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An Improved Honey Badger Algorithm for Electric Vehicle Charge Orderly Planning

Ran-Fan Chen

College of Computer Science and Mathematics
Fujian University of Technology
Fuzhou, 350118, China
386482798@qq.com

Hao Luo

School of Aeronautics and Astronautics
Zhejiang University
HangZhou, 310000, China
luohao@zju.edu.cn

Kuan-Chun Huang

Department of Industrial and Systems Engineering
Chung Yuan University
Taoyuan, 320-33,Taiwan
khuang@cycu.edu.tw

Trong-The Nguyen[1,2]

[1]Multimedia Communications Lab,
VNUHCM-University of Information Technology
Ho Chi Minh City 700000, Vietnam
[2]Vietnam National University,
Ho Chi Minh City 700000, Vietnam
jvnthe@gmail.com

Jeng-Shyang Pan*

Fujian Provincial Key Laboratory of Big Data Mining and Applications
Fujian University of Technology
Fuzhou 350118, China
College of Computer Science and Engineering
Shandong University of Science and Technology
Qingdao, 266590, China
*Correponding Author:jengshyangpan@gmail.com

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ABSTRACT. *Multiple electric vehicles simultaneously connected to a distribution load network will significantly impact the stability of the power grid. This paper proposes an improved Honey-badger algorithm (IHBA) through elite reverse learning, spiral update, and wild dog survival strategies to optimize the orderly charging of electric vehicles (EV). Objective functions of EV charge orderly planning are taken by using load fluctuation satisfaction, user cost satisfaction, and user convenience satisfaction to achieve the high efficiency of orderly charging. The benchmark test function and the electric vehicle sequential charging problem were employed to evaluate the proposed IHBA approach. The obtained results are compared with the other algorithms in the literature, which indicate that the IHBA algorithm does not only provides more accurate outcome but better convergence speed than the other competitors.*
Keywords: Electric vehicle, Orderly charging, Improved honey badger algorithm

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1. **INTRODUCTION.** With the aggravation of global energy shortage [1], environmental pollution [2], and driving safety challenges, the automobile industry has been steering its course toward electrification, intelligence, networking and sharing. As global energy conservation and emission reduction becomes the general trend, gradually replacing traditional fuel vehicles with new energy vehicles [3] such as electric vehicles (EV) grows into our country's social consensus and development direction. Charging of electric vehicles simultaneously connected to the power grid on a large scale may bring load impact to the power grid and create new challenges to the reliable operation of the power system [4]. Efficiently realizing the optimal scheduling of large-scale electric vehicles has increasingly become a hot issue [5].

In recent years, using an efficient control strategy [6] and advanced optimization algorithm to achieve orderly charging of electric vehicles has become an effective means of electric vehicle scheduling. The optimization objective function of the main control layer for "peak load shifting and valley filling" [7] is established and the hierarchical collaborative control strategy of multiple secondary level optimization objectives enhances the real-time practicability of electric vehicle optimal scheduling.

More and more attention has been paid to the application of the metaheuristic algorithm in resolving issues in engineering such as the typical Cuckoo Search algorithm (CS)[8], Particle swarm optimization (PSO) [9, 10], simulated annealing algorithm (SA) [11], Whale optimization algorithm (WOA) [12], Cat Swarm Optimization(CSO) [13], Grey wolf optimization algorithm(GWO) [14], Fish Migration Optimization (FMO) [15], etc. And many algorithms have been applied in engineering field, such as wireless sensor problem [16, 17, 18], vehicle routing problem [19, 20, 21], hydropower station dispatching problem [22, 23], security and communication network issues [24, 25, 26], reactive power optimization problem [27, 28, 29], job shop scheduling problem [30, 31, 32],orderly charging strategy of electric vehicle [33, 34, 35] etc. The Honey badger (HBA) [36] used in this paper is a new swarm intelligence optimization algorithm. Many scholars have put forward advanced improvement methods while studying the algorithm.

As a new swarm intelligence algorithm, the Honey badger algorithm was proposed by Fatma A. Hashima et al. in 2021. It mainly simulates the dynamic search behavior of Honey badger mining and searching honey. Because of its good experimental results and simple structure, it has a wide application prospect in the future.

In this paper, the HBA algorithm is studied and improved for its global search ability and convergence speed in large-scale problems. Taking private electric vehicles [37] as the main research object, the battery condition of large-scale electric vehicles is simulated by Monte Carlo method [38]. The multi-objective optimization function is established considering the maximum load fluctuation satisfaction, the cost satisfaction of the largest users, and maximum user convenience satisfaction. Finally, the IHBA is used to solve the optimization objective function.

2. **Related work.**

2.1. **Honey badger optimization algorithm.**

Badger is a mammal with black and white furry fur [39] which usually lives in the semi-desert and tropical rainforest of Africa, southwest Asia, and the Indian subcontinent.With a size of 59 - 76 cm in body length and 6.5- 14 kg in body weight,this forager preys on 60 different species, including some dangerous snakes..Its staple food is honey and prefers to stay alone in its nest and only meets other badgers in the breeding season. However, honey badgers don't have a specific period of time for breeding as their cubs are born all year round. Moreover, when there is no easy way to escape, these fearless creatures will not hesitate to attack larger predators. A technique called the rat sniffing was used while walking slowly so it could continuously discover its preys by roughly excavating the locations of interest. In order to find sufficient supply of food, it can dig 50 holes in a radius of 40 kilometers or more a day.

The problem lies in that honey badgers are not good at finding beehives. On the other hand, honeyguide birds are capable of locating hives but they cannot find honey. These phenomena lead to a form of commensalism between the two species. The bird leads the badger to the hive, helps it open the hive with its long claws, and they both enjoy the reward of teamwork.

2.1.1. *Population initialization.*

Some parameters need to be preset for population initialization, such as population size N, the number of iterations L, parameters of some algorithms, etc. Initialize the population X of honey badgers in the search space. X is a population composed of N honey badger individuals, it can be expressed as:

$$\begin{cases} X = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & \cdots\cdots & X_{1D} \\ X_{21} & X_{22} & X_{23} & X_{24} & \cdots\cdots & X_{2D} \\ X_{31} & X_{32} & X_{33} & X_{34} & \cdots\cdots & X_{3D} \\ X_{41} & X_{42} & X_{43} & X_{44} & \cdots\cdots & X_{4D} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdot \\ X_{n1} & X_{n2} & X_{n3} & X_{n4} & \cdots\cdots & X_{nD} \end{pmatrix} \\ X_j = \begin{bmatrix} X_j^1 & X_j^2 & \cdots\cdots & X_j^D \end{bmatrix} \end{cases} \tag{1}$$

Randomly generate the initial position of honey badger, defined as:

$$X_j = lb_j + r_1 \cdot (ub_j - lb_j) \tag{2}$$

Where, r_1 is a random number uniformly distributed on [0, 1]. $X_j$is the position of the j^{th} individual among the N candidate individuals,and lb_j, ub_j are the lower and upper bounds of the optimization space, respectively.

2.1.2. *Prey attraction.*

The attraction of prey is related to the concentration intensity of prey and the distance between prey and the j^{th} honey badger. K_j represents the odor intensity of the prey. If the value of K_j is larger, it indicates that the j^{th} honey badger can find the location of the prey more accurately and then move to the prey faster, it is mathematically expressed as:

$$K_j = r_2 \cdot \frac{S}{4\pi d_j^2} \tag{3}$$

$$S = (X_j - X_{j+1})^2 \tag{4}$$

$$d_j = X_p - X_j \tag{5}$$

Where, S can be called source intensity or concentrated intensity.$d_j$is the distance between the prey and the j^{th} honey badger. X_p is the position of the prey, which is regarded as the position of an optimal individual in the algorithm. From Eq.(3) and (5), the closer the honey badger to its prey, the stronger the attraction (odor) will develop.

2.1.3. *Density factor.* The density factor decreases slowly with the number of iterations to ensure a smooth transition from exploration to precise development. Eq.(6) is used to update the decreasing factor with the number of iterations in order to reduce randomization. It is mathematically expressed as:

$$\alpha = C_0 \cdot \exp\left(\frac{l}{l_{\max}}\right) \tag{6}$$

Where, C_0 is a constant greater than or equal to 1 with a default value 2. l is the current number of iterations, and l_{max} is the maximum number of iterations.

2.1.4. *Update the location of the search agent.* The update process of HBA location is divided into two parts. The first process is the "Mining stage" in which honey badgers follow similar to Cardioid shape to look for preys as the expression:

$$X_{\text{new}} = X_p + F \cdot \beta \cdot K \cdot X_p + F \cdot r_3 \cdot d_j \cdot \left|\cos\left(2\pi r_4\right)\left[1 - \cos\left(2\pi r_5\right)\right]\right| \tag{7}$$

Where, the location of prey is the best location found so far; that is, the global best location. β , the ability of honey badgers to obtain food is set to be greater than or equal to 1 (the default value is 6). d_j is the distance between the prey and the j^{th} honey badger. r_3, r_4 and r_5 are three different random numbers between 0 and 1. F stands for the search direction of the search agent as shown in Eq.(8):

$$F = \begin{cases} 1 & r_6 \leq 0.5 \\ -1 & r_6 > 0.5 \end{cases} \tag{8}$$

The second location update process is the "Honey stage". The honey badger and the honeyguide have an inherent cooperative and mutually beneficial relationship. A honeyguide can easily find a hive but is not capable of destroy it. Once the honeyguide finds the location of the hive, it makes a strange sound to attract the honeybadger . The situation that the honey badger follows the honeyguide to the hive can be simulated as Eq.(9):

$$X_{\text{new}} = X_p + F \cdot r_7 \cdot \alpha \cdot d_j \tag{9}$$

In the above formula, X_{new} refers to the new location of the honey badger, while X_p refers to the location of the prey, F and α Use Eq.(8) and (6) respectively. From Eq.(9), it can be observed that according to the distance information d_j, the honey badger searches at a position close to X_p.

2.2. Mathematical model of charge EV orderly planning.

2.2.1. *Travel rules of electric vehicles.* The disordered mode of electric vehicles [40] indicated that any strategy could not control the charging behavior of electric vehicles, which was mainly affected by users' daily travel habits. Family electric vehicles are primarily used for users' commuting and leisure. For household electric vehicles, the time of network access follows the normal distribution, and its probability density function [41] is

$$f_w\left(t_w\right) = \begin{cases} \frac{1}{\sigma_w \sqrt{2\pi}} \exp\left[-\frac{\left(t_w - \mu_w\right)^2}{2\sigma_c^2}\right] & \mu_w - 12 \leq t_w \leq 24 \\ \frac{1}{\sigma_w \sqrt{2\pi}} \exp\left[-\frac{\left(t_w + 24 - \mu_w\right)^2}{2\sigma_c^2}\right] & 0 \leq t_w \leq \mu_w - 12 \end{cases} \tag{10}$$

The starting time of charging is t_w, $\mu_w = 17.6$ and $\sigma_w = 3.4$ represent the expected value with 17.6 is the starting charging time, and its standard deviation is 3.4.

The daily mileage [42, 43] also follows the normal distribution approximation, and its probability density function is:

$$f_d(S) = \frac{1}{S\sigma_d\sqrt{2\pi}} \exp\left[-\frac{(\ln S - \mu_d)}{2\sigma_d^2}\right] \tag{11}$$

Where d is the daily driving distance. The expected value of d, μ_d is 3.20 and its standard deviation σ_d is 0.88.

$$E_s = \left(1 - \frac{d}{D}\right) \cdot 100\% \tag{12}$$

Where E_s is the current remaining power of the battery, d is the daily driving distance, and D is the maximum distance after draining a set of batteries. The charging time of electric vehicles can be described as

$$t_i = \frac{(1 - Es) \cdot C_b}{p_i} \tag{13}$$

Where t_i is the charging time of the i^{th} electric vehicle.C_b is the capacity of the battery and P_i is the charging power.

2.2.2. *Mathematical model of orderly charging.* The formula of orderly charging model is as follows

$$Q = 1 - \frac{q(t) - q\left(t^*\right)}{q\left(t_0\right)} \tag{14}$$

In Eq.(14), Q, the price satisfaction [44] is related to the charging time and electricity price. $q(t_0)$, the power cost without implementing the TOU price policy is the current charging cost after the optimization. $q(t^*)$, the cost of all charging in the valley period is the minimum cost. The less electricity charges are paid, the higher the satisfaction of users will increase accordingly.

The convenience satisfaction index reflects the change of their personal electricity consumption habits, which is measured by the change of electricity consumption in each time period. When the power grid does not participate in the dispatching, users can choose the appropriate time to charge according to the circumstances. And there is no need to specify which time period to start charging. In this case, the satisfaction of convenience reaches its maximum. When a user responds to the orderly charging strategy, his satisfaction of convenience will be likely to decline. As a consequence, the charging start time will change and the change of power consumption in each time period will also change. The greater the power consumption change in each time period is produced, the lower the convenience satisfaction will be signaled. When no change is made, the convenience reaches the maximum , which is defined explicitly as

$$B = 1 - \frac{\int_1^{24} \left|f_0(t) - f(t)\right| dt}{\int_1^{24} f_0(t)dt} \tag{15}$$

Where B is satisfaction of convenience, $\int_1^{24} \left|f_0(t) - f(t)\right| dt$ is the sum of power consumption changes in each time period, $\int_1^{24} f_0(t)dt$ is the charging amount in disordered charging mode, and B is a function of starting charging time. It can be seen from Eq.(15) that when the user makes any adjustment due to disobedience to the grid response during charging, the convenience satisfaction is 1. However, when the change degree of power consumption in each time period is more prominent, the more users obey the regulation of the power grid, the lower the convenience satisfaction will become.

This paper takes the power grid variance as an index to reflect the stability of power grid. The smaller the grid load variance is, the more stable the grid load is, specifically, such as Eq.(16) and Eq.(17).

$$P_a = \frac{1}{T}\sum_{m=1}^{M}\left(P_0^m + \sum_x P_x^t\right) \tag{16}$$

$$V^2 = \frac{1}{T}\sum_{m=1}^{M}\left(P_0^m + \sum_x P_x^t - P_{\mathrm{a}}\right)^2 \tag{17}$$

The above formula: V^2 is the standard deviation of power grid. T is the number of time cycles. There are 24 cycles, 1 hour per cycle. P_0^m is the basic load of residents without electric vehicle charging load in the t^{th} time period. P_x^t is the charging power of M electric vehicles in the t^{th} time period; P_a is the average value of the total load of the community in a day. Therefore, the degree of satisfaction Eq.(14) describing the degree of charge fluctuation can be obtained.

$$Z = 1 - \frac{V_t^2 - V_{\min}^2}{V_{\max}^2 - V_{\min}^2} \tag{18}$$

Where Z represents the degree of satisfaction of grid load fluctuation, V_t^2 represents the variance of the grid after the implementation of the optimization strategy, V_{min}^2 represents the minimum grid load variance before and after the implementation of the strategy, and V_{max}^2 represents the maximum grid load variance before and after the implementation of the strategy. The greater the fluctuation of load, the smoother the load curve and the smaller the peak valley difference.

Normalize the three indexes of Eqs.(14), (15) and Eq.(18) to obtain Eq.(19)

$$Y = \omega_1 Q + \omega_2 B + \omega_3 Z \tag{19}$$

Where Y is the sum of the objective function of all three users' satisfaction factors in the power grid. The larger Y is, the higher the recognition of power grid and users for the strategy is $\omega_1 + \omega_2 + \omega_3 = 1$, and the three are proportional coefficients.

2.2.3. *Constraints.* Considering the security of the distribution network, the charging load in all periods should not exceed the upper limit of the distribution network power. Namely:

$$P_{base} + \sum_{i=1}^{T} C_{i\tau} p_i < P_{std} \tag{20}$$

Where P_{base} represents the basic load of the distribution network before electric vehicles are connected in a large scale; P_{std} is the upper limit of power that the distribution network can bear. p_i is the charging power of electric vehicle,$C_{i\tau}$ is the number of electric vehicles in the i^{th} time period.

The upper and lower limits of state of charge are constrained. In order to avoid over-charge and discharge of EV power battery, its state of charge meets the following requirements:

$$S_{\min} \le S_{t,m} \le S_{\max} \tag{21}$$

S_{min} and S_{max} represent the lower limit and upper limit of state of charge S, respectively.

Charging power constraint represents the charging power of electric vehicle in the process of charging cannot exceed the maximum power that the battery can bear.

$$P_{t,m}^{d} \leq P_{max}^{EV} \tag{22}$$

$P_{t,m}^{d}$ is the charging power of the m^{th} EV, P_{max}^{EV} is the maximum charging power that the electric vehicle can withstand.

3. Improved HBA algorithm.

3.1. Algorithm improvement.

Reverse learning was proposed by Tizhoosh in 2005 [45]. The article points out that generating reverse solutions can effectively improve the diversity of solutions with better results close to the optimal solution. However, with this reverse population, it may be more difficult to approximate the optimal solution than the original population. OBL strategy is to select some individuals with the best function values to form an elite population from all individual objective functions. This population with the reverse solution of the elite population, then integrates the population based on by the reverse learning strategy with the initial population. It will select high-quality individuals with the same number as the initial population to form a new initial population. Although elite individuals carry more practical information, the best individual will become even harder to be found if the number of elite individuals is large. Subsequently, the search agent would be wandering in a region and have difficulty to jump out of local optimal solutions. The equation is as follows:

$$X_m^{'} = r(u + e) - X_m \tag{23}$$

Where r is the random value on [0, 1], u and e represent the upper and lower bounds of the search space respectively, and X_m is the position of the current individual. Certain excellent individuals are selected from the reverse and current populations to form a new population. EBOL mechanism has a good effect on enhancing the diversity and quality in the population.

In the original HBA, the exploration stage of the honey badger starts from the local search in the algorithm. Due to the heart-shaped update mechanism, this local search ability could be relatively weak. Therefore, a spiral motion mechanism is introduced to strengthen the exploration ability of the algorithm of which the update mode of the honey badger is controlled through a random parameter R. It will be updated around the current position if $R < 0.3$. Otherwise, it will be updated around the globally optimal location as shown in Eq.(24)

$$X_{\text{new}} = \begin{cases} d_j \cdot e^{bt} \cdot \cos(2\pi l) + X_i & R < 0.3 \\ d_j \cdot e^{bt} \cdot \cos(2\pi l) + X_b & R \geq 0.3 \end{cases} \tag{24}$$

Where d_j is the distance between the j^{th} honey badger and the prey, b is the logarithmic spiral shape constant, t is the value range of $[-1, 1]$, X_{new} is the updated position of the honey badger, X_i is the current position of the honey badger, and X_b is the global optimal position (i.e. prey).

Dingo optimization algorithm (DOA) is a new intelligent optimization algorithm proposed in 2021[46]. The algorithm was designed according to the social behavior of Australian dingo, which possesses the characteristics of strong optimization ability and fast convergence speed. It ensures the global development ability of the algorithm by introducing a survival strategy. Firstly, the survival rate of wild dogs was calculated by a fitness value as shown in Eq.(25).

$$S(i) = \frac{f_{\max} - f(i)}{f_{\max} - f_{\min}} \tag{25}$$

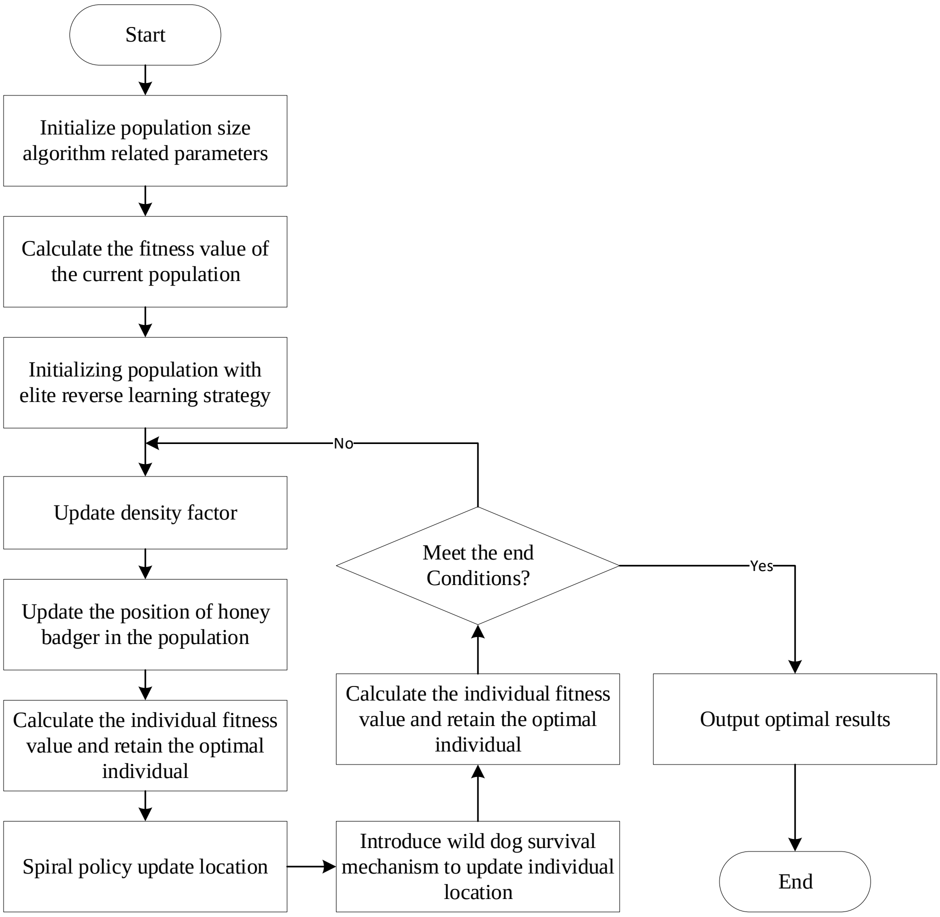


FIGURE 1. Flow chart of the IHBA.

Where f_{max} and f_{min} are the best value and the worst value of the fitness of the current generation respectively. $f(i)$ is the current fitness value of the i^{th} honey badger. $S(i)$ is the normalized fitness within the range with the survival rate of [0,1]. Eq.(26) is used in case of low survival rate, for example, where $S(i)$ is less than or equal to 0.5.

$$X_i(t+1) = X_b(t+1) + 0.5[X_{r1}(t) - (-1)^y \cdot X_{r2}(t)] \tag{26}$$

Where $X_i(t+1)$ is the honey badger with the lowest survival rate to be updated, r_1 and r_2 are random numbers generated from 1 to the population size range with a premise $r_1 \neq r_2$. $X_{r1}(t)$ and $X_{r2}(t)$ are the r_1^{th} and r_2^{th} honey badgers randomly selected, $X_b(t)$ is the best honey badger found in the last iteration, and Y is a binary number randomly generated by the algorithm, which is [0, 1]. The flow chart of the algorithm is shown in Figure 1.

3.2. **Experimental results on mathematic test function.** In order to prove that IHBA has a better performance, the CEC2013 standard mathematical test functions were used in comparison of the results between HBA, GWO, MFO, and DOA. In order to ensure the fairness and accuracy of the investigation, 50 runs of each function were tested independently. The parameter settings of these algorithms are shown in Table 1.

In this paper, the best value(BP), average value(AVE) and standard deviation(STD) are used to evaluate the performance of different algorithms. Table 2 and Table 3 show the average, standard and optimal values of different algorithms and IHBA under the standard test functions.

Table 1. Parameter setting of each algorithm.

Algorithms	**Parameters setting**
$IHBA$	$Pop = 30, iteration = 300, C = 2, \beta = 6$
HBA	$Pop = 30, iteration = 300, C = 2, \beta = 6$
DOA	$Pop = 30, iteration = 300, P = 0.5, Q = 0.7$
MFO	$Pop = 30, iteration = 300, b = 1$
GWO	$Pop = 30, iteration = 300, C = 2, \alpha = [0, 2]$

Table 2. Comparison of optimization performance of HBA, MFO, IHBA on 28 classical test functions.

50D	**HBA**			**MFO**			**IHBA**		
	BP	**AVE**	**STD**	**BP**	**AVE**	**STD**	**BP**	**AVE**	**STD**
F1	4.28E-11	2.82E-08	3.90E-08	6.28E+03	2.01E+04	1.29E+04	**9.10E-13**	**3.25E-12**	**3.10E-12**
F2	1.41E+06	2.89E+06	1.10E+06	2.92E+07	8.91E+07	3.41E+07	**1.01E+06**	**1.78E+06**	**4.90E+05**
F3	8.47E+08	2.89E+09	1.90E+09	9.22E+10	1.32E+11	4.09E+10	**9.42E+07**	**6.61E+08**	**5.65E+08**
F4	2.31E+04	3.00E+04	3.83E+03	9.61E+04	1.55E+05	3.98E+04	**8.12E+02**	**2.47E+03**	**9.80E+02**
F5	4.30E-09	7.83E-08	9.91E-08	3.94E+03	6.95E+03	3.25E+03	**3.59E-09**	**9.81E-09**	**8.29E-09**
F6	4.35E+01	7.02E+01	3.54E+01	3.10E+02	1.28E+03	8.13E+02	**4.35E+01**	**5.62E+01**	**2.21E+01**
F7	5.81E+01	8.34E+01	**1.36E+01**	1.59E+02	2.32E+02	3.59E+01	**5.45E+01**	**7.74E+01**	1.38E+01
F8	**2.11E+01**	**2.12E+01**	5.05E-02	2.11E+01	2.12E+01	5.64E-02	2.11E+01	2.12E+01	**3.93E-02**
F9	**4.46E+01**	5.45E+01	6.34E+00	5.20E+01	5.99E+01	**5.46E+00**	4.32E+01	**5.06E+01**	6.21E+00
F10	1.35E-01	8.37E-01	4.43E-01	1.46E+03	3.78E+03	1.26E+03	**3.33E-02**	**7.88E-02**	**2.75E-02**
F11	1.33E+02	1.97E+02	4.76E+01	3.18E+02	4.87E+02	1.79E+02	**1.18E+02**	**1.86E+02**	**3.44E+01**
F12	2.00E+02	2.86E+02	7.27E+01	6.37E+02	7.63E+02	1.13E+02	**1.71E+02**	**2.31E+02**	**3.65E+01**
F13	3.98E+02	5.16E+02	8.63E+01	5.89E+02	8.31E+02	1.63E+02	**2.96E+02**	**4.33E+02**	**8.05E+01**
F14	3.90E+03	**5.67E+03**	1.42E+03	4.49E+03	6.97E+03	**1.22E+03**	**3.89E+03**	6.19E+03	1.98E+03
F15	7.02E+03	1.01E+04	2.94E+03	7.92E+03	9.46E+03	**1.21E+03**	**6.16E+03**	**8.63E+03**	2.00E+03
F16	2.80E+00	3.59E+00	4.02E-01	**1.19E+00**	**1.86E+00**	**8.34E-01**	1.29E+00	3.15E+00	1.15E+00
F17	**1.70E+02**	2.83E+02	5.09E+01	3.08E+02	8.27E+02	5.59E+02	2.01E+02	2.92E+02	**4.51E+01**
F18	2.81E+02	**3.73E+02**	**7.49E+01**	4.58E+02	1.17E+03	4.40E+02	**2.31E+02**	3.79E+02	1.34E+02
F19	1.36E+01	2.95E+01	1.23E+01	1.64E+04	4.65E+05	3.38E+05	**9.81E+00**	**1.64E+01**	**4.25E+00**
F20	2.15E+01	2.24E+01	8.41E-01	2.18E+01	2.38E+01	**9.32E-01**	**1.89E+01**	**2.19E+01**	1.64E+00
F21	**2.00E+02**	**8.87E+02**	**2.80E+02**	1.13E+03	2.13E+03	8.66E+02	**2.00E+02**	9.44E+02	2.94E+02
F22	5.13E+03	7.23E+03	1.90E+03	5.00E+03	7.32E+03	1.24E+03	**4.89E+03**	**6.59E+03**	**1.13E+03**
F23	**7.48E+03**	1.10E+04	1.95E+03	9.27E+03	**1.06E+04**	**9.23E+02**	7.57E+03	1.10E+04	2.11E+03
F24	3.96E+02	4.31E+02	2.60E+01	**3.21E+02**	**3.56E+02**	**1.73E+01**	3.43E+02	3.86E+02	2.87E+01
F25	4.04E+02	4.53E+02	2.17E+01	**3.57E+02**	**3.75E+02**	**1.19E+01**	3.77E+02	4.10E+02	2.25E+01
F26	4.03E+02	4.71E+02	3.34E+01	**2.06E+02**	**4.30E+02**	7.89E+01	4.10E+02	4.47E+02	**1.80E+01**
F27	1.62E+03	2.07E+03	2.21E+02	1.69E+03	1.88E+03	**1.19E+02**	**1.60E+03**	**1.87E+03**	1.83E+02
F28	**4.00E+02**	1.54E+03	1.83E+03	1.59E+03	4.52E+03	1.87E+03	**4.00E+02**	**1.42E+03**	**1.64E+03**
Win	22	22	19	22	22	18	—	—	—
Lose	5	6	9	6	6	10	—	—	—
Draw	1	0	0	0	0	0	—	—	—

In the table, it should be noted that, the smaller the value corresponding to the algorithm, the better their performance. 'Lose', 'Win', or 'Draw' give the numbers of worse, better, and similar performances compared to the proposed IHBA respectively. If the improved honey badger algorithm is superior to other algorithms in the same test function and corresponding items, one will be added to the column of "win", if it is worse, "lose" plus one; otherwise, add one to "draw". According to Table 2, from the optimal value, IHBA algorithm has 22 better, 1 similar and 5 worse performances than HBA algorithm respectively. from the average value, it has 22 better, 0 similar and 6 worse performances respectively. from the perspective of standard deviation, it has 19 better, 0

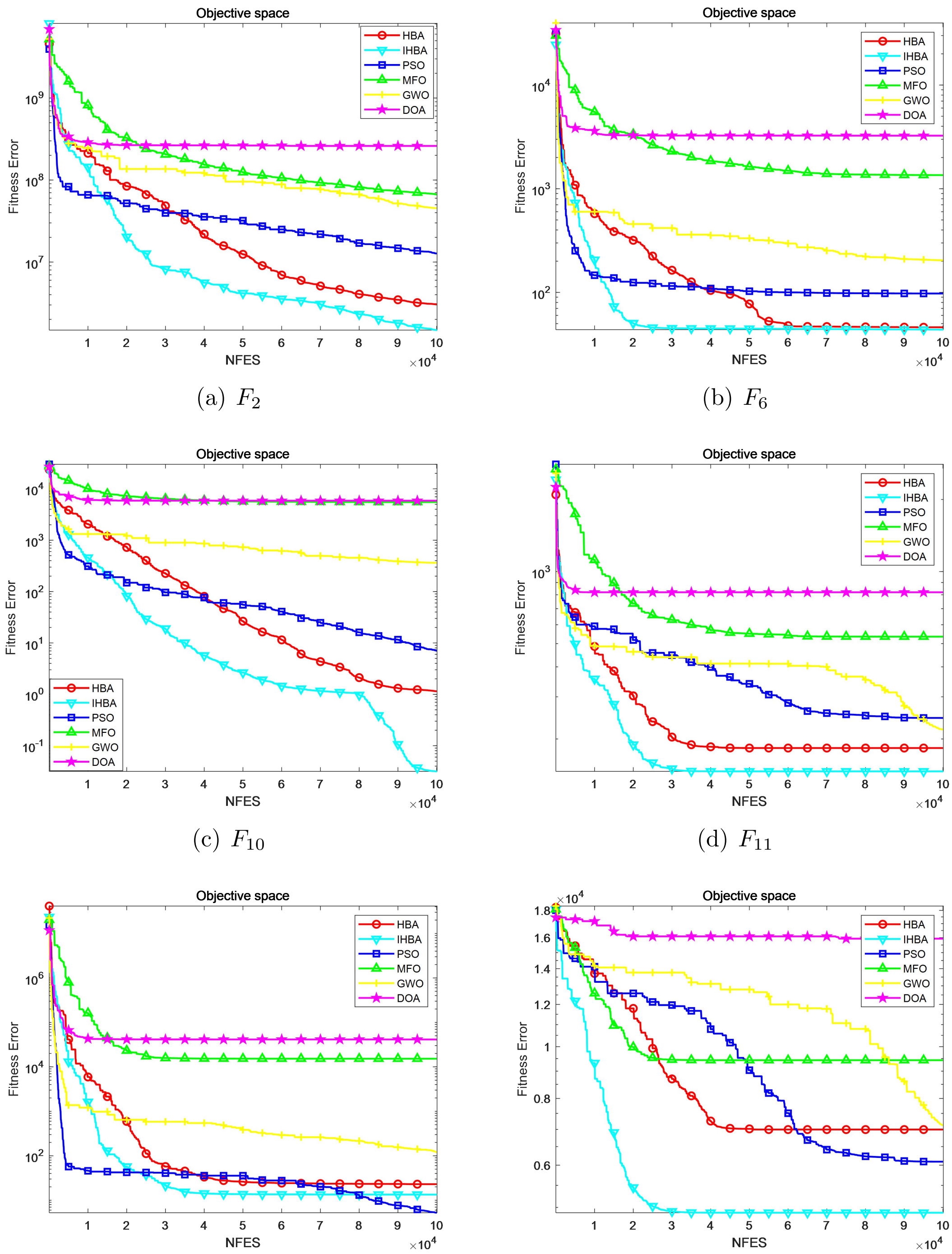
Table 3. Comparison of optimization performance of GWO, DOA, IHBA on 28 classical test functions

50D	GWO			DOA			IHBA		
	BP	AVE	STD	BP	AVE	STD	BP	AVE	STD
F1	1.29E+03	3.28E+03	1.23E+03	3.23E+04	4.54E+04	9.09E+03	**9.10E-13**	**3.25E-12**	**3.10E-12**
F2	1.40E+07	4.18E+07	2.90E+07	1.59E+08	2.89E+08	1.22E+08	**1.01E+06**	**1.78E+06**	**4.90E+05**
F3	1.03E+10	1.85E+10	6.46E+09	5.27E+10	4.63E+12	1.40E+13	**9.42E+07**	**6.61E+08**	**5.65E+08**
F4	4.36E+04	5.32E+04	7.03E+03	4.20E+04	6.29E+04	1.27E+04	**8.12E+02**	**2.47E+03**	**9.80E+02**
F5	5.98E+02	9.21E+02	2.73E+02	3.56E+03	5.85E+03	2.28E+03	**3.59E-09**	**9.81E-09**	**8.29E-09**
F6	1.63E+02	2.38E+02	6.16E+01	3.56E+03	5.85E+03	2.28E+03	**4.35E+01**	**5.62E+01**	**2.21E+01**
F7	**4.20E+01**	**6.22E+01**	1.82E+01	1.42E+02	1.99E+02	5.51E+01	5.45E+01	7.74E+01	**1.38E+01**
F8	**2.11E+01**	2.12E+01	5.10E-02	2.11E+01	2.12E+01	4.06E-02	2.11E+01	**2.12E+01**	**3.93E-02**
F9	**3.85E+01**	**4.04E+01**	**2.53E+00**	5.64E+01	6.41E+01	5.54E+00	4.32E+01	5.06E+01	6.21E+00
F10	4.01E+02	5.40E+02	7.97E+01	2.27E+03	5.13E+03	1.56E+03	**3.33E-02**	**7.88E-02**	**2.75E-02**
F11	1.66E+02	2.20E+02	2.99E+01	6.06E+02	7.73E+02	1.23E+02	**1.18E+02**	**1.86E+02**	**3.44E+01**
F12	1.90E+02	2.46E+02	3.60E+01	6.56E+02	7.69E+02	9.32E+01	**1.71E+02**	**2.31E+02**	**3.65E+01**
F13	3.16E+02	**4.00E+02**	**6.64E+01**	5.67E+02	8.11E+02	1.28E+02	**2.96E+02**	4.33E+02	8.05E+01
F14	5.54E+03	7.17E+03	2.19E+03	1.10E+04	1.31E+04	**1.58E+03**	**3.89E+03**	**6.19E+03**	1.98E+03
F15	6.47E+03	9.67E+03	3.46E+03	1.11E+04	1.41E+04	**1.51E+03**	**6.16E+03**	**8.63E+03**	2.00E+03
F16	3.47E+00	**3.76E+00**	**1.97E-01**	3.32E+00	4.11E+00	5.14E-01	**1.29E+00**	3.15E+00	1.15E+00
F17	2.56E+02	3.52E+02	8.57E+01	7.53E+02	1.13E+03	1.64E+02	**2.01E+02**	**2.92E+02**	**4.51E+01**
F18	4.58E+02	5.64E+02	**5.78E+01**	1.08E+03	1.23E+03	1.02E+02	**2.31E+02**	**3.79E+02**	1.34E+02
F19	3.16E+01	2.94E+02	2.74E+02	1.61E+04	5.21E+04	3.76E+04	**9.81E+00**	**1.64E+01**	**4.25E+00**
F20	1.99E+01	**2.13E+01**	8.05E-01	2.35E+01	2.43E+01	**4.24E-01**	**1.89E+01**	2.19E+01	1.64E+00
F21	1.15E+03	2.28E+03	8.10E+02	3.76E+03	4.06E+03	**1.56E+02**	**2.00E+02**	**9.44E+02**	2.94E+02
F22	5.96E+03	6.95E+03	**6.84E+02**	1.07E+04	1.31E+04	1.60E+03	**4.89E+03**	**6.59E+03**	1.13E+03
F23	**6.25E+03**	8.86E+03	2.78E+03	1.09E+04	1.32E+04	**1.52E+03**	7.57E+03	**1.10E+04**	2.11E+03
F24	**2.80E+02**	**3.09E+02**	1.73E+01	3.84E+02	4.06E+02	**1.54E+01**	3.43E+02	3.86E+02	2.87E+01
F25	**3.30E+02**	3.47E+02	**1.10E+01**	4.03E+02	4.28E+02	**2.29E+01**	3.77E+02	4.10E+02	2.25E+01
F26	3.83E+02	**3.98E+02**	**8.58E+00**	**2.06E+02**	4.21E+02	1.07E+02	4.10E+02	4.47E+02	1.80E+01
F27	**1.13E+03**	**1.40E+03**	1.39E+02	2.03E+03	2.18E+03	**1.10E+02**	1.60E+03	1.87E+03	1.83E+02
F28	7.02E+02	**1.06E+03**	**3.63E+02**	5.87E+03	7.33E+03	7.98E+02	**4.00E+02**	1.42E+03	1.64E+03
Win	20	18	18	27	27	16	—	—	—
Lose	8	10	10	1	1	12	—	—	—
Draw	0	0	0	0	0	0	—	—	—

similar and 9 worse performances respectively. Compared with the MFO algorithm, the IHBA algorithm achieves the best performance of 78.6% in 28 classical test functions.. From the perspective of average value, the IHBA algorithm has won 78.6% of 28 classical test functions. IHBA algorithm lost 21.4% of MFO algorithm in 28 test functions. From the perspective of standard deviation, the IHBA algorithm achieved 64.3% success in 28 classical test functions. IHBA algorithm lost 35.7% of the MFO algorithm in 28 test functions. It can be seen from Table 3 that among the 28 test functions, the number of winners of the IHBA algorithm is much higher than that of the GOA and GWO algorithms.

Figure 2 shows the convergence curves of the proposed algorithms of IHBA, GWO, HBA, PSO, MFO, and DOA for several selected test functions. It could be seen that the proposed IHBA algorithm has faster convergence speed under 28 classical mathematical test functions in general.

4. **Application of IHBA on Electric Vehicle Charge Orderly Planning.** Taking the residential area as an example, the orderly charging of large electric vehicles is realized by using IHBA algorithm, HBA algorithm and PSO algorithm. In order to reflect its significance in practical engineering, performance indicators include user cost satisfaction, user convenience satisfaction, load fluctuation satisfaction, and the efficiency of these three algorithms. According to the distribution of users' working hours and rest hours, the large-scale disorderly charging of electric vehicles will focus on the peak load of the power grid. Therefore, the control center will divide 24 hours a day into 24 cycles and



(a) F_2 (b) F_6

(c) F_{10} (d) F_{11}

(e) F_{19} (f) F_{20}

FIGURE 2. Convergence curves of different algorithms on F2(a), F6(b), F10(c), F11(d), F19(e), F20(f) with 50D.

refresh the charging request data and the real-time power of the distribution network each hour. The optimal charging load curve and initial charging point time of electric vehicle are calculated by using the optimization algorithms. The control center makes an orderly charging arrangement for the cycle based on the proposed optimal solutions.

In this paper, 500 electric vehicles are set for dispatching. The maximum charging power of electric vehicles is 5 kW, and the maximum capacity of batteries is 25 . Taking

24 hours as the dispatching cycle, the maximum number of iterations is 500 and the number of collecting agents is set to 50. In this paper, we should not only consider the relevant benefits of the power grid, but also ensure the benefits of users, and finally set the parameter optimization of Eq. (15) as $\omega_1 = 0.2$, $\omega_1 = 0.4$, $\omega_3 = 0.2$. The following assumptions are made for the charging example of electric vehicle:

1) The electric vehicle consumes 15kw·h for every 100km.
2) Electric vehicles are charged immediately after the last trip and only once a day.
3) Charge the battery to 100% each time.
4) The charging start time and daily driving distance are uncorrelated random variables.
5) It is assumed that all-electric vehicles participate in dispatching.

The basic load of the residential area is shown in Table 4. The TOU price of the residential area is shown in Table 5.

Table 4. Basic load of the residential area

Time	**Load/kW**	**Time**	**Load/kW**	**Time**	**Load/kW**
1:00	1670.4	9:00	2345.2	17:00	2382.8
2:00	1740.6	10:00	2399.2	18:00	2402.3
3:00	1699.8	11:00	2449.6	19:00	2543.1
4:00	1605.1	12:00	2200.3	20:00	2533.3
5:00	1776.6	13:00	2230.7	21:00	2382.8
6:00	1830.4	14:00	2263.8	22:00	2386.9
7:00	1894.2	15:00	2242.4	23:00	1990.5
8:00	2103.4	16:00	2243.4	24:00	1808.4

Table 5. TOU price of residential area

Period	The charging time	Electricity price yuan/ kW·h
Valley period	24,1,2,3,4,5,6,7	0.2
Peak period	9,10,11,19,20,21,22,23	0.59
Flat period	8,12,13,14,15,16,17,18	0.4

The disordered charging mode and ordered charging mode are simulated by Monte Carlo simulation, Figure 3 is obtained.

It can be seen from Figure 3 that the orderly charging model can significantly cut the peak and fill the valley of the load curve under the disordered charging mode. The effect is the best under the optimization of IHBA, and the specific data are shown in Table 6.

Table 6. Comparison of indicators under various algorithms

Algorithm	Peak value/kW	Valley value/kW	Peak valley difference /%	cost/yuan
IHBA	2628	1943	26.07	1197
HBA	2658	1938	27.09	1296
PSO	3015	1692	43.88	1273
Disorderly	3588	1605	55.27	2560

From Table 6, we can clearly see the superiority of the IHBA algorithm, which can not only cut peak and fill the valley, but can also obtain a more economical result. The fitness values of each algorithm are compared in Table 7.

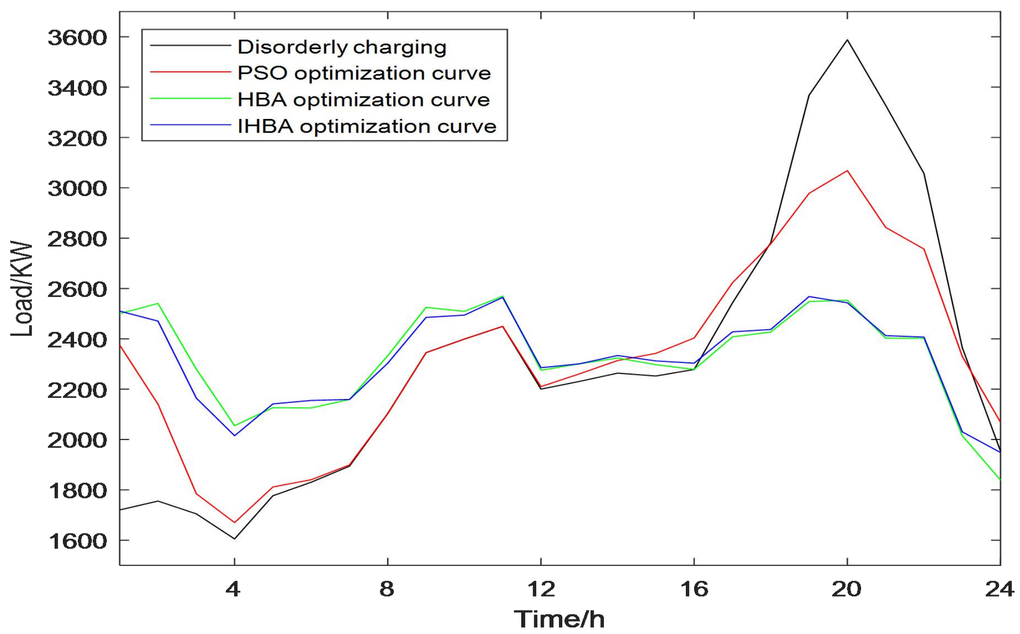


FIGURE 3. Total load curve of orderly charging of electric vehicles.

TABLE 7. Comparison of fitness values of various algorithms

Algorithm	User cost satisfaction Q	User convenience satisfaction B	Load fluctuation satisfaction Z	Objective function value Y
PSO	0.6538	0.3572	0.8792	0.6253
HBA	0.7857	0.2316	0.9817	0.6425
IHBA	0.8517	0.2007	0.9931	0.6478

It can be concluded from Table 7 that the algorithm with the most significant overall satisfaction is the IHBA, followed by HBA, and finally PSO.

5. **Conclusion.** In this paper, an improved honey badger algorithm (IHBA) was proposed for rectifying the original honey badger algorithm's drawbacks such as its slow convergence speed, ease to fall into local extremum, and low-quality solution of a high-dimensional search space. Different approaches were employed to improve the IHBA: the reverse elite learning to generate a uniform initial solution, the spiral update strategy, and a wild dog survival scheme in order to develop the algorithm's ability effectively and avoid falling into local optimization.

Test findings of the IHBA algorithm were compared with the HBA, MFO, GWO, and DOA algorithms for the selected 28 benchmark functions in CEC2013. Compared results indicated that IHBA had certain advantages in solving the optimal solution of the test functions in terms of the algorithm's convergence speed, convergence accuracy, and stability. The applied IHBA algorithm for solving the orderly charging of electric vehicles shows that a large EV charge planning scheme reduces the peak load of the power grid and enhances the strength of the valley.

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