Arabian Journal for Science and Engineering (2021) 46:9399–9411
https://doi.org/10.1007/s13369-020-05308-6

RESEARCH ARTICLE-ELECTRICAL ENGINEERING

Hybrid MHHO-DE Algorithm for Economic Emission Dispatch with Valve-Point Effect

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Received: 20 August 2020 / Accepted: 30 December 2020 / Published online: 15 January 2021

Abstract
Economic emission dispatch with valve-point effect in power systems is a complex multimodal, nonconvex and constrained multi-objective optimization problem. To solve this problem, a hybrid multi-objective algorithm with effective constraint handling method based on Harris hawks optimization and differential evolution is proposed: (1) the concept of Pareto domination is integrated into Harris hawks optimization to deal with economic emission dispatch problem with two conflicting objectives; (2) the optimization mechanism of Harris hawks optimization is modified to enhance its optimization capabilities; (3) a non-dominated sorting method based on new crowding distance, which can obtain Pareto optimal front with excellent uniformity, is used to maintain the external archive and to select the guiders; (4) aiming at the constraints of economic emission dispatch problem, a feasible solution dominated constraint processing method is adopted to obtain feasible solutions; (5) moreover, to enhance the convergence performance of the algorithm, a differential evolution is used to evolve the individuals in the archive. Experimental results on the IEEE 30-bus 6-unit test system demonstrate that the quality of the solutions obtained by the suggested approach is better than that of several existing algorithms.

Keywords Hybrid multi-objective algorithm · Economic emission dispatch · Valve-point effect · Constraints handling · Multi-objective optimization

1 Introduction

Most thermal power plants in the world use coal as their main fuel to generate electricity. How to reasonably allocate the active power outputs of the thermal generator set to minimize the fuel cost, while satisfying various equality and inequality constraints, that is, economic dispatch (ED), has been an important research topic [1, 2]. However, with the enhancement of people's awareness of environmental protection, reducing the emission of pollutants has become another important objective of thermal power plants. Economic emission dispatch (EED) that considers both fuel cost objective and pollution emission objective has gradually attracted widespread attention [3].

There are two aspects to be considered when solving EED problems. One is to establish a reasonable model of the EED problem, and the other is to find a suitable method to solve the established model.

In terms of the EED problem model, Dhanalakshmi et al. [4] used a quadratic function to establish the function model of the fuel cost. However, the influence of the valve point effect is not considered in the fuel cost function. Zhao et al. [3] and Zhang et al. [5] established the fuel cost function model with valve point effect, but the valve point effect is ignored in the simulation experiments of the IEEE 30-node 6-unit test system.

In terms of solving the EED problem model, many techniques have been suggested at present. The numerical optimization methods were initially developed. Chen and Chen [6] presented an alternative Jacobian matrix-based direct Newton–Raphson method for solving the EED problem with line flow constraints. Farag et al. [7] proposed a linear programming optimization algorithm by adding the environmental constraints in the economic dispatch problem to obtain an optimal dispatch scheme. El-Keib et al. [8] suggested a Lagrangian-relaxation-based method to deal with environmentally constrained economic dispatch. However, these conventional numerical optimization methods are

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sensitive to their initial solutions and easy to fall into local optimum, they are difficult to obtain satisfactory results [9].

Recently, heuristic optimization methods have been more and more used to solve EED problems, which can make up for the shortcomings of conventional numerical optimization methods [10]. The methods of solving the multi-objective EED problem by the heuristic algorithms are mainly divided into two categories: The methods based on single objective optimization algorithms and the methods based on multi-objective optimization algorithms.

The first solution method solves EED problems by a single-objective optimization algorithm, which is not efficient and has some shortcomings. Srivastava and Das [11] adopted the price penalty factor to convert the emission of pollution gas into cost, then solved the EED problem by a new Kho–Kho optimization algorithm, which failed to give the trade-off relations between objectives and failed to form the Pareto optimal front. Singh et al. [12] utilized the linear weighting method to transform the multi-objective EED problem into a single objective problem, then introduced an adaptive predator–prey optimization algorithm to find the Pareto optimal front of the EED problem. However, this method requires multiple runs of a single-objective algorithm to get the Pareto optimal front, and it is difficult to select appropriate weight coefficients.

The second method uses the multi-objective optimization algorithm to optimize the two objectives of the EED problem simultaneously, and a set of Pareto optimal solutions can be obtained in one operation, which is very efficient and overcomes the shortcomings of the first solution method. Modiri-Delshad and Rahim [13] applied the multi-objective backtracking search algorithm with one control parameter to optimize the EED problem as a multi-objective problem. Liang et al. [14] developed a multi-objective hybrid bat algorithm based on the non-dominated sorting method to deal with the EED problem with power flow constraints. Some other multi-objective optimization algorithms such as multi-objective ant colony optimization (MMACO_R) [15], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [16] and multi-objective bacterial algorithm (MBFO-cl) [17] are also used to solve the EED problems. Although the above algorithms can achieve certain results in the EED problem, the evaluation of the quality of the solutions obtained by the multi-objective algorithms and the consideration of the distribution uniformity and convergence of Pareto optimal front are slightly inadequate. In addition, for the EED problem, finding a better multi-objective optimization algorithm to further improve the scheduling performance of the EED problem will be a continuous hot spot in the field of power system optimization scheduling.

This paper presents a hybrid multi-objective optimization approach (MHHO-DE) based on Harris hawks optimization (HHO) and differential evolution (DE) to solve the highly constrained EED problem considering the valve point effect. The algorithm modifies and extends HHO appropriately, and combines with the DE algorithm to achieve better performance. A feasible solution dominated constraint processing method is integrated into the algorithm to deal with the constraints of the EED problem. In addition, a modified crowding distance is proposed to improve the uniformity of Pareto optimal front distribution. The simulation experiments are carried out on the IEEE 30-bus 6-unit test system and compared with several existing algorithms. Three different performance metrics including the Spacing Metric (SP), the Normalized Distance (ND), and the Two Set Coverage (SC) are used to evaluate the quality of the solutions obtained by the multi-objective algorithms. The effectiveness of the proposed algorithm for solving the EED problem is proved by comparison with several other algorithms.

The rest of this paper is organized as follows: Sect. 2 describes the EED problem model with valve-point effect and optimization objectives. Section 3 briefly reviews the principles of Harris hawks optimization. Section 4 introduces the proposed MHHO-DE. Section 5 analyzes the performance of the MHHO-DE. Section 6 is the conclusion of this paper.

2 Problem Formulation of the EED and Optimization Objectives

The economic emission dispatch (EED) problem requires that the fuel cost and the pollution emission are minimized simultaneously on the premise of satisfying the constraints. In this section, the mathematical model of the EED problem is first established. Then optimization objectives and objective functions of the EED problem are described. Finally, various constraints are taken into consideration.

2.1 Mathematical Model

The EED problem is a constrained multi-objective optimization problem with two competing objectives and several constraints. Its mathematical model can be described as: find a vector $x^* = \left[P_1^*, P_2^*, \ldots, P_N^*\right]$ such that

$$\begin{cases} f(x^*) = \min\left\{f_1(x), f_2(x)\right\} \\ \text{s.t.} \\ \sum_{i=1}^{N} P_i - P_D - P_L = 0 \\ P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1, 2, \ldots, N \end{cases} \tag{1}$$

where $x = \left[P_1, P_2, \ldots, P_N\right]$ (N is the number of the generators in the power system), and P_i is the real power output of the ith generator. $f_1(x)$ and $f_2(x)$ are two objective functions related to x. $\sum_{i=1}^{N} P_i - P_\mathrm{D} - P_\mathrm{L} = 0$ is the power balance constraint [18], where P_D is the power load demand and P_L is the total power loss. P_i^{min} and P_i^{max} are the minimum and maximum bounds of the real output power of the ith generator.

2.2 Optimization Objectives

The EED problem is a bi-objective optimization problem, and its two objectives are in conflict with each other. The dominance relationship needs to be used to judge the relationship between two feasible solutions. Here, feasible solutions refer to solutions that satisfy all the constraints of the EED problem. Suppose that x_1^* and x_2^* are two feasible solutions. For the minimization problem, x_1^* is said to dominate x_2^* and the symbolic representation is $f\left(x_1^*\right) \prec f\left(x_2^*\right)$, which meets one of the following conditions:

$$\begin{cases} f_1\left(x_1^*\right) \le f_1\left(x_2^*\right) \quad \text{and} \quad f_2\left(x_1^*\right) < f_2\left(x_2^*\right) \\ \text{or} \\ f_1\left(x_1^*\right) < f_1\left(x_2^*\right) \quad \text{and} \quad f_2\left(x_1^*\right) \le f_2\left(x_2^*\right) \end{cases} \tag{2}$$

In the feasible domain, if no other solution dominates x_1^*, x_1^* is called the Pareto optimal solution of the problem, also known as the non-dominated solution. All Pareto optimal solutions constitute the optimal solution set. The surface formed by the objective function corresponding to the optimal solution set is called the Pareto optimal front. Solving the EED problem is to find a set of Pareto optimal solutions and make their corresponding objective function values widely and evenly distributed on Pareto optimal front, and the obtained Pareto optimal front has good convergence.

2.3 Objective Functions

2.3.1 Fuel Cost Function

Typically, the fuel cost of each generator unit is represented by a quadratic function. The total fuel cost $f_1(x)$ (dollars per hour) is expressed as [19]:

$$f_1(x) = \sum_{i=1}^{N} \left(a_i + b_i P_i + c_i P_i^2\right) \tag{3}$$

where a_i, b_i and c_i are fuel cost coefficients of the ith generator.

However, in the actual power generation process, when the steam turbine is suddenly turned on, a ripple curve will be added to the generator's fuel cost curve to produce a valve point effect, which is shown in Fig. 1 [20]. The fuel cost of a generator unit is a unimodal function when the valve point effect is ignored. Adding the valve point effect into the fuel cost function can make the model more realistic, but the fuel cost function becomes multimodal and nonconvex. The total fuel cost with valve point effect can be expressed as [21]:

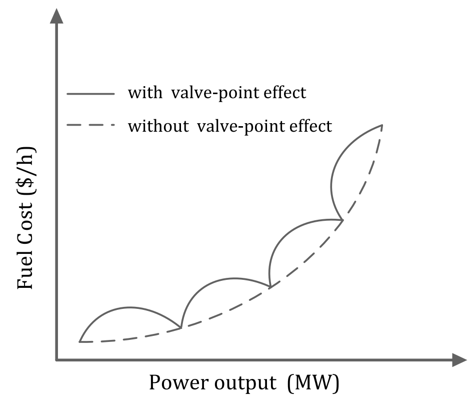

Fig. 1 Illustration of the valve point effect

$$f_1(x) = \sum_{i=1}^{N} \left(a_i + b_i P_i + c_i P_i^2\right) + \left| e_i \sin\left(g_i\left(P_i^{min} - P_i\right)\right)\right| \tag{4}$$

Here e_i and g_i are the valve-point effect coefficients of the ith generator.

2.3.2 Pollution Emission Function

The total pollution emission $f_2(x)$ (tons per hour) of thermal power units includes carbon oxide, nitrogen oxide, etc., which can be expressed as the sum of quadratic function and exponential function:

$$f_2(x) = \sum_{i=1}^{N} \left[10^{-2}\left(\alpha_i + \beta_i P_i + \gamma_i P_i^2\right) + \zeta_i \exp\left(\lambda_i P_i\right)\right] \tag{5}$$

where α_i, β_i, γ_i, ζ_i and $_i$ are the emission coefficients of the ith generator.

2.4 Constraints

In this paper, an equality constraint of power balance and several inequality constraints of power output limits are considered.

2.4.1 Equality Constraint

The total real power must include the power load demand P_D and the total power lost P_L in the transmission network, which can be:

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{6}$$

Here, P_L is usually expressed by Kron's loss formula [22] as:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{7}$$

where B_{ij}, B_{oi} and B_{00} are the transmission line power loss coefficients.

2.4.2 Inequality Constraints

The generation capacity of each generator is limited by its minimum and maximum bounds [23] during operation.

$$P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1, 2, \ldots, N \tag{8}$$

3 Standard Harris Hawks Optimization

The standard Harris hawks optimization is a heuristic optimization technique based on the hunting behavior of Harris hawks proposed by Heidari et al. [24], which is used to solve the single objective unconstrained optimization problems. In the Harris hawks optimization, an eagle swarm is composed of many hawks, each eagle represents a possible solution, and the rabbit represents the optimal solution. Each eagle moves in the multi-dimensional search space, and the eagle group adopts different arrest strategies according to the energy change of the rabbit to achieve the purpose of catching the rabbit. The process of catching a rabbit by the hawks consists of the exploration phase and exploitation phase.

3.1 Exploration Phase

At this stage, the Harris hawks randomly inhabit some locations and wait for a rabbit according to two strategies expressed by the following equation:

$$X(t+1) = \begin{cases} X_{\text{rand}}(t) - r_1 \left| X_{\text{rand}}(t) - 2r_2 X(t) \right| & q \ge 0.5 \\ X_{\text{rabbit}}(t) - X_m(t) - r_3 \left(\text{LB} + r_4(\text{UB} - \text{LB}) \right) & q < 0.5 \end{cases} \tag{9}$$

where $X(t)$ is the location of hawks in the current iteration t $X(t+1)$ is the location of hawks in the next iteration, $X_{\text{rabbit}}(t)$ is the location of rabbit, $X_m(t)$ is the average location of population in the current iteration t, X_{rand}. is a randomly selected hawk from the current hawks, UB and LB is the maximum and minimum bound of variables, r_1, r_2, r_3, r_4 and q are real numbers between 0 and 1. $X_m(t)$ is attained using the following equation:

$$X_m(t) = \frac{1}{n} \sum_{i=1}^{n} X_i(t) \tag{10}$$

where $X_i(t)$ is the position of i-th hawk in current iteration t and n indicates the number of all hawk the population.

3.2 Transition from Exploration to Exploitation

The HHO transforms between exploration and exploitation through the energy change of the rabbit. The energy E of the rabbit can be modeled as:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{11}$$

where T denotes the maximum number of iterations, and E_0 indicates the initial energy of the rabbit. E_0 changes randomly within $(-1, 1)$ at each iteration. Exploration occurs when $|E| \ge 1$, while exploitation occurs according to Sect. 3.3 when $|E| < 1$.

3.3 Exploitation Phase

r, which represents the rabbit escape's chance, is a random number between 0 and 1. In this phase, the energy of the rabbit is less than 1. According to the chance of rabbit escape and the change of energy, there are four possible capture strategies.

3.3.1 Soft Besiege

When $r \ge 0.5$ and $|E| \ge 0.5$, update the positions of the hawks according to the following equation:

$$X(t+1) = X_{\text{rabbit}}(t) - X(t) - E\left| J X_{\text{rabbit}}(t) - X(t) \right| \tag{12}$$

where r_5 is a random number between (0, 1) and $J = 2(1 - r_5)$.

3.3.2 Hard Besiege

When $r \ge 0.5$ and $|E| < 0.5$, the current positions of the hawks are modeled as:

$$X(t+1) = X_{\text{rabbit}}(t) - E\left| X_{\text{rabbit}}(t) - X(t) \right| \tag{13}$$

3.3.3 Soft Besiege with Surprise Pounce

When $r < 0.5$ and $|E| \ge 0.5$, the positions of the hawks is:

$$X(t+1) = \begin{cases} Y \text{ if } & F(Y) < F(X(t)) \\ Z \text{ if } & F(Z) < F(X(t)) \end{cases} \tag{14}$$

where $F(\cdot)$ represents the fitness function of the single-objective unconstrained optimization problem to be solved. Y and Z can be obtained from the following equations:

$$Y = X_{\text{rabbit}}(t) - E\left|JX_{\text{rabbit}}(t) - X(t)\right| \tag{15}$$

$$Z = Y + S \times \mathrm{LF}(D), \quad \mathrm{LF}(D) = 0.01 \times \frac{u(D) \times \rho}{|v(D)|^{\frac{1}{\beta}}},$$
$$\rho = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2 \wedge \left(\frac{\beta-1}{2}\right)} \right)^{\frac{1}{\beta}} \tag{16}$$

where D is the dimension of the problem to be solved, S is a random vector by $1 \times D$, u and v are vectors composed of random numbers based on the normal distribution $N(0, 1)$, β is 1.5, Γ is a Gamma function.

3.3.4 Hard Besiege with Surprise Pounce

When $r < 0.5$ and $|E| < 0.5$, this strategy is performed according to the following equation:

$$X(t+1) = \begin{cases} Y & \text{if} \quad F(Y) < F(X(t)) \\ Z & \text{if} \quad F(Z) < F(X(t)) \end{cases}. \tag{17}$$

where Y and Z can be obtained using the following new rules:

$$Y = X_{\text{rabbit}}(t) - E\left|JX_{\text{rabbit}}(t) - X_m(t)\right| \tag{18}$$

$$Z = Y + S \times \mathrm{LF}(D) \tag{19}$$

where $X_m(t)$ can be obtained by Eq. (10).

4 Hybrid MHHO-DE with Constraints Handling Method

This section introduces the proposed MHHO-DE with constraint handling method. The main idea of MHHO-DE is to construct a powerful multi-objective optimizer by combining several approaches like external archive based on new crowding distance, modified HHO, DE, constraint handling method and guider selection strategy for solving the constrained EED problem with valve-point effect. The steps of the proposed algorithm MHHO-DE to solve the EED problem are given in Sect. 4.6.

4.1 External archive Based on New Crowding Distance

Single-objective algorithms have only one optimal solution, while multi-objective algorithms usually have multiple optimal solutions (non-dominated solutions). Most multi-objective optimization algorithms use a fixed-size external archive to store the non-dominated solutions obtained in the iterative process. When the number of non-dominated solutions exceeds the archive size, a certain diversity preserving strategy is used to prune the external archive. In this paper, a non-dominated sorting method based on crowding distance [25] is adopted to prune the external archive to maintain a fixed number of non-dominated solutions. In [25], the individuals in the merged group are sorted based on their dominance relationship and crowding distances. All non-dominated individuals are marked as rank 1, those solutions dominated by rank 1 are marked as rank 2, and so on. Then, those individuals in different ranks are classified based on ranks from small to large. Those individuals in the same rank are arranged in descending order based on their crowding distance. And in [25], the algorithm deletes all individuals that exceed the archive size at once according to the rank and the crowding distance. Taking Fig. 2a as an example, the crowding distance of individual C except the boundary point is calculated as

$$\mathrm{CD}(C) = \sum_{k=1}^{m} \left|f_k(A) - f_k(B)\right| \tag{20}$$

where m is the number of optimization objectives, $f_k(A)$ and $f_k(B)$ are the function values of individuals A and B on the kth objective, respectively.

However, the above formula is insufficient to evaluate the uniformity of individual C. As can be seen from Fig. 2b, when there is only one individual between individual A and individual B, it is obvious that individual C is more uniform than individual C', although they have the same crowding distance. To obtain the excellent even Pareto optimal front, this paper presents a new formula for calculating the crowding distance. The new crowding distance of individual C can be defined as:

$$\mathrm{CD}(C) = \sum_{k=1}^{m} \left|f_k(A) - f_k(B)\right| + \frac{\min(|\mathrm{AC}|, |\mathrm{BC}|)}{|\mathrm{AB}|} \times \sum_{k=1}^{m} \left|f_k(A) - f_k(B)\right| \tag{21}$$

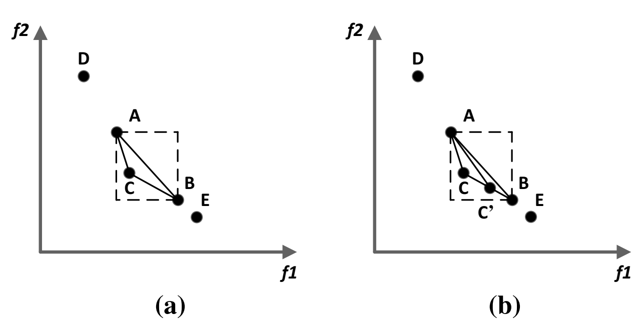

Fig. 2 Crowding distance of individual C

where |AC| is the Euclidean distance between individual A and individual C.

In addition, the one-time deletion strategy in [25] may cause large gaps on the Pareto optimal front. To prevent the occurrence of gaps of the Pareto optimal front, a dynamic deletion strategy [26] is introduced: each time a solution with the smallest crowding distance and the largest rank is deleted, then the crowding distances and ranks of the remaining non-dominated solutions are recalculated, and thus repeated until the archive size is reached.

4.2 Modified Harris Hawks Optimization

In this subsection, some modifications have been made to HHO to improve its exploratory performance and exploitative performance. In addition, the comparison of the function values in the standard HHO is changed to their dominance relationship to adapt to the multi-objective optimization problem.

4.2.1 Improved Exploration Phase

The standard HHO algorithm produces a new solution $X(t+1)$ in the exploration phase with Eq. (9) in which the range of the new solution is limited. Replacing Eq. (9) with an improved exploration formula inspired by Bare Bones particle swarms [27] is proposed as follows:

$$X(t+1) = \begin{cases} N\left(X_{\text{rand}}(t), \left|X_{\text{rand}}(t) - 2r_2X(t)\right|^2\right) & q \geq 0.5 \\ N\left(X_{\text{rabbit}}(t) - X_m(t), \left(\text{LB} + r_4(\text{UB} - \text{LB})\right)^2\right) & q < 0.5 \end{cases} \tag{22}$$

where $N(a, b)$ is a Gaussian sampling with expectation a and variance b.

4.2.2 Improved Transition from Exploration to Exploitation

In Eq. (11) of the standard HHO, the rabbit energy E is a linearly decreasing function, which can control HHO from exploration to exploitation but is not conducive to exploitation. To aid local exploitation, a modified rabbit energy E_1 used to replace E is expressed as:

$$E_1 = 2E_0 \exp\left[-\left(\frac{2.4t}{T}\right)^2\right] \tag{23}$$

where E_1 simulates the escape energy of the rabbit, and it changes randomly between the interval $(-2, 2)$ at each iteration. When E_1 decreases from 0 to -2, it means that the rabbit's escape strength is weakened exponentially, and when E_1 increases from 0 to 2, the rabbit's escape strength increases exponentially. E_1 shows a decreasing trend as the iteration progresses, and its changes are shown in Fig. 3.

4.2.3 Improved Exploitation Phase

The improved exploitation phase is: (1) The switch between different exploitation behaviors is based on E_1 instead of E; (2) E in exploitation equations of the standard HHO is replaced by G.

E used in Eqs. (12), (13), (15) and (18) is a scalar, which makes each element of the rabbit's position $X_{\text{rabbit}}(t)$ change at the same step size. For the improved exploitation phase, a multi-dimensional space variable G which makes each element of the rabbit's position change at different step size is used to replace E and used for the location update of the Harris hawks as well:

$$G = 2\left(2R_1 - 1\right) \exp\left[-\left(\frac{2.4t}{T}\right)^2\right] \tag{24}$$

where R_1 is a D dimension random vector, in which each dimension is a random number inside (0,1).

In addition, the function value comparison in the standard HHO is changed to the comparison of the dominance relationship to adapt to the multi-objective optimization problem. Hence, Eqs. (14) and (17) are changed as:

$$X(t+1) = \begin{cases} Y & \text{if} \quad F(Y) \prec F(X(t)) \\ Z & \text{if} \quad F(Z) \prec F(X(t)) \end{cases} \tag{25}$$

4.3 Differential Evolution

Differential evolution [28] has good convergence performance. In this subsection, differential evolution is adopted to evolve the members in the external archive to enhance the convergence performance of the proposed algorithm. For each member Ar_i in external archive, the jth variable of a new solution newAr_i is:

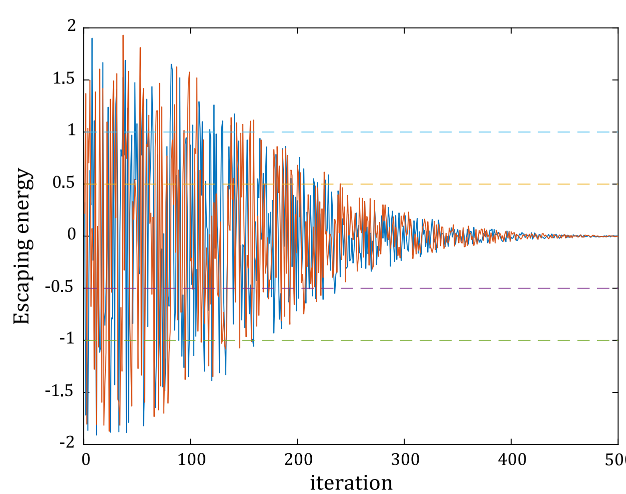

Fig. 3 Behavior of the energy E_1 during 500 iterations and two runs

$$\text{newAr}_i^j = \begin{cases} \text{Ar}_{s1}^j + F \cdot \left(\text{Ar}_{s2}^j - x_{s3}^j\right) & \text{if} \quad \text{rand} \le \text{CR} \quad \text{or} \quad j = k \\ \text{Ar}_i^j & \text{otherwise} \end{cases}. \tag{26}$$

where Ar_{s1}, Ar_{s2} and Ar_{s3} are three members from external archive and the indexes $s_1 \ne s_2 \ne s_3 \ne i$. $\text{rand} \in (0, 1)$ is a real random number. $k \in \{1, 2, \ldots, D\}$ is a random integer. $F \in [0, 2]$ and $\text{CR} \in (0, 1)$ are two control parameters.

4.4 Constraints Handling

Inequality constraints from Eq. (8) are easy to deal with: (1) each generator output power is set within t limited range during initialization; (2) during the iteration process, any value beyond the boundary will be re-limited within the boundary range.

Equality constraint from Eq. (6) is not easy to deal with directly. Thus, equality constraint is usually transformed into inequality constraint by a small threshold δ, which can be expressed as:

$$\sum_{i=1}^{N} P_i - P_\text{D} - P_\text{L} = h = 0 \Rightarrow |h(x)| - \delta \le 0 \tag{27}$$

where δ is the tolerance parameter of the equality constraint.

After the above conversion, any solution that satisfies inequalities (8) and (27) is called a feasible solution, and vice versa is an infeasible solution. The constraint violation of an infeasible solution is:

$$V(x) = \max(|h(x)| - \delta, 0) \tag{28}$$

In order to acquire feasible solutions, a feasible solution dominated constraint processing technology [25] is introduced to handle the infeasible solutions.

In [25], a solution x_a is said to constraint dominate (superior to) a solution x_b, if any of the following rules is met.

(1) x_a is a feasible solution and x_b is an infeasible solution;
(2) When x_a and x_b are both feasible solutions, x_a dominates x_b;
(3) x_a and x_b are both infeasible solutions, but x_a has a smaller overall constraint violation.

4.5 Guider Selection Strategy

The single objective Harris hawk algorithm guides the population to update through the absolute optimal value (rabbit) in the iterative process. However, there is no absolute optimal value for the multi-objective Harris hawk algorithm, so it is necessary to select an appropriate individual from the archive as the guider (rabbit) to guide the hawk swarm to update the positions. In this paper, the ranks, crowding distances, and constraint violations of the individuals in the external archive are calculated firstly. Then, the individuals are assigned a serial number value, the larger serial number value is assigned to the individual with the smaller rank value, the larger crowding distance and the smaller constraint violation value. Finally, the roulette rule is adopted to select an individual as the leader from the archive.

4.6 Solution Procedure of the Proposed MHHO-DE Algorithm for the EED Problem

Based on the above operators, the procedure of the proposed algorithm to solve the bi-objective EED problem is described by the following steps:

Step 1: Parameter setting

(1.1) Specify the cost coefficients, valve point effect coefficients, emission coefficients, loss coefficients and output power limits of each thermal power generator, and the total power load demand of the system.
(1.2) Set parameters of the MHHO-DE algorithm such as population size NP, archive size NA, the scaling factor F and crossover probability CR.
(1.3) Specify maximum iteration number T.

Step 2: Initialization

(2.1) Initialize the modified Harris hawk population $\text{POP}_i (i = 1, 2, \ldots, \text{NP})$ and external archive $\text{Ar}E_i (i = 1, 2, \ldots, \text{NA})$ considering variable limits. The unknown decision variables of the described EED problem are the real power outputs of all the generators. These decision variables constitute an individual of the modified Harris hawk population. The initial modified Harris hawk population POP is:

$$\text{POP} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{i-1} \\ x_i \\ x_{i+1} \\ \vdots \\ x_\text{NP} \end{bmatrix} = \begin{bmatrix} P_1^1 & P_2^1 & \cdots & P_N^1 \\ P_1^2 & P_2^2 & \cdots & P_N^2 \\ \vdots & \vdots & \vdots & \vdots \\ P_1^{i-1} & P_2^{i-1} & \cdots & P_N^{i-1} \\ P_1^i & P_2^i & \cdots & P_N^i \\ P_1^{i+1} & P_2^{i+1} & \cdots & P_N^{i+1} \\ \vdots & \vdots & \vdots & \vdots \\ P_1^\text{NP} & P_2^\text{NP} & \cdots & P_N^\text{NP} \end{bmatrix}_{NP \times N} \tag{29}$$

where $x_i = \left[P_1^i, P_2^i, \ldots, P_j^i, \ldots, P_N^i\right]$ is the ith individual of MHHO-DE population. The jth dimensional variable of individual i is generated according to the upper limit $P_j^{i,\max}$ and lower limit $P_j^{i,\min}$ of the generator j:

$$P_j^i = P_j^{i,\min} + \text{rand1} \times \left(P_j^{i,\max} - P_j^{i,\min} \right) \quad (30)$$

where rand1 is a uniform number in the range (0,1).

The generation method of the initial population in the external archive ArE is the same as the Harris hawk population POP.

(2.2) Evaluate the individuals in the initial external archive ArE. Set $fV^i = \left(f_1\left(x^i\right), f_2\left(x^i\right), V\left(x^i\right)\right)$ corresponding to the cost objective function (Eq. (4)), the emission objective function (Eq. (5)) and the constraint violation function Eq. (28).

(2.3) Set iteration counter, $t = 1$.

Step 3: Update

(3.1) The update of Harris hawk population

(3.1.1) 3.1.1) Select a guider based on Sect. 4.5 for the modified Harris hawk population.

(3.1.2) Update the Harris hawk population according to Sect. 4.2.

(3.1.3) Repair
If a certain dimension element of an individual in the population exceeds the boundary, its value is set as the boundary.

(3.1.4) Evaluate the individuals of the new Harris hawk swarm newPOP using the objective functions [i.e. Eqs. (4) and (5)] and constraint violation function [i.e. Eq. (28)]. The evaluation vector of the individual i is $fV^i = \left(f_1\left(x^i\right), f_2\left(x^i\right), V\left(x^i\right)\right)$.

(3.2) The evolution of external archive

(3.2.1) Generate a new population newAr by the DE algorithm (Sect. 4.3) from the external archive.

(3.2.2) Repair
If a certain dimension element of an individual in the new population newAr is out of its boundary, its value is set as the boundary.

(3.2.3) Evaluate the individuals of new population newAr using the objective functions [i.e. Eqs. (4) and (5)] and constraint violation function [i.e. Eq. (28)]. The evaluation vector of the individual i is $fV^i = \left(f_1\left(x^i\right), f_2\left(x^i\right), V\left(x^i\right)\right)$.

Step 4: Update of members in external archive

(4.1) Combine the new Harris hawk population newPOP, the new population newAr and the old external archive.

(4.2) Maintain the external archive based on Sects. 4.1 and 4.4

The combined individuals are sorted according to their ranks, crowding distances and constraint violations. Those individuals with smaller rank values, larger crowding distances, and smaller constraint violations are kept in the fixed-size external archive.

Step 5: Stopping condition
If the maximum iteration number T is reached, Stop. Else, $t = t+1$, go to Step 3.

Step 6: Output
Output the final members in the external archive.

Figure 4 is the flowchart about the steps of the MHHO-DE algorithm for the EED problem.

5 Simulation Results and Analysis

In this section, the standard IEEE 30-bus 6-unit grid is used as the test system in our work, and the system's single-line diagram can be found in [29]. The system load demand is 283.4 MW. The generators' parameters including fuel cost coefficients [3], emission coefficients [3], valve point effect coefficients [30] and generation capacity limits are listed in Table 1. The B-coefficients [3] (the standard unit value under the system's reference capacity of 100MVA) of Eq. (7) are:

$$B = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}$$

$$B_0 = [-0.0107\ 0.0060\ -0.0017\ 0.0009\ 0.0002\ 0.0030]$$

$$B_{00} = 9.8573 \times 10^{-4}$$

In addition, to verify the performance of the proposed MHHO-DE algorithm, three well-known multi-objective algorithms including multi-objective differential evolution (MODE) [31], non-dominated sorting genetic algorithm II (NSGA-II) [25] and non-dominated Sorting Particle Swarm Optimizer (NSPSO) [32] are used as comparison algorithms. The constraint processing method introduced in this paper is embedded in the three algorithms. The parameter settings of the four algorithms including MHHO-DE are listed in Table 2.

The experiments were carried out in two steps. First, the four algorithms were run one time to acquire extreme

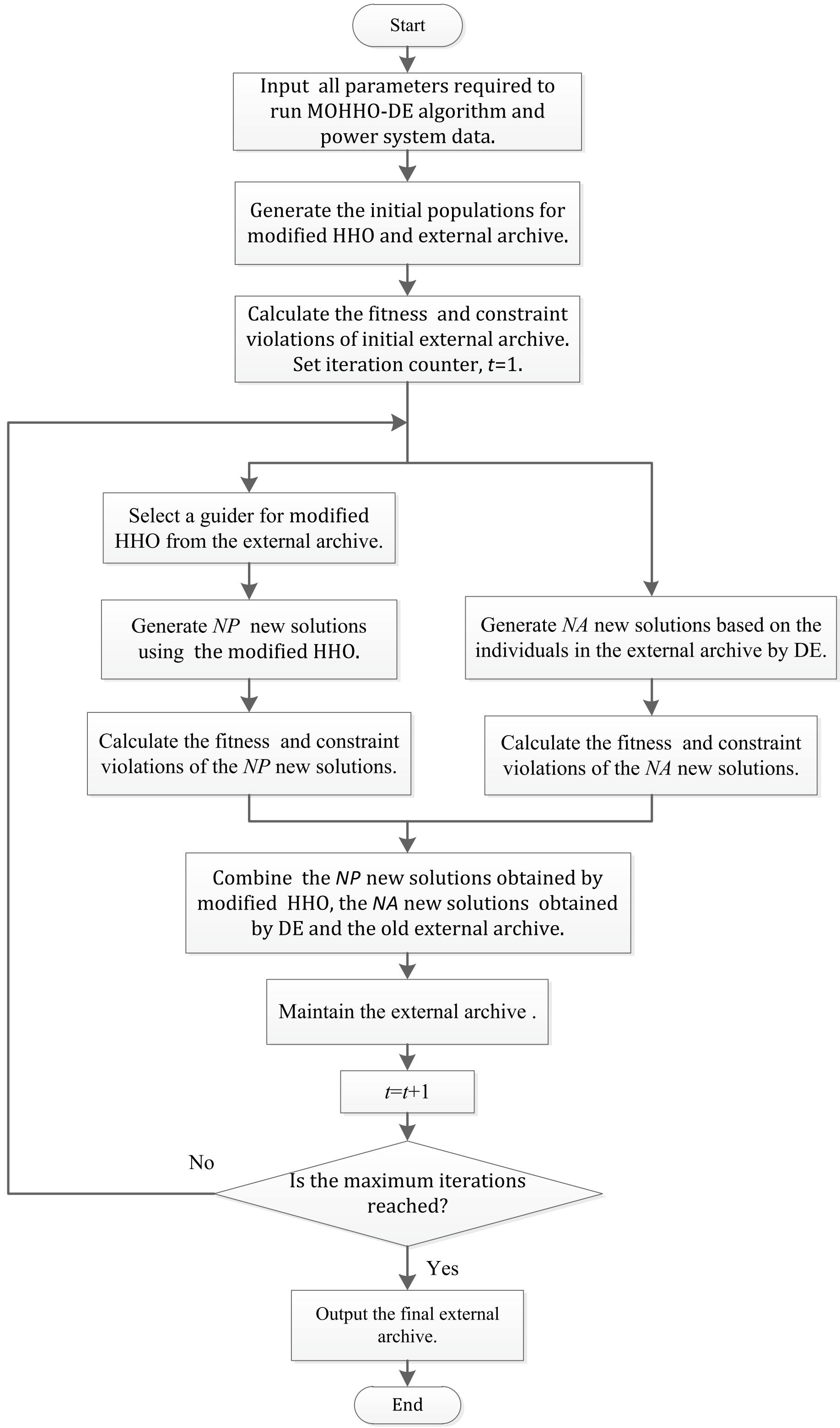

Fig. 4 The flowchart of the proposed MHHO-DE algorithm

solutions related to the best cost and the best emission. Then, the four algorithms were run 30 times to obtain results related to the performance of the multi-objective algorithms.

5.1 Extreme Solutions

In this experiment, all algorithms were run once, and the Pareto optimal fronts are shown in Fig. 5. The best cost

Table 1 Generators' parameters in the IEEE 30-bus 6-generator test system

Generator	a	b	c	e	g	P^{min}
P_1	10	2.00	0.0100	18	0.037	5
P_2	10	1.50	0.0120	16	0.038	5
P_3	20	1.80	0.0040	14	0.04	5
P_4	10	1.00	0.0060	14	0.045	5
P_5	20	1.80	0.0040	13	0.042	5
P_6	10	1.50	0.0100	13.5	0.041	5
Generator	α	β	γ	ζ	λ	P^{max}
P_1	4.091	-5.554×10^{-2}	6.490×10^{-4}	2.0×10^{-4}	2.857×10^{-2}	150
P_2	2.543	-6.047×10^{-2}	5.638×10^{-4}	5.0×10^{-4}	3.333×10^{-2}	150
P_3	4.258	-5.094×10^{-2}	4.586×10^{-4}	1.0×10^{-6}	8.000×10^{-2}	150
P_4	5.326	-3.550×10^{-2}	3.380×10^{-4}	2.0×10^{-3}	2.000×10^{-2}	150
P_5	4.258	-5.094×10^{-2}	4.586×10^{-4}	1.0×10^{-6}	8.000×10^{-2}	150
P_6	6.131	-5.555×10^{-2}	5.151×10^{-4}	1.0×10^{-5}	6.667×10^{-2}	150

solutions and the best emission solutions are listed in Tables 3 and 4, respectively, and the best results are shown in bold black.

From Fig. 5, it can be seen intuitively that the Pareto front obtained by the proposed algorithm is evenly distributed, which illustrates the effectiveness of the new crowding distance proposed in the article. From Tables 3 and 4, it can be seen that the power outputs obtained by the four algorithms are within their limits, and the violations obtained by the four algorithms are within the threshold δ, which illustrates the validity of the constraint processing method in this article. Furthermore, the proposed algorithm obtains the best results with the smallest threshold δ, which shows that the algorithm has good optimization performance.

5.2 Performance Analysis of Multi-objective Optimization

Dissimilar to single-objective optimization algorithms, the quality of the solutions obtained by multi-objective optimization algorithms is generally evaluated from the following three aspects [33]: (1) evenness. The solutions should be uniformly distributed on the Pareto optimal front. (2) Coverage. The coverage of the Pareto optimal front should be as large as possible. (3) Convergence. The smaller the distance between the obtained Pareto optimal front and the true Pareto optimal front, the better.

To evaluate the quality of the solutions obtained by the suggested algorithm, three indicators including Spacing Metric (SP), Normalized Distance (ND) and Two Set Coverage (SC) used in [33] are applied as metrics in this paper.

In this experiment, all algorithms were run 30 times, and the statistical results obtained are presented in Tables 5, 6 and 7, respectively. (The best results are marked in boldface.) In Table 5, the worst SP of MHHO-DE is also better than the best SP of other algorithms, which indicates that the uniformity of MHHO-DE is much better than the other algorithms. In Table 6, the worst performance of the normalized distance of MHHO-DE is the best, although the best normalized distance of NSPSO is the largest, which shows that the coverage of the optimal front obtained by MHHO-DE is competitive. In Table 7, MHHO-DE dominates 71.61%, 97.5% and 94.83% of the solutions from MODE, NSGA-II and NSPSO, respectively. However, only less than 35.3% of solutions of the MHHO-DE are dominated by the other algorithms. This shows that the convergence of MHHO-DE is the

Table 2 Parameter settings of the four comparison algorithms

Algorithm	Population size	Archive size	Maximum iteration	Threshold δ (MW)	Other parameters
MHHO-DE	60	60	10,000	**0.0001**	Crossover probability CR = 0.9; scaling factor F = 0.5
MODE	60	60	10,000	0.001	Crossover probability CR = 0.9; scaling factor F = 0.5
NSGA-II	60	60	10,000	0.001	Distribution index for crossover is 20; distribution index for mutation is 20; mutation probability is 1/6; crossover probability is 0.5
NSPSO	60	60	10,000	0.001	c_1 and c_2 are set to 1; w = 0.4

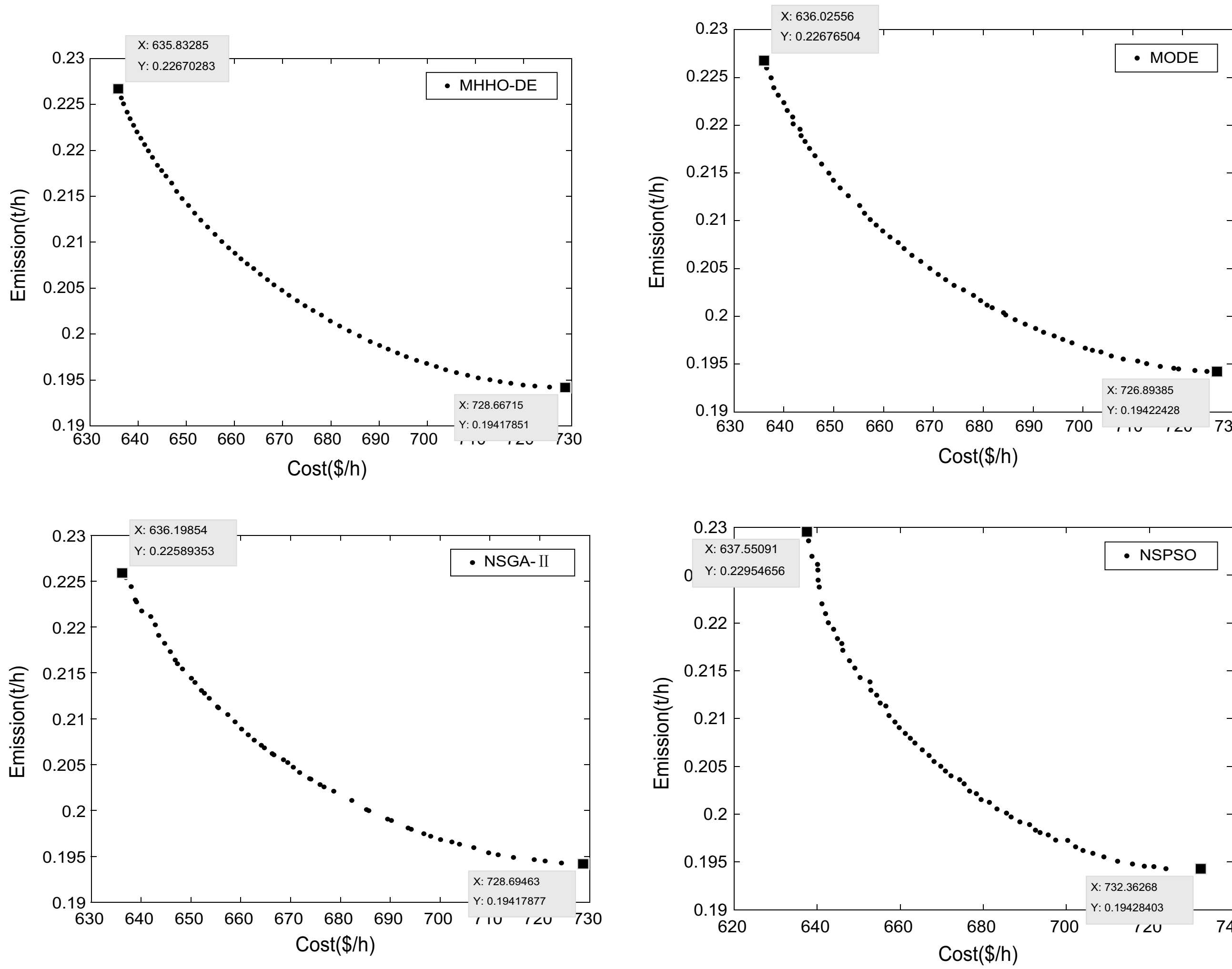

Fig. 5 Pareto optimal fronts obtained by the four algorithms

Table 3 Best solutions for cost with four algorithms

Algorithm	MHHO-DE	MODE	NSGA-II	NSPSO
P_1/MW	5.00001	5.3112	5.0035	5.7826
P_2/MW	12.4635	12.5238	18.0107	5.0019
P_3/MW	83.5398	83.5725	83.5409	84.1108
P_4/MW	75.0045	75.1352	74.8251	75.7570
P_5/MW	79.7998	79.8949	79.8523	80.5251
P_6/MW	29.4750	28.8403	24.0885	34.1010
Fuel cost	**635.8329**	636.0256	636.1985	637.5509
Emission	0.2267	0.2268	0.2259	0.2295
$\left\|\sum_{i=1}^{N} P_i - P_D - P_L\right\|$	8×10^{-6}	9.1×10^{-4}	7×10^{-5}	6.7×10^{-4}

Table 4 Best solutions for emission with four algorithms

Algorithm	MHHO-DE	MODE	NSGA-II	NSPSO
P_1/MW	41.0923	39.0196	41.0872	42.8091
P_2/MW	46.3663	47.5775	46.3893	48.8199
P_3/MW	54.4427	53.6975	54.3927	51.5616
P_4/MW	39.0368	39.7713	39.1090	38.7020
P_5/MW	54.4472	54.9118	54.2821	53.6348
P_6/MW	51.5477	51.8631	51.6762	51.6070
Fuel cost	728.6672	726.8939	728.6946	732.3627
Emission	**0.1941785**	0.194224	0.1941788	0.194284
$\left\|\sum_{i=1}^{N} P_i - P_D - P_L\right\|$	9.9×10^{-5}	9.9×10^{-4}	5×10^{-4}	9.6×10^{-4}

best among the four algorithms. In addition, from Tables 5, 6 and 7, it also can be seen that the robustness of MHHO-DE is the best because its standard deviation is the smallest.

Based on the above analysis and discussion, it can be concluded that the suggested algorithm has terrific performances for solving EED problems.

Table 5 Statistical results of the SP with four algorithms

	MHHO-DE	MODE	NSGA-II	NSPSO
Best	**0.0025**	0.0053	0.0120	0.0062
Worst	**0.0049**	0.0100	0.0172	0.0260
Median	**0.0034**	0.0076	0.0142	0.0107
Average	**0.0035**	0.0076	0.0143	0.0124
Std.	**0.0006**	0.0013	0.0012	0.0059

Table 6 Statistical results of the ND with four algorithms

	MHHO-DE	MODE	NSGA-II	NSPSO
Best	0.8342	0.8331	0.8495	**0.9151**
Worst	**0.8207**	0.7747	0.4701	0.7507
Median	0.8257	0.8030	0.8057	**0.8335**
Average	0.8261	0.8047	0.7629	**0.8344**
Std.	**0.0035**	0.0129	0.0919	0.0390

Table 7 Statistical results of the SC with four algorithms

	MHHO-DE	MODE	NSGA-II	NSPSO
SC(MHHO-DE,*)	–	0.7161	0.9750	0.9483
SC(MODE,*)	**0.3522**	–	0.9628	0.9244
SC(NSGA-II,*)	**0.0383**	0.1311	–	0.5139
SC(NSPSO,*)	**0.0972**	0.2961	0.9161	–

6 Conclusion

In this paper, a hybrid multi-objective optimization algorithm, which is combined with an effective constraint handling technique, is presented to solve the constrained economic emission dispatch problem with valve-point effect. This algorithm extends and improves the single objective HHO, and combines with DE to form a powerful optimizer. A new crowding distance is devised to acquire an evenly distributed Pareto optimal front. Furthermore, a constraint processing method is integrated into the MHHO-DE to deal with the strong constraints of the EED problem. The experimental results on the IEEE 30-bus 6-uint test system show that the suggested algorithm is efficient: (1) a set of non-dominated solutions can be obtained in one simulation operation; (2) the non-dominated solutions strictly meet the various constraint conditions of the EED problem; (3) the Pareto optimal front obtained by the developed algorithm has excellent convergence and well distribution; (4) the given algorithm has excellent robustness. In the future, our research work will focus on applying the proposed algorithm to other kind of power systems with renewable energy sources due to the successful application of the proposed algorithm on the IEEE 30-bus 6-uint system.

Acknowledgements This work is supported by the National Natural Science Foundation of China (No. 61671222) and the Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX19_1693).

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