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Chaos Firefly Algorithm With Self-Adaptation Mutation Mechanism for Solving Large-Scale Economic Dispatch With Valve-Point Effects and Multiple Fuel Options

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ABSTRACT This paper presents a new metaheuristic optimization algorithm, the firefly algorithm (FA), and an enhanced version of it, called chaos mutation FA (CMFA), for solving power economic dispatch problems while considering various power constraints, such as valve-point effects, ramp rate limits, prohibited operating zones, and multiple generator fuel options. The algorithm is enhanced by adding a new mutation strategy using self-adaptation parameter selection while replacing the parameters with fixed values. The proposed algorithm is also enhanced by a self-adaptation mechanism that avoids challenges associated with tuning the algorithm parameters directed against characteristics of the optimization problem to be solved. The effectiveness of the CMFA method to solve economic dispatch problems with high nonlinearities is demonstrated using five classic test power systems. The solutions obtained are compared with the results of the original algorithm and several methods of optimization proposed in the previous literature. The high performance of the CMFA algorithm is demonstrated by its ability to achieve search solution quality and reliability, which reflected in minimum total cost, convergence speed, and consistency.

INDEX TERMS Economic dispatch, firefly algorithm, multiple fuel options, valve-point effects.

I. INTRODUCTION

Facing the reduction of energy reserves and environmental degradation due to excessive use of conventional fuels, the Economic Dispatch (ED)problem has become the focus of researchers [1], [2]. For ED, the main objective is to find the operating point leading to optimal generator output power so as to minimize the operating cost while meeting all the physical and operational constraints [3]. The ED is considered as an important economic operation optimization problem in power system. Under normal circumstances, the objective of the problem can be modeled as a convex cost function whose satisfactory solution can be found at a small cost. However, when actual characteristics of real power systems such as prohibited operating zones, transmission loss, ramp rate limits, and multiple fuel options are taken into consideration, the cost function becomes highly quadratic, non-smooth, non-convex, and multi-modal [4]–[7]. Solving such a problem is no longer an easy task. Ignoring, approximating or inaccurately handling these characteristics may lead to erroneous results of the ED problem and significant economic losses or accidents [8]–[10]. In the published article on this issue, many methods have been applied to deal with the ED problem. These methods can be divided into two categories as 1) classical optimization methods and 2) metaheuristic optimization methods.

Classical optimization technologies include Lagrange relaxation [11], λ-iteration method [12] and nonlinear programming [13],etc. The advantages of the classical optimization methods are the guarantee of optimization convergence, the lack of parameters requiring special settings depending on the characteristics of the problem and computational efficiency; however, they deal mainly with convex cost functions because this kind of optimization method is based on the gradient theory, which has powerful ability when facing smooth and continuous functions. Regrettably, practical features of real power system form a complex non-convex model of ED problem with extremely high complexity and the application of the classical optimization methods is faced with difficult-to-handle restrictions. In order to improve the ability of classic optimization algorithms to solve ED problems, some improved algorithms have been proposed in recent years. Examples of this include, the dimensional steepest decline method [13] and Big-M method [14]. Although these methods show a stronger ability to solve non-convex objective functions, the tradeoff introduces additional variables that need additional computation. Its performance, therefore, is increasingly worsened by the dimension of the problem.

Many modern metaheuristic optimization methods, such as the genetic algorithm (GA) [15], the particle swarm optimization (PSO) [16], [17], and Differential Evolution (DE) [18] have been developed and utilized successfully to solve the ED problem due to their ability to find global or near-global solution of a nonconvex optimization problem. Furthermore, modified and improved versions of the metaheuristic methods, with the intention of improving the convergence and global optimum search capability of the original algorithms, have been proposed for dealing with the ED problem. Examples of these improved versions include, conventional genetic algorithm with multiplier updating (CGA-MU) [19], fuzzy adaptive particle swarm optimization (FAPSO) [20], new global particle swarm optimization (NGPSO) [21] and shuffled differential evolution (SDE) [22]. Also, hybrid methods, generally combined with two methods, one method is used as the primary search tool, while the other is used to fine-tune the search process, like combined DE and PSO algorithms [23], hybrid chemical reaction optimization with differential evolution(HCRO-DE) [24], have been applied for solving the ED problem and achieved satisfactory effect by improving the global search capability while using fast computational analysis. However, for hybrid methods, how to determine the integration points between methods and balance the positive and negative effects of methods is a headache for practitioners.

Many of the metaheuristic optimization methods reported in previous literature have a disturbing limitation. They require adjustment of the algorithm parameters based on the particular problem before they can be applied. When the parameters of the algorithm are determined, a satisfactory result may be obtained in a test system, but at the same time, satisfactory results may not always be obtained in another test system. Changes in system load or unit constraints will lead to the need for algorithm parameter adjustment, which is a difficult problem. To solve this problem, the mechanism for adaptively adjusting parameter values must be added to the algorithm. However, any metaheuristic optimization method that adds a parameter to the self-tuning mechanism may obtain the result of reduced computational efficiency because additional computational effort is required because of the need for adjusting algorithm parameters when solving the main optimization problem. Because of this reason, only the method that adds self-adjusting parameter is highly efficient. A novel high efficiency optimization algorithm, firefly algorithm(FA), has been proposed in [25]. Yang [26] showed that the FA could compete and outperform many of metaheuristic optimization algorithms in many aspects, like convergence rate, numerical stability, and calculation accuracy. In fact, the FA has proven to have a great advantage over other recently developed algorithms in solving a variety of optimization problems, for instance the dynamic economic dispatch problem of power systems [27] and the optimal chiller loading design [28]. The author of the firefly algorithm, Yang, has successfully applied the FA to solve ED problem of small and medium power systems in [29], but the ED problem consider multiple fuel options was not considered in the study, which is the contribution of this paper.

In this paper, FA is applied for solving non-convex and complex ED problem of five (medium and large) power systems considering actual characteristics such as prohibited operating zones, transmission loss, ramp rate limits, and multiple fuel options. Large-scale test systems with both multiple fuel options and valve-point effects are included. Furthermore, after carefully considering different components in designing the algorithms, two modifications are proposed to significantly increase the FA efficacy. The proposed modifications are to replace the fixed-parameters of the FA with a new dynamic adjustment of parameters in the FA, and to add a new powerful self-adaptive mutation mechanism while replacing the parameter of the mechanism as a fixed value. An improved version of firefly algorithm, called chaos mutation firefly algorithm(CMFA), is thus generated. In addition, in most of metaheuristic optimization methods, the equality constraints are usually handled using the penalty-function technique, which makes it difficult to generate feasible solutions and maintain feasibility after crossover and mutation operations, resulting in no good result. Thus, a constraint handling scheme was proposed for correcting a solution in infeasible domain region to the space of feasible region without adding any additional goal on the objective function. This mechanism not only has the ability to handle constraints, but also has the ability to prevent premature convergence by introducing a diversity strategy, which ensures that the fireflies always be a feasible solution to the problem. Indeed, the proposed measures have positive and reliable effect on the convergence of the algorithm and the quality of the solution provided by algorithm. Results of the proposed technique for solving the known ED problems are compared with other algorithms that are recently published. The numerical analysis of results proves the superiority performance of the proposed method over the other methods mentioned in this paper.

The rest of this paper is organized as the follows: Section 2 presents the ED problem formulation. Section 3 introduces the proposed methodology. Application of CMFA for solving ED shown in Section 4. Section 5 introduces the simulation results and discussion, followed by the conclusions and future work in Section 6.

II. MATHEMATICAL FORMULATION OF THE ED PROBLEM

A. OBJECTIVE FUNCTION

The mathematical model of the ED problem of considering different conditions can be modeled as different objective functions. A comprehensive mathematical model of the ED problem can be presented as [30]:

$$\text{Minimize: } F_C = \sum_{i=1}^{NG} F_i(P_i). \tag{1}$$

where, P_i represents the power output of ith generator; F_C denotes the total generation cost; $F_i(P_i)$ are generation cost of unit i; NG meaning the total number of generator.

The objective function as a quadratic polynomial is convex when neglecting the VPE. It can be shown as:

$$F_i(P_i) = a_i * P_i^2 + b_i * P_i + c_i. \tag{2}$$

where, a_i(\$/MW^2), b_i(\$/MW), c_i(\$) are the cost coefficients of the ith unit.

Furthermore, the objective function becomes non-convex by adding a sinusoidal term to the quadratic objective function when considering the VPE and can be modeled as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i(f_i \sin(P_i^{min} - P_i))| \tag{3}$$

where, e_i(\$) and f_i(rad/MW) are the valve-point coefficients of generator i, P_i^{min} is the minimum power output of the ith unit.

If generators with multiple fuel options and the VPE are also considered, the objective function can be written as follows:

$$F_i(P_i) = a_{ij} P_i^2 + b_{ij} P_i + c_{ij} + |e_{ij}(f_{ij} \sin(P_{ij}^{min} - P_i))| \quad \text{if } P_{ij}^{min} \le P_i \le P_{ij}^{max}. \tag{4}$$

where, a_{ij}(\$/MW^2), b_{ij}(\$/MW), c_{ij}(\$) are the cost coefficients, and e_{ij}(\$), f_{ij}(rad/MW) are the valve-point coefficients of the ith unit using fuel type j; P_{ij}^{min} and P_{ij}^{max} are the lower bound and upper bound of the ith unit using the jth fuel type, respectively.

The objective function is subject to the following constraints.

B. POWER BALANCE CONSTRAINTS

The sum of generator output powers must be equal to the sum of load demand and transmission loss.

$$\sum_{i=1}^{NG}(P_i) = P_{load} + P_{loss}. \tag{5}$$

where P_{load} and P_{loss} are the load demand and the transmission loss, respectively. P_{loss} is calculated by B matrix coefficients as follow:

$$P_{loss} = \sum_{i=1}^{NG}\sum_{i=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00}. \tag{6}$$

where B_{ij}, B_{0i} and B_{00} are the loss coefficients.

C. POWER OUTPUT AND PROHIBITED OPERATING ZONES LIMITS

In realistic power systems, the output of the generator should be within its output range. Also there are some prohibited operating zones for the generator due to the VPE. The limits can be described as follows:

$$P_i = \begin{cases} P_i^{min} \le P_i \le P_{i,1}^l; \\ \ldots \\ P_{i,z-1}^u \le P_i \le P_{i,z-1}^l; \quad z = 2, 3, \ldots, N \\ P_{i,z}^u \le P_i \le P_i^{max}. \end{cases} \tag{7}$$

where P_i^{min} and P_i^{max} are the minimum and maximum output powers of the ith unit, and N is the total number of prohibited operating zones for unit i. $P_{i,z}^u$ and $P_{i,z}^l$ presented upper limit and lower limit the zth prohibited zone of unit i, respectively.

D. RAMP RATE LIMITS

In practice, the output of the generator cannot be adjusted instantaneously without limitation. The operating range of each generator is restricted by their corresponding ramp-up and ramp-down constraints, which can be formulated as follow:

$$\max(P_i^{min}, P_i^0 - DR_i) \le P_i \le \min(P_i^{max}, P_i^0 + UR_i). \tag{8}$$

where, P_i^0 is power output of the ith unit at the previous time interval; DR_i and UR_i are down-ramp rate and upper-ramp rate limitation of the ith generator, respectively.

III. PROPOSED METHODOLOGY

A. FIREFLY ALGORITHM

The FA is categorized as one of the population-based algorithm proposed by Yang (2008) [25]. It simulates the social behavior of the flashing characteristics of fireflies. For the FA, a firefly of population means a potential solution of the optimal problem. In terms of the search space, a firefly represents a point that moves in the search space with the optimization process. The structure of each firefly in the candidate solution for solving ED problem, in this paper, can be described as the following:

$$X_i = [P_{i,1}, P_{i,2}, \ldots, P_{i,D}]; \quad i = 1, 2, \ldots, N. \tag{9}$$

where N is the total number of population, and D is the dimensionality of the problem. In this paper, it if defined as $D = NG$.

The higher the light intensity of a firefly, the greater its attractiveness to other nearby fireflies, and the attractiveness β of a firefly can be defined as:

$$\beta(r) = \beta_0 e^{-\gamma r^2}. \tag{10}$$

where γ is absorption coefficient and commonly set to 1 [26]. β_0 is the maximum attractiveness obtained when $r = 0$; r is the Cartesian or Euclidean distance between the mth and nth fireflies, which can be written as:

$$r_{mn}^k = \sqrt{\sum_{i=1}^{NG}(X_{m,i}^k - X_{n,i}^k)^2}; \quad m, n = 1, 2, \ldots, N. \tag{11}$$

where $X_{m,i}^k$and $X_{n,i}^k$ are the ith variables of the kth generation of mth and nth fireflies, respectively.

In the previous study, it was found that when β changes according to Eq.10, the resulting effects could not achieve the desired effect. So the researchers proposed a variety of transformation strategies for it. The most obvious strategy was proposed by Fister *et al.* [31] and can be described as:

$$\beta = \beta_{min} + (\beta_{max} - \beta_{min})e^{-\gamma r^2}. \tag{12}$$

where β_{max} and β_{min} are set to 1 and 0.2, respectively.

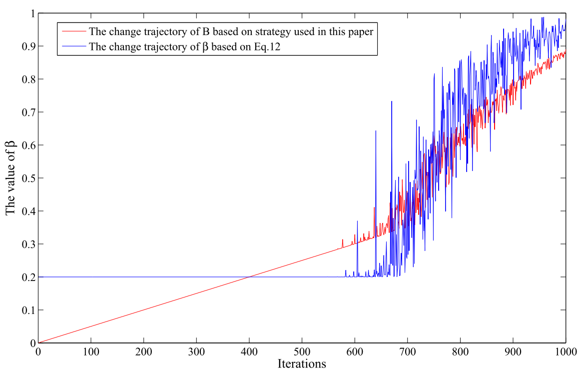

Fig. 1. **Change of β based on different strategies.**

However, there are potential pitfalls. As we can see from Fig.1, Eq.12's strategy keeps β's value at the beginning of 0.2, and quickly increases to 1 after reaching a certain number of iterations. The value of β stays at 0.2 for too long, and increase from 0.2 to 1 too quickly. This will have an adverse influence on the optimization. Therefore, improved strategy based on Equation 12 was proposed, which can be written as:

$$\beta = (\beta_{min} + (\beta_{max} - \beta_{min})e^{-\gamma r^2}) \times (\frac{k}{K_{max}}). \tag{13}$$

where β_{max} and β_{min} are set to 0.9 and 0.4, respectively. k and K_{max} represent the current number of iterations and the maximum number of iterations, respectively.

Figure 1 shows the effect of the proposed strategy. It can be clearly seen that, compared to Eq.12, the increase speed of β is significantly slower, which increases the ability to escape from the local optimum; and the later change is more gradual, which can increase the speed of convergence.

Similar to other evolutionary algorithms, in the firefly algorithm, the fireflies update their position by moving towards the brighter fireflies which means better position in search space, and the modified position can be formulated as:

$$X_m^{k+1} = \begin{cases} X_m^k + \beta^k(X_n^k - X_m^k) + \alpha^k(rand(.)_{1\times D} - 0.5), \\ \qquad if\ F_C(X_n^k) < F_C(X_m^k); \\ X_m^k, \quad otherwise. \end{cases} \tag{14}$$

where α is the randomness parameter which commonly selected in the rang $[0, 1]$, and *rand* represents a random number generated from a uniformly distributed set between 0 and 1.

The framework of the FA is given in Algorithm1.

Algorithm 1 The Standard FA

Generate an initial population $X = (X_1^k, X_2^k, \ldots, X_N^k)$ and set $k = 0$.
Define initial value of α and γ.
Evaluate the fitness values $F(X_i^k)$ of all N initial fireflies.

while $k < K_{max}$ **do**
  for $i = 1$ to n **do**
    for $j = 1$ to n **do**
      if $F(X_j^k) < F(X_i^k)$ **then**
        Update position of X_i^k using the formula in (14).
        Evaluate the fitness values of $X_{i,move}^k$
        if $F(X_{i,move}^k) < F(X_i^k)$ **then**
          $X_i^{k+1} = X_{i,move}^k$; else,$X_i^{k+1} = X_i^k$.
        end if
      end if
    end for
  end for
  $k = k + 1$.
end while
Output the Optimum solution X_{best}.

B. CHAOS MUTATION FIREFLY ALGORITHM

Because of its advantages, the application of FA to solve the problems in various aspects of the power system has aroused great concern Simple concept and low number of parameters need for tuning are its obvious advantages, Having the ability to seek global optimums and local optima at the same time makes it highly applicable. However, it also has a vexing defects. For instance, premature convergence or convergence to an inappropriate position often occurs because the algorithm falls into a local optimum. However, the existing mechanism of diversifying populations does not have the ability to help it escape from the local optimum. Even if the algorithm can successfully avoid the local optimum, the cost is an unbearable computational burden. When the FA is applied to solve constrained optimization problems, its performance depends largely on the selection of control parameters. Also, the population diversity has a great effect on computational efficiency and convergence rate. In addition, it is obvious that an appropriate constraint handling mechanism can improve the performance of the algorithm. Therefore, special care in redesigning the algorithm based on these considerations has been taken in this paper. The control parameters and mutation mechanism are discussed in the following few subsections.

1) DYNAMIC ADJUSTMENT OF α AND γ

As we know, a powerful optimization algorithm, not only have the ability to effectively exploit the current solutions that have good fitness, but also has a strong ability to explore the unknown fields in the search space. The random movement factor, α, controls the range of random search of firefly, and generally determined in the range [0, 1], has a huge impact on the balance between the ability of algorithm exploration and exploitation in search space. Too large value of an α makes the random search range of solution too large to cause convergence difficulties and the smaller α will trap firefly in the local optimum. The absorption coefficient γ controls the decrease of light intensity and commonly set to 1 [26]. It is a fact that FA's parameter control deeply influences its performance, and how to select the appropriate parameter is an intractable optimization problem..

Numerous studies showed that the performance of the evolutionary optimization algorithms are improved when chaotic sequences were used [32]. Therefore, after testing different chaotic operator, a dynamic adjustment mechanism base on chaotic sequences for the random movement factor is deployed in this paper, opposed to monotonically decreased as the iterations progress in basic firefly algorithm, parameter α of the proposed methods also being variety decreased from its initial value based on chaotic formula with optimization process, which can be calculated as:

$$\alpha_c^k = x^k \times \alpha_l^k. \tag{15}$$

where, α_c^k and α_l^k are the chaotic-based random movement factor and the random movement factor with linear decrease at iteration k. The value of α_l^k is decreased linearly from a set initial value to zero, and x^k is the chaotic parameter at iteration k, which produced by a so-called sinusoidal iterator [32], can be represented as the following:

$$x^{k+1} = sin(\pi \times x^k). \tag{16}$$

in this paper, x^0 was set to 0.7.

The chaotic-based α we introduced enhance the searching capability and efficiency of FA and illustrated in the numerical results. Also, the performance of α in dynamic adjustment mechanism is shown in Fig. 2 for better understanding.

As for the absorption coefficient γ, a fixed value is replaced with a variable that needs to be optimized, and then it was added to the firefly as a variable in the candidate solution vector [27]. The new structure of solution vector can be written in the following form:

$$X_i = [P_{i,1}, P_{i,2}, \ldots, P_{i,D}, \gamma_i], \quad i = 1, 2, \ldots, N. \tag{17}$$

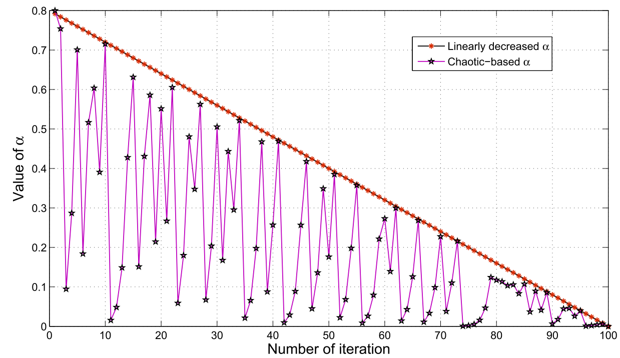

Fig. 2. Two change trajectories of α.

2) ADAPTIVE MUTATION MECHANISM

In the previously mentioned methods, inappropriate convergence and local optima traps may still be impossible to avoid. Also, each enhancement of the algorithm optimization will become very slow before the global optimal solution is obtained. We have noticed that the optimization mechanism of FA itself is simple and efficient, even adding additional strategies that increase search power will not have an unacceptable negative impact on the computational efficiency of the algorithm. Therefore, a new powerful mutation mechanism, which mainly for enhancing the ability of the algorithm to exploit the unknown area of the search space, is introduced to solve the afore-discussed problems, thus the ability of the FA to eventually be enhanced.

Since mutation has been applied to the algorithmic process, many mutation operators have been proposed. Unfortunately, there exists no single optimal solution to all problems. Therefore, a new powerful mutation strategy that contains two mutation operators is considered in this paper. First, three vectors m_1 to m_3 obtained from solution are randomly selected as $m_1 \neq m_2 \neq m_3 \neq m$. Consequently, a mutant firefly X_m^{mut} is generated as the following:

$$X_m^{mut} = \begin{cases} X_{m_1}^k + F_m(X_{m_2}^k - X_{m_3}^k), \\ \qquad if\ rand_1 \leq Cr_m\ and\ rand_2 \leq 0.5; \\ X_m^k + F_m((X_{m_1}^k - X_{m_3}^k) + (X_{besk}^k - X_{m_2}^k)), \\ \qquad if\ rand_1 \leq Cr_m\ and\ rand_2 > 0.5; \\ X_{m_1}^k, \quad otherwise. \end{cases} \tag{18}$$

where, $rand_1$ and $rand_2$ are random numbers generated from a uniform distribution in the interval [0, 1]. F_m is the scale factor and Cr_m is the crossover rate. They should be fixed values, but picking the optimum values for a specific problem is tricky. Thus, a self-adaptation strategy was introduced to select the most appropriate value. For each firefly in the search space, with two control parameters (F and Cr) of the mutation mechanism. In the beginning, $\vec{F} \in N(0.5, 0.1)$ and $\vec{C}r \in N(0.5, 0.1)$. $N(0.5, 0.1)$ means a normal distributions whose mean equals to 0.5 and standard deviation is 0.1. Consequently, F_m and Cr_m in (18) are generated as described below:

$$F_m = \begin{cases} \vec{F}_{m_1} + rand_1(\vec{F}_{m_2} - \vec{F}_{m_3}), & if\,(rand_2 < \delta); \\ rand_3, & otherwise. \end{cases} \tag{19}$$

$$Cr_m = \begin{cases} \vec{C}r_{m_1} + rand_4(\vec{C}r_{m_2} - \vec{C}r_{m_3}), & if\,(rand_5 < \delta); \\ rand_6, & otherwise. \end{cases} \tag{20}$$

where $\vec{F}_{m_\lambda}$ and $\vec{C}r_{m_\lambda}$ $(\lambda = 1, 2, 3)$ are parameters of corresponding firefly $(X^k_{m_\lambda})$ in $\vec{F}$ and $\vec{C}r$, respectively; and $rand_\mu \in (0, 1)(\mu = 1, 2, \ldots, 6)$, are generated using uniform distribution of 0 to 1. The value of δ, in this paper, set to 0.75 according to the test, appropriate range of F_m and Cr_m is 0.1 to 1, so, if their value is outside this range, it is truncated to 0.1 and 1, respectively [33].

The proposed mutation mechanism followed by a greedy selection process is such that, the brightest one between the current firefly (X^k_m) and the mutant firefly(X^{mut}_m), will replace the position of the current firefly and become the new offspring of the fireflies. The process can be written as:

$$X^{k+1}_m = \begin{cases} X^{k,mut}_i, & if\,(F_C(X^{k,mut}_i) \le F_C(X^k_m)); \\ X^k_m, & otherwise. \end{cases} \tag{21}$$

It is important to point out that the value of $\vec{F}$ and $\vec{C}r$ are also updated with the optimization process. If the mutant firefly is better than the current firefly, then, $\vec{F}_m = F_m$ and $\vec{C}r_m = Cr_m$.

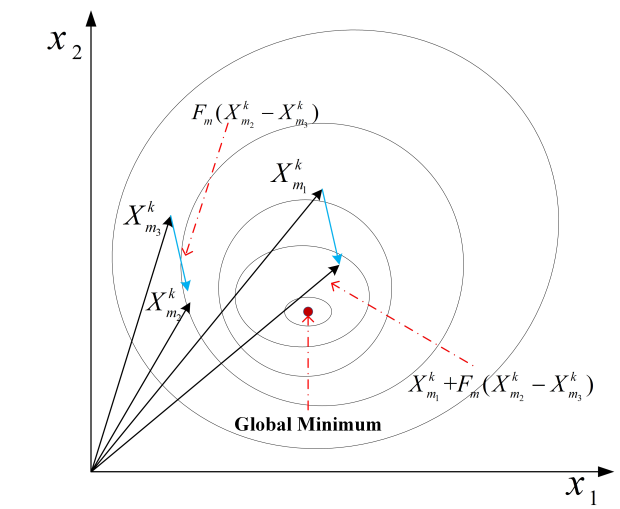

Fig. 3. A schematic diagram of the role of the first mutation operator.

The main effect of the first mutation operator is to speed up the convergence, as shown in Fig. 3. The main purpose of the second one is to diversify population. The point behind using two multi-operators instead of more is to control the computing burden within a reasonable range. The main function of this mechanism is to provide better information to the main algorithm of the proposed algorithm, rather than determine the optimization process of algorithm.

The framework of the CMFA is given in Algorithm2.

Algorithm 2 The Proposed CMFA

```
Generate an initial population (X=X_1^k, X_2^k, ..., X_N^k) and
  set k = 0.
Define initial value of α, F and Cr.
Evaluate the fitness values F(X_i^k) of all N initial fireflies.

while k < K_max do
  for i = 1 to N do
    for j = 1 to N do
      if F(X_j^k) < F(X_i^k) then
        Update position of X_i^k using the formula in
        (14).
        Evaluate the fitness values of X_i^{move,k}
        if F(X_i^{move,k}) < F(X_i^k) then
          X_i^k = X_i^{move,k};
        else
          X_i^{k+1} = X_i^k;
        end if
      end if
    end for
  end for
  for i = 1 to N do
    Generate mutant firefly X_m^mut using the formula in
    (18).
    Evaluate the fitness values of X_m^mut using the for-
    mula in (1).
    if F(X_m^{mut,k}) < F(X_i^k) then
      X_i^{k+1} = X_m^{mut,k};
    else
      X_i^{k+1} = X_i(k);
    end if
  end for
  Update α using the formula in (15).
  Update F_m and Cr_m according to (19)-(20).
  k = k + 1.
end while
Output the Optimum solution X_best.
```

IV. IMPLEMENTING CMFA FOR SOLVING ED PROBLEM

In this section, the steps of the proposed CMFA for solving the ED problems under various constraints of power system will be described. But before that, various constraints, especially equality constraints, will be described. The ED problem is a nonlinear constrained optimization problem, which contains a large amount of equality and inequality constraints. Thus, the initial fireflies are hard to satisfy all the constraints due to the fact that they are randomly generated, even though one may satisfy all the constraints, it is difficult to maintain it feasible after updating its position. Generally, there are two strategies to deal with constraints of the ED problem, one is to use a penalty function which is achieved through adding an extra objective function for punishing violations of constraints on the original objective function, and the other way is to generate solutions that satisfy all constraints by some strategies and maintain the feasibility of the solution in the optimization process so that optimization is only done in the feasible region. The first method is simple and can maintain population diversity but not adequate for handling constraints. The second method will lose a certain population diversity but with high efficiency in finding feasible solution. Therefore, in this paper, the latter method is chosen since mutation mechanism has been applied for diversifying the population. Also, the constraints handling mechanism we used, which will be described in detail next, will also improve the diversity of the population simultaneously.

Implementing the CMFA for solving ED problem can be briefly described via the following steps:

1) Generate initial individual $X_i (i = 1, 2 \ldots, N)$, considering ramp rate limits:

$$X_i = P_{i,t}^{min} + rand(.)(P_{i,t}^{max} - P_{i,t}^{min});$$
$$\begin{cases} P_{i,t}^{min} = max(P_i^{min}, P_i^0 - DR_i) \\ P_{i,t}^{max} = min(P_i^{max}, P_i^0 + UR_i) \end{cases} \tag{22}$$

where $P_{i,t}^{max}$ and $P_{i,t}^{min}$ are the maximum and minimum output powers of the ith unit in tth, respectively.

2) Check whether the solution satisfies the other system constraints such as the prohibited operating zones, if the output of a unit(P_i) fall in a prohibited zone of $[L, U]$, its value will be determined by the following way:

$$P_i = \begin{cases} L, & if\ (P_i - L) < (U - P_i); \\ U, & otherwise. \end{cases} \tag{23}$$

3) To make solutions satisfy equality constraints, the feasibility of a solution is checked as:

$$|\sum_{i=1}^{NG}(P_i) - (P_{load} + P_{loss})| < \varepsilon. \tag{24}$$

where, ε is a tolerance limit factor, the value of ε, in this paper, from a larger initial value gradually reduced to a small final value set to 10^{-5}(an acceptable accuracy [34]). The way ε changes can be given as [35]:

$$\varepsilon(0) = \phi(x_\theta) = \varepsilon_\theta^{intial}; \tag{25}$$
$$\varepsilon(k) = \begin{cases} \varepsilon(0)(1 - \dfrac{k}{T_c})^{cp}, & if\ 0 < k < T_c; \\ 10^{-8}, & k \geq T_c. \end{cases} \tag{26}$$

where x_θ is the top θth individual and $\theta = 0.4N$. cp is a control parameter of the θ level and set to 5 in this paper. With the number of iterations k increase to the control generation T_c, The θ level has been updated. There are no solutions that violates the constraints in the population when the control generation is reached. The value of T_c is 150 in this paper.

If the value of the power deviation is larger than the preset value, a slack unit P_s ($s = 1, 2, \ldots, NG$) that choose randomly from the unit poor was used to balance the power deviation follow the following rules:

$$\begin{cases} P_s = (P_{load} + P_{loss}) - \sum_{i=1(i \neq s)}^{NG}(P_i); \\ P_s = \begin{cases} P_{i,t}^{max}, & if\ P_s > P_{i,t}^{max}; \\ P_{i,t}^{min}, & if\ P_s < P_{i,t}^{min}. \end{cases} \end{cases} \tag{27}$$

If the power balance constraint is still not satisfied, similarly, one unit from the remaining units is randomly select as the slack generator to balance the power deviation. This process continues until all units are selected, and when the output is in a prohibited operation zone after balancing power deviation, its output can be determined using Eq.21.

4) Calculating the value of the objective function of all fireflies using the formula in Eq.1.
5) Update the position of each firefly using Eq.14, calculate fitness of new firefly as described in Step4, and select the best solution among all fireflies as P_{best}^k.
6) Generation mutant firefly using the formula in Eq.18.
7) Modify the fireflies produced by the mutation mechanism to satisfy the constraints using Step2 and Step3, and generation offspring fireflies using the formula in Eq.21.
8) Check stopping criterion. In this paper, the termination condition of the algorithm is reaching the maximum number of iterations. If the termination condition has not been reached, go to Step5. If the maximum number of iterations has been reached, stop and output the best optimization results.

Figure 4 shows the flowchart of the CMFA method.

V. SIMULATION RESULTS

For comparison with other methods, several commonly ED tests of different sizes are used. A list of state-of-the-art algorithms and abbreviations of each algorithm mentioned in this paper is showed in Table 1. There are 65 methods in Table 1. The references for these methods are also exhibited in the same table. The simulations are carried out on MATLAB (R2013a) environment using a desktop machine, which CPU is Intel Core(TM) i7 processor with 3.6 G-Hz clock frequency and 8 GB of RAM.

In order to more effectively verify the effectiveness of the proposed method of solving ED problem in large-scale systems, a few systems used by a large number of literature that involve up to 160 units are tested. Large-scale systems, like 160-unit system, make the cost function of ED problem highly non-convex and complex when both considering VPE and multiple fuel options. Thus, the ability to consistently

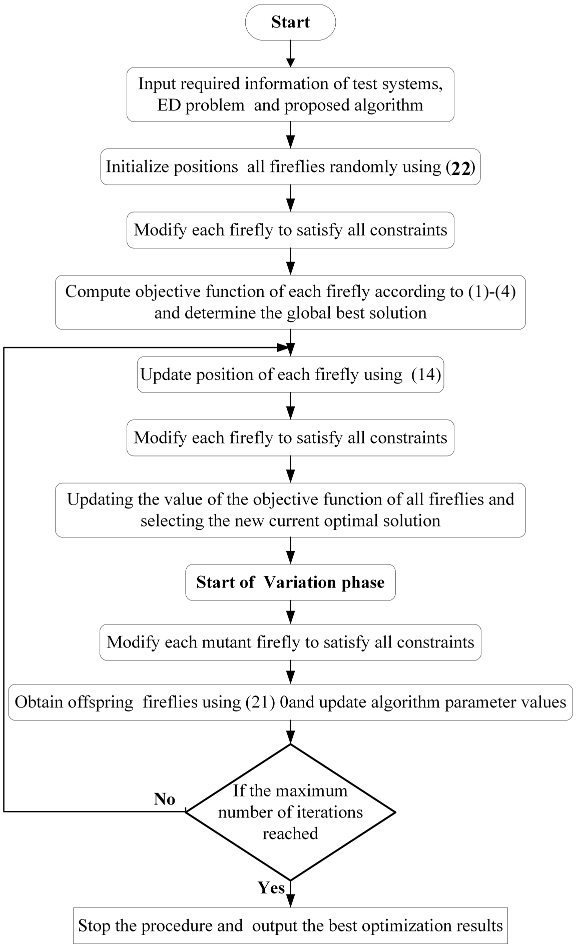

Fig. 4. **The flow chart of the CMFA algorithm.**

obtain good optimization results, will demonstrate the efficiency of the algorithm. The robustness of the proposed algorithm, in this paper, will be validated from the results of 100 independent runs for each case study. The quality of the solution provided in this paper is compared with the results provided by the most advanced methods reported in the previous literature.

In this paper, the number of populations is set to 20 for 6-unit,10-unit and 15-unit system. The maximum number of generations for these three systems are 500. The population size of 80- and 160-unit are 25, and the optimized process will stop when 1000 generations are reached.

A. CASE 1: 6-UNIT SYSTEM

The system of this case study has six thermal generators and supply a total load demand of 1263 MW. In this case study, the prohibited operating zones, the ramp rate limits, and the transmission losses are considered. The data of the test system are the same as reported in [16].

The detailed best output dispatch optimization results provided by the FA, CMFA and other 8 algorithms reported in previous literature are listed in Table 2 for comparing the differences among the results of different methods. The accuracy of the calculations of the FA and CMFA are for this case are 3.28946E-08 and 9.89811E-06, respectively.

TABLE 1. **List of algorithms mentioned in the previous literature and corresponding Acronyms.**

Algorithms	Abbreviation
Artificial bee colony algorithm	ABC[36]
Adaptive real coded genetic algorithm	ARCGA[37]
Biogeography-based optimization	BBO[38]
Backtracking search algorithm	BSA[15]
Chaotic bat algorithm	CBA[13]
Conventional genetic algorithm with multiplier updating	CGA_MU[19]
Cuckoo search algorithm	CSA[39]
Crisscross optimization algorithm	CSO[40]
Differential evolution	DE[18]
Differential harmony search	DHS[41]
Distributed Sobol PSO and TSA	DSPSO-TSA[42]
Elitist cuckoo search	ECS[43]
Estimation of distribution and differential evolution cooperation	ED-DE[44]
Exchange market algorithm	EMA[45]
Fuzzy adaptive particle swarm optimization	FAPSO[20]
Fuzzy based hybrid PSO-DE	FBHPSO-DE[46]
Fast λ-iteration method	FλI[12]
Foraging activity based predator-prey optimization algorithm	FWPPO[47]
Genetic algorithm	GA[15]
Global-best harmony search algorithm	GHS[48]
Global particle swarm optimization	GPSO[49]
Group search optimizer	GSO[50]
Grey wolf optimization	GWO[51]
Hybrid particle swarm optimization-differential evolution	HPSO-DE[46]
Hybrid shuffled frog leaping algorithm and GHS	SFLA-GHS[48]
Immune algorithm for economic dispatch problem	IA_EDP[52]
Improved fast evolutionary programming	IEEP[53]
Improved genetic algorithm with multiplier updating	IGA_MU[19]
Improved orthogonal design particle swarm optimization	IODPSO[54]
Improved particle swarm optimization	IPSO[55]
Improved random drift particle swarm optimization	IRDPSO[30]
Kinetic gas molecule optimization	KGMO[56]
Modified artificial bee colony algorithm	MABC[34]
Modified differential evolution algorithm	MDE[57]
Multi-gradient particle swarm optimization	MG-PSO[58]
Multi-strategy ensemble biogeography-based optimization	MsEBBO[59]
Modified shuffled frog leaping algorithm	MSFLA[48]
Modified Symbiotic Organisms Search	MSOS[60]
New global particle swarm optimization	NGPSO[21]
Oppositional real coded chemical reaction algorithm	ORCCRO[61]
One rank cuckoo search algorithm	ORCSA[62]
Particle swarm optimization	PSO[16]
Particle swarm optimization with chaotic sequences	CSPSO[63]
Particle swarm optimization with Gaussian mutation	PSO-GM[64]
Pseudo-inspired chaotic bat algorithm	PI-CBA[65]
PSO with the proposed constraint treatment strategy	CTPSO[63]
PSO with both chaotic sequences and crossover operation	CCPSO[63]
Quantum particle swarm optimization	QPSO[66]
Random drift particle swarm optimization	RDPSO[30]
Real coded chemical reaction algorithm	RCCRO[38]
Real-coded genetic algorithm	RCGA[67]
Synergic predator-prey optimization	SPPO[68]
Species-based quantum particle swarm optimization	SQPSO[66]
Stochastic weight trade-off particle swarm optimization	SWT_PSO[69]
Teaching-learning-based optimization with Lvy flight	TLBO[70]
Tabu search algorithm	TSA[42]
Water cycle algorithm	WCA[71]
θ-particle swarm optimization	θ-PSO[72]

TABLE 2. The system generator parameters in case 1 (6-unit system).

Power output (MW)	GA[15]	MTS[15]	PSO[16]	BSA[15]	TSA[42]	CBA[13]	FA	CMFA
P_1	474.8066	448.1277	447.497	447.4902	449.3651	447.4187	439.293500	447.5026568
P_2	178.6363	172.8082	173.3221	173.3308	182.252	172.8255	175.0455644	173.3160988
P_3	262.2089	262.5932	263.4745	263.4559	254.2904	264.0759	265.0000000	263.4717081
P_4	134.2826	136.9605	139.0594	139.0602	143.4506	139.2469	140.7740665	139.0669181
P_5	151.9039	168.2031	165.4761	165.4804	161.9682	165.6526	167.042084	165.4677395
P_6	74.1812	87.3304	87.128	87.1409	86.0185	86.7652	88.78165465	87.13305585
Total power (MW)	1276.03	1276.023	1276.01	1275.958	1277.345	1275.9848	1275.9367	1275.958177
P_{loss}(MW)	13.0217	13.0205	12.9584	12.9583	14.3449	12.9848	12.93686954	12.95818715
Total generation cost ($/h)	15459	15450.06	15450	15449.898	15451.63	15450.23	15450.50896	15449.899391

TABLE 3. Comparison of results in the 6-unit system.

Methods	Total generation cost ($/h)			Std.dev	time(s)
	Minimum	Average	Maximum		
GA[15]	15459	15469	15,469.00	NA	41.58
TSA[42]	15451.63	15462.26	15506.451	5.98	18.09
CBA[13]	15450.2381	15454.76	15518.6588	2.965	0.704
PSO[16]	15450.14	15465.83	15,492.00	6.82	10.1502
MTS[15]	15450.06	15451.17	15453.64	0.93	1.29
SPPO[68]	15450.0	NA	NA	NA	NA
DHS[41]	15449.8996	15449.9264	15449.9884	0.0204	**0.01**
BSA[15]	15449.8995	15449.9001	15449.9056	0.0010	0.56
MABC[34]	15449.8995	15449.8995	15449.8995	**6.04E-8**	NA
RDPSO[30]	15449.89	15458.01	NA	13.647	0.707
IRDPSO[30]	15449.89	15456.55	NA	10.9865	0.676
FA	15450.50896	15452.53099	15458.44268	2.048	1.965
CMFA	**15449.89939**	**15449.89941**	**15449.89944**	8.96E-06	2.724

NA: data not available.

Table 3 shows the super efficiency of the CMFA in obtaining high quality solutions over 100 independent experiments, when compared with other methods. The bold values indicate the best result provided by its corresponding method. Obviously, the CMFA can provide better solutions than other algorithms under the condition of guaranteeing stability and computing efficiency. The standard deviation of GA is smaller than the proposed algorithm in this paper, however, even the worst result of the CMFA is better than the best solution of GA, which proves the superior ability of the proposed method to avoid trapping into local optimum.

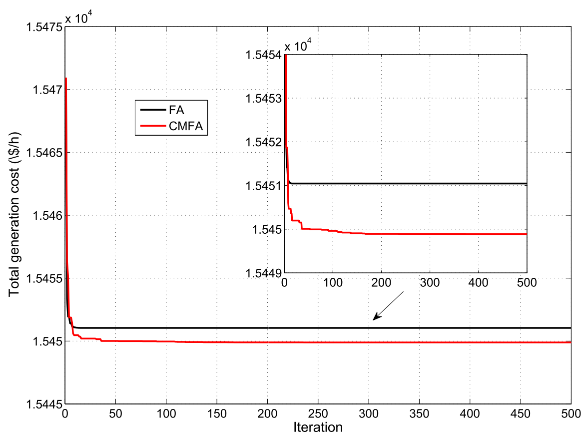

Fig. 5. Convergence characteristics of FA and CMFA (6-units system).

Figure 5 shows the convergence properties of the FA and CMFA when the optimal results are obtained in 100 independent trials. It can be seen that the FA settles at about 20 iterations and provides a value of the total generation cost of about 15451($/h); the settle iteration number of the CMFA is about 80 and achieves about 15450($/h). This indicates that the CMFA provides more accurate results, although more iterations are needed, compared to the FA. The cost value distribution of the FA and CMFA running 100 times independently are shown in Fig.6, which proves that the CMFA has an obvious effect on improving the stability of results when comparing with the FA.

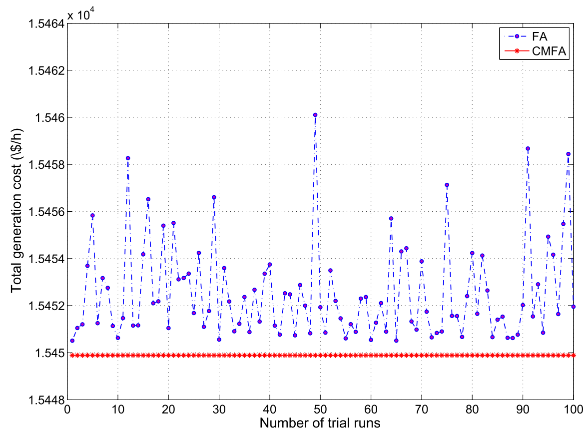

Fig. 6. Generation cost distribution of FA and CMFA (6-unit system).

B. CASE 2: 15-UNIT SYSTEM

In this case study, a 15 thermal-unit system with the prohibited operating zones, ramp rate limits, transmission losses and the valve point effects are considered [16]. The detailed information of the generator parameters and the loss coefficients are provided in [15]. The total power load demand is 2630MW. Table 4 lists the detailed best results obtained by the CMFA and the FA, as well as the best solutions provided by the other eight methods reported in the previous literature. It can be seen that both the FA and the CMFA provide solutions that satisfy all constraints. The minimum, average and maximum generation cost value of the CMFA and the FA obtained from 100 independent trials are presented in Table 5 with the other twenty-seven state-of-the-art methods. Also, standard deviation(Std.dev) and computational average time are given in the same table. Obviously, the best solution of the proposed algorithm is better than the FA and many

TABLE 4. Best results for case 2 (15-unit system).

Power output (MW)	GA[15]	PSO[16]	APSO[15]	MTS[15]	AIS[21]	TSA[42]	DSPSO-TSA[42]	BSA[15]	FA	CMFA
P_1	415.3108	439.1162	455	453.9922	441.1587	440.5	453.627	455	455	455
P_2	359.7206	407.9727	380.01	379.7434	409.5873	346.8	379.895	380	380	380
P_3	104.425	119.6324	130	130	117.2983	110.88	129.482	130	129.9999	130
P_4	74.9853	129.9925	126.52	129.9232	131.2577	122.46	129.923	130	130	130
P_5	380.2844	151.0681	170.01	168.0877	151.0108	177.74	168.956	170	169.9906	170
P_6	426.7902	459.9978	460	460	466.2579	459.11	459.907	460	460	460
P_7	341.3164	425.5601	428.28	429.2253	423.3678	406.41	429.971	430	429.9993	430
P_8	124.7867	98.5699	60	104.3097	99.948	107.55	103.673	71.6368	91.0013	71.195
P_9	133.1445	113.4936	25	35.0358	110.684	107.27	34.909	59.0234	57.7144	58.9897
P_{10}	89.2567	101.1142	159.79	155.8829	100.2286	140.56	154.593	160	136.0273	160
P_{11}	60.0572	33.9116	80	79.8994	32.0573	78.47	79.559	80	79.9957	79.9897
P_{12}	49.9998	79.9583	80	79.9037	78.8147	74.17	79.388	80	79.9958	80
P_{13}	38.7713	25.0042	33.7	25.022	23.5683	31.95	25.487	25.0001	25.0076	25.0048
P_{14}	41.9425	41.414	55	15.2586	40.2581	37.38	15.952	15.0001	19.5467	15
P_{15}	22.6445	35.614	15	15.0796	36.9061	22.47	15.64	15.0005	15.4951	15.01228
Total power (MW)	2668.4	2662.4	2658.32	2661.36	2662.04	2663.7	2660.96	2660.661	2659.778	2660.192
Power loss (MW)	38.2782	32.4306	28.37	31.3523	32.4075	33.811	30.952	30.6609	29.7779	30.19217
Total generation cost ($/h)	33113	32858	32724.78	32716.87	32854	32918	32715.06	32704.45	32704.03	32699.2

TABLE 5. Comparison of results in the 15-unit system.

Methods	Total generation cost ($/h)			Std.dev	Average time(s)
	Minimum	Average	Maximum		
GA[15]	33113	33228	33337	NA	49.31
TSA[42]	32917.87	33066.76	33245.54	66.82	25.75
GPSO[49]	32891.83	33850.95	33137.55	197.33	3.5901
PSO[16]	32858	33039	33331	NA	26.59
TLBO[70]	32770.72	33073.882	32819.743	NA	NA
MTS[15]	32716.87	32767.21	32796.15	17.51	3.65
DSPSO-TSA[42]	32715.06	32724.63	32730.39	8.4	2.3
IA_EDP[52]	32712.63	32920.70	32817.73	43.3935	1.652
ABC[36]	32707.85	32707.95	32708.27	NA	NA
QPSO[66]	32707.42	32713.48	32763.98	13.8115	8.46
θ-PSO[72]	32706.68	32711.49	32744.03	9.8874	5.5794
MDE[57]	32704.9	32708.1	32711.5	NA	12.88
SQPSO[66]	32704.57	32707.08	32711.62	1.077	7.45
BSA[15]	32704.45	32704.47	32704.58	0.028	3.74
WCA[71]	32704.45	NA	NA	NA	NA
CCPSO[63]	32704.45	32704.45	**32704.45**	**0.00**	16.2
SWT_PSO[69]	32704.45	NA	NA	NA	NA
IFEP[69]	32701.92	**32703.35**	32705.23	NA	NA
ECS[43]	32701.48	NA	NA	NA	17.5
FλI[12]	32701	NA	NA	NA	**0.015**
MG-PSO^a[58]	32677.91	32678.02	32677.96	0.0348	9.2084
KGMO^b[56]	32548.17	32548.21	32548.37	NA	7.24
FA	32704.48	32708.71	32719.17	3.9327	2.86
CMFA	**32699.20**	32704.63	32710.92	2.7779	4.35

a: The loss coefficients B_{0i} and B_{00} without considered.
b: Ramp rate limits without considered.
NA: data not available.

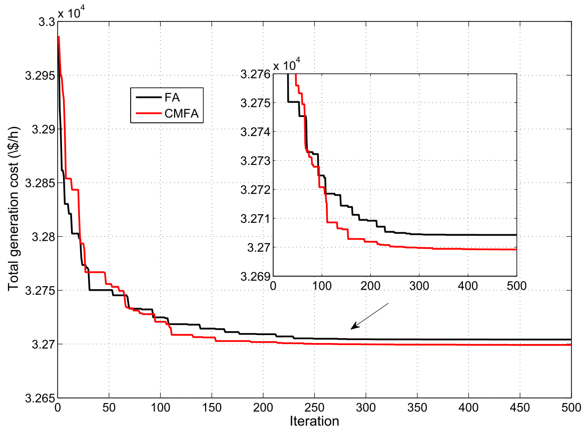

Fig. 7. Convergence characteristics of FA and CMFA (15-unit system).

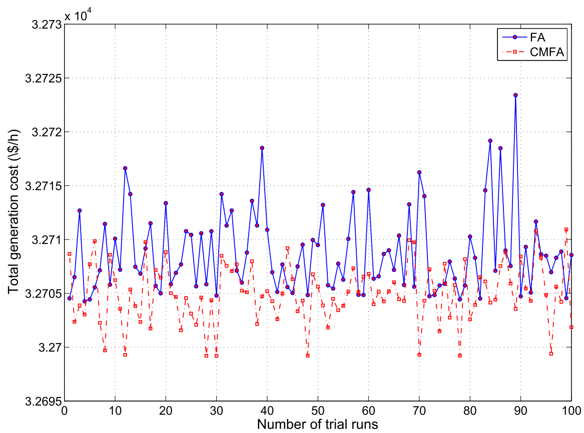

Fig. 8. Generation cost distribution of FA and CMFA (15-unit system).

algorithms that have been recognized as efficient in solving ED problems, which proves the superiority performance of the proposed algorithm. Furthermore, a small standard deviation reflects the robustness of the CMFA.

Figure 7 shows the convergence properties of the FA and the CMFA. It can be seen that the FA and the CMFA settles at about 270 and 240 iterations with cost value of about 32705($/h$) and 32700 ($/h$), respectively. This shows that the CMFA is superior to the FA in both efficiency and accuracy as the complexity of the problem increases. Fig. 8 shows the distribution of the generation cost value obtained from running the FA and the CMFA with 100 independent trials, respectively. This figure clearly shows that the CMFA provides more consistent and reliable solutions, compared to those of the FA.

C. CASE 3: 10-UNIT SYSTEM

In this case study, a slightly larger benchmark system that has 10 units is used. The total load demand of the system is 2700MW. The valve point effects, the ramp rate limits, and multiple fuel options are considered when optimizing the allocation of unit output. The generators' cost coefficients, the valve-point coefficients, and multiple fuel data of this test system are given in [19]. The optimal allocation of unit output and fuel types provided by the FA and the

TABLE 6. Best results for case 3 (10-unit system).

Output power (MW)	Methods											
	IGA-MU[19]		TSA[42]		PSO[16]		BSA[15]		FA		CMFA	
	PG (MW)	Fuel type	PG (MW)	Fuel type	PG (MW)	Fuel type	PG (MW)	Fuel type	PG (MW)	Fuel type	PG (MW)	Fuel type
P_1	219.1261	2	219.4959	2	225.5729	2	218.5777	2	219.6434	2	218.6003	2
P_2	211.1645	1	206.7093	1	208.224	1	211.2153	1	212.7272	1	210.9692	1
P_3	280.6572	1	291.3532	1	278.8078	1	279.5619	1	279.6276	1	280.6565	1
P_4	238.477	3	237.6731	3	238.0062	3	239.5024	3	238.5630	3	239.6396	3
P_5	276.4179	1	279.2478	1	282.4136	1	279.9724	1	281.0941	1	279.9307	1
P_6	240.4672	3	237.3793	3	239.6464	3	241.1174	3	239.3707	3	239.7734	3
P_7	287.7399	1	277.9598	1	285.4269	1	289.7965	1	288.0566	1	287.7242	1
P_8	240.7614	3	238.9435	3	239.1045	3	240.5785	3	239.2376	3	239.7738	3
P_9	429.337	3	429.9256	3	425.5856	3	426.8873	3	426.5232	3	427.0638	3
P_{10}	275.8518	1	281.3126	1	277.2121	1	272.7907	1	275.1567	1	275.8686	1
Total power (MW)	2700		2700		2700		2700		2700		2700	
Generation cost ($/h)	624.5178		624.3078		624.3046		623.9016		623.9351		623.8334	

TABLE 7. Comparison of results in case 3 (10-unit system).

Methods	Total generation cost ($/h)			Std.dev	Average time(s)
	Minimum	Average	Maximum		
CGA_MU[19]	624.7193	627.6087	633.8652	NA	26.64
IGA_MU[19]	624.517	625.8692	630.8705	NA	7.32
GA[15]	624.505	624.7419	624.8169	0.1005	18.37
TSA[42]	624.3078	624.8285	635.0623	1.1593	9.71
PSO[16]	624.3045	624.5054	625.9252	0.1749	11.04
PSO-GM[64]	624.305	624.6749	625.0854	0.158	NA
FAPSO[20]	624.2189	624.2951	624.2782	NA	5.9
MSFLA[48]	624.1157	624.8958	628.3428	NA	NA
HPSO-DE[46]	624.1034	NA	NA	NA	4.09
CBPSO-RVM[64]	623.9588	624.0816	624.2930	0.0576	NA
BSA[15]	623.9016	623.9757	624.0838	NA	**0.25**
IPSO[55]	623.8730	623.8887	623.8900	**0.00085**	1.032
CSA[39]	623.8684	623.9495	626.3666	0.2438	1.587
ORCSA[62]	623.8608	623.8963	623.9353	0.0154	1.54
CTPSO[63]	623.8588	632.9313	624.0368	0.0332	3.3
FWPPO[47]	623.85	NA	NA	NA	3.16
GHS[48]	623.8491	624.1341	625.3157	NA	NA
GSO[50]	623.8465	623.9829	624.257	NA	17.81
CSPSO[63]	623.8402	623.8988	623.9852	0.0269	3.3
SFLA-GHS[48]	623.8406	623.9521	624.7804	NA	NA
DSPSO-TSA[42]	623.8375	**623.8625**	**623.9001**	0.0106	3.44
GWO*[51]	605.6818	605.6263	605.7937	1.02	2.36
FA	623.9351	623.9939	624.2512	0.1016	2.43
CMFA	**623.8334**	623.8666	623.9062	0.0189	3.78

*:The total computed cost by the authors for the optimal solutions reported in [51] are much higher than reported in references
NA: data not available.

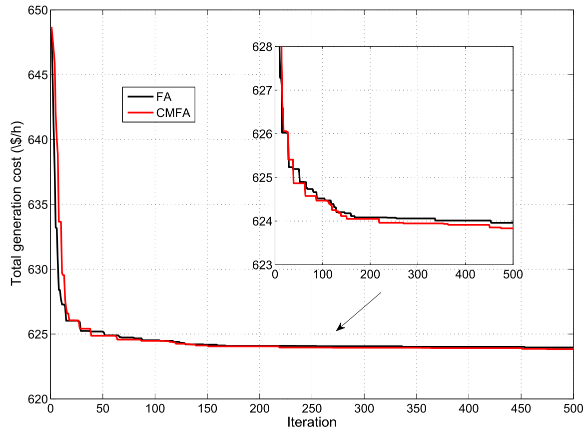

Fig. 9. Generation cost distribution of FA and CMFA (10-unit system).

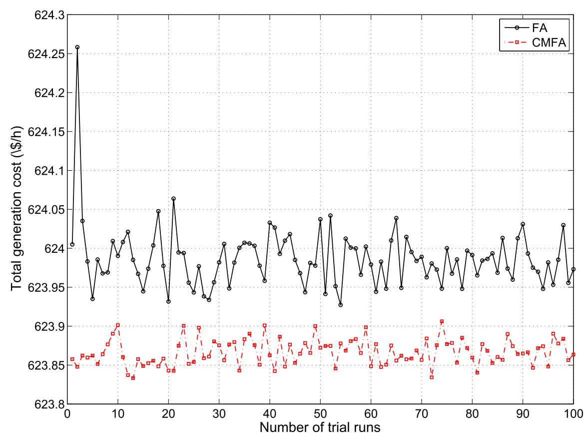

Fig. 10. Generation cost distribution of FA and CMFA (10-unit system).

CMFA are presented in Table 6, with the best solutions of 4 literature published in recent years. It can be sure that the solution satisfies all the generation limit constraints. The total generation cost obtained by the CMFA is 623.8334 ($\$/h$) when meeting the power demand of 2700MW while the violation of power balance is zero, which reveals a powerful ability of the proposed algorithm that provides better results in the case of keeping accuracy. Table 7 lists the comparison of generation cost values among the FA, the CMFA and other 23 methods. It can be seen that the least generation cost is provided by the CMFA with a good standard deviation (0.0189) and a fast calculation time (3.78 s). The FA also provides a good standard deviation of results and calculation time, but it falls into a mediocre local minimum of 623.9351($\$/h$), although it's better than the other 11 methods.

Figure 9 shows the convergence properties of the FA and the CMFA. It can be seen that both the FA and the CMFA provide smooth convergence. Fig. 10 shows the distribution of the total generation cost value provided by running the FA and CMFA with 100 independent trials, respectively. It intuitively shows that the results provided by the CMFA are in a small range between 623.8334 ($\$/h$) and 623.9062 ($\$/h$), and the solutions of the FA are in a larger range between 623.9351 ($\$/h$) and 624.2512 ($\$/h$). This demonstrates that the CMFA is more accurate, stable and reliable than the FA.

TABLE 8. Best results for case 4 (80-unit system).

Unit	FA Output(MW)	CMFA Output(MW)	Fuel type	Unit	FA Output(MW)	CMFA Output(MW)	Fuel type	Unit	FA Output(MW)	CMFA Output(MW)	Fuel type	Unit	FA Output(MW)	CMFA Output(MW)	Fuel type
G_1	214.6768	220.0854	2	G_{21}	221.6592	218.5876	2	G_{41}	202.3496	221.5771	2	G_{61}	222.5073	218.3111	2
G_2	214.2034	213.6888	1	G_{22}	213.7086	210.7270	1	G_{42}	210.7252	211.4615	1	G_{62}	212.1928	211.4507	1
G_3	272.5517	282.7161	1	G_{23}	285.9261	282.9041	1	G_{43}	279.1123	285.7622	1	G_{63}	283.1551	281.6243	1
G_4	239.6338	240.3123	3	G_{24}	241.3704	241.1210	3	G_{44}	241.5169	238.8336	3	G_{64}	240.1839	240.5803	3
G_5	279.9324	281.2814	1	G_{25}	284.9724	275.2641	1	G_{45}	277.3431	279.9167	1	G_{65}	279.1448	279.3733	1
G_6	237.2130	241.3849	3	G_{26}	240.1811	239.1008	3	G_{46}	241.0066	240.3111	3	G_{66}	238.6957	238.6983	3
G_7	286.9389	284.6647	1	G_{27}	287.3132	285.7905	1	G_{47}	292.2747	286.0424	1	G_{67}	282.0482	288.6673	1
G_8	238.5608	239.1023	3	G_{28}	236.8020	240.1735	3	G_{48}	239.3699	237.8927	3	G_{68}	239.2352	239.3714	3
G_9	424.8441	423.2263	3	G_{29}	432.3391	423.7396	3	G_{49}	431.8699	423.3299	3	G_{69}	425.7379	427.1530	3
G_{10}	273.2563	277.8224	1	G_{30}	279.8028	271.1403	1	G_{50}	277.8151	277.9563	1	G_{70}	270.7472	275.5865	1
G_{11}	220.7616	220.7842	2	G_{31}	216.1175	215.5818	2	G_{51}	214.0925	219.7209	2	G_{71}	218.3198	219.6253	2
G_{12}	209.7294	211.9482	1	G_{32}	210.4939	213.4437	1	G_{52}	210.7533	211.7136	1	G_{72}	214.1919	208.7501	1
G_{13}	286.4163	281.2083	1	G_{33}	287.5734	287.7624	1	G_{53}	280.0570	278.9925	1	G_{73}	281.5130	279.8381	1
G_{14}	238.1615	238.8331	3	G_{34}	241.9306	240.0396	3	G_{54}	240.1775	241.9235	3	G_{74}	241.2503	241.1195	3
G_{15}	279.7888	276.4529	1	G_{35}	281.3822	284.0416	1	G_{55}	281.4912	275.3101	1	G_{75}	282.7339	270.1158	1
G_{16}	238.1685	240.0412	3	G_{36}	239.7666	239.2346	3	G_{56}	241.7915	238.8320	3	G_{76}	238.6903	240.9832	3
G_{17}	296.5628	290.5925	1	G_{37}	286.8823	284.7568	1	G_{57}	289.6894	289.6645	1	G_{77}	292.8880	286.1451	1
G_{18}	238.1583	239.3725	3	G_{38}	237.7603	240.4446	3	G_{58}	240.7379	237.8933	3	G_{78}	240.4406	242.7281	3
G_{19}	423.7026	427.4155	3	G_{39}	430.2566	428.9713	3	G_{59}	416.1985	432.8728	3	G_{79}	418.4742	421.5532	3
G_{20}	272.0008	279.6887	1	G_{40}	276.9149	276.0346	1	G_{60}	274.5754	272.8368	1	G_{80}	276.4871	276.0011	1
Total generation cost ($/h):					4994.0583	4992.0655		Total power output(MW):					21600	21600	

D. CASE 4: 80-UNIT SYSTEM

In the third case study, an 80-unit power system 8 times larger than the system of case-3 supplying a load demand of 21600 MW is utilized. Multiple fuel options and the VPE are considered. The problem has become more complex due to the existence of as many as 80 nonconvex cost functions. It may be more difficult to solve an ED problem under such conditions than the real power system, because not all the units in a real system need to consider the valve-point effects. Table 8 shows the optimal unit output allocation results obtained by the FA and the CMFA. It is clear that all the constraints of the ED problem are satisfied. The comparison of objective function values among the FA, the CMFA and other recently reported methods are presented in Table 9, which shows that the cost of the CMFA is the lowest among the other methods, and the standard deviation is the least of all methods except for the ORCSA [62].

Figure 11 shows the convergence properties of the FA and the CMFA. It can be seen that both the FA and the CMFA provide smooth convergence, and settles at about 240 and 200 iterations, respectively. It indicates that, in spite of facing such a high dimension ($d = 80$) ED problem, both the FA and the CMFA can still converge at a fast speed. Fig. 12 shows the distribution of the total generation cost value provided by running the FA and the CMFA with 100 independent trials, respectively. It intuitively shows that the results provided by the CMFA vary between 4992.06 ($\$/h$) and 4994.97 ($\$/h$), and in the FA, it varies between 4994.06 ($\$/h$) and 5006.63 ($\$/h$). This demonstrates that the CMFA is more accurate, stable and reliable than the FA.

E. CASE 5: 160-UNIT SYSTEM

In this case study, a 160-unit system is generated by combining sixteen 10-unit systems, and supplying a load demand of 43200MW. Multiple fuel options and the VPE are considered. In such a large system, the cost function is highly non-smooth and dimensionality. Therefore, finding the global optimal result of this system is a very difficult challenge. In recent research, a large number of algorithms have been applied to solve this problem. Though have shown good results, but there still exists room for further improvement. The detailed optimization results provided by the CMFA are listed in Table 10. The detailed optimization results of other methods are no longer shown, as in previous cases. Table 11 shows a comparison of the solution of the FA, the CMFA, and

TABLE 9. Comparison of results in case 4 (80-unit system).

Methods	Total generation cost ($/h) Minimum	Average	Maximum	Std.dev	Average time(s)
CGA-MU[19]	5008.143	NA	NA	NA	309.41
IGA-MU[19]	5003.883	NA	NA	NA	85.67
BSA[15]	4995.127	4997.551	5000.983	1.0961	**4.78**
ED-DE[44]	4992.71	NA	NA	NA	NA
CSA[39]	4992.685	**4993.731**	5003.429	1.0931	18.25
ORCSA[62]	4992.422	4994.499	4995.672	**0.4939**	15.24
FA	4994.0583	4997.5182	5006.6316	4.2667	17.52
CMFA	**4992.0655**	4993.7483	**4994.9760**	0.7240	23.84

*NA: data not available.

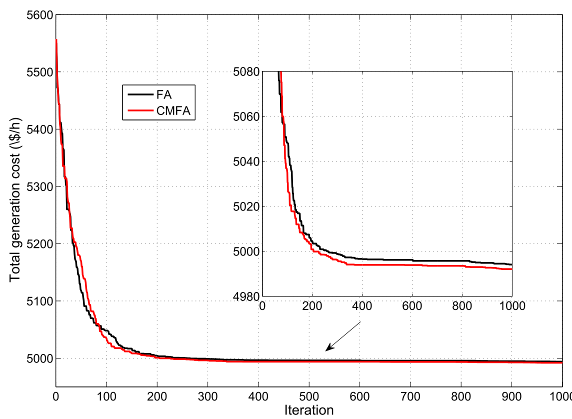

Fig. 11. Convergence characteristics of FA and CMFA (80-unit system).

TABLE 10. Best results for case 5 (160-unit system).

Unit	Output(MW)	Fuel type	Unit	Output(MW)	Fuel type	Unit	Output(MW)	Fuel type	Unit	Output(MW)	Fuel type	Unit	Output(MW)	Fuel type
G_1	221.9636	2	G_{33}	280.4331	1	G_{65}	284.2236	1	G_{97}	285.5699	1	G_{129}	426.6207	3
G_2	213.9288	1	G_{34}	238.6961	3	G_{66}	239.7727	3	G_{98}	239.9016	3	G_{130}	273.0512	1
G_3	280.6310	1	G_{35}	278.8651	1	G_{67}	287.7888	1	G_{99}	421.1971	3	G_{131}	226.2088	2
G_4	242.1929	3	G_{36}	241.2524	3	G_{68}	242.4567	3	G_{100}	275.3600	1	G_{132}	209.2391	1
G_5	284.3912	1	G_{37}	288.9952	1	G_{69}	421.0851	3	G_{101}	227.5996	2	G_{133}	282.1344	1
G_6	237.0879	3	G_{38}	238.9676	3	G_{70}	278.4603	1	G_{102}	212.7017	1	G_{134}	238.9642	3
G_7	287.6546	1	G_{39}	433.8875	3	G_{71}	224.7192	2	G_{103}	275.5033	1	G_{135}	278.0948	1
G_8	238.9705	3	G_{40}	282.0451	1	G_{72}	212.4253	1	G_{104}	242.4617	3	G_{136}	241.5306	3
G_9	432.6141	3	G_{41}	219.8887	2	G_{73}	280.4753	1	G_{105}	273.8717	1	G_{137}	291.6681	1
G_{10}	272.1067	1	G_{42}	212.4634	1	G_{74}	239.9055	3	G_{106}	240.8500	3	G_{138}	240.3108	3
G_{11}	219.2781	2	G_{43}	278.7995	1	G_{75}	278.2885	1	G_{107}	292.6097	1	G_{139}	431.0884	3
G_{12}	210.9637	1	G_{44}	238.1696	3	G_{76}	240.9832	3	G_{108}	238.1632	3	G_{140}	268.9722	1
G_{13}	280.6246	1	G_{45}	279.6021	1	G_{77}	288.0648	1	G_{109}	428.9940	3	G_{141}	219.3540	2
G_{14}	237.2225	3	G_{46}	240.0402	3	G_{78}	240.9971	3	G_{110}	277.8815	1	G_{142}	211.1744	1
G_{15}	282.8932	1	G_{47}	288.4727	1	G_{79}	419.4645	3	G_{111}	220.5089	2	G_{143}	280.9284	1
G_{16}	239.7742	3	G_{48}	240.0447	3	G_{80}	277.1086	1	G_{112}	211.9746	1	G_{144}	240.4493	3
G_{17}	291.1901	1	G_{49}	424.7444	3	G_{81}	217.5805	2	G_{113}	277.7493	1	G_{145}	276.5820	1
G_{18}	238.2993	3	G_{50}	272.9769	1	G_{82}	211.9571	1	G_{114}	240.5752	3	G_{146}	240.0403	3
G_{19}	427.9873	3	G_{51}	222.8882	2	G_{83}	278.5453	1	G_{115}	278.3002	1	G_{147}	287.0040	1
G_{20}	276.4210	1	G_{52}	209.7710	1	G_{84}	239.6428	3	G_{116}	239.3618	3	G_{148}	238.8289	3
G_{21}	211.1136	2	G_{53}	282.5274	1	G_{85}	277.3197	1	G_{117}	290.4911	1	G_{149}	426.3411	3
G_{22}	209.9899	1	G_{54}	240.4486	3	G_{86}	243.9387	3	G_{118}	239.5018	3	G_{150}	277.1389	1
G_{23}	279.6295	1	G_{55}	277.6104	1	G_{87}	291.4335	1	G_{119}	427.5232	3	G_{151}	216.7567	2
G_{24}	241.3869	3	G_{56}	239.2311	3	G_{88}	240.4538	3	G_{120}	273.7198	1	G_{152}	209.4809	1
G_{25}	274.4303	1	G_{57}	291.6438	1	G_{89}	428.2689	3	G_{121}	212.9348	2	G_{153}	282.6100	1
G_{26}	238.1750	3	G_{58}	241.1150	3	G_{90}	277.1636	1	G_{122}	212.1934	1	G_{154}	237.8966	3
G_{27}	281.7884	1	G_{59}	420.3728	3	G_{91}	216.5329	2	G_{123}	281.1074	1	G_{155}	279.7538	1
G_{28}	239.9105	3	G_{60}	277.1215	1	G_{92}	210.9612	1	G_{124}	238.1617	3	G_{156}	239.3712	3
G_{29}	432.1459	3	G_{61}	217.5685	2	G_{93}	275.6833	1	G_{125}	279.9547	1	G_{157}	289.8992	1
G_{30}	275.1992	1	G_{62}	212.6544	1	G_{94}	240.4472	3	G_{126}	239.1045	3	G_{158}	240.5898	3
G_{31}	218.3116	2	G_{63}	280.1882	1	G_{95}	274.8983	1	G_{127}	285.1209	1	G_{159}	421.2496	3
G_{32}	213.4316	1	G_{64}	240.0492	3	G_{96}	237.7620	3	G_{128}	239.9081	3	G_{160}	273.7605	1
Total generation cost ($/h):				9985.5965						Total power output(MW):			432000	

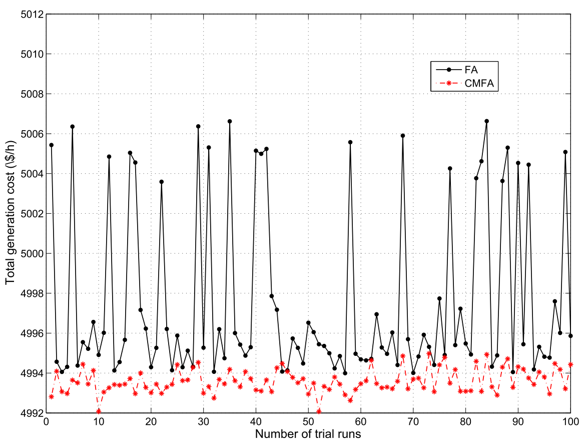

Fig. 12. Generation cost distribution of FA and CMFA (80-unit system).

TABLE 11. Best results for case 5 (160-unit system).

Methods	Generation cost ($/h)			Std.dev	Average time(s)
	Minimum	Average	Maximum		
CGA_MU[19]	10143.72	10143.72	NA	NA	621.3
IGA_MU[19]	10042.47	10042.47	NA	NA	174.62
PSO[46]	10036.199	NA	NA	NA	204.73
BSA[15]	10014.085	10035.403	10060.93	9.037	9.44
HPSO-DE^a[46]	10013.008	NA	NA	NA	101.44
ED-DE[44]	10012.68	NA	NA	NA	NA
FBHPSO-DE^a[46]	10011.072	NA	NA	NA	97.01
RCCRO[38]	10009.518	10009.52	10009.58	NA	50.216/iter
BBO[38]	10008.71	10009.16	10010.59	NA	0.62/iter
DE/BBO[38]	10007.05	10007.56	10010.26	NA	0.56/iter
ORCCRO[61]	10004.20	10004.21	10004.45	NA	0.019/iter
CBA[15]	10002.859	10006.33	10045.23	9.5811	**5.71**
CSA[39]	9996.639	9996.639	10014.02	4.9268	75.42
PI-CBA[65]	9995.805	10029.08	10069.74	NA	NA
ORCSA[62]	9989.9444	9992.0503	9996.832	1.4138	67.50
FA	9995.6720	10011.185	10038.068	8.8454	43.86
CMFA	9985.5965	9987.5525	9996.9409	2.5174	76.78

a:Lack of detailed optimization result.
NA: Data not available.

the other 15 methods. It's clear that the best generation cost provided by the CMFA is the lowest among all the methods mentioned. Furthermore, the average generation cost is better than the best cost value of residual algorithm, and a standard deviation is a small number that equal to 2.5174.

Figure 13 shows the convergence curve of the FA and the CMFA when provided the best solution for case-5. It can be seen that the FA settles at about 350 iterations and for the CMFA is about 500, which indicates that the FA converges faster than the CMFA. However, the cost value provided by the CMFA is significantly better than that of the FA, which indicates that the FA has early convergence and trapped into a local minimum but the CMFA successfully avoided. The generation costs distribution of the 100 independent run validates the robustness of the CMFA, which shown in Fig. 14 with the FA. This makes clear that the CMFA has the ability to provide a consistent and reliable optimal solution. On the other hand, The performance of the FA is weak and the optimal solution cannot be provided due to the high complexity of the problem.

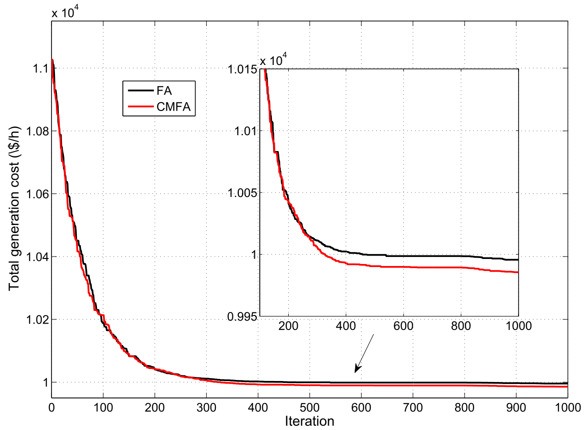

Fig. 13. Convergence characteristics of FA and CMFA (160-units system).

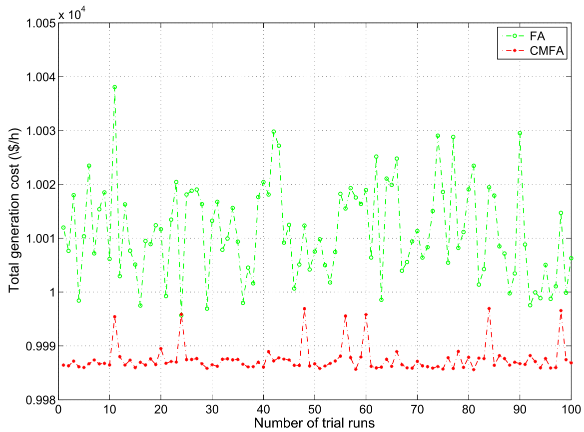

Fig. 14. Generation cost distribution of FA and CMFA (160-units system).

VI. CONCLUSION

In this paper, a new metaheuristic algorithm called firefly algorithm (FA) is proposed in which the concept is simple and easy to implement. The Firefly Algorithm is used to solve non-convex and large scale economic dispatch problems when considering both the valve-point effects and the multiple fuel options. Furthermore, a modified version of the FA, the CMFA, is proposed for solving the ED problems after carefully considering different components in designing the method. A sinusoidal chaotic map was incorporated into FA for the adaptation of the random movement factor (α), and the absorption coefficient (γ) was introduced into candidate solutions as variables that need to be optimized for enhancing the search capability of the FA and eliminate the need for manually tuning the algorithm. Besides, a new powerful self-adaptive mutation mechanism is used to maintain diversity in the population and enhance the global searching ability of the CMFA. In addition to the above contribution, a new equality constraint handling mechanism is set up, a dynamic relaxation factor has been used and some solutions that slight violations of the constraint but have good fitness for the objective function are retained. This mechanism biases the optimization towards the feasible region, which enhances convergence rate and handling different constraints in ED problems simultaneously. The FA and the CMFA were applied to five test systems having 6, 10, 15, 80, 160-units and the analysis of simulation results demonstrates that the proposed methods exhibit superior performances in solving ED problems including the prohibited operating zones, the valve-point effects, the transmission losses, the multiple fuel options, and other constraints of power systems like ramp rate limits and so on, compared to previously proposed state-of-the-art methods.

In future work, we intend to apply these methods to solve other problems related to power systems optimization because the CMFA has shown good performance in solving the ED problem.

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