = \sum_{t=1}^{24}\sum_{i=1}^{N}\sum_{j=1}^{N} R_{ij} I_{ij}(t)^2 \tag{6}$$

where Z_2 is the grid side comprehensive evaluation, $L(t)$ is the load of power grid at tth hour, L_{var} is the daily load curve variance, $Var(L(1), \cdots, L(24))$ the variance of the array $(L(1), \cdots, L(24))$, R_{ij} is the resistance between node ith and jth in the power grid, I_{ij} is the current between ith and jth node at tth hour in the power grid, $L_{var,max}$ is the set upper limit of resistance, NL is the network loss, NL_{max} is the set upper limit of network loss, and α_L, α_{NL} are the daily load curve variance and the corresponding importance weights of the network loss, respectively. Here, $\alpha_L \in (0, 1)$ and $\alpha_{NL} = 1 - \alpha_L$.

D. DUAL OPTIMIZATION OBJECTIVE FUNCTION FOR THE OCP OPTIMIZATION PROBLEM OF EVCS PASSENGERS AND EVG

In fact, both charging user preferences and power grid quality should be taken into account for OCP of EVCs passengers and EVG in tourist attractions. In this case, by linearly weighting Eq. (1) and Eq.(4), the dual optimization objective function for OCP of EVCs passengers and EVG can be obtained, which is detailed as follows:

$$\min\ z = \alpha_1 Z_1 + \alpha_2 Z_2 \tag{7}$$

where z is the final value, and α_1, α_2 are the corresponding weights of charging user preference and grid quality, respectively.

E. CONSTRAINT CONDITIONS FOR THE OCP OPTIMIZATION PROBLEM OF EVCS

Taking the actual situation into account, the OCP optimization problem of EVCs needs to consider the line node voltage constraint, line node voltage constraint, vehicle battery capacity constraint and vehicle charging time constraint, which are detailed as follows:

$$Subject\ to\ tc_{p,t} \in \{0, 1\} \tag{8}$$

$$U_{i,t} \in [U_{i,min}, U_{i,max}] \tag{9}$$

$$TC_p \leq TC_{p,max} \tag{10}$$

$$S_{p,t} \in [S_{p,min}, S_{p,max}] \tag{11}$$

where $tc_{p,t}$ is the charging state of pth vehicle at tth hour (1 represents that the vehicle is in the charging state, otherwise it is 0), $U_{i,t}$ is the voltage of ith node at tth hour in the power grid, $U_{i,min}$ and $U_{i,max}$ are the minimum and maximum voltage of ith node in the power grid respectively, TC_p is the charging time of pth vehicle, $TC_{p,max}$ is the maximum charging time of pth vehicle, $S_{p,t}$ is the battery capacity of pth vehicle in tth hour, and $S_{p,min}$, $S_{p,max}$ are the Minimum and maximum battery capacity of pth vehicle, respectively.

F. OPTIMIZATION MODEL FOR THE OCP OPTIMIZATION PROBLEM OF EVCS

For any constrained objective model, the corresponding approximate optimal solution can be obtained by using optimization algorithm. For the OCP optimization problem of EVC in tourist attractions, the constraints are relatively fixed. According to the different actual requirements, different objective functions are selected to construct different constraint objective models. The specific constrained and objective functions of the optimization problem are described as follows:

$$\begin{cases} & \min\{F(x)\} \\ s.t. & g(x) \leq 0, i = 1, 2, \cdots, m \\ & x = (x_1, x_2, \cdots, x_n), x \in \Omega \end{cases} \tag{12}$$

where m is the constraint function number, n is the decision variable dimension, $F(x)$ is the objective function value; in this word, it is the same as final value z for the dual optimization objective function for the OCP optimization problem of EVCs passengers and EVG, $g(x)$ is the constraint function, which can choose the corresponding inequality constraints or equality constraints for the different practical demand, and x is the decision variable.

In this work, the decision variable x is the OCP scheme, and it is also the operation plans of charging stations in tourist attractions. If the different OCP scheme is chosen, the objective function value $F(x)$ will also be different.

III. IMPROVED MOTH-FLAME OPTIMIZATION INTEGRATED WITH GENETIC MECHANISM

The MFO has a shortcoming in accuracy and other aspects when it is used to solve some optimization problems [17]. Thus, some improvements are usually to be carried out when the algorithm is applied in practice. Certainly, for the different problems, it is necessary to implement the different improvements using diverse methods [18].

A. BASIC PRINCIPLE OF MFO

In MFO, the moth population is the candidate solution set, and the flame set is the elite solution set. M can be defined as the moth population, and it can be expressed as

$$M = \begin{bmatrix} M_{11} & M_{12} & \cdots & M_{1d} \\ M_{21} & M_{22} & \cdots & M_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ M_{n1} & M_{n2} & \cdots & M_{nd} \end{bmatrix} \tag{13}$$

where n is population size, and d is the dimension of the solution.

Let OM be the fitness value vector of moth population. One can get

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{14}$$

Let F be the flame set. One can get

$$F = \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1d} \\ F_{21} & F_{22} & \cdots & F_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ F_{n1} & F_{n2} & \cdots & F_{nd} \end{bmatrix} \tag{15}$$

Let OF be the fitness value vector of flame set, which can be expressed as

$$OM = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{16}$$

The optimization process of MFO can be abstracted as a triple

$$MFO = (I, P, T) \tag{17}$$

Here, I is the behavior of initializing moth populations and flame sets, which is generate randomly. And then, its fitness value is calculated, which can be expressed as

$$I : \phi \rightarrow \{M, OM\} \tag{18}$$

T is the individual updated behavior of moth based on logarithmic spiral function. Based on the current situation of itself and the flame set, the moth individual updates itself with the help of the logarithmic spiral function. It can be expressed as

$$\begin{cases} M_i = S(M_i, F_j) = D_{ij}e^{\tau l}\cos(2\pi l) + F_j \\ D_{ij} = |M_i i - F_j| \end{cases} \tag{19}$$

where M_i is the ith individual moth, F_j is the jth flame, D_{ij} is the straight-line distance between the ith individual moth and jth flame, τ is the logarithmic spiral morphological constant, l is a random number between -1 and 1, and $S(M_i, F_j)$ is the logarithmic spiral function.

In Eq.(17), P is the behavior of moth populations to update their trajectory. If the fitness value of the moth after updated is better than the fitness value of the flame, the flame will be updated, which can be expressed as

$$P : M, F \rightarrow F \tag{20}$$

To speed up the convergence of the algorithm, the size of the flame set is adaptively reduced with the increase of the number of iterations. The specific update formula of the flame set scale is as follows.

$$N_{flame} = round\left(n - t\frac{n-1}{T_{\max}}\right) \tag{21}$$

where N_{flame} is the updated number of flames, t is the current number of iterations, and $T_{\max}$ is the the maximum number of iterations [19].

B. MOTH-FLAME OPTIMIZATION INTEGRATED WITH GENETIC MECHANISM

Compared with the traditional optimal technology, MFO has attracted the attention of many scholars for its good algorithm convergence, simple parameter setting and computational form, and can be effectively applied to the research field of optimization problems. However, in the calculation process, when a certain flame position has obvious advantages, a large number of moths in the moth population will quickly move closer to it. If the flame position is in the local optimum at this time, the moth population will be difficult to search for a new better solution, which is easy to make the algorithm fall into premature convergence [20].

To improve the problem that the MFO is easy to fall into local convergence, this work integrates the genetic mechanism, and the purpose is to improve the global optimization performance of MFO with the help of genetic algorithm. In the iterative process, the MFO quickly draws each moth closer to the current optimal flame, which provides direction guidance for the evolution of genetic moth-flame population and is conducive to accelerating convergence and global optimization. Meanwhile, due to the existence of genetic mechanism, the moth population will not immediately stop searching for optimization when it falls into local extremum. The three operators of crossover, selection and mutation cause a certain degree of evolutionary disturbance in the evolution process of the moth population, which will help it jump out of the dilemma of local convergence and enhance its global optimization performance [21].

C. ADAPTIVE NONLINEAR DECREASING STRATEGY FOR WEIGHT COEFFICIENT

If the weight coefficient is larger, the algorithm search range also becomes larger, and its global optimization ability becomes stronger [14]. On the contrary, if the weight coefficient is smaller, the algorithm search range becomes smaller too, and the local optimization ability becomes stronger. In this work, the weight coefficient is introduced into the log-spiral update mechanism of MFO, and the moth position update formula with weight coefficient is detailed as follows.

$$\begin{cases} M_i = S(M_i, F_j) = D_{ij}e^{\tau l}\cos(2\pi l) + \omega F_j \\ D_{ij} = |M_i i - F_j| \end{cases} \tag{22}$$

where ω is the inertia weight.

In the process of moths flying to the flame, the weight coefficient is gradually reduced, such that the local optimization ability of MFO is enhanced in the later iteration, and the global optimization quality is improved. The actual optimization method of MFO is not linear, and the linear decreasing weight is difficult to reflect the real situation, which affects the improvement of MFO effect. In this work, an adaptive nonlinear decreasing strategy of weight coefficient is proposed, and the formula for calculating the weight coefficient is described as follows.

$$\omega = \omega_{max} - \omega_d\left(\frac{t}{T_{max}}\right)^{\beta} \tag{23}$$

where ω is the nonlinear decline rate, which makes a significant difference in the decline rate throughout the iteration process. If $\omega = 1$, it is equivalent to the linear decline of the weight coefficient. ω_{max} is the maximum weight coefficient, and ω_d is the weight coefficient decreasing quantity, i.e., the difference between the maximum weight coefficient and the minimum weight coefficient.

The weight coefficient is non-linearly decreasing, and the weight coefficient will be non-linearly decreasing with the evolution generation in the whole iterative calculation process. The relation curves of specific weight coefficients and evolution generations are shown in Fig. 2.

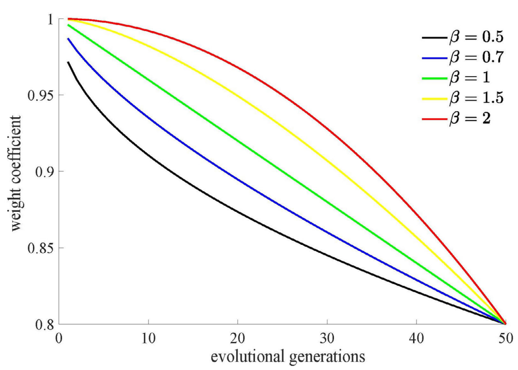

FIGURE 2. The relationship between weight coefficient and evolutionary algebra.

In Fig. 2, ω_{max} and ω_d are taken as 1 and 0.2, respectively, from which one can get that, under the above weight coefficient adaptive nonlinear decline strategy, the weight coefficient ω decreases nonlinearly with the decreasing rate of the iteration progress, and the global optimization ability of the algorithm can be improved to the greatest extent by selecting the best nonlinear decreasing rate α.

D. ADAPTIVE NONLINEAR DECREASING STRATEGY FOR SELECTION, CROSSOVER, MUTATION PROBABILITY

The smaller the selection probability is, the stronger the algorithm's ability to retain effective information will be, but it needs to lose the self-updating ability of the population. Meanwhile, the larger the crossover probability and mutation probability are, the more likely the algorithm is to generate new individuals with large differences, but it needs to lose the population diversity [22]. However, this approach is not conducive to effectively improving the global optimization performance of the algorithm. In this work, an adaptive nonlinear decreasing strategy of selection, crossover and mutation probabilities is proposed, and the specific formulas are described as follows.

$$sp = sp_{\max} - sp_d\left(\frac{t}{T_{max}}\right)^{s\alpha} \tag{24}$$

$$cp = cp_{\max} - cp_d\left(\frac{t}{T_{max}}\right)^{c\alpha} \tag{25}$$

$$mp = mp_{\max} - mp_d\left(\frac{t}{T_{max}}\right)^{m\alpha} \tag{26}$$

where sp, cp and mp are selection, crossover and mutation probabilities, respectively; $s\alpha$, $c\alpha$ and $m\alpha$ are the adaptive nonlinear decline rate of selection, crossover and mutation probabilities, respectively, which make a significant difference in the decline rate in the whole iteration process; $sp_{\max}$, $cp_{\max}$ and $mp_{\max}$ are the maximum probability of selection, crossover and mutation; sp_d, cp_d and mp_d are the decreasing probability of selection, crossover, mutation.

The probability of selection, crossover and mutation is non-linearly decreasing. In the whole iterative calculation process, the probability of sp, cp and mp is non-linearly decreasing with the increase of evolution generation.

E. OPPOSITION-BASED LEARNING STRATEGY

The opposition-based learning (OBL) strategy is an effective strategy for improving global optimization quality of intelligent optimization algorithms, it was proposed by Tizhoosh [23]. For infeasible solutions generated in the optimization process, the traditional processing method replaces the out-of-bounds value with a critical value or a random value within the allowable range. However, as the number of iterations increases, it will aggravate the waste of computing resources. By generating a large number of opposite solutions far from the local optimum, OBL guides the population away from the local optimum area, thus widening the search range and improving the global optimization performance.

If the ith individual is out of bounds in the tth iteration, the OBL strategy will be involved. The specific OBL solution $x(t)_i'$ can be obtianed according to the following equations.

$$\begin{cases} x(t)_i' = a_i + \beta(x(t)_i - b_i) & x(t)_i > b_i \\ x(t)_i' = a_i + \beta(a_i - x(t)_i) & x(t)_i < a_i \end{cases} \tag{27}$$

Here, $x(t)_i'$ is the individual out of bounds, a_i and b_i are the minimum boundary and maximum boundary of the solution space, respectively; $\beta \in [0, 1]$ is the coefficient to avoid excessive individual escape. If the OBL solution is still out of bounds, a random value within the allowed range is invoked.

F. DESIGN OF IMFO-G

In this work, an IMFO-G is proposed. Specifically, the genetic mechanism and OBL strategy are integrated into the MFO, and an adaptive nonlinear decreasing strategy of weight coefficient and selection crossover and mutation is given, so as to effectively improve the global optimization ability of IMFO-G. The flowchart of the specific IMFO-G is shown in Fig. 3.

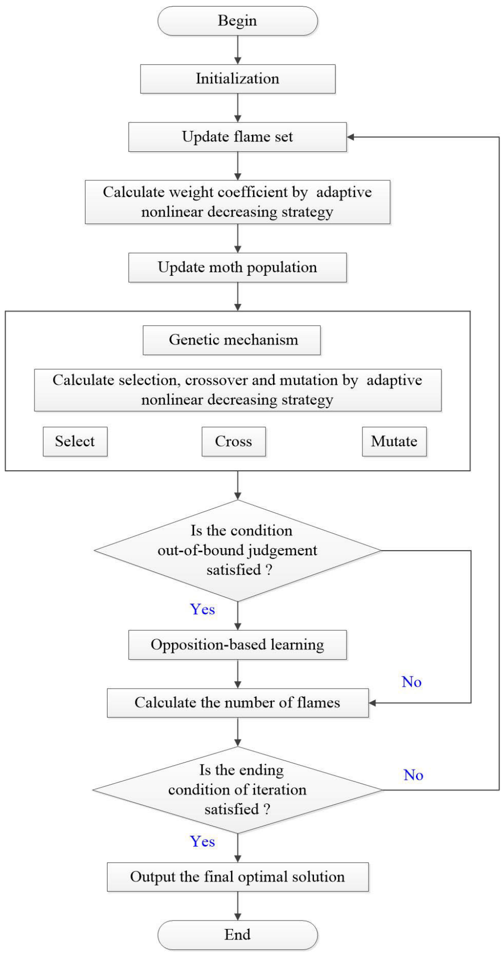

FIGURE 3. Flowchart of the IMFO-G.

IV. SIMULATION VERIFICATION OF AN EXAMPLE OF THE OCP OPTIMIZATION PROBLEM OF EVCS IN TOURIST ATTRACTIONS

In this section, the effectiveness of the improved moth algorithm is verified for the OCP optimization problem of EVCs in tourist attractions. Specifically, this section gives an example of the OCP optimization problem of EVCs in tourist attractions. On the basis of taking into account user preferences and comprehensive evaluation indicators on the grid side, the proposed IMFO, the traditional MFO, the traditional PSO, the improved PSO (IPSO) proposed in reference [9] and the improved Honey-badger algorithm (IHBA) proposed in reference [10] are used as optimization algorithms for the practical OCP optimization problem of EVG in tourist attractions. The simulation results show that the improved MFO algorithm can find a more ideal charging planning scheme for EVG, and the convergence speed is faster. This shows that the IMFO can better improve the defects of MFO, is of the optimization performance, and is more suitable for solving the OCP optimization problem of EVCs.

A. DATA SOURCES FOR AN EXAMPLE OF THE OCP OPTIMIZATION PROBLEM FOR EVCS

The fundamental conditions about tourist attractions' trip of China are different from America and Western Europe. In America and Western Europe, people have enough money and time to take a trip with your own ideas. There were plenty of Americans willing to spend their days in Las Vega, their lives traveling the world, the money and time for a trip around the world is not a big deal. However, in China, the situation is different, people living in dire straits. Only several days and scarce tourism expenses can be used for a trip, even a holiday during two months business trip, or travel by foot for saving money. In Chinese, using group travel type is a good choice, and when a tourist is planning a trip, they may decide which travel agency to sign a trip contract, and visiting tourist attractions are listed in the specific trip contract. In a trip, the drivers and electric vehicles are provided by travel agency, based on cost and convenient, the drivers and electric vehicles are employed in the local tourist attraction. During the entire process of trip, electric vehicles often need to be fully used, and "run fast" and "fully loaded" are two purposes. In actual, the proportion for self-driving travel is relatively low, and the proportion for self-driving travel is relatively high.

In this work, the OCP optimization problem of EVG in Dalian bonded area scenic spot is taken as the research object. The environment of OCP optimization problem for EVCs in tourist attractions in the simulation is built with real data sources for Dalian bonded area scenic spot. The real data sources for load data of the smart grid system and EVs charging can be obtained form the specific charging station control center and smart grid system self, and these data sources belong to the electric vehicle traffic network operating company in Dalian bonded area scenic spot. There are 33 nodes in the smart grid of this district, and the type, applicable voltage range and voltage phase of each node are known, and the resistance between each node is known. The specific load data of the smart grid system is shown in Tab. 1, and the specific smart grid system diagram is shown in Fig. 4.

In Tab. 1, the head node and end node, active resistance and active resistance, active power and active power about the end node for a specific branch have been listed. The specific value for the above Dalian bonded area scenic spot is obtained by real measuring.

In the smart grid of the community, the charging station control center is set up at the 15th, 18th, and 32th nodes, which respectively supply electric energy to the smart

TABLE 1. Load data of the smart grid system.

Branch No.	Head node	End node	active R(Ω)	reactive R(Ω)	active P(kW)	reactive P(kVar)
1	1	2	0.0922	0.0470	100	60
2	2	3	0.4930	0.2511	90	40
3	3	4	0.3660	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.8190	0.7070	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	0.7114	0.2351	200	100
8	8	9	1.0300	0.7400	60	20
9	9	10	1.0440	0.7400	60	20
10	10	11	0.1966	0.0650	45	30
11	11	12	0.3744	0.1238	60	35
12	12	13	1.4680	1.1550	60	35
13	13	14	0.5406	0.7129	120	80
14	14	15	0.5910	0.5260	60	10
15	15	16	0.7463	0.5450	60	20
16	16	17	1.2890	1.7210	60	20
17	17	18	0.7320	0.5740	90	40
18	18	19	0.1640	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	22	23	0.4512	0.3083	90	50
23	23	24	0.8980	0.7091	420	200
24	24	25	0.8960	0.7011	420	200
25	25	26	0.2030	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.0590	0.9337	60	20
28	28	29	0.8042	0.7006	120	70
29	29	30	0.5075	0.2585	200	60
30	30	31	0.9744	0.9630	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.3410	0.5302	60	40

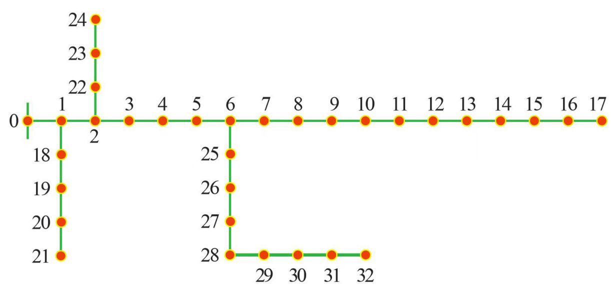

FIGURE 4. Schematic diagram of smart grid system.

charging piles in the area under their jurisdiction for charging electric vehicles.

In actuality, for implementing simulation verification of engineering examples of OCP optimization problem for EVCs in tourist attractions, the data sources for EV charging are necessary to forecast in advance. However, precise forecast results are very difficult to forecast, and it is next to impossible to achieve. So, in this paper, the real history results of EVs charging for the Dalian bonded area scenic spot collected from Liaoning Northeast Asia Travel Group Co., Ltd. (a company the partially manages the electric vehicle traffic network for Dalian bonded area scenic spot) have been chosen for simulation verification, the specific date is February 26, 2022. February 26, 2022, it is a Saturday nearby school started day. On February 26, 2022, there are exceed 10000 tourists, a fair number of tourists is university student, and there are 1400 Dalian bonded area registration EVs and unregistered 241 EVs (the EVs come from other areas or newly purchased has unregistered in Dalian bonded area) were charged in this scenic spot, the number of EVCs and drivers employed in Liaoning Northeast Asia Travel Group Co., Ltd. are 845 and 620. Due to the considerable tourists amount and EVCs scale, February 26, 2022 is chosen. Here, the charging types are divided into "only once/day", "twice/day" and "three times/day", the corresponding number of vehicles is 866, 437 and 198, respectively, the total number is 1501, and the other 140 EVs had been charged more than three times. The real data comes from EVC data sensing and management system for Dalian bonded area scenic spot, only the 1501 EVs charged frequency less than or equal to "three times/day" for research in this paper. Their battery capacity is known before and after charging. There are four types of smart charging piles in the district, which are the slow charging mode suitable for households and the $L-1$, $L-2$ and $L-3$ modes suitable for parking lots and shopping malls. Their charging powers are

3.5kW, 7kW, 12kW and 24kW respectively, and the charging power factor is 0.9. All of them can charge any type of vehicle in the district car group and charge truth-telling.

Compared with the ordinary day, February 26, 2022 is a holiday. In this day, a fair number of university students from various parts of China has tripped in Dalian bonded area scenic spot. Due to the influx of visitors, Liaoning Northeast Asia Travel Group Co., Ltd. has employed significantly more EVs and drivers. Obviously, data of February 26, 2022 has very high value for study.

B. PARAMETERS SETTING FOR THE SPECIFIC EXAMPLE OF THE OCP OPTIMIZATION PROBLEM FOR EVCS AND IMFO-G

The parameters setting of the specific example of the OCP optimization problem for EVCs are taken as follows. The importance weights α_1 and α_2 of charging user preference and grid quality are set to 0.75 and 0.25, respectively. The corresponding importance weights α_L and α_{NL} of daily load curve variance and network loss are set to 0.6 and 0.4, respectively. The upper limits of daily load curve variance and network loss $L_{var,max}$ and NL_{max} are set to 10^8 and 10^4 kW, respectively. The corresponding importance weights α_C and α_p of the matching degree of charging fee and charging plan preference are set to 0.5 and 0.5, respectively, and the upper limit of charging fee is set to 10^4 yuan.

The parameters setting of specific IMFO-G are taken as follows. The moth population size n is 100, the number of iterations t_{max} is 50, the logarithmic spiral waveform τ state is 1, the maximum weight coefficient ω_{max} is 1, the inertia weight decreasing quantity ω_d is 0.2, and the optimization factor β of nonlinear decreasing weight coefficient is 1.65. The maximum selection of sp_{max}, crossover cp_{max} and mutation probability mp_{max} are 0.6, 0.85 and 0.09, respectively. sp_d, cp_d, mp_d are set as 0.2, 0.15 and 0.03, respectively. the nonlinear decreasing $s\alpha$, $c\alpha$, $m\alpha$ are 1.25, 1.53, and 0.85, respectively.

C. CONFIGURATION OF SIMULATION PLATFORM

The specific detailed configuration of the simulation platform is shown below: the Matlab/Simulink revision for computation and figures drawn is "Matlab GUI 2016b"; the major computer configuration is "Core i7-7700K @ 4.2GHZ" and "Windows 10"; display software revision is "Internet Explorer 11"; data storage software is "office2019 excel".

D. SIMULATION AND VERIFICATION OF OCP OPTIMIZATION PROBLEM FOR EVCS IN TOURIST ATTRACTIONS

Aiming at the practical problem of OCP optimization problem for EVCs, both charging user preferences and grid quality should be taken into account. To verify the effectiveness of the algorithm proposed in this work, the simulation experiment is implemented, which takes the preferences of charging users and the power grid quality into account. The proposed IMFO-G in this paper is used for optimization verification, the traditional MFO, the traditional PSO, the IPSO and the IHBA are used for optimization comparison and evaluation. The specific optimization results are shown in Figs. 5-11.

As can be seen from Fig. 5, compared with the traditional PSO, the traditional MFO, the improved PSO and the improved Honey-badger algorithm used for comparison, the

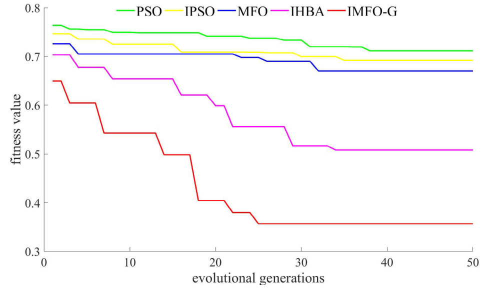

FIGURE 5. Iterative convergence curves of each algorithm considering charging user preferences and power grid quality.

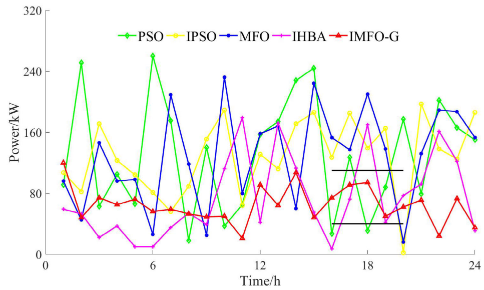

FIGURE 6. Schematic diagram of the operation plan curves of charging station 1 considering both charging user preferences and grid quality.

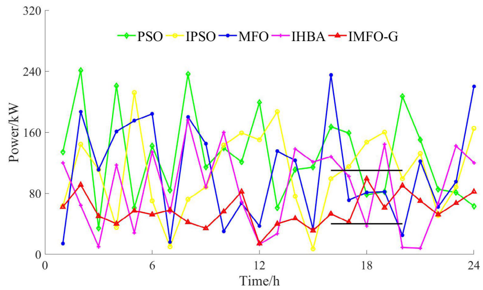

FIGURE 7. Schematic diagram of the operation plan curves of charging station 2 considering both charging user preferences and grid quality.

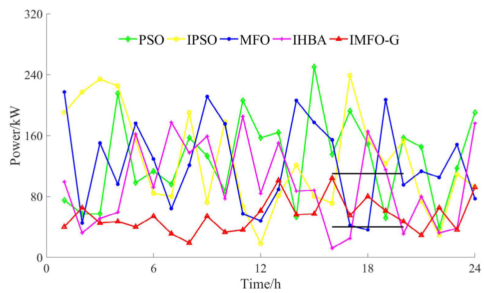

FIGURE 8. Schematic diagram of the operation plan curves of charging station 3 considering both charging user preferences and grid quality.

TABLE 2. The specific total charging power of the charging stations 1-3.

Time	PSO(kW)	IPSO(kW)	MFO(kW)	IHBA(kW)	IMFO-G(kW)
1th	300	360	327	278	222
2th	549	443	277	149	204
3th	154	516	407	83	169
4th	541	383	353	213	152
5th	225	470	449	200	169
6th	515	235	339	236	162
7th	355	146	289	267	148
8th	411	351	419	367	114
9th	387	311	381	286	137
10th	263	510	437	349	139
11th	392	290	204	433	139
12th	513	299	243	139	166
13th	399	380	392	349	205
14th	392	368	389	338	210
15th	608	273	434	264	136
16th	329	297	542	147	231
17th	478	539	250	199	188
18th	258	441	327	372	273
19th	222	448	427	301	172
20th	541	254	136	117	199
21th	374	403	367	180	170
22th	326	218	356	260	141
23th	364	322	430	302	176
24th	403	443	450	327	209

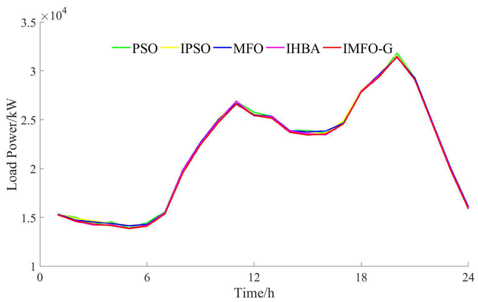

FIGURE 9. The overall grid load variation curves considering both charging user preferences and grid quality.

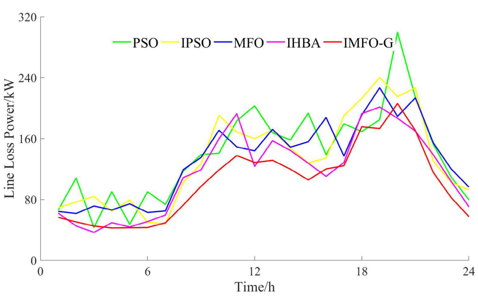

FIGURE 10. Line loss power curves considering both charging user preferences and grid quality.

IMFO-G has a faster global convergence speed and better global convergence accuracy under the condition of taking into account the preferences of charging users and the quality of the power grid. As can be seen from Figs. 6-8, compared with the traditional PSO, the traditional MFO, the

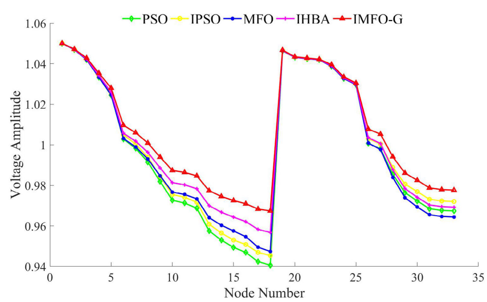

FIGURE 11. Node voltage amplitude curves considering both charging user preferences and grid quality.

improved PSO and the improved Honey-badger algorithm used for comparison, the operation plan curves of charging stations 1-3 obtained by the IMFO-G are more straight, and it is beneficial to reduce line loss power; in addition, the distribution network load fluctuation of the ordered charging planning of charging stations 1-3 obtained by the IMFO-G in the peak period (16h,20h) is much smaller, and does not exceed 70kW. As can be seen from Figs. 9-10 that when considering the preferences of charging users and the quality of the power grid, compared with the traditional PSO, the traditional MFO, the improved PSO and the improved Honey-badger algorithm used for comparison, the IMFO-G can better realize ''peak and valley filling'', to effectively ensures the load stability of the power grid and reduces the network loss more significantly. As can be seen from Fig. 11, when considering the preferences of charging users and the quality of power grid, compared with the traditional PSO, the traditional MFO, the improved PSO and the improved

TABLE 3. The specific objective function results.

Optimization algorithms	Preference matching degree	Network loss(kW)	Dual optimization objective function values
PSO	0.25	$3.35 * 10^3$	0.71
IPSO	0.40	$3.21 * 10^3$	0.69
MFO	0.44	$3.17 * 10^3$	0.67
IHBA	0.64	$2.78 * 10^3$	0.51
IMFO-G	0.85	$2.46 * 10^3$	0.36

Honey-badger algorithm used for comparison, the node voltage amplitude of 33 nodes in the OCP scheme obtained by proposed IMFO-G in this paper belongs to the range of 0.97-1.05, and its fluctuation is small.

The total charging power of the charging stations 1-3 obtained by proposed IMFO-G and comparison optimization algorithms are listed in Tab. 2 below. The specific performance evaluation results for the final ordered charging planning obtained by proposed IMFO-G and comparison optimization algorithms are listed in Tab. 3 below.

As shown in Tab. 2, compared with optimization algorithms used for comparison, the proposed IMFO-G exhibits significantly better total charging power of the charging stations 1-3, the average value and fluctuate degree can be efficaciously reduced. As shown in Tab. 3, compared with optimization algorithms used for comparison, the proposed IMFO-G exhibits significantly better preference matching degree, network loss, and dual optimization objective function values. This confirms the high optimization quality of IMFO-G.

In summary, compared with optimization algorithms used for comparison, the improved moth-flame optimization algorithm proposed in this paper not only better meets the preferences of charging users, but also better improve the quality of the power grid.

V. CONCLUSION

In order to solve the OCP optimization problem for EVCs in tourist attractions, this paper proposes an improved moth-flame optimization algorithm that integrates the adaptive nonlinear decreasing strategies of selection, crossover, mutation probability and weight coefficient and the opposition-based learning strategy. Compared with other enhanced optimization algorithms, our algorithm demonstrates significantly superior optimization performance. Simulation results for an actual example of the OCP optimization problem of EVCs in tourist attractions reveal two key contributions of the proposed moth-flame algorithm:

(I) The iterative convergence curve illustrates the strong optimization quality of our algorithm, obtaining improved optimization solutions.

(II) The iterative convergence curve shows that the improved moth-flame algorithm proposed has fast global convergence speed.

The following summarizes the main innovative points of the paper:

(I) Innovations of optimization model design for the OCP optimization problem of EVCs in tourist attractions: addressing the suboptimal resolution of the OCP optimization problem for EVCs, we design an optimization model with a dual objective function, considering both charging plan preference matching degree and the quality of power supply appropriately.

(II) Innovations of the MFO algorithm: this paper introduces an improved moth-flame optimization algorithm with three specific novel strategies: (1) integrating a genetic mechanism in the iterative process to enhance optimization quality, (2) incorporating adaptive nonlinear decreasing strategies for selection, crossover, mutation probability, and weight coefficient, and (3) introducing the OBL mechanism to further improve optimization quality.

In summary, the improved moth-flame algorithm proposed in this paper is effective. To validate its effectiveness, a simulation comparison of an OCP example for EVCs in tourist attractions is conducted, demonstrating the efficacy of the proposed algorithm.

However, there are several shortcomings in this research, and targeted suggestions for improvement in the context of the OCP optimization problem for EVCs in tourist attractions based on the improved moth-flame optimization are provided:

(I) There exists a gap between the actual scenario and the designed optimization model for the OCP optimization problem for EVCs in tourist attractions. Further studies should focus on specific optimization model design, adjusting several objective functions and constraint conditions to align with reality.

(II) The effectiveness of the adaptive nonlinear decreasing strategies of selection, crossover, mutation probability and weight coefficient are limited, additional strategies, such as Gaussian mutation, cosine or sine decreasing modes, segmented adaptive nonlinear decreasing modes, etc., can be introduced to strengthen optimization abilities.

(III) The effectiveness of the introduced genetic mechanism is finite. Combining the improved MFO with other algorithms, such as differential evolution (DE), memetic algorithms, etc., could enhance the potential for optimization performance improvement.

(IV) The simulation comparison of the OCP optimization problem for EVCs in tourist attractions still lacks of an effective precise EVs charging forecast algorithm. To enhance the effectiveness of the specific simulation comparison, further research on a precise EVs charging forecast algorithm is necessary.

(V) Several special situations for the OCP optimization problem for EVCs in tourist attractions are lack, such as the number of vehicles invaded to the tourist attraction increased few times than the normal day. Therefore, further research on several special situations for the OCP optimization problem for EVCs in tourist attractions is necessary.

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