Application of Multi-objective New Whale Optimization Algorithm for Environment Economic Power Dispatch Problem

Gonggui Chen, Xingzhong Man, Yi Long, and Zhizhong Zhang*

***Abstract*— This study proposes a multi-objective new whale optimization algorithm (MONWOA) to solve environment economic power dispatch (EED) problem. The EED problem is a nonlinear multi-constrained multi-objective optimization problem, which can be solved by MONWOA method that has strong ability to find the best compromise solution (BCS). In order to balance exploration and exploitation of the algorithm, the Gaussian mutation operator, variation process of differential evolution algorithm and search mode parameter are adopted to improve the standard multi-objective whale optimization algorithm (MOWOA). Furthermore, a new constraint handling method combined with the MONWOA is put forward to find the Pareto solution set with better distribution. Six experiments aimed at simultaneously optimizing fuel cost and emission, fuel cost with valve-point effect and emission, power loss and emission are carried on IEEE 30 bus, 57 bus and 118 bus systems. Compared with MOWOA and traditional MOPSO methods, the results of Pareto fronts and BCS show the superiority of WONWOA to solve EED problems. Moreover, the result of two performance indicators, it is clearly show that the stability and diversity of MONOWA method were stronger than the other two comparison algorithms.**

***Index Terms*—Environment economic power dispatch; multi-objective optimization; multi-objective new whale optimization algorithm; a new constraint handling method**

I. Introduction

THE electric energy is inextricably linked with each department of the national economy, thus improving the quality of electric power has very important practical significance [1-4]. In the early research of the power system optimization operation, it was limited to the economic load dispatch (ELD) of the system, which operating at absolute minimum cost is the only criterion [5-7]. The research shows that this method cannot fully consider the safety constraints to make the system operate safely. The increasing scarcity of fossil energy (coal, oil, natural gas.) and the prominence of the greenhouse effect make it necessary to consider the issue of pollutant emission while using fossil energy efficiently, which is one of the core tasks for the energy industry to establish an environment-friendly form of fossil energy utilization [8, 9].

Thermal power plants convert chemical energy into electrical energy by burning fossil fuels, which is the main body of fossil energy consumption and one of the important sources of polluted gases. In order to ensure sustainable development, it is necessary to perform the emission dispatch into the ELD problem [10, 11]. The ELD problem considering the emission objective transforms to an EED problem. The EED problem is a nonlinear multi-objective optimization problem with many equality and inequality constraints [12]. There is usually a conflicting relationship between different optimization objectives, when solving a single objective usually result in the demotion of another goal.

The EED problem is a research focus in recent years. Different from the single-objective optimization problem, the multi-objective optimization problem needs to optimize multiple objectives at the same time, and find a series of Pareto optimal solution sets, and finally find the best compromise solution (BCS) in the Pareto solution set [13]. Therefore, obtaining the BCS solution becomes very difficult for multi-objective optimization problems. Traditional methods include linear weighted sum method, multi-constraint method, linear programming method, and objective weighted method. They all have the common drawback that they must be run multiple times to get the solution for the problem [14-17]. And the above method is difficult to deal with the problem of non-differentiable and non-convex, which further limits their application in multi-objective problem [18, 19].

In view of the shortcomings of traditional methods, the evolutionary algorithm is used to solve the EED problem. The evolutionary algorithm can get a set of Pareto solutions in a single simulation and can easily handle discontinuous solutions [20-23]. In recent years, a large number of algorithms have been successfully applied to solve EED problem [24-26]. Such as interactive honey bee mating optimization algorithm [27], multi-objective differential

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evolution algorithm [28], modified non-dominated sorting genetic algorithm II [29], fuzzy based bacterial foraging algorithm [30], multi-objective particle swarm optimization algorithm and hybrid multi-objective cultural algorithm [31, 32]. Since the whale optimization algorithm proposed by Mirjalili and Lewis, it has been successfully applied to various optimization problems. In [33], a hybrid whale optimization algorithm is proposed to solve the permutation flow shop scheduling problem. In [34], the researcher proposed a hyper-heuristic for improving the initial population of whale optimization algorithm. In [35], a modified whale optimization algorithm is presented for large-scale global optimization problems. In [36], Control strategy for MGT generation system optimized by improved the whale optimization algorithm to enhance demand response capability. In [37], an improved chaotic whale optimization algorithm was used to aim at parameter estimation of photovoltaic cells.

MOWOA is also a meta-heuristic optimization algorithm, which has advantages of fewer parameters, high efficiency in search and stronger search capability [34], and makes it some certain advantage when solving multi-objective optimization problems. But the MOWOA may lead to premature convergence [37], falling into local optimal and failing to balance global search and local search capabilities when dealing with EED problems. Thus, the Gaussian mutation operator is added to avoid premature convergence and escape local optima. Furthermore, Instead of standard parameters controlling MOWOA global search and local search, the search mode parameters are used to control two different search mode, and the local search and global search of the algorithm are more effectively balanced to obtain a more effective Pareto optimal solution set. Furthermore, a constraint handling method and non-inferior sorting strategy is proposed to obtain the Pareto optimal set with better distribution. After the above operations, the multi-objective new whale optimization algorithm (MONWOA) is obtained.

In order to verify the superiority of the proposed MONWOA method, MONWOA, MOWOA and MOPSO algorithms were tested on IEEE30 bus system, IEEE57 bus system and IEEE118 bus system. Besides, the generational distance (*GD*) and spacing (*SP*) indicators are used to calculate the stability and diversity of the three methods [38].

The structure of this paper is generalized as follows. The mathematical model of EED is shown in Section II. The MOWOA and MONWOA algorithms are introduced in Section III. In addition, Section III gives the main steps of MONWOA algorithm to solve the EED problem. Simulation results and performance analysis of the three algorithms are showed in Section IV, and to further verify the superiority of the proposed algorithm, the Wilcoxon signed ranks method is also adopted. Section V gives a final summary.

II. Mathematical Description

Generally, the EED problem is to minimize the objective functions of fuel cost and emissions, while satisfying the equality and inequality constraints of the system. However, the power loss of the system will affect the economic operation of the system, so the EED problem must consider the power loss objective function. The EED mathematical model can be mathematically described as follows:

$$\text{minimize } F = (f_1(P_G), f_2(P_G), \cdots f_m(P_G)) \tag{1}$$

$$G_j(P_G) \geq 0, \quad j = 1, 2, \cdots, g \tag{2}$$

$$H_k(P_G) = 0, \quad k = 1, 2, \cdots, h \tag{3}$$

The premise of the objective function optimization is that it must satisfy equality constraints and inequality constraints, $f_i(P_G)$ is the ith objective function, m is the number of objective functions, P_G is the active output of the generator. g, h is the number of inequality constraints and equality constraints.

The mathematical model of EED includes objective functions and system constraints. The objective function includes the minimization of fuel costs, emission and power loss. The system constraints include equality constraints and inequality constraints.

A. Objective Function

1) Fuel cost minimization

The total cost of the system includes fuel cost, labor cost and other cost, labor costs and other cost account for a fixed proportion. Thus, the total fuel cost (F_{cost}) of each generator is represented by a quadratic polynomial.

$$F_{\text{cost}} = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2)(\$/\text{h}) \tag{4}$$

where a_i, b_i and c_i are the cost coefficients.

The fuel cost function considering valve-point effect (F_{cost_vp}) is more practical, which will cause a high degree of nonlinearity and discontinuity, making it more difficult to optimize the objective function.

$$F_{\text{cost\_vp}} = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \times \sin(e_i \times (P_{Gi}^{\min} - P_{Gi})) \right|)(\$/\text{h}) \tag{5}$$

where d_i and e_i are the cost coefficients with valve-point effect.

2) Emission minimization

Pollution emission (E_e) is given as a function of generator output, which can be expressed as:

$$E_e = \sum_{i=1}^{N} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \zeta_i \exp(\lambda_i P_{Gi})(\text{ton/hr}) \tag{6}$$

where α_i, β_i, γ_i, ξ_i and λ_i are emission coefficients of the ith generator.

3) Power loss minimization

Transmission loss in the power system will cause the economic loss of the power company, the power loss (P_{loss}) of the line will affect the economic operation and safe operation of the system, so it must be minimized to obtain the maximum economic benefits. Which can be described as:

$$P_{loss} = \sum_{i}^{N} \sum_{j \neq i}^{N} g_{ij} \left[V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij} \right] (\text{MW}) \tag{7}$$

where N is the number of buses, i and j is the number of bus; g_{ij} is the conductance of the branch of bus i and bus j; V_i and V_j are the voltage of bus i and bus j, respectively; δ_{ij} is the phase angle difference of the voltage between bus i and bus j.

B. Constraints of EED

1) Equality constraints

The total power generation must meet the total load demand (P_D) and the total power loss (P_{loss}), this equality constrain can be expressed as:

$$\sum_{i=1}^{N} P_i - P_D - P_{loss} = 0 \tag{8}$$

The load flow equations shown as:

$$\begin{aligned} & P_{Gi} - P_{Di} - V_i \sum_{j\in N_i} V_j (G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}) = 0 \qquad i \in N \\ & Q_{Gi} - Q_{Di} - V_i \sum_{j\in N_i} V_j (G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) = 0 \qquad i \in N_{PQ} \end{aligned} \tag{9}$$

where N_{PQ} is the number of load nodes, Q_{Gi} and Q_{Di} are the injected reactive power and actual active power of bus *i*, respectively; P_{Gi} and P_{Di} are the injected active power and actual active power of bus *i*, respectively; G_{ij} and B_{ij} are the conductance and susceptance between bus *i* and bus *j*, respectively.

2) Inequality constraints

In order to ensure the safety and economic operation of the system, the following inequality constraints must be satisfied. The active power output of the generator, the bus voltage and the reactive power output are constrained by the upper and lower limits as follows:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{10}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{11}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \tag{12}$$

Line power flow constraint is an important condition for the safe operation of the system, any line has its ultimate power carrying capacity. This constraint can be showed as follows:

$$P_{Lf,k} | \le P_{Lf,k}^{\max} \qquad k \in L \tag{13}$$

where $P_{Lf,k}$ is the actual active power of line *k*, $P_{Lf,k}^{max}$ is the maximum active power that line *k* can withstand. *L* is the number of transmission lines.

III. Proposed Algorithms for EED Problem

A. Overview of MOWOA

Whale optimization algorithm is a new metaheuristic algorithm proposed by Mirjalili and Lewis and mimics the foraging of humpback whales [39]. Similar to other population-based algorithms, WOA uses a set of random candidate solutions and uses three rules to update and improve its position at different times, which are encircling prey, spiral update position and search for prey [35]. The main steps are shown as follows.

1) Search for prey phase ($p < 0.5$ and $A \ge 1$)

In the phase of search for prey, whale individuals search randomly according to each other's positions, which corresponds to the global search stage of the algorithm. The mathematical model can be expressed as follows:

$$D = | C * X_{rand}(t) - X(t) | \tag{14}$$

$$X(t+1) = X_{rand}(t) - A * D \tag{15}$$

where $X_{rand}(t)$ is a randomly selected individual from the current whale population, $X(t)$ is the current individual whales position. *A* and *C* are the coefficient vectors, which are defined as follows:

$$A = 2a * r_1 - a \tag{16}$$

$$C = 2 * r_2 \tag{17}$$

where r_1 and r_2 are random vector in [0, 1], and *a* is called the control parameter, which decreases linearly from 2 to 0 as the number of iteration increases, which are defined as follow:

$$a = 2 - 2t / Max\_iter \tag{18}$$

where *Max_iter* is the maximum number of iterations.

2) Encircling prey phase ($p < 0.5$ and $A < 1$)

In the stage of encircling prey, whale individuals will approach the best whale individual in its current position, the mathematical model of encircling prey stage can be expressed as:

$$D = | C * X_{best}(t) - X(t) | \tag{19}$$

$$X(t+1) = X_{best}(t) - A * D \tag{20}$$

where $X_{best}(t)$ is the best whale individual.

3) Bubble-net attacking method ($p \ge 0.5$)

In the stage of spiral updating position, it will prey in a spiral way to search for the optimal solution, which are defined as:

$$D' = | X_{best}(t) - X(t) | \tag{21}$$

$$X(t+1) = D' * e^{bl} * \cos(2\pi l) + X_{best}(t) \tag{22}$$

where *b* is a constant and *l* is a random number between 0 and 1.

B. MONWOA

1) Gaussian mutation operator

The standard multi-objective whale optimization algorithm is similar to the general random intelligent algorithm, and the search process of the algorithm is easy to fall into the local optimal, which will result in the poor optimization effect of the algorithm. In order to avoid this problem, the Gaussian mutation operator is added to avoid premature convergence and escape local optima. The Gaussian distribution can be defined as follows:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{23}$$

where μ is the expectation of the Gaussian distribution, and σ^2 is the variance of the Gaussian distribution, when $\mu = 0$ and $\sigma = 1$ it is the standard Gaussian distribution. The three search processes of MOWOA are changed as:

$$X_{IWOA}(t+1) = X_{WOA}(t+1) * (1 + k * Guass(0,1)) \tag{24}$$

where *k* is a number that decreases between 0 and 1.

2) Differential evolution algorithm

In order to improve the global search ability of WOA and avoid WOA's premature convergence, the variation process of differential evolution algorithm is introduced. Which can be expressed as follows:

$$x(t+1) = x_{best}(t) + F * (x_{r1}(t) - x_{r2}(t)) \tag{25}$$

where *F* is the weight factor of differential evolution algorithm, $x_{r1}(t)$ and $x_{r2}(t)$ is selected randomly in the population.

3) Search mode parameter

General bionic algorithms involve the trade-off between exploration and exploitation, and balancing the two search modes of the algorithm is of great significance to improve the performance of the algorithm. The local search ability of the standard MOWOA is in a dominant position, and the global search ability of MOWOA method is weakened, causing the algorithm to converge prematurely. In the MOWOA, the value of p is randomly selected and A is decreased over time. Therefore, the search for prey, the encircling prey and the spiral update position phases are randomly selected to optimize the population, which can't well balance the exploration and exploitation of the algorithm. Thus, the search mode parameter (*SMP*) is adopted to solve this problem.

By tracking the change of the solution in the population, the *SMP* can adaptively change the current update state of the population. To ensure that exploration is the early stages of the algorithm, the *SMP* is set to 1 and then the parameter of p is set to 0.8. If the two parameters are set according to the above steps, the probability of entering the exploration is much greater than the exploitation. If the best solution has not been improved after multiple updates, the *SMP* is set to 2 and the update status of the current population is transformed to the stage of exploitation. In order to ensure that the best solution is changed after multiple runs, the parameter of *count* is used to track the best solution over time and *maxnum* is a threshold to decide whether to change the value of the *SMP*. The most important thing is the setting of the initial value of *maxnum*, it cannot be too large or too small. The smaller value of *maxnum* will cause the search mode of the algorithm to be changed frequently, and the optimization process cannot be carried out reasonably. The larger value of *maxnum* may cause the algorithm to fall into local optimum. Thus, the threshold is set to 10.

4) Search process improvements

In order to further balance the two search mechanisms of the MOWOA, the search for prey and the encircling prey stages is changed as follows:

$$X(t+1) = X_{rand1}(t) - A*(X(t) - X_{rand1}(t)) \tag{26}$$

$$X(t+1) = X_{rand2}(t) - A*(X_{best}(t) - X(t)) \tag{27}$$

5) Constraint handling method and non-inferior sorting

- *Constraint handling method*

In the EED problem, when an individual violates the constraint of the inequality of the active power output of the generator, modify the individual using formula (28).

$$p_i = \begin{cases} p_{min} & if\ \ p_i < p_{min} \\ p_{max} & if\ \ p_i > p_{max} \\ p_i & if\ \ p_{min} < p_i < p_{max} \end{cases} \tag{28}$$

The total value of the individual who violates the state variable inequality constraint can be expressed as:

$$Svio(P_G) = \sum_j \max(g_j(P_G, x), 0) \tag{29}$$

where $Svio(P_G)$ is the total value of the state variable inequality constraint violation, $g_j(P_G, x)$ is the value of jth state variable inequality constraint violation. The state variables include V_i, Q_{Gi} and $P_{Lf,k}$.

The individual p_p and p_q are randomly selected and calculating the $Svio(p_p)$ and $Svio(p_q)$, their relationship can be judged by the following rules.

Constraint Handling Rules:
1. if $Svio(p_p) < Svio(p_q)$ p_p dominates p_q;
2. if $Svio(p_p) > Svio(p_q)$ p_q is judged to be superior to p_p;
3. if $Svio(p_p) = Svio(p_q)$
4. if $f_i(p_p) \le f_i(p_q)$ for all $i \in \{1, 2, \ldots, M\}$ and $f_j(p_p) < f_j(p_q)$ for any $j \in \{1, 2, \ldots, M\}$
   the individual p_p is superior to individual p_q;
5. else p_q dominates p_p.

According to the above rules, all individuals can be divided into n levels, the value of level is expressed as $rank(x)$. The smaller value of $rank(x)$, and the individual is much stronger.

- *Non-inferior sorting*

All individuals in the population are divided into different hierarchy by the constraint handling method. If the value of $rank(x_i)$ is equal to $rank(x_j)$, calculating the crowded distance can determine their individual strength, then the crowded distance of ith individual is defined as $distance(x_i)$. At the same hierarchy, if $distance(x)$ of the individual is greater, the individual is much stronger. The following rules are adopted to determine the dominant relationship between individuals.

Constraint Handling Rules:
1. if $rank(x_i) < rank(x_j)$ individual i is stronger than individual j.;
2. if $rank(x_i) > rank(x_j)$ individual j dominates individual i.;
3. if $rank(x_i) == rank(x_j)$
4. if $distance(x_i) > distance(x_j)$ individual i is superior to individual j;
5. else individual j will be selected to the next iteration.

After the above steps, the original MOWOA algorithm is improved to obtain the MONWOA algorithm. The pseudo code is shown as follows.

```
Begin
Generate the initial population X_i (i =1, 2, …,N);
Select the best individual x_best;
Set p = 0.8, maxnum = 10, count = 0, SMP = 1, F = 0.6;
t=1;
while t < t_max
 for i = 1 to N
  if (SMP ==1 && rand1 <= p) || (SMP == 2 && rand1 > p)
   if (rand2 < CR || i = round(N * rand3 +0.5))
     x(i) = x(best) + F * (x(r_1) - x(r_2))
   else
     x(i) = (x(r_3) - A*(x(i) - x(r_3))) * (1 + k * Guass(0,1))
   end if
  else if (SMP ==2 && rand4 <= p) || (SMP == 1 && rand4 > p)
   if rand5 <= 0.5
     x(i) = (x(r_4) - A*(x(best) - x(r_4))) * (1 + k * Guass(0,1))
   else
   end if
  end if
 end for
 Obtain the new population and the new best individual x*_best;
 Use constraint handling and non-inferior sorting method judge the dominant relationship between x*_best and x_best
 if x*_best dominates x_best
   count = 0;
 else
   count = count + 1;
   if count > maxnum
     if SMP == 1
       SMP == 2, count = 0, maxnum = maxnum*2;
```

else
SMP == 1, *count* = 0, *maxnum* = 10;
end if
end if
end if
t = *t* +1;
end while
end

C. Proposed MONWOA for EED problem

The main goal of this paper is to solve the EED problem using the proposed MONWOA method. Using the proposed method, a set of non-dominated solutions based on the concept of Pareto optimal can be obtained, these solutions are continuously updated until the iteration stops. After the iteration select the strongest solution as the best compromise solution (BCS).The steps of the MONWOA to solve the EED problem are as follows.

Proposed MONWOA for EED Problem	
Step1:	Establish mathematical model of EED and set relevant parameters of MONWOA.
Step2:	Initialize the population randomly and set each individual within the feasible region.
Step3:	Calculate the objective function and the constraint violation value of each individual in the population.
Step4:	Sort all individuals in the population by constraint handling and non-inferior sorting method.
Step5:	Save the new population to the initial external repository and start the iteration.
Step6:	Update the population using the proposed MONWOA method and obtain a new population.
Step7:	Integrate the new population and the initial external repository into a global population.
Step8:	Delete replicate individuals of the global population and sort all individuals in the global population by constraint handling and non-inferior sorting method.
Step9:	Select individuals with a smaller level and a larger crowded distance from global population to update the external repository, and keep the size of external repository unchanged.
Step10:	Select the strongest solution in the external repository as the BCS solution.
Step11:	If the number of iterations t satisfies $t = t_{max}$, the iteration will stop and obtain the BCS. If not, the iteration will continue.

IV. Simulation Results

Based on MATLAB 2014a and a PC with Intel(R) Core(TM) i5-7400 CPU @ 3.00GHz with 3.00GHz. MOWOA, MOPSO and MONWOA are used to solve the EED problem in the IEEE 30 bus system (system 1), IEEE 57 bus system (system 2) and IEEE 118 bus system (system 3).

A. Parameter settings

The number of population size and maximum iterations will affect the effectiveness of the proposed algorithm in solving EED problem. Therefore, choosing the appropriate parameters is of great significance for this optimization problem. After repeated experiments, the parameters of the three algorithms are set in TABLE II.

The values of the fuel and emission coefficients of the system 1 can be found in TABLE I, the line data and bus data are given in [40] and the detail data are given in [27]. The detail data of system 2 are given in [41, 42]. In order to verify the effectiveness of the proposed algorithm in the large bus systems, three algorithm are tested on the system 3. Its detail data can be found in [42, 43]. The structure diagram of three system are shown in Fig. 1-3.

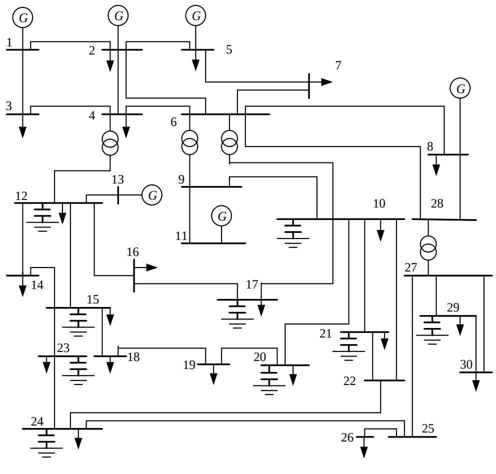

Fig. 1. The structure diagram of system 1

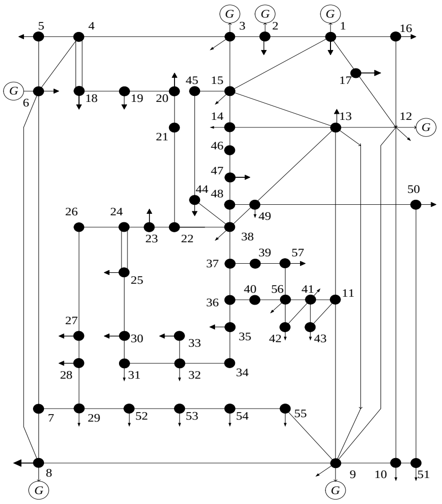

Fig. 2. The structure diagram of system 2

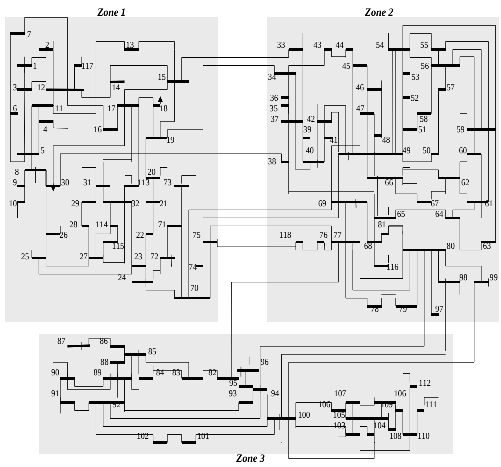

Fig. 3. The structure diagram of system 3

B. Trials on system 1

1) Case1: Optimization of F_{cost} and E_e

In this simulation process, the F_{cost} and E_e are optimized at the same time on IEEE 30 bus system. Fig. 4 gives the Pareto fronts obtained by MONWOA, MOWOA and MOPSO method, we can easily find that the proposed algorithm can obtain the better Pareto optimal front. The minimum fuel cost (*MF*), minimum emission (*ME*) and the BCS obtained by MONWOA method are shown in Fig. 5. The active power output of generators of the BCS solutions obtained by the three algorithms are given in TABLE III, and the comparison results of other published literatures are also shown in TABLE III. It clearly show that the BCS of MONWOA algorithm with 0.1972 ton/h of E_e and 621.12 \$/h of F_{cost} dominates the BCS solutions of other comparative methods. TABLE IV and TABLE V gives the detail data of *ME* and *MF* obtained by three method and other published literatures, it gives the value of *MF* is 611.23 \$/h and *ME* is 0.1942 ton/h. Meanwhile, it also shows that the proposed MONWOA can obtain a better boundary solution.

2) Case2: Optimization of F_{cost_vp} and E_e

The non-convexity of the valve point effect will make the EED problem more complicated. Thus in case2 aims to optimize F_{cost_vp} and E_e. The Pareto fronts obtained by three algorithms are given in Fig. 6. It can be found that MONWOA method can obtain the evenly distributed Pareto front, which is better than MOWOA and MOPSO method. And the minimum F_{cost_vp} (MF_{vp}) and *ME* of MONWOA method are shown in Fig. 7. TABLE VI gives the detail data of the BCS solutions obtained by MONWOA, MOWOA, MOPSO algorithm, and the comparison results of other published literature are also shown in TABLE VI. TABLE VII shows the result of *ME* and MF_{vp} obtained by three method and the published literature. The BCS of MONWOA algorithm which includes 0.1966 ton/h of E_e and 638.68 \$/h of F_{cost_vp} is better than the BCS solutions of MOWOA, MOPSO algorithm and the published literature. In addition, the superiority of proposed MONWOA method in handling the non-convexity of the valve-point effect is verified.

3) Case3: Optimization of P_{loss} and E_e

P_{loss} is an indicator to ensure the economic and safe operation of the power system. Thus in case3, P_{loss} and E_e are optimized simultaneously. The simulation results of three methods illustrated in Fig. 8-9. It is clearly observed from Fig. 8 that the minimum P_{loss} (*MP*) is 1.2423 MW and *ME* is 0.1942 ton/h. The simulation results of BCS solutions are given in TABLE VIII and the result of *ME* and *MP* obtained by three method are given in TABLE IX. It can be found that P_{loss} and E_e are 1.5496 MW and 0.2016 ton/h for MONWOA method, which dominates the BCS of two comparison algorithm.

C. Trials on system 2

1) Case4: Optimization of F_{cost} and E_e

Fig. 10 shows the Pareto fronts of MONWOA and other comparison algorithms, which takes the optimization of F_{cost} and E_e goals. It can be found that the Pareto front obtained by MONWOA algorithm is superior to the Pareto fronts obtained by MOWOA and MOPSO method. Fig. 11 gives the *MF* and *ME* of the proposed algorithm. The BCS solutions of three method is shown in TABLE X. It can be seen that the BCS found by MONWOA, F_{cost} of 43118.61 \$/h and E_e of 1.2622 ton/h, is better than the BCS solutions found by MOWOA and MOPSO. TABLE XI gives the *MF* and *ME* of MONWOA method, which is 41662.88 \$/h and 1.0341 ton/h. It's less than other methods. Thus, it shows that the proposed method can obtain the smaller boundary value.

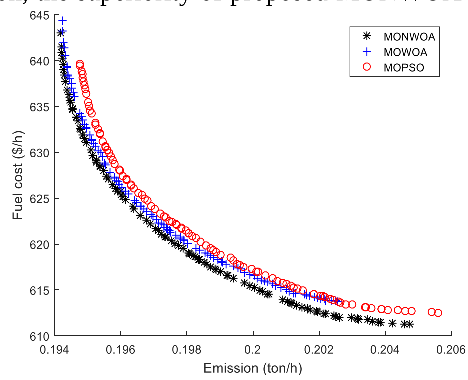

Fig. 4. The simulation results of case1 obtained by MONWOA, MOWOA and MOPSO

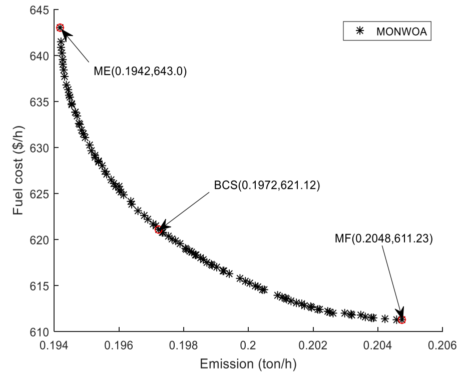

Fig. 5. The Pareto fronts of MONWOA in case1

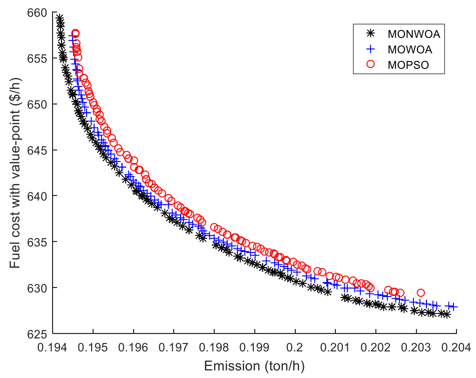

Fig. 6. The simulation results of case2 obtained by MONWOA, MOWOA and MOPSO

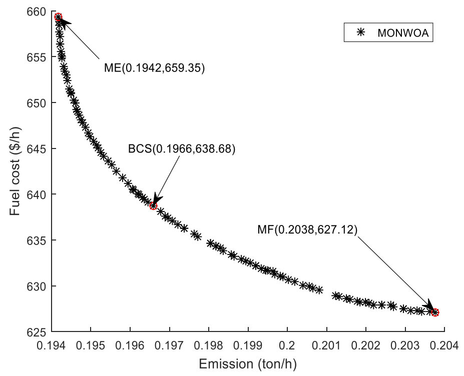

Fig. 7. The Pareto fronts of MONWOA in case2

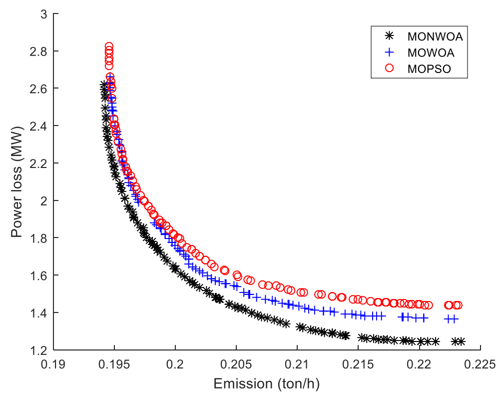

Fig. 8. The simulation results of case3 obtained by MONWOA, MOWOA and MOPSO

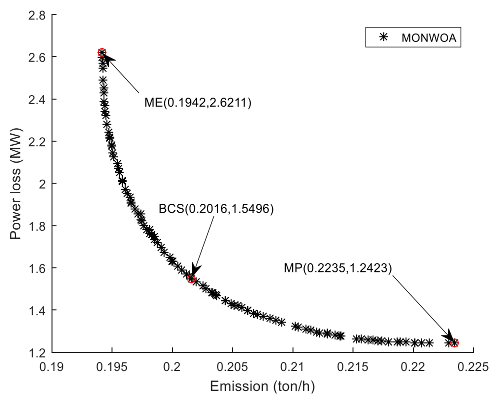

Fig. 9. The Pareto fronts of MONWOA in case3

TABLE I
GENERATOR AND EMISSION COEFFICIENTS OF IEEE 30 BUS SYSTEM

NO. gen	λ	ζ	γ	β	α	*c*	*b*	*a*	P_{Gmin}	P_{Gmax}
P_{G1}	2.857	0.0002	0.06490	-0.05554	0.04091	100	200	10	5	150
P_{G2}	3.333	0.0005	0.05638	-0.06047	0.02543	120	150	10	5	150
P_{G5}	8.000	0.000001	0.04586	-0.05094	0.04258	40	180	20	5	150
P_{G8}	2.000	0.002	0.03380	-0.03550	0.05326	60	100	10	5	150
P_{G11}	8.000	0.000001	0.04586	-0.05094	0.04258	40	180	20	5	150
P_{G13}	6.667	0.00001	0.05151	-0.05555	0.06131	100	150	10	5	150

TABLE II
SIMULATION PARAMETER SETTINGS

Algorithms	Parameters	Values	
	Population	100	
Common parameters	Repository	100	
	Max_iter	300(case1-case5)	500(case6)
MOPSO	c1	2	
	c2	2	
	ω	0.9	
MOWOA	b	1	
MONWOA	σ	1	
	μ	0	
	b	1	
	F	0.6	

TABLE III
SIMULATION RESULTS OF BCS FOR CASE1

Generators	MONWOA	MOWOA	MOPSO	MBFA[30]	SPEA[7]	MOPSO[31]	NSBF[22]	DE[8]	NSGA-II[20]
P_{G1}(MW)	0.3064	0.3096	0.2833	0.2983	0.3052	0.2882	0.2911	0.3877	NA
P_{G2}(MW)	0.4019	0.4183	0.3983	0.4332	0.4389	0.3965	0.3704	0.5201	NA
P_{G5}(MW)	0.5699	0.5645	0.6151	0.7350	0.7163	0.7320	0.6230	0.2538	NA
P_{G8}(MW)	0.5890	0.5947	0.5760	0.6899	0.6978	0.7520	0.5897	0.7281	NA
P_{G11}(MW)	0.5419	0.5418	0.5128	0.1569	0.1552	0.1489	0.5613	0.4655	NA
P_{G13}(MW)	0.4436	0.4280	0.4714	0.5503	0.5507	0.5463	0.4252	0.5101	NA
$\boldsymbol{F_{cost}}$ **(\$/h)**	**621.12**	622.08	622.54	629.56	629.59	626.10	621.71	626.03	625.36
$\boldsymbol{E_e}$ **(ton/h)**	**0.1972**	0.1973	0.1975	0.2080	0.2079	0.2106	0.1983	0.1979	0.1984

TABLE IV
SIMULATION RESULTS OF ME FOR CASE1

Generators	MONWOA	MOWOA	MOPSO	MBFA[30]	SPEA[7]	MOPSO[31]	NSBF[22]	NSGA[24]	NPGA[21]
P_{G1}(MW)	0.4113	0.4161	0.3930	0.4716	0.4419	0.4589	0.4047	0.4403	0.4753
P_{G2}(MW)	0.4574	0.4764	0.4009	0.5127	0.4598	0.5121	0.4533	0.4940	0.5162
P_{G5}(MW)	0.5398	0.5371	0.5883	0.6189	0.6944	0.6524	0.5439	0.7509	0.6513
P_{G8}(MW)	0.3934	0.4058	0.4458	0.5032	0.4616	0.4331	0.3921	0.5060	0.4363
P_{G11}(MW)	0.5411	0.5257	0.5127	0.1788	0.1952	0.1981	0.5454	0.1375	0.1896
P_{G13}(MW)	0.5143	0.5028	0.5281	0.5822	0.6131	0.6129	0.5246	0.5364	0.5988
$\boldsymbol{F_{cost}}$ **(\$/h)**	643.0	644.30	639.60	651.93	651.71	656.87	644.41	649.24	657.59
$\boldsymbol{E_e}$ **(ton/h)**	**0.1942**	0.1943	0.1948	0.2019	0.2019	0.2014	0.1942	0.2048	0.2017

TABLE V
SIMULATION RESULTS OF MF FOR CASE1

Generators	MONWOA	MOWOA	MOPSO	MBFA[30]	SPEA[7]	MOPSO[31]	NSBF[22]	NSGA[24]	NPGA[21]
P_{G1}(MW)	0.1569	0.1945	0.1390	0.1175	0.1319	0.1524	0.178	0.1358	0.1127
P_{G2}(MW)	0.3625	0.4130	0.3810	0.3617	0.3654	0.3427	0.3366	0.3151	0.3747
P_{G5}(MW)	0.6220	0.5764	0.6788	0.7899	0.7791	0.7857	0.7292	0.8418	0.8057
P_{G8}(MW)	0.7089	0.7110	0.7113	0.9591	0.9282	1.0180	0.5908	1.0431	0.9031
P_{G11}(MW)	0.590	0.5328	0.5187	0.1457	0.1308	0.0995	0.5766	0.0631	0.1347
P_{G13}(MW)	0.4114	0.4297	0.4259	0.4916	0.5292	0.4669	0.4474	0.4664	0.5331
$\boldsymbol{F_{cost}}$ **(\$/h)**	**611.23**	613.75	612.54	618.06	619.60	618.54	619.61	620.87	620.46
$\boldsymbol{E_e}$ **(ton/h)**	0.2048	0.2028	0.2056	0.2264	0.2244	0.2308	0.2027	0.2368	0.2243

TABLE VI
SIMULATION RESULTS OF BCS FOR CASE2

Generators	MONWOA	MOWOA	MOPSO	PSO[25]
P_{G1}(MW)	0.3111	0.3394	0.3129	0.1409
P_{G2}(MW)	0.4174	0.4028	0.3970	0.3442
P_{G5}(MW)	0.550	0.5682	0.6134	0.6756
P_{G8}(MW)	0.5718	0.5760	0.5620	0.8397
P_{G11}(MW)	0.5371	0.5520	0.5002	0.4904
P_{G13}(MW)	0.4663	0.4174	0.4707	0.3980
F_{cost_vp}($/h)	**638.68**	639.04	639.71	639.65
E_e (ton/h)	**0.1966**	0.1969	0.1969	0.2111

TABLE VII
SIMULATION RESULTS OF ME AND MF_{vp} FOR CASE2

Method	objective	P_{G1}	P_{G2}	P_{G5}	P_{G8}	P_{G11}	P_{G13}	F_{cost_vp}	E_e
MONWOA	Best F_{cost}	0.1793	0.3643	0.5970	0.7067	0.5920	0.4136	**627.12**	0.2038
	Best E_e	0.4108	0.4625	0.5438	0.3903	0.5414	0.5109	659.35	**0.1942**
MOWOA	Best F_{cost}	0.1661	0.4073	0.6030	0.7091	0.5699	0.3989	627.87	0.2039
	Best E_e	0.4029	0.4101	0.5549	0.3831	0.5916	0.5144	657.41	0.1945
MOPSO	Best F_{cost}	0.1881	0.3774	0.6157	0.7114	0.4894	0.4756	629.44	0.2031
	Best E_e	0.4006	0.4381	0.6193	0.3907	0.5225	0.4891	657.71	0.1946
PSO[17]	Best F_{cost}	0.0994	0.3625	0.4835	0.8736	0.6643	0.3900	**626.96**	0.2139
	Best E_e	0.3788	0.3932	0.4995	0.5344	0.5734	0.4865	659.44	0.1957

TABLE VIII
SIMULATION RESULTS OF BCS FOR CASE3

Generators	MONWOA	MOWOA	MOPSO
P_{G1}(MW)	0.2202	0.2101	0.1737
P_{G2}(MW)	0.3821	0.4396	0.3842
P_{G5}(MW)	0.8077	0.8111	0.8267
P_{G8}(MW)	0.4311	0.5190	0.4448
P_{G11}(MW)	0.6038	0.5002	0.6348
P_{G13}(MW)	0.4046	0.370	0.3861
P_{loss} (MW)	**1.5496**	1.5965	1.6267
E_e (ton/h)	**0.2016**	0.2026	0.2040

TABLE IX
SIMULATION RESULTS OF MP AND ME FOR CASE3

Method	objective	P_{G1}	P_{G2}	P_{G5}	P_{G8}	P_{G11}	P_{G13}	P_{loss}	E_e
MONWOA	Best P_{loss}	0.2200	0.2964	0.8408	0.4853	0.6402	0.3636	**1.2423**	0.2235
	Best E_e	0.4112	0.4623	0.5452	0.3884	0.5452	0.5079	2.6211	**0.1942**
MOWOA	Best P_{loss}	0.2022	0.4468	0.7834	0.5540	0.5021	0.3637	1.3661	0.2229
	Best E_e	0.4150	0.4625	0.5628	0.4493	0.5196	0.4514	2.6592	0.1946
MOPSO	Best P_{loss}	0.2492	0.2964	0.8573	0.4560	0.6321	0.3575	1.4376	0.2232
	Best Ee	0.3954	0.4513	0.5280	0.4147	0.6020	0.4708	2.8238	0.1945

2) Case5: Optimization of P_{loss} and E_e

In case5, The MONWOA, MOWOA and MOPSO are tested for minimization of P_{loss} and E_e. The Pareto front formed by a series of Pareto solutions obtained by the three algorithms is shown in Fig. 12. It obviously shows that MONWOA method obtains the Pareto front with more superior performance. As we can see in TABLE XII, the BCS solution of MONWOA algorithm with 1.1389 ton/h of E_e and 13.37 MW of P_{loss} dominates the BCS solution of MOWOA and MOPSO algorithms. Especially in the objective of power loss, the proposed algorithm obtains smaller value compared to other two comparison algorithms. As is shown in Fig. 13 and TABLE XIII, the *MP* and *ME* of the MONWOA method are 9.47 MW and 1.0343 ton/h, respectively. The obtained results is better than other two methods.

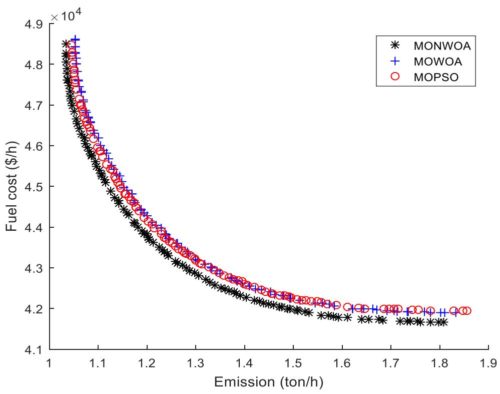

Fig. 10. The simulation results of case4 obtained by MONWOA, MOWOA and MOPSO

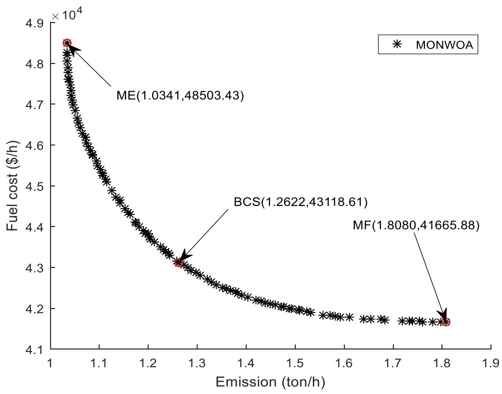

Fig. 11. The Pareto fronts of MONWOA in case4

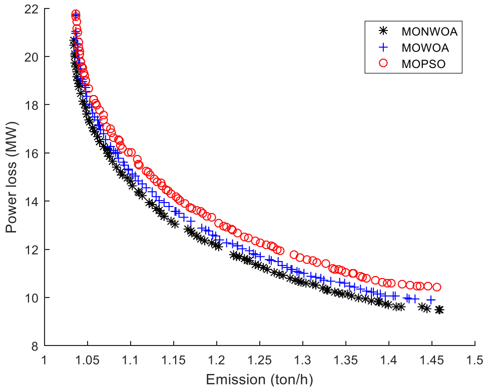

Fig. 12. The simulation results of case5 obtained by MONWOA, MOWOA and MOPSO

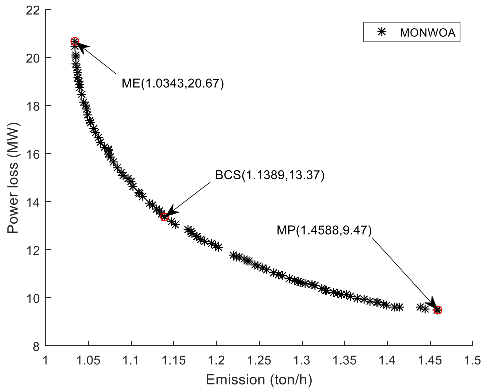

Fig. 13. The Pareto fronts of MONWOA in case5

TABLE X
SIMULATION RESULTS OF BCS FOR CASE4

Generators	MONWOA	MOWOA	MOPSO
P_{G1}(MW)	224.23	219.06	222.35
P_{G2}(MW)	100.0	99.97	99.89
P_{G3}(MW)	87.37	85.50	83.62
P_{G6}(MW)	99.96	99.65	99.32
P_{G8}(MW)	340.29	344.74	348.20
P_{G9}(MW)	99.94	99.70	99.92
P_{G12}(MW)	312.57	321.33	316.10
F_{cost} ($/h)	**43118.61**	43205.42	43170.06
E_e (ton/h)	**1.2622**	1.3005	1.2999

TABLE XI
SIMULATION RESULTS OF ME AND MF FOR CASE4

Method	objective	P_{G1}	P_{G2}	P_{G3}	P_{G6}	P_{G8}	P_{G9}	P_{G12}	F_{cost}	E_e
MONWOA	Best F_{cost}	139.98	99.67	43.33	99.96	431.87	99.98	349.84	**41665.88**	1.8080
	Best E_e	331.61	99.66	140.0	99.95	261.33	100.0	238.72	48503.43	**1.0341**
MOWOA	Best F_{cost}	137.29	98.14	41.98	98.91	427.45	99.28	366.41	41904.44	1.8335
	Best E_e	327.69	99.97	140.0	99.78	266.34	100.0	244.87	48608.82	1.0519
MOPSO	Best F_{cost}	139.36	99.97	41.54	98.63	433.87	99.76	358.08	41945.69	1.8553
	Best E_e	327.01	99.64	140.0	100.0	270.44	100.0	238.73	48468.16	1.0455

TABLE XII
SIMULATION RESULTS OF BCS FOR CASE5

Generators	MONWOA	MOWOA	MOPSO
P_{G1}(MW)	220.76	227.81	215.47
P_{G2}(MW)	100.0	98.35	98.51
P_{G3}(MW)	139.96	138.18	139.95
P_{G6}(MW)	99.69	99.92	100.0
P_{G8}(MW)	275.37	266.90	275.26
P_{G9}(MW)	99.96	99.83	100.0
P_{G12}(MW)	328.42	333.62	335.62
P_{loss} (MW)	**13.37**	13.80	14.01
E_e (ton/h)	**1.1389**	1.1448	1.1574

TABLE XIII
SIMULATION RESULTS OF MP AND ME FOR CASE5

Method	objective	P_{G1}	P_{G2}	P_{G3}	P_{G6}	P_{G8}	P_{G9}	P_{G12}	P_{loss}	E_e
MONWOA	Best P_{loss}	162.04	53.56	140.00	100.00	294.67	100.00	410.00	**9.47**	1.4588
	Best E_e	330.22	100.00	139.87	100.00	262.29	99.90	239.19	20.67	**1.0343**
MOWOA	Best P_{loss}	121.35	91.01	139.54	95.96	303.24	99.60	410.00	9.89	1.4489
	Best E_e	334.90	100.00	139.88	100.00	258.67	100.00	239.07	21.71	1.0360
MOPSO	Best P_{loss}	145.20	75.41	130.04	100.00	301.81	98.77	410.00	10.43	1.4555
	Best E_e	331.59	100.00	140.00	100.00	260.05	100.00	240.92	21.76	1.0364

TABLE XIV
SIMULATION RESULTS OF ME AND MF FOR CASE6

MONWOA		MOWOA		MOPSO	
F_{cost} ($/h)	E_e (ton/h)	F_{cost} ($/h)	E_e (ton/h)	F_{cost} ($/h)	E_e (ton/h)
58025.08	2.7771	58428.15	2.9902	59138.62	2.7248
68222.51	**0.6090**	66764.67	0.7743	68590.75	0.7028

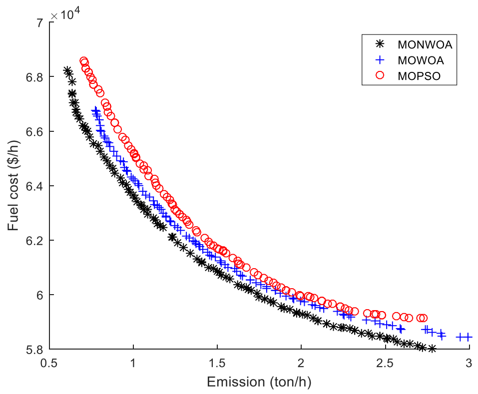

Fig. 14. The simulation results of case6 obtained by MONWOA, MOWOA and MOPSO

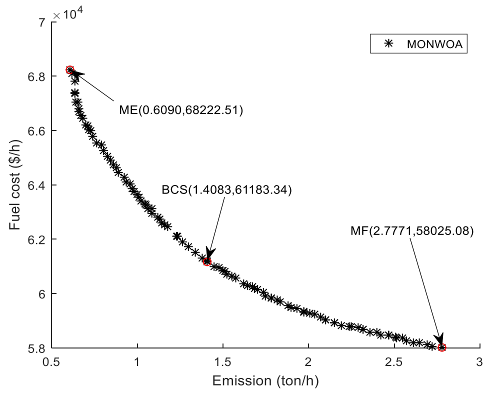

Fig. 15. The Pareto fronts of MONWOA in case6

TABLE XV
SIMULATION RESULTS OF BCS FOR CASE6

Generators	MONWOA	MOWOA	MOPSO	Generators	MONWOA	MOWOA	MOPSO
P_{G4}(MW)	5.0	5.0	5.0	P_{G66}(MW)	115.44	107.89	106.08
P_{G6}(MW)	5.0	28.92	5.0	P_{G69}(MW)	52.0	74.10	43.11
P_{G8}(MW)	5.01	5.21	5.02	P_{G70}(MW)	31.81	30.02	30.20
P_{G10}(MW)	115.32	124.40	155.27	P_{G72}(MW)	10.0	10.0	10.0
P_{G12}(MW)	299.79	298.90	290.05	P_{G73}(MW)	5.0	5.02	5.02
P_{G15}(MW)	10.32	10.43	10.83	P_{G74}(MW)	5.11	5.0	5.02
P_{G18}(MW)	88.88	99.88	76.98	P_{G76}(MW)	28.40	25.0	25.0
P_{G19}(MW)	5.0	5.08	5.02	P_{G77}(MW)	25.0	25.0	25.11
P_{G24}(MW)	5.0	5.02	5.10	P_{G80}(MW)	283.18	298.47	300.0
P_{G25}(MW)	100.16	100.02	100.0	P_{G82}(MW)	32.22	25.93	68.23
P_{G26}(MW)	100.0	100.0	100.0	P_{G85}(MW)	10.35	28.35	10.04
P_{G27}(MW)	9.19	9.02	8.02	P_{G87}(MW)	242.24	238.23	170.73
P_{G31}(MW)	8.08	8.0	8.0	P_{G89}(MW)	188.39	164.06	173.69
P_{G32}(MW)	99.39	25.09	25.02	P_{G90}(MW)	8.12	8.06	8.0
P_{G34}(MW)	8.53	8.02	8.01	P_{G91}(MW)	20.37	20.01	20.02
P_{G36}(MW)	25.03	25.15	25.0	P_{G92}(MW)	121.64	140.20	168.71
P_{G40}(MW)	8.0	8.15	8.14	P_{G99}(MW)	201.58	158.53	216.51
P_{G42}(MW)	8.01	8.0	8.0	P_{G100}(MW)	193.83	191.37	146.47
P_{G46}(MW)	54.69	71.90	98.08	P_{G103}(MW)	8.03	8.0	8.0
P_{G49}(MW)	249.01	250.0	248.46	P_{G104}(MW)	28.18	29.64	25.13
P_{G54}(MW)	50.10	50.0	50.16	P_{G105}(MW)	25.0	25.06	25.0
P_{G55}(MW)	25.23	25.0	25.05	P_{G107}(MW)	8.0	8.07	8.01
P_{G56}(MW)	25.0	25.0	25.0	P_{G110}(MW)	25.97	25.0	25.44
P_{G59}(MW)	50.98	50.0	50.70	P_{G111}(MW)	25.0	26.04	25.25
P_{G61}(MW)	199.18	199.92	199.04	P_{G112}(MW)	30.88	25.63	25.01
P_{G62}(MW)	53.29	25.17	97.34	P_{G113}(MW)	55.06	100.0	76.96
P_{G65}(MW)	420.0	420.0	420.0	P_{G116}(MW)	26.50	43.60	44.73
F_{cost} ($/h)	**61183.34**	61558.66	61838.56	**E_e (ton/h)**	**1.4083**	1.4418	1.4607

D. *Trials on system 3*

1) *Case6: Optimization of F_{cost} and E_e*

To verify the effectiveness of the proposed algorithm in a large bus system, two objectives of F_{cost} and E_e are optimized at the same time on the IEEE 118 bus system. The Pareto fronts of three method are given in Fig. 14. It can be intuitively seen that MONWOA can obtain a better distribution of Pareto front. Furthermore, Fig. 15 give the value of *ME* and *MF*. TABLE XV and TABLE XIV give the details of BCS solutions and the boundary solution. The BCS of MONWOA algorithm, which includes 61183.34 $/h of F_{cost} and 1.4083 ton/h of E_e. It obviously shows that the BCS of MONWOA method is better than the ones found by MOWOA and MOPSO algorithm. Besides, the proposed method is capable to obtain 58025.08 $/h of *MF* and 0.6090 ton/h of *ME*. It can be seen that the proposed algorithm MONWOA is superior to MOWOA and MOPSO algorithm, especially in the complex structure and large scale IEEE 118 bus system.

E. *Performance evaluation*

The time complexity of the algorithm represents by the running time, which is used to evaluate the performance of the algorithm. TABLE XVII shows the running time of the six cases of the three algorithms. The running time of the proposed MONWOA method is longer than MOPSO algorithm, but shorter than MOWOA method.

In order to further verify the superiority of the proposed algorithm, the Wilcoxon signed ranks method is adopted. Furthermore *SP* and *GD* performance indicators were selected to evaluate MONWOA, MOWOA and MOPSO method. The *SP* and *GD* indicators are employing to evaluate the distribution and convergence of Pareto optimal solution set.

1) Wilcoxon signed ranks method

In the Wilcoxon signed ranks method, it adds the rank of the absolute value of the difference between the observation value and the center position of the null hypothesis according to different signs as its test statistic. The optimal compromise of F_{cost} and E_e of MONWOA are compared with the ones of other algorithms. The Wilcoxon test results are exhibited in TABLE XVI.

TABLEXVI
WILCOXON TEST RESULT FOR CASE1(REF=MONWOA(F_{cost}=621.12, E_e=0.1972))

Method	F_{cost} (\$/h)	T	E_e (ton/h)	T
MOWOA	622.08	+	0.1973	+
MOPSO	622.54	+	0.1975	+
MBFA[21]	629.56	+	0.2080	+
SPEA[5]	629.59	+	0.2079	+
MOPSO[22]	626.10	+	0.2106	+
NSBF[15]	621.71	+	0.1983	+
DE[13]	626.03	+	0.1979	+
NSGA-II[18]	625.36	+	0.1984	+
		R^+=36 R^-=0 p=0.0117		R^+=36 R^-=0 p=0.0117

The values of p (p=0.0117 and 0.0117 in system 1 for case1) are all far less than the significance level (α=0.05), the optimal compromise of F_{cost} and E_e are all more optimized by our proposed MONWOA method, a conclusion can be drawn that the MONWOA's outperformance is significant.

2) SP

The *SP* indicator has been defined in (30), it evaluates the distribution of the Pareto optimal solution set by calculating the variance range of the neighbor solution. The meaning of the specific symbols in the following formula are clearly stated in the literature [38].Which can be expressed as follows:

$$SP = \sqrt{\frac{1}{Nr-1}\sum_{i=1}^{Nr}\left(\frac{1}{Nr}\sum_{i}^{Nr} d_i - d_i\right)^2} \tag{30}$$

$$d_i = \min_{j=1,2,\cdots Nr}\left(\sum_{k=1}^{M}\left|O_k^i - O_k^j\right|\right) \tag{31}$$

Boxplot is a commonly technique for data analysis, it can intuitively represent the median and abnormal values of data. Fig. 16 shows the boxplots of *SP* indicator for MONWOA, MOWOA and MOPSO among case1-6. It clearly shows that the proposed algorithm MONWOA has a lower value of *SP* than two comparison method, which indicate that it can obtain the Pareto solution with better distribution. The average and standard deviation of *SP* index are shown in TABLE XVIII. As we can see, the value of average and standard deviation of MONWOA are better than the other two algorithms, it also shows that the MONWOA method has certain competitive advantages in these cases.

3) GD

The *GD* indicator is used to describe the distance between the Pareto optimal solution obtained by the algorithm and the real Pareto solution of the problem, the *GD*=0 indicate that all the solution is the real Pareto solution [38, 44]. Which can be described as follow:

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{32}$$

where n represents the number of all solutions, d_i is the distance between the ith solution and the true Pareto solution.

The boxplots of *GD* for three method among case1-6 are shown in Fig. 17, it intuitively indicates that the MONWOA can obtain the optimal Pareto solution set closest to the true Pareto solution, which dominates the MOWOA and MOPSO method. TABLE XIX shows the value of mean and standard deviation of three method. It can be seen that the proposed method can get a lower value of mean and standard deviation than the other comparison method. It shows that the MONWOA algorithm has better stability in handling the EED problem.

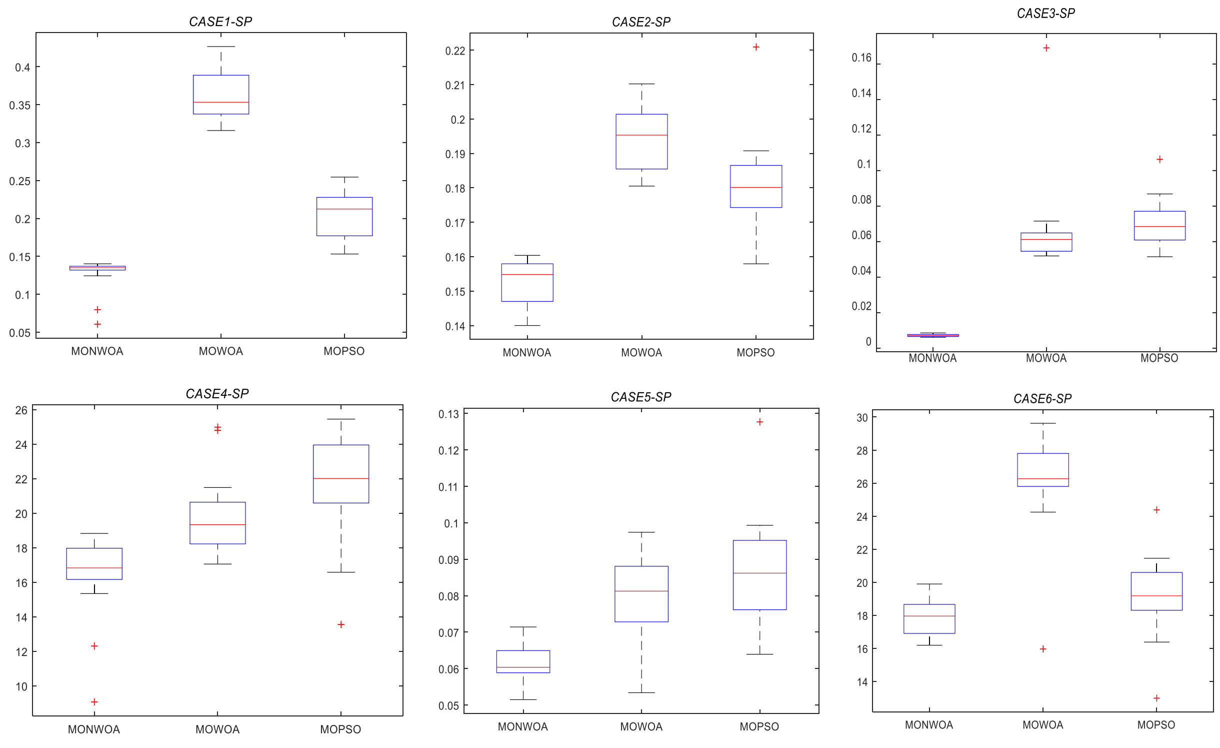

Fig. 16. Boxplots of *SP* for MONWOA, MOWOA and MOPSO method

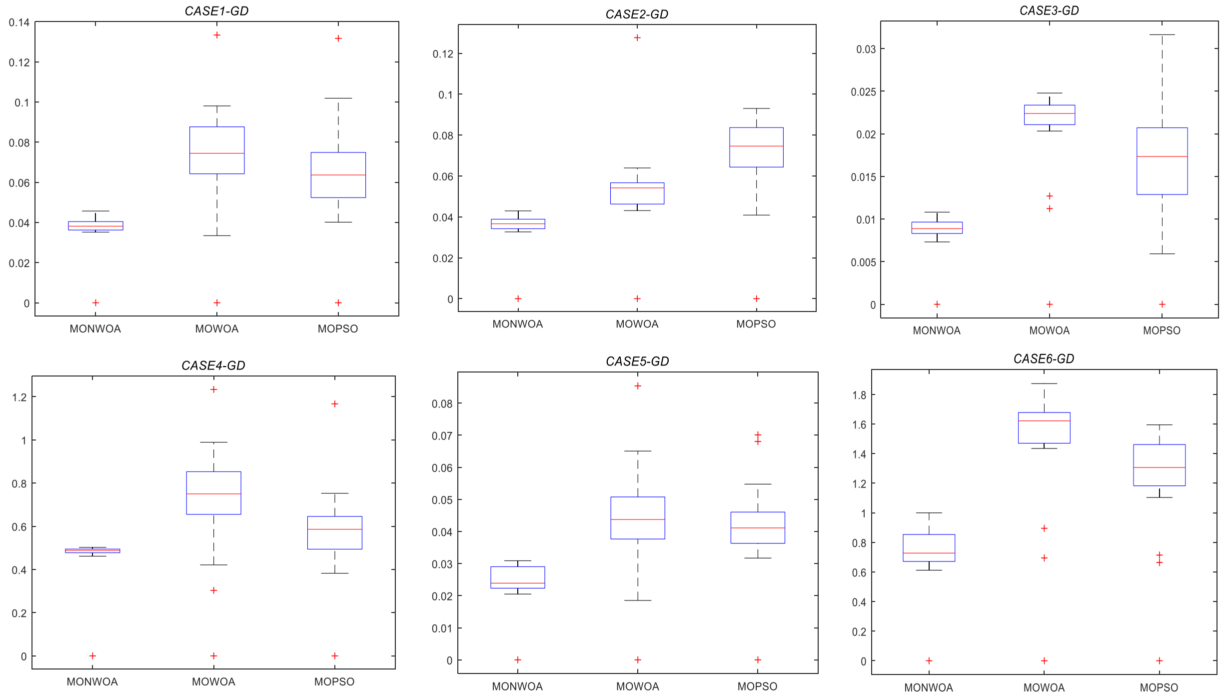

Fig. 17. Boxplots of GD for MONWOA, MOWOA and MOPSO method

TABLE XVII
The Average Running Time (sec) of MONWOA, MOWOA and MOPSO Method

algorithm	case1	case2	case3	case4	case5	case6
MOPSO	225.80	229.06	227.56	340.84	345.95	1243.26
MONWOA	234.24	237.78	230.44	348.65	354.81	1281.54
MOWOA	241.56	245.38	243.84	359.23	367.42	1321.92

TABLE XVIII
THE MEAN AND STANDARD DEVIATION OF *SP* FOR MONWOA, MOWOA AND MOPSO METHOD

Indicator	Test Case	MONWOA		MOWOA		MOPSO	
		mean	deviation	mean	deviation	mean	deviation
SP	Case1	0.13064	0.01704	0.36136	0.03139	0.20448	0.03017
	Case2	0.15237	0.00644	0.19496	0.00947	0.18017	0.01128
	Case3	0.00719	0.00066	0.06404	0.02074	0.07026	0.01212
	Case4	16.6669	1.91010	19.6055	1.97604	21.8522	2.67388
	Case5	0.06145	0.00524	0.08047	0.01012	0.08629	0.01291
	Case6	17.8431	1.08477	26.4510	2.49917	19.2825	1.95756

TABLE XIX
THE MEAN AND STANDARD DEVIATION OF *GD* FOR MONWOA, MOWOA AND MOPSO METHOD

Indicator	Test Case	MONWOA		MOWOA		MOPSO	
		mean	deviation	mean	deviation	mean	deviation
GD	Case1	0.03759	0.00765	0.07396	0.02309	0.06440	0.02238
	Case2	0.03574	0.00725	0.05336	0.01802	0.07157	0.01833
	Case3	0.00875	0.00186	0.02108	0.00497	0.01607	0.00718
	Case4	0.47001	0.08934	0.73718	0.22209	0.58026	0.18142
	Case5	0.02468	0.00580	0.04365	0.01450	0.04159	0.01217
	Case6	0.74925	0.18586	1.51665	0.37507	1.24684	0.31512

V. CONCLUSION

In order to deal with EED problems more effectively and ensure the economic, environmental and safe operation of the power system, a novel MONWOA is proposed in this paper. The MONWOA method obtains a better Pareto solution by balancing exploration and exploitation of the algorithm and the handling method of constraints. Six experiments carried on IEEE 30 bus, 57 bus and 118 bus systems have proved the effectiveness of the three algorithms in dealing with EED problems. Compared with MOWOA and MOPSO methods, the results of Pareto fronts and the BCS show the superiority of WONWOA to solve EED problems. Furthermore, the result of *SP* and *GD* indicates, it is obvious that MONOWA method were outstanding than MOPSO and MOWOA method.

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