Research on Hybrid Modified Cuckoo Search Algorithm for Optimal Reactive Power Dispatch Problem

Gonggui Chen, *Member, IAENG*, Zhengqin Lu, Zhizhong Zhang, Zhi Sun

Abstract—**In this paper, an efficient and reliable approach based on hybrid modified cuckoo search algorithm (MCS) combining with differential evolutionary algorithm (DE) (named MCS-DE) is proposed to solve optimal reactive power dispatch (ORPD) problem with minimization of power losses (P_{loss}) , voltage stability index (*Lindex*) and voltage deviation (V_d) as objectives. The original CS method often converges to local optima. In order to avoid this shortcoming, a series of modifications is purposed to the assimilation policy rule of CS. The variations of the two main parameters and an improved search equation are introduced into the MCS-DE to improve local search near the global best, and it profits from DE to further improve the optimization performance. The proposed MCS-DE is examined and implemented on IEEE 30-bus and IEEE 57-bus test power systems with three different objectives. The simulation results presented in this paper demonstrate the effectiveness and robustness of hybrid MCS-DE approach for solving ORPD problem and it can be made better results compared to the CS, DE, and other methods reported in the literature as demonstrated by simulation results.**

Index Terms—**Optimal reactive power dispatch, Hybrid modified cuckoo search algorithm, Cuckoo search algorithm, Differential evolutionary algorithm.**

I. Introduction

OPTIMAL reactive power dispatch (ORPD) plays an increasingly significant role for secure, economic and reliable operation of power systems and is gaining much more attention. It is one of the main sub problems of optimal power flow (OPF) calculation which can be used to figure out control variables, and to minimize desired objective functions including transmission power losses (P_{loss}), voltage stability index (*L*index) or voltage deviation (V_d) while simultaneously fulfilling a given set of equality and inequality system constraints. The main purpose of ORPD problem is to regulate the corresponding settings of control variables and find the optimal operating state of a power system and so as to improve the reactive power distribution. However, it is formulated as a complex combinatorial optimization problem taking into account nonlinear functions having multiple local minima because of the presence of control variables contain continuous variables like generator bus voltages and discrete variables such as tap setting of transformers and reactive power output of compensators [1,2].

Many conventional optimization algorithms have been applied in the literatures in order to solve ORPD problem such as Newton's based approach [3], Quadratic Programming [4], dynamic programming [5] and Interior-point method [6] in the past few decades. Bakirtziss in [7] handle the shunt reactive compensation devices with a linear-programming and in [8] Jan and Chen combined the sensitivity factor method with the fast Newton-Raphson economic dispatch to solve the OPF problem. Although most of these classical methods have excellent convergence characteristics but they face challenges in handling the problems with discrete nature and integer thus make the solution process computationally complex [9,10]. Later, some of the similar stochastic search algorithms such as gravitational search algorithm (GSA) [11], particle swarm optimization (PSO) [12,13], harmony search algorithm (HSA) [14], genetic algorithm (GA) [15,16], differential evolution (DE) [17], etc. have been found to be suitable to overcome these drawbacks and shown better results in solving ORPD problem. In [18], a self-adaptive differential evolutionary (SADE) algorithm is adopted to search the optimal control settings. Mahadevan in [19] solved the ORPD problem by introducing a learning strategy to overcome the drawback of premature convergence in PSO. In opposition-based GSA (OGSA) [20], the idea of opposite number is blended with GSA for population initialization and also for generating new population. Most of these approaches have no restrictions on the nature of objective functions and have the great possibility capacity to find global optimal solution, and proved themselves to be more efficient alternatives for solving any non-linear, non-convex optimization problems. Additionally, there are also researchers who used hybrid techniques to solve ORPD problem such as Nelder Mead (NM) simplex subroutine [2] is

Manuscript received February 2, 2018; revised April 19, 2018. This work was supported by Innovation Team Program of Chongqing Education Committee (CXTDX201601019), Chongqing University Innovation Team under Grant KJTD201312 and the National Natural Science Foundation of China (Nos. 51207064 and 61463014).

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introduced in the internal architecture of the firefly algorithm (FA). A modified PSO called as PSO with aging leader and challenges (ALC-PSO) has been presented in [21] is applied. M.Basu in [22] proposed a quasi-oppositional differential evolution (QODE) to solve ORPD problem by employing quasi-oppositional based learning (QOBL). And the results show that the hybrid method has better convergence characteristics and robustness than the original version of algorithms.

In recent years, the Cuckoo Search (CS) algorithm is found to be one of the successful techniques of the present power system domain [23, 24] and has demonstrated great effectiveness in both critical factors of convergence rate and capability in achieving global optimal. It is proposed by YANG Xinshe and DEB Suash [25, 26] of the University of Cambridge in the year 2009, inspired by the parasitic behavior of cuckoo birds in reproduction process based on the probability for a host bird in discovering an alien egg in its nest. The application of CS into some optimization problems has been done such as OPF problem [27], advanced machining process [28], combined heat and economic dispatch [29]. The CS has three main advantages: it uses few number of control parameters, its convergence is fast and it can find near optimal solution regardless the initial parameter values. Based on the above considerations, in this paper, a new hybrid modified cuckoo search algorithm (MCS) combine with differential evolutionary algorithm (DE), called MCS-DE algorithm is used to solve ORPD problem. In the proposed MCS-DE algorithm, improving the search equation in order to improve the solution vectors, and to adjust the convergence rate, dynamically variable parameters namely discovery probabilities P_a and the step size α are incorporated instead of the fixed values. In addition, introducing the crossover operator of DE to further improve the optimization performance and enhance the quality of solution.

In this work, the proposed MCS-DE is applied for the solution of ORPD problem of power systems. Two IEEE standard power systems like IEEE 30-bus and 57-bus systems are adopted and the ORPD problem of these test systems are solved with three different objectives that reflect minimization of either P_{loss} or that of *L*index or V_d. Results obtained by MCS-DE are compared with other different computational intelligence-based methods surfaced in the state-of-the-art literatures including basic CS and DE. The simulation results show the potential and effectiveness of MCS-DE and it can improve the convergence performance and get the better solution at the same time.

The rest of this article are classified in five sections as follows: Section 2 covers formulation of optimal reactive power dispatch while Section 3 explains the standard structure of the CS, DE and the proposed hybrid modified MCS and DE (MCS-DE) algorithms, and next, Section 4 gives the implementation of MCS-DE for ORPD problem. Section 5 of the paper is allocated to presenting optimization results and undertaking comparison and analysis of the performance of the mentioned methods used to solve the case studies of ORPD problem on IEEE 30-bus, IEEE 57-bus systems and finally, the conclusion of the implementation for the proposed hybrid method is presented in Section 6.

II. Mathematical Model

In this paper, the objective functions of the ORPD problem is to minimize the transmission real power losses (P_{loss}), the voltage stability index (*Lindex*) and the voltage deviation (V_d) while satisfying several equality and inequality constraints. The main purpose behind using an ORPD problem in a power system operation is to redistribute reactive power in the way that the minimum amount of transmission line losses, maximize voltage stability margin and also minimum voltage deviation can be attained.

The integral formulation of the proposed ORPD problem is expressed as follows:

$$\min f\left(u,x\right) \tag{1}$$

$$s.t.\begin{cases} G(u,x)=0 \\ H(u,x)\le 0 \\ u_{\min}\le u\le u_{\max} \\ x_{\min}\le x\le x_{\max} \end{cases} \tag{2}$$

where f is the objective function of the system active power losses, voltage stability index and voltage deviation, respectively; $G(u,x)$ is the equality constraints and $H(u,x)$ is the inequality constraints of the power system; u and x respective represent the vector of control variables and state variables which can be expressed as:

$$u^T=\left[V_{Gi},T_i,Q_{ci}\right]\,\&\,x^T=\left[V_i,Q_{Gi},S_{li}\right] \tag{3}$$

where V_{Gi} is the voltage at the generator bus i; T_i is the tap ratio of the transformer i; Q_{ci} is the reactive power output of compensator i; V_i is the voltage at the load bus i; Q_{Gi} and S_{li} are the reactive power output at the generator i and apparent power of the transmission i, respectively; and T is transposition.

A. Objective Functions

1) Minimization of transmission power losses (P_{loss})

The objective function of the real power losses in the transmission lines for whole network is expressed as follows:

$$\min f_1=\min\left\{P_{loss}=\sum_{k\in N_L} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\delta_{ij}\right)\right\} \tag{4}$$

where P_{loss} denotes the objective function of total power losses; N_L is the number of transmission lines; g_k is the conductance of branch k connected between the ith and jth bus; δ_{ij} is the voltage angle difference between bus i and j; V_i and V_j are the voltage magnitude of bus i and j, respectively.

2) Minimization of voltage stability index (*Lindex*)

For any load bus j, the *Lindex* can be worked out:

$$Lindex=\max_{j\in N_{PQ}} L_j=\max_{j\in N_{PQ}}\left|1-\sum_{i=1}^{N_{PV}} F_{ji}\frac{V_i}{V_j}\right| \tag{5}$$

where L_j is the *Lindex* value for load bus j; i denotes the generator bus (*PV* bus) and j denotes the load bus (*PQ* bus); N_{PV} and N_{PQ} are the number of generator buses and load buses, respectively.

By classifying the *PV* buses and *PQ* buses, we obtain as:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix}=\begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix}\begin{bmatrix} V_G \\ V_L \end{bmatrix} \tag{6}$$

$$Z_{LL}=Y_{LL}^{-1} \tag{7}$$

Rearranging(6), we can get:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL}^{-1} & -Z_{LL}^{-1}Y_{LG} \\ Y_{GL}Z_{LL}^{-1} & Y_{GG}-Y_{GL}Z_{LL}^{-1}Y_{LG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{8}$$

where

$$[F] = -[Z_{LL}]^{-1}[Y_{LG}] \tag{9}$$

The *Lindex* value varies between 0 (no load point) and 1 (voltage collapse point) in the system voltage stability margin and it indicates the system is almost stable if the value of *Lindex* close to 0. Hence, mathematically, to minimize the maximum value *Lindex* which representing the voltage stability of the total power system, the objective function can be expressed as:

$$\min f_2 = \min(Lindex) \tag{10}$$

3) Minimization of total voltage deviation (V_d)

The purpose of this problem is to minimize the load bus voltage deviation and improve the voltage profile of electric power network and then help the system to operate more securely, which can be modeled as in:

$$\min f_3 = \min\left\{ V_d = \sum_{i=1}^{N_{PQ}} \left| V_i - V^{REF} \right| \right\} \tag{11}$$

where V_i is the bus voltage at the *i*th load bus; V^{REF} represents the specified reference voltage value magnitude at load bus *i* which is equal to 1.0 p.u. and V_d is the sum of the absolute value of load bus voltages from 1.0 p.u.

B. System Constraints

All the above mentioned objective functions(4), (10) and (11) are optimized while satisfying following system equality and inequality constraints.

1) Equality constraints

The active and reactive power balance equations described by a set of power flow equations which can be expressed as following equality constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij} \right) = 0, 1 \le i \le N \tag{12}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij} \right) = 0, 1 \le i \le N_{PQ} \tag{13}$$

where P_{Gi} and Q_{Gi} are the active power and reactive power at generator *i*, respectively; P_{Di} and Q_{Di} are the load active power and reactive power at the load *i*, respectively; V_i and V_j, respectively, denote the voltage magnitude of the *i*th and *j*th bus; G_{ij} and B_{ij}, represent the real part and imaginary part of Y_{ij} which is the element of the bus admittance matrix at the *i*th row and the *j*th column, respectively; *NB* is the number of the buses connecting with the *i*th bus; *N* is the number of total buses except for swing bus and N_{PQ} is the number of *PQ* buses.

2) Inequality constraints

Inequality constraints of control variables: the limit for generator bus voltages, tap setting of transformers and reactive power output of compensators.

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, 1 \le i \le N_{PV} \tag{14}$$

$$T_i^{\min} \le T_i \le T_i^{\max}, 1 \le i \le N_T \tag{15}$$

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, 1 \le i \le N_C \tag{16}$$

Inequality constraints of state variables: the limit for voltages at *PQ* bus, reactive power output at *PV* bus and apparent power of transmission line.

$$V_i^{\min} \le V_i \le V_i^{\max}, 1 \le i \le N_{PQ} \tag{17}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, 1 \le i \le N_{PV} \tag{18}$$

$$S_{li} \le S_{li}^{\max}, 1 \le i \le N_L \tag{19}$$

where N_{PV} denotes the number of generators; N_T is the number of transformers; N_C is the number of the compensators and N_L is the number of network branches.

C. Handling of constraints

The control variables can be self-constrained according to their limits by the algorithm but the state variables themselves cannot satisfy the constraints. In this paper, the state variables are incorporated into the objective function. Hence, the overall objective function is formulated by penalizing strategy taking power system operational limitations into account and mathematically it is expressed as:

$$\min f' = \min\left\{ f + \sigma_V \sum_{i \in N_{PQ}} \left(V_i - V_i^{\lim} \right)^2 + \sigma_Q \sum_{i \in N_{PV}} \left(Q_{Gi} - Q_{Gi}^{\lim} \right)^2 + \sigma_L \sum_{i \in N_L} \left(S_{li} - S_{li}^{\lim} \right)^2 \right\} \tag{20}$$

where $(V_i - V_i^{\lim})$, $(Q_{Gi} - Q_{Gi}^{\lim})$ and $(S_{li} - S_{li}^{\lim})$ are the violations associated with voltages at *PQ* buses, reactive power outputs at the generators and apparent power of the transmission lines, respectively; σ_V, σ_Q and σ_L are penalty coefficients of the state variables. $V_i^{\lim}$、$Q_{Gi}^{\lim}$ and $S_{li}^{\lim}$ are defined as:

$$K_x^{\lim} = \begin{cases} K_x^{\max} & K_x > K_x^{\max} \\ K_x^{\min} & K_x < K_x^{\min} \\ K_x & K_x^{\min} \le K_x \le K_x^{\max} \end{cases} \tag{21}$$

where *K* represent V_i, Q_{Gi} and S_{li}; max and min are the maximum and minimum limiting value of V_i, Q_{Gi} and S_{li}.

III. MCS-DE ALGORITHM

A. The standard Cuckoo search algorithm (*CS*)

The cuckoo search (CS) algorithm is a novel heuristic stochastic optimization approach based on the breeding parasitism behavior of the cuckoo species and its Lévy Flights characteristics. It is needed to set three idealized rules [27, 30] to form the mathematical model of CS:

(1) Each cuckoo can only lays one egg at a time and puts it into a randomly chosen host nest.

(2) The highest quality egg in the host nest will be hatching and retaining to the next generation.

(3) The number of available host nests for the cuckoos is fixed as *m*, and the host bird will discover the alien eggs laid by cuckoos with a probability $P_a \in [0,1]$.

The algorithm starts with the randomly generated solution and population. Randomly initialize the search space $X_i = (x_i^1, x_i^2, \ldots, x_i^d)$ with *d* dimension for host nest *i* (*i* =1,2,…, *m*). Based on above rules, the CS includes two randomized processes.

1) Generating new solution via Lévy Flights

Generally, Cuckoos engage the obligate brood parasitism by laying their eggs in the communal nests or the nests of the other species birds. In this case, the host birds may be recognizing the eggs of the Cuckoos are not their own, they will probably either throw the eggs away or simply abandon the current nest to build a new one in a new location. This concept is transformed to optimization technique and each egg in the host represents a potential solution. Host *i* of a global random walk can be expressed as(22).

$$x_i^{(k+1)} = x_i^{(k)} + \alpha \oplus L\acute{e}vy(\lambda) \tag{22}$$

$$L\acute{e}vy(\lambda) \sim u = t^{-\lambda} (1 < \lambda < 3) \tag{23}$$

where $x_i^{(k)}$ denotes the current position of *i*th nest (for i=1,2,…,m) in generation k; $x_i^{(k+1)}$ is the new solution in generation k+1; α is the step size parameter related to the scale of the problem; $\oplus$ denotes the entry wise multiplication and $L\acute{e}vy(\lambda)$ is the Lévy distribution which can be approximated as:

$$L\acute{e}vy(\lambda) \sim \frac{\phi u}{|v|^{1/\beta}} \tag{24}$$

where u and v are taken from a normal distribution:

$$u = raud(); v = raud() \tag{25}$$

$$\phi = \left\{ \frac{\Gamma(1+\beta) \times \sin(\pi \times \beta / 2)}{\Gamma\left\{ \left[(1+\beta)/2 \right] \times \beta \times 2^{(\beta-1)/2} \right\}} \right\}^{1/\beta} \tag{26}$$

where *rand*() is a normally distributed stochastic number in range [0,1]; β is the distribution factor and $\Gamma()$ is the gamma distribution function.

In the growth stage, $x_i^{(k)}$ starts with the donor vector $v_i^{(k)}= x_i^{(k)}$ and a new solution vector is computed, which is given by:

$$v_i^{(k)} = x_i^{(k)} + \alpha \times \frac{\phi u}{|v|^{1/\beta}} \times (x_i^{(k)} - x_{gbest}^{(k)}) \times rand() \tag{27}$$

where x_{gbest} is the best solution. It is worth pointing out that, according to(22), it indicates that the global explorative random walk and the next moving position of the nest is determined based on the current position and the transition probability. Furthermore, the Lévy Flights behavior has been applied to the optimum random search, and it shows a good performance.

2) Discovery alien eggs with the probability P_a

The other part of CS is to place some nests by constructing a new solution and there is a probability rate $P_a \in [0,1]$ to discover alien eggs. Whenever building a new solution, the random $rand \in [0,1]$ is compared with P_a. Host *i* of a local random walk can be expressed as:

$$x_i^{(k+1)} = v_i^{(k)} + H(u)(x_j^{(k)} - x_g^{(k)})$$
$$H(u) = \begin{cases} 1, if & rand > P_a \\ 0, & otherwise \end{cases} \tag{28}$$

where $x_j^{(k)}$ and $x_g^{(k)}$ are two randomly selected solutions in generation k; $H(u)=H(P_a–rand)$ denotes a Heaviside function ; *rand* is drawn from a uniform distribution.

After producing the new solution $x_i^{(k+1)}$, it will be evaluated and compared to the $v_i^{(k)}$. If the objective fitness of $x_i^{(k+1)}$ is smaller than $v_i^{(k)}$, $x_i^{(k+1)}$ is accepted as a new solution, else $v_i^{(k)}$ would be obtained.

B. Modified Cuckoo search algorithm (MCS)

The standard CS algorithm use constant value of α (step size) and P_a (probability$\in$[0,1]), the fine-tuning of solution vectors are dependent on the two parameters, which can be potentially used in adjusting convergence rate of the algorithm. The two important parameters are used to obtain the global and local improved solutions, respectively. In order to eliminate the drawback of the fixed values of the parameters α and P_a and enhance the performance of the algorithm, the MCS utilizes variable α and P_a which are dynamically varied with the increase of generations and can be described as follows:

$$\alpha(k) = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) \times ((k_{\max} - k) / k_{\max})^2 \tag{29}$$

$$P_a(k) = P_{a\min} + (P_{a\max} - P_{a\min}) \times ((k_{\max} - k) / k_{\max})^2 \tag{30}$$

where $k_{\max}$ is the number of total generations and k is the current generation, respectively.

According to (29) and (30), in the initial generations, the values of α and P_a are large enough to push the algorithm to increase the diversity of the solution vectors. It is worth mentioning that, the decreased parameter values in the final generations will result in a better fine-tuning of the solution vectors. Hence, the quality of solutions is slowly improved and the algorithm will converge near the global best solution in the latter part of the generations.

Moreover, in order to improve local search near the global best and further enhance the convergence rate for achieving a better solution quality, formula (28) is changed as follows:

$$\begin{aligned} x_i^{(k+1)} =& v_i^{(k)} + H(u)(x_j^{(k)} - x_g^{(k)}) + H(u)(x_{pb} - x_i^{(k)}) \\ &+ H(u)(x_{gb} - x_i^{(k)}) \end{aligned} \tag{31}$$

where x_{pb} and x_{gb}, respectively, denote the best position of nest *i* and the best potion in host nests in the *d*th dimension at generation *k*, which is helpful to the nests to move to the global best position. In this paper, the difference between (31) and (28) is the update modes of velocity and position which are crucial for the artificial intelligence-based algorithms.

C. The crossover operator of DE

In order to prevent population from trapping into local minimum, the crossover operator of differential evolution (DE) algorithm which is carried out in which the donor vector exchanges its components with those of the current member is embedded into the evolutionary process of MCS-DE to enhance population diversity and improve global searching capability as shown in (32).

$$x_{ij}^{(k+1)} = \begin{cases} v_{ij}^{(k)}, & rand \le C_R \parallel j = round(d \times rand + 0.5) \\ v_{ij}^{'(k+1)}, & otherwise \end{cases}$$
$$i = 1,2,...,m,\ j = 1,2,\ldots,d \tag{32}$$

where *rand* is a uniform random value generated within the range [0,1], which is generated once for each *j*th dimension of the *i*th trial vector; $C_R \in [0,1]$ is the control parameter, called crossover factor; $j \in [1,d]$ is a random integer which ensures that at least one dimension of $x_{ij}^{(k+1)}$ is inherited from the mutant vector $v_{ij}^{(k)}$.

D. The proposed hybrid Cuckoo search algorithm

Based on the above-mentioned rules, the advantages of local search capability provided by modified CS and global search ability of DE can be effectively combined, and resultantly a novel hybrid modified CS (named MCS-DE) algorithm is proposed. The steps of the MCS-DE can be summarized as follows:

Step 1: Initialize the population of m host nests x_i (i=1,2,…,m), parameters and random values.

Step 2: Fitness evaluation of the population.

Step 3: Lay random cuckoo eggs into nests by Lévy Flights according to(22), (27) and (29) to evaluate the fitness of every nest.

Step 4: Updating the position of the nests by (30) and(31), worse nests (P_a) are abandoned and new ones are built.

Step 5: Generate new population by introducing the crossover operator of DE according to(32).

Step 6: Build new nests and keep the best solutions with the best fitness (or nests with quality solution).

Step 7: Repeat steps 3 until a stopping criterion is met.

IV. Implementation of MCS-DE for ORPD Problem

The proposed MCS-DE method is used to find the settings of control variables such as generator bus voltages (V_{Gi}), tap settings of transformers (T_i) and reactive power output of compensators (Q_{ci}) in order to achieve minimum transmission power losses (P_{loss}), voltage stability index (*Lindex*) and total voltage deviation (V_d). In the implementation of MCS-DE for solving the ORPD problem, the basic steps of MCS-DE are depicted as follows:

Step 1: Set the parameters and generate the initial population.

The initial population is made up of m host nests, randomly initialize the search space $X_i = (x_i^1, x_i^2,\ldots, x_i^d)$ (i =1,2,…, m) and $m \times d$ represent the dimension of the population. The d-dimension parameter vectors of the population are restricted by the maximum and minimum limits as follows:

$$\begin{aligned} \vec{X}_{i\min} &= \left\{x_{i\min}^1, x_{i\min}^2, \cdots x_{i\min}^d\right\} \\ \vec{X}_{i\max} &= \left\{x_{i\max}^1, x_{i\max}^2, \cdots x_{i\max}^d\right\} \end{aligned} \tag{33}$$

The initial velocity of population is set as a zero matrix with $m \times d$ dimension and the d-dimension problem for the ith host nest can be generated as:

$$\begin{aligned} & x_{j,i} = x_{j,\min} + rand \times (x_{j,\max} - x_{j,\min}) \\ & i = 1,2,\ldots,m;\ j = 1,2,\ldots,d \end{aligned} \tag{34}$$

Step 2: Compute the objective function value: evaluate the fitness F_i for X_i.

Step 3: Update the position of all nests based on Lévy Flights according to (22), (27) and (29). Then choose a nest 'j' randomly from all the nests, evaluate the fitness F_j for X_j again.

Step 4: If $F_j < F_i$, then replace X_i with the new solution X_j.

Step 5: Then the worse nests are abandoned with a probability (P_a) and new ones are built based on (30) and (31).

Step 6: Generate new population by introducing the crossover operator of DE according to (32) and then record the current position as follows:

```
for i=1:m
  for j=1:d
    if (rand<C_R) or (j==round (d · rand +0.5))
       Y (j, i) = X (j, i);
  else
       Y (j, i) = P_best (i). Position (j);
  end
end
pSample (i). Position = Y (1: d, i)
```

Step 7: Calculate the fitness function again and keep the best solutions: go to the next step if the number of iterations reaches the maximum number of iterations; otherwise update the position and continue the *Step 3*.

Step 8: Rank the solutions and find the global best solution: the solution with the best fitness (the lowest P_{loss}, *L*index and V_d) is the best solution.

And the computational flowchart of MCS-DE for ORPD problem is shown in Fig.1.

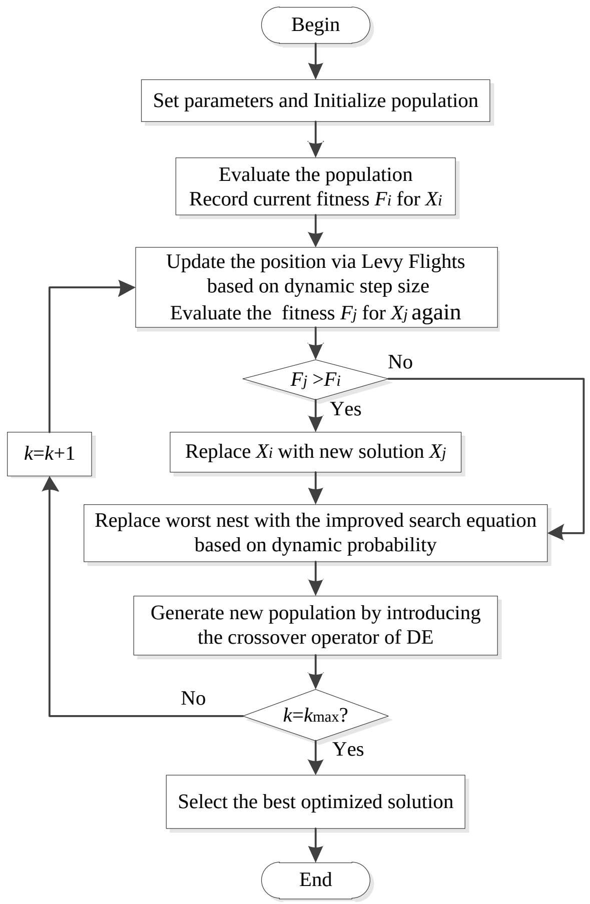

Fig.1. computational flowchart of MCS-DE for ORPD problem

V. Simulation Experiments

For the purpose of verifying the effectiveness of the proposed MCS-DE algorithm applied for ORPD problem, in the following section, numerical results extracted from solving ORPD problems by implementation of CS, DE and MCS-DE algorithms in the simulation runs will be presented.

Test systems are carried out on the three algorithms on IEEE30-bus and IEEE57-bus power systems. And the description of the two test systems is depicted in TABLE I. The three code of the algorithms are written by MATLAB R2014a programming language and run on PC with Intel(R) Core(TM) i5-7500 CPU @ 3.40GHz with 8.00 GB RAM. In this study, iterations are limited to maximum number of 1000 for IEEE30-bus and 1500 for IEEE57-bus power systems. The results of CS, DE and hybrid MCS-DE algorithms, which follow, are the best solutions for 30 independent trails.

A. Parameter settings

In general, the performances of evolutionary algorithms are sensitive to algorithm parameters. In this paper, we perform repeated simulations to find optimal values for the parameters and the parameters for the MCS-DE, CS and DE are given in TABLE II.

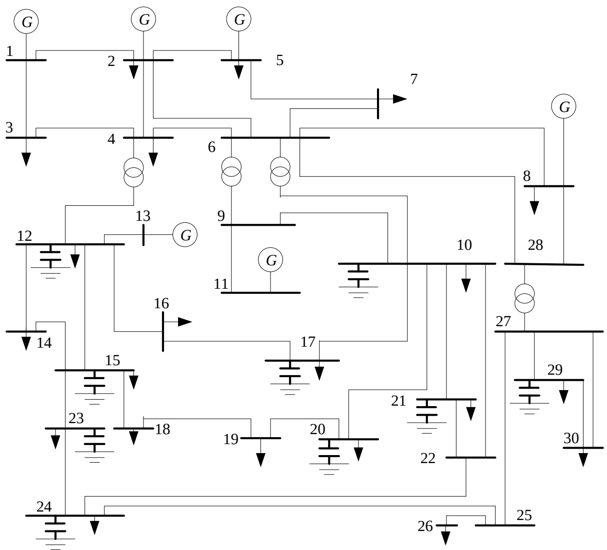

Fig.2. Network configuration of IEEE30-bus system

B. Example 1: IEEE 30-bus test system

IEEE 30-bus power system is taken as test system 1 and the representation is shown in Fig.2. This system has 30 buses, whose network consists of six generators (at the buses 1, 2, 5, 8, 11 and 13), four transformers (at lines 6–9, 6–10, 4–12 and 28–27) and nine shunt compensators (at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29). Hence, the numbers of control variables to be optimized are 19. The limits of reactive power of generators are seen in TABLE III and TABLE IV lists the minimum and maximum limits for the control variables. The detailed data (load data, line data, minimum and maximum limits for active power sources, bus voltages) for this test system are taken from [11, 17]. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 p.u. including *PQ* buses. The initial total active power losses are 5.832 MW which is calculated in Matpower3.2. In this example, three cases with different objective functions such as minimizing the P_{loss}, *Lindex* and V_d are considered.

1) Case1: Minimization of P_{loss} for IEEE30-bus system

The objective function of minimization of transmission power losses (P_{loss}) is defined as Eq.(4) and Eq.(20). TABLE V illustrates the best P_{loss} (BOV), average P_{loss} (AOV), worst P_{loss} (WOV) and the standard deviation (SD) obtained by three different methods in the 30 trials. The obtained optimal values of control variables and average CPU times of MCS-DE, CS, and DE are shown in TABLE VI. The results show that employing MCS-DE is less than the amount obtained by CS and DE. The obtained minimum value of P_{loss} yielded by MCS-DE is 4.5128 MW and is less by 22.62% compared to base case of 5.832 MW.

In order to verify the efficiency of the proposed algorithm, the results obtained by MCS-DE are compared with other methods reported in the literatures like GSA [11], HFA [2], BBO [31], DE [17], CLPSO [19] and PSO [19] and their details are shown in TABLE VII. Judging from the presented results, it turns out that active power losses obtained from MCS-DE is the least and MCS-DE has better performance than other methods. The computational times of the compared algorithms are also shown in TABLE VII. It may be seen from this table that the computing time of MCS-DE is less than other algorithms including GSA [11], CLPSO [19] and PSO [19]. TABLE VIII lists the saving percent of the reactive power losses (%P_{save}) for different algorithms. The TABLE VIII indicates that a 22.62% decrease in active power losses achieved by employing the MCS-DE algorithm, which is the biggest reduction of active power losses compared to that obtained by the other reported approaches.

TABLE I
DESCRIPTION OF TEST SYSTEMS

Description	IEEE 30-bus	IEEE 57-bus
number of buses, *NB*	30	57
number of generators, N_{PV}	6	7
number of transformers, N_T	4	17
shunt compensators, N_C	9	3
branches, N_L	41	80
control variables	19	27
base case for P_{loss} , MW	5.832	27.864

TABLE II
PARAMETER SETTINGS OF THREE ALGORITHMS

Parameter	CS	DE	MCS-DE
population size: *m*	30	30	30
dynamically step size: $\alpha_{\min}/\alpha_{\max}$	--	--	0.05/0.5
constant step size: α	0.1	--	--
dynamically probability: $P_{a\min}$/ $P_{a\max}$	--	--	0.005/0.5
constant probability: P_a	0.25	--	--
distribution factor: β	1.5	--	1.5
crossover factor: C_R	--	0.8	0.8

TABLE III
LIMITS OF GENERATORS REACTIVE POWER OUTPUTS IN IEEE 30-BUS SYSTEM

Generators	$Q_{i\max}$ (MVAr)	$Q_{i\min}$ (MVAr)
G_1	200	-20
G_2	100	-20
G_5	80	-15
G_8	60	-15
G_{11}	50	-10
G_{13}	60	-15

TABLE IV
LIMITS OF CONTROL VARIABLES IN IEEE 30-BUS SYSTEM

Control variables	$X_{i\max}$	$X_{i\min}$	Step
V_G (p.u.)	1.1	0.95	Continuous
T	1.1	0.9	0.0001
Q_C (p.u.)	0.05	0.0	0.0001

TABLE V: COMPARISONS OF SOLUTIONS FOR THREE METHODS IN IEEE30-BUS SYSTEM

Compared item	Case1			Case2			Case3		
	MCS-DE	CS	DE	MCS-DE	CS	DE	MCS-DE	CS	DE
BOV	4.5128	4.7316	4.7561	0.1242	0.1261	0.1266	0.0884	0.1823	0.1689
AOV	4.5131	4.9185	4.9461	0.1251	0.1278	0.1282	0.0933	0.2346	0.2465
WOV	4.5184	5.0355	5.0489	0.1260	0.1292	0.1297	0.1107	0.2929	0.2998
SD	0.0031	0.1533	0.1485	0.0009	0.0015	0.0016	0.0117	0.0553	0.0658

BOV: best objective value; AOV: average objective value; WOV: worst objective value; SD: standard deviation.

TABLE VI: OPTIMAL SETTINGS OF CONTROL VARIABLES IN IEEE30-BUS SYSTEM

Control variables	Case1			Case2			Case3		
	MCS-DE	CS	DE	MCS-DE	CS	DE	MCS-DE	CS	DE
V_{G1}	1.1	1.1	1.091909	1.099254	1.1	1.1	1.014657	1.01438	1.025614
V_{G2}	1.094303	1.092107	1.082942	1.096208	1.084671	1.091488	1.010071	1.007515	1.018501
V_{G5}	1.074749	1.087273	1.062394	1.099577	1.1	1.081827	1.017975	1.015087	1.033676
V_{G8}	1.076597	1.075078	1.068903	1.093269	1.053813	1.093246	1.010427	0.993313	0.991545
V_{G11}	1.1	1.097443	1.098454	1.099887	1.086178	1.1	1.009599	1.04299	1.015005
V_{G13}	1.1	1.096589	1.1	1.099963	1.061142	1.071683	1.002139	1.038982	1.067512
$T_{6\text{-}9}$	1.0433	1.0087	0.9980	0.9959	0.9353	1.1000	1.0241	0.9777	0.9627
$T_{6\text{-}10}$	0.9000	1.0726	0.9105	0.9002	0.9646	1.1000	0.9000	0.9803	0.9436
$T_{4\text{-}12}$	0.9792	1.1000	0.9404	0.9705	0.9805	0.9000	0.9656	0.9986	1.0848
$T_{28\text{-}27}$	0.9647	1.0218	0.9521	0.9564	0.9168	0.9427	0.9684	0.9451	0.9570
Q_{C10}	0.0500	0.0500	0.0000	0.0342	0.0123	0.0000	0.0434	0.0178	0.0194
Q_{C12}	0.0500	0.0010	0.0111	0.0150	0.0012	0.0000	0.0233	0.0181	0.0412
Q_{C15}	0.0483	0.0278	0.0003	0.0491	0.0500	0.0179	0.0500	0.0486	0.0162
Q_{C17}	0.0500	0.0061	0.0398	0.0350	0.0500	0.0500	0.0000	0.0165	0.0151
Q_{C20}	0.0402	0.0500	0.0432	0.0335	0.0261	0.0396	0.0500	0.0285	0.0500
Q_{C21}	0.0500	0.0500	0.0229	0.0057	0.0130	0.0295	0.0500	0.0109	0.0000
Q_{C23}	0.0252	0.0500	0.0000	0.0000	0.0159	0.0114	0.0500	0.0195	0.0469
Q_{C24}	0.0500	0.0337	0.0084	0.0117	0.0000	0.0180	0.0500	0.0322	0.0402
Q_{C29}	0.0219	0.0154	0.0246	0.0000	0.0000	0.0056	0.0257	0.0310	0.0144
BOV	**4.5128**	4.7316	4.7561	**0.1242**	0.1261	0.1266	**0.0884**	0.1823	0.1689
CPU time (s)	93.6761	95.1646	111.1095	80.4418	86.5848	103.2117	90.2348	95.7710	115.6832

BOV: best objective value.

TABLE VII: COMPARISONS OF DIFFERENT APPROACHES FOR IEEE30-BUS SYSTEM WITH MINIMIZING P_{loss}

Variables	MCS-DE	GSA[11]	HFA[2]	BBO[31]	DE[17]	CLPSO[19]	PSO[19]
V_{G1}	1.1	1.071652	1.1	1.1000	1.1000	1.1000	1.1000
V_{G2}	1.094303	1.022199	1.054332	1.0944	1.0931	1.1000	1.1000
V_{G5}	1.074749	1.040094	1.075146	1.0749	1.0736	1.0795	1.0867
V_{G8}	1.076597	1.050721	1.086885	1.0768	1.0756	1.1000	1.1000
V_{G11}	1.1	0.977122	1.1	1.0999	1.1000	1.1000	1.1000
V_{G13}	1.1	0.967650	1.1	1.0999	1.1000	1.1000	1.1000
$T_{6\text{-}9}$	1.0433	1.098450	0.980051	1.0435	1.0465	0.9154	0.9587
$T_{6\text{-}10}$	0.9000	0.982481	0.950021	0.90117	0.9097	0.9000	1.0543
$T_{4\text{-}12}$	0.9792	1.095909	0.970171	0.98244	0.9867	0.9000	1.0024
$T_{28\text{-}27}$	0.9647	1.059339	0.970039	0.96918	0.9689	0.9397	0.9755
Q_{C10}	0.0500	1.653790	4.700304	4.9998	5.0000	4.9265	4.2803
Q_{C12}	0.0500	4.372261	4.706143	4.987	5.0000	5.0000	5.0000
Q_{C15}	0.0483	0.119957	4.700662	4.9906	5.0000	5.0000	3.0288
Q_{C17}	0.0500	2.087617	2.30591	4.997	5.0000	5.0000	4.0365
Q_{C20}	0.0402	0.357729	4.80352	4.9901	4.4060	5.0000	2.6697
Q_{C21}	0.0500	0.260254	4.902598	4.9946	5.0000	5.0000	3.8894
Q_{C23}	0.0252	0.000000	4.804034	3.8753	2.8004	5.0000	0.0000
Q_{C24}	0.0500	1.383953	4.805296	4.9867	5.0000	5.0000	3.5879
Q_{C29}	0.0219	0.000317	3.398351	2.9098	2.5979	5.0000	2.8415
P_{loss}(MW)	**4.5128**	4.51431	4.529	4.5511	4.555	4.5615	4.6282
CPU time (s)/k_{max}	**93.6761/1000**	94.6938/200	NR[a]/200	NR[a]/300	NR[a]/500	138/50	130/50

NR[a] means not reported in the referred literature.

TABLE VIII: COMPARISONS OF DIFFERENT METHODS FOR MINIMIZING P_{loss} IN IEEE30-BUS SYSTEM

Compared item	PSO[19]	CLPSO[19]	BBO[31]	DE[17]	HFA[2]	MCS-DE
Initial P_{loss}(MW)	5.812	5.812	5.812	5.842	5.811	5.832
Best P_{loss}(MW)	4.6282	4.5615	4.5511	4.555	4.529	4.5128
$\%P_{save}$	20.37	21.5158	21.6948	22.0301	22.0616	**22.62**

TABLE IX: COMPARISONS OF DIFFERENT APPROACHES FOR IEEE30-BUS SYSTEM WITH MINIMIZING *Lindex* and V_d

Compared item	Best *Lindex*	CPU time (s)/k_{max}	Best V_d	CPU time (s)/k_{max}
MCS-DE	**0.1242**	80.4418/1000	**0.0884**	90.2348/1000
CS	0.1261	86.5848/1000	0.1823	95.7710/1000
DE	0.1266	103.2117/1000	0.1689	115.6832/1000
ABC[2]	NR[a]	NR[a]/200	0.135	NR[a]/200
FA[2]	NR[a]	NR[a]/200	0.1157	NR[a]/200
BBO[31]	NR[a]	NR[a]/300	0.0926	NR[a]/300
DE[17]	0.1246	NR[a]/500	0.0911	NR[a]/500
HFA[2]	NR[a]	NR[a]/200	0.098	NR[a]/200

NR[a] means not reported in the referred literature

2) Case2: Minimization of Lindex for IEEE30-bus system

In this case, the proposed MCS-DE approach has been applied for enhancement of voltage stability i.e. minimization of *Lindex* which is defined as Eq.(5), Eq.(10) and Eq.(20). Results obtained by CS, DE and the proposed MCS-DE algorithm are also presented in TABLE V. The optimal values of control variables and average CPU times of the three algorithms for case 2 also are shown in TABLE VI. It is also observed that MCS-DE performs best after that it follows CS and DE. The comparisons of the results obtained from the reported methods in the literatures are shown in TABLE IX. Form TABLE IX, one can see that the value of *Lindex* obtained from MCS-DE is the lowest among all the methods.

3) Case3: Minimization of V_d for IEEE30-bus system

In this case, the proposed MCS-DE has been applied for improvement of voltage profile i.e. minimization of voltage deviation (V_d) which is defined as Eq.(11) and Eq.(20). The best, average and worst V_d and the standard deviation yielded by CS, DE and the proposed MCS-DE among 30 runs of solutions are summarized in TABLE V. The optimal values of control variables and average CPU times obtained from the three methods are given in TABLE VI. The V_d obtained by the proposed MCS-DE is compared to those reported in the literatures like ABC [2], FA [2], BBO [31], DE [17] and HFA [2] are shown in TABLE IX. It is seen from TABLE IX, that V_d obtained from MCS-DE is the lowest among all other methods. It is also observed that MCS-DE approach performs best after that it follows HFA, DE, BBO, FA and ABC.

When considering average convergence characteristics for different cases and to illustrate the convergence of the proposed MCS-DE algorithm, fitness values of different objectives with 1000 iterations are plotted in Figs.3–5. It is seen that the convergence speed of the proposed MCS-DE algorithm converges rapidly towards the optimal solution and gives better improvement of transmission power losses, voltage stability index and voltage deviation profiles compared to CS and DE algorithm.

Comparative distribution of the values of CS, DE and the proposed MCS-DE in the 30 trials for different objectives are presented in Fig.6–8. From these figures it may be observed that the convergence profile of P_{loss}, *Lindex* and V_d obtained by the proposed MCS-DE approach for this test system is promising one and MCS-DE has a stronger robustness. This is consistent with the standard deviation in TABLE V.

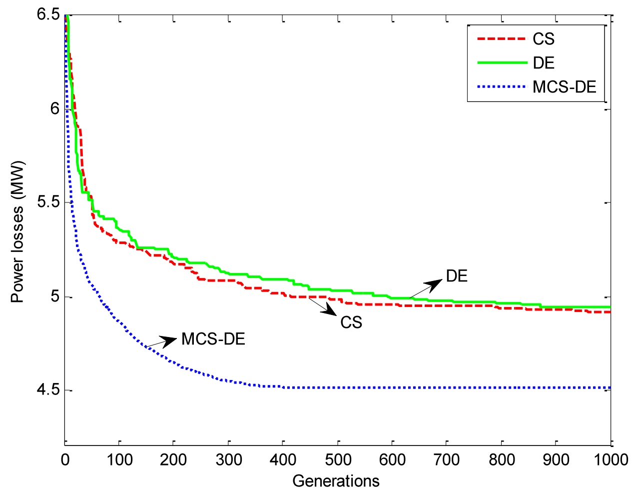

Fig.3. Comparative average convergence curves of power losses for IEEE30-bus system

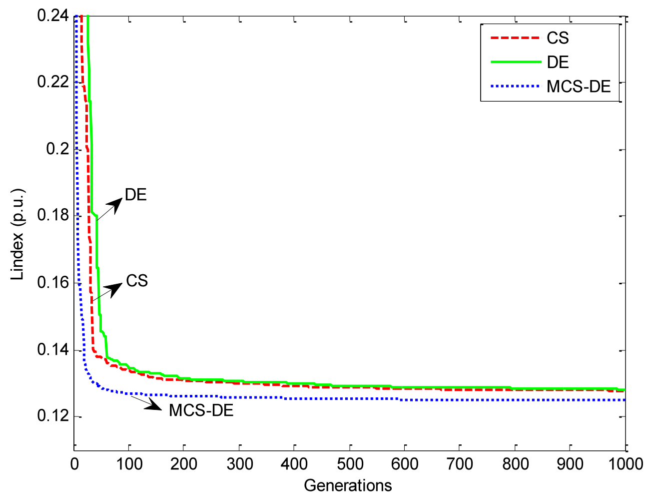

Fig.4. Comparative average convergence curves of *Lindex* for IEEE30-bus system

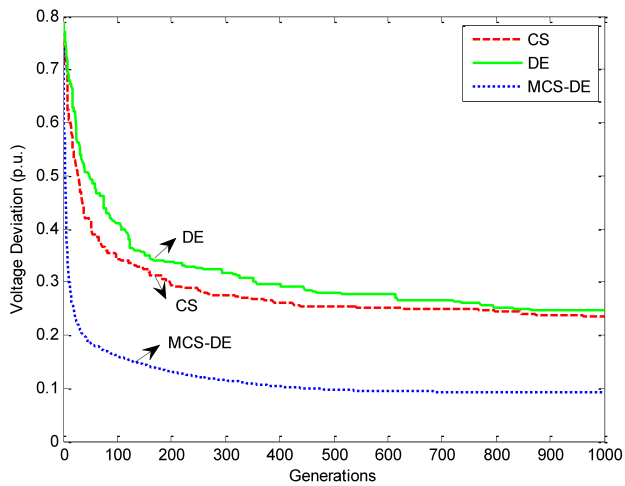

Fig.5. Comparative average convergence curves of voltage deviation for IEEE30-bus system

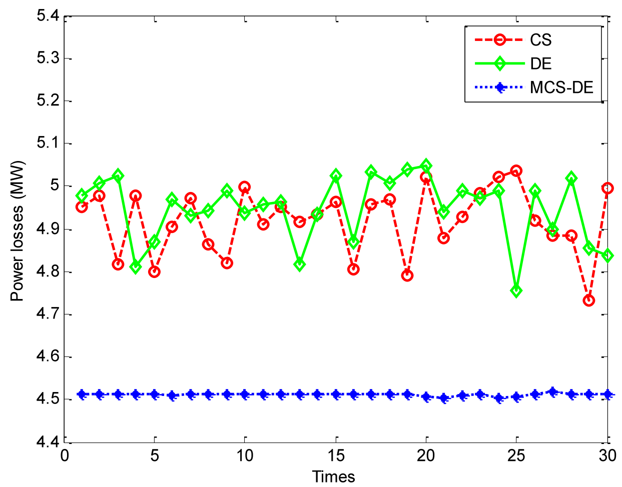

Fig.6. Comparative distribution of the values of power losses for IEEE30-bus system

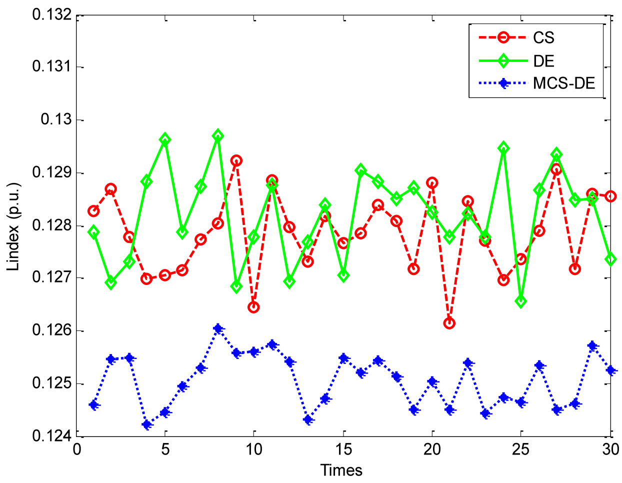

Fig.7. Comparative distribution of the values of *Lindex* for IEEE30-bus system

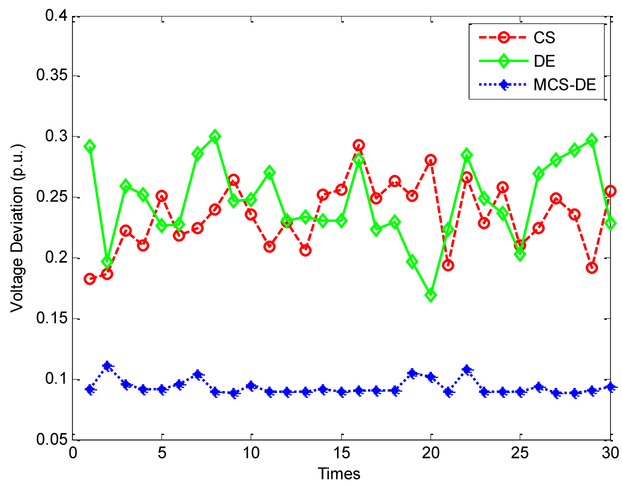

Fig.8. Comparative distribution of the values of voltage deviation for IEEE30-bus system

C. *Example 2: IEEE 57-bus test system*

The standard IEEE57-bus system is shown in Fig.9 and the detailed data are given in [32, 33]. Totally this system has 57 buses, including seven generators (at the buses 1, 2, 3, 6, 8, 9, 12), seventeen transformers and three shunt compensators (at buses 18, 25 and 53); therefore, the search space of this case system has twenty seven dimensions. The limits of reactive power of generators are seen in TABLE X and TABLE XI lists the minimum and maximum limits for the control variables. For *PQ* buses, the lower and upper voltage magnitude limits are 0.94 and 1.06 p.u. The initial total active power losses are 27.864 MW which is calculated by Matpower3.2.

1) Case4: Minimization of P_{loss} for IEEE57-bus system

For this case, the solution result for P_{loss} minimization objective are tabulated in TABLE XII. The optimal control variables and average CPU times of MCS-DE, CS, and DE are shown in TABLE XIII. In order to verify the efficiency of the proposed MCS-DE, the concerned performance indexes including the best P_{loss}, the worst P_{loss}, the average P_{loss}, the standard deviation and the saving percent of the reactive power losses (%P_{save}) for 30 independent runs are compared with other methods reported in the literatures like EC-DE [33], SOA [32] and L-SaDE [32] and their details are shown in TABLE XIV. TABLE XIV demonstrates that a power loss reduction of 16.49% (from base case of 27.864 MW to 23.269 MW) is accomplished by using the proposed MCS-DE approach, which is the biggest reduction of power losses compared to that obtained by the other reported approaches. Moreover, the standard deviation of MCS-DE is the lowest. It turns out that MCS-DE algorithm literally has better performance and robustness than other algorithms.

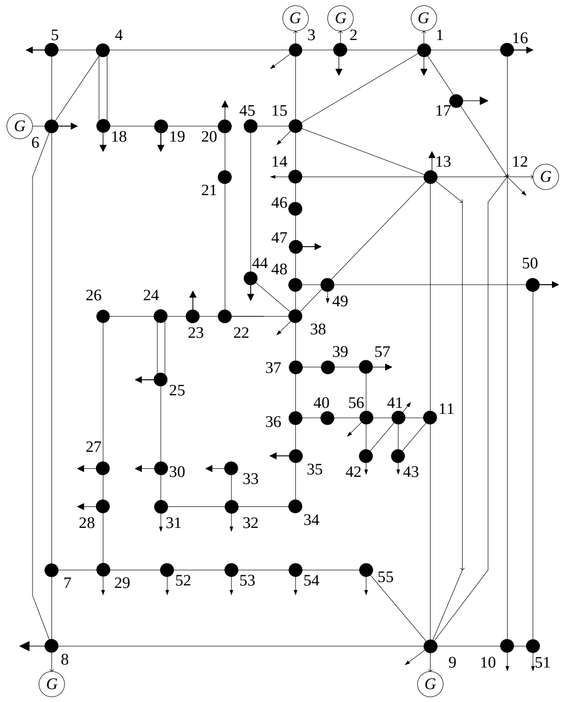

Fig.9. Network configuration of IEEE57-bus system

TABLE X
REACTIVE POWER GENERATION LIMITS IN IEEE57-BUS SYSTEM

Generators	Q_{imax} (MVAr)	Q_{imin} (MVAr)
G_1	200	-140
G_2	50	-17
G_3	60	-10
G_6	25	-8
G_8	200	-140
G_9	9	-3
G_{12}	155	-150

TABLE XI
LIMITS OF CONTROL VARIABLES IN IEEE 57-BUS SYSTEM

Control variables	X_{imax}	X_{imin}	Step
V_G (p.u.)	1.1	0.9	Continuous
T	1.1	0.9	0.01
Q_{C18}(p.u.)	0.2	0.0	0.005
Q_{C25}(p.u.)	0.18	0.0	0.006
Q_{C53}(p.u.)	0.18	0.0	0.006

TABLE XII
COMPARISONS OF SOLUTIONS FOR THREE METHODS IN IEEE 57-BUS SYSTEM

Compared item	Case4			Case5		
	MCS-DE	CS	DE	MCS-DE	CS	DE
BOV	**23.2690**	23.7592	23.7476	**0.2658**	0.2673	0.2725
AOV	23.8450	24.6163	24.8872	0.2711	0.2768	0.2806
WOV	24.4244	25.5375	26.3291	0.2758	0.2832	0.2925
SD	0.5777	0.8893	1.2937	0.0050	0.0080	0.0100
CPU time(s)	283.0721	290.9116	292.0554	282.9279	283.5402	287.1492

BOV: best objective value; AOV: average objective value; WOV: worst objective value; SD: standard deviation.

TABLE XIII
OPTIMAL SETTINGS OF CONTROL VARIABLES IN IEEE57-BUS SYSTEM

Control variables	Case4			Case5		
	MCS-DE	CS	DE	MCS-DE	CS	DE
V_{G1}	1.085241	1.099199	1.099702	1.100000	1.100000	1.100000
V_{G2}	1.074555	1.086942	1.088470	1.081606	1.085585	1.084406
V_{G3}	1.063154	1.092038	1.079738	1.083648	1.088533	1.083170
V_{G6}	1.057265	1.090687	1.082360	1.077414	1.075027	1.093528
V_{G8}	1.075219	1.099870	1.097615	1.096466	1.096144	1.100000
V_{G9}	1.055731	1.087465	1.078957	1.098056	1.095393	1.091404
V_{G12}	1.049382	1.098502	1.100000	1.100000	1.099930	1.100000
$T_{4\text{-}18}$	1.02	1.06	1.10	0.92	1.10	0.94
$T_{4\text{-}18}$	1.08	1.02	1.10	1.05	1.10	1.10
$T_{21\text{-}20}$	1.06	0.95	1.03	1.00	0.90	1.10
$T_{24\text{-}25}$	0.91	0.91	1.10	0.90	1.10	0.97
$T_{24\text{-}25}$	1.10	1.10	0.92	1.10	0.92	0.90
$T_{24\text{-}26}$	1.01	1.07	1.10	1.10	1.10	0.94
$T_{7\text{-}29}$	1.00	1.10	1.10	0.96	0.99	1.10
$T_{34\text{-}32}$	0.94	0.94	0.94	0.93	0.91	0.93
$T_{11\text{-}41}$	0.90	0.95	0.90	0.94	0.90	0.95
$T_{15\text{-}45}$	0.99	0.99	1.01	0.97	1.02	0.96
$T_{14\text{-}46}$	0.97	1.04	0.99	0.99	0.95	0.98
$T_{10\text{-}51}$	0.98	1.08	0.97	0.99	1.00	1.02
$T_{13\text{-}49}$	0.94	0.99	0.98	1.02	0.99	1.07
$T_{11\text{-}43}$	0.99	0.99	1.06	1.04	1.10	1.05
$T_{40\text{-}56}$	0.99	1.06	1.09	0.91	1.09	1.06
$T_{39\text{-}57}$	0.97	0.90	0.91	0.95	0.94	1.10
$T_{9\text{-}55}$	1.00	1.10	1.04	1.10	1.10	1.06
Q_{C18}	0.135	0.185	0.195	0.000	0.195	0.125
Q_{C25}	0.108	0.174	0.150	0.072	0.084	0.150
Q_{C53}	0.132	0.180	0.156	0.180	0.150	0.180
BOV	**23.269**	23.7592	23.7476	**0.2658**	0.2673	0.2725
CPU time(s)	283.0721	290.9116	292.0554	282.9279	283.5402	287.1492

BOV: best objective value.

TABLE XIV
COMPARISONS OF DIFFERENT METHODS IN IEEE57-BUS SYSTEM WITH MINIMIZING P_{loss}

Methods	Initial P_{loss}	Best P_{loss}	Average P_{loss}	Worst P_{loss}	Standard deviation	$\%P_{save}$
MCS-DE	27.864	**23.269**	23.845	24.4244	0.5777	**16.49**
CS	27.864	23.7592	24.6163	25.5375	0.8893	14.73
DE	27.864	23.7476	24.8872	26.3291	1.2937	14.77
EC-DE[33]	27.8637	23.3403	23.7920	24.5325	0.6019	16.23
SOA[32]	28.462	24.6248	25.741	28.7541	2.1360	13.48
L-SaDE[32]	28.462	24.6712	26.0983	28.2335	1.7928	13.32

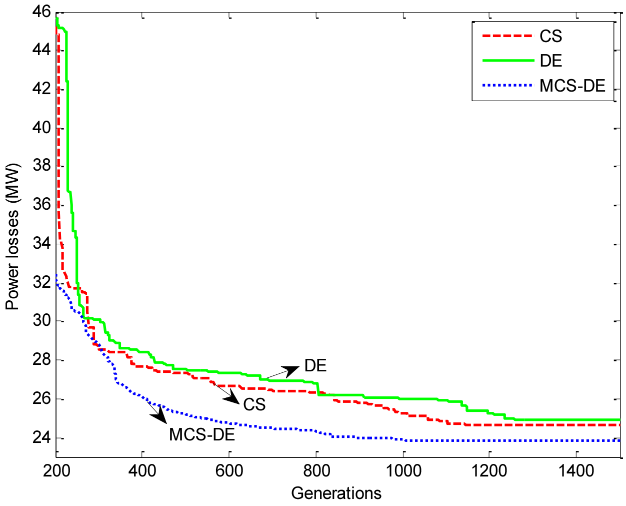

Fig.10. Comparative average convergence curves of power losses for IEEE57-bus system

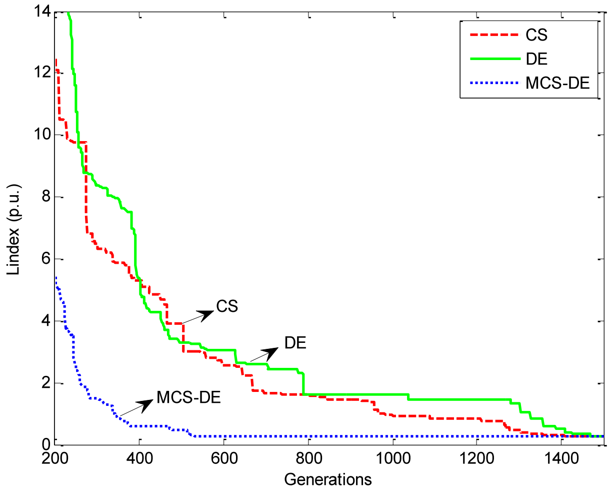

Fig.11. Comparative average convergence curves of *Lindex* for IEEE57-bus system

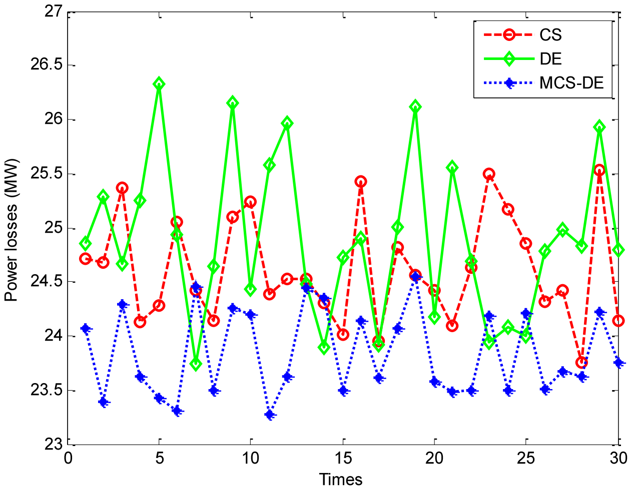

Fig.12. Comparative distribution of the values of power losses for IEEE57-bus system

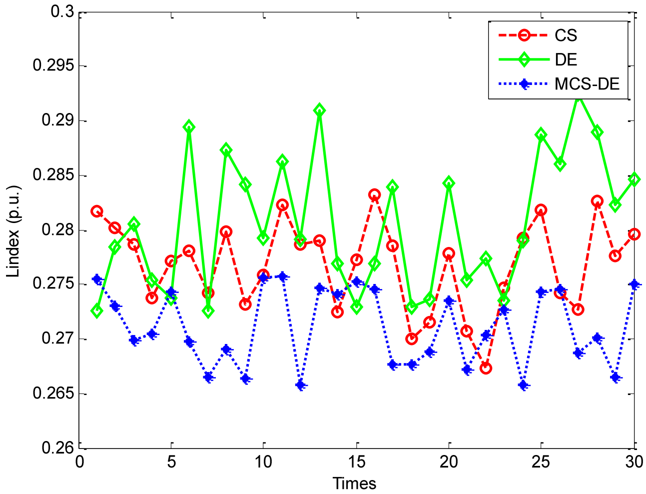

Fig.13. Comparative distribution of the values of *Lindex* for IEEE57-bus system

2) Case5: Minimization of Lindex for IEEE57-bus system

The statistical comparison of the results obtained from MCS-DE, CS, and DE are shown in TABLE XII and the optimal control variables and average CPU times of three algorithms for case 5 are also presented in TABLE XIII. From this table it may be inferred that the proposed MCS-DE yields better results as compared to CS and DE. It is also observed that MCS-DE approach performs best after that it follows CS and DE.

Furthermore, in order to illustrate the proposed MCS-DE algorithm also has better convergence in larger IEEE57-bus power system, the average convergence characteristics of different objectives for two cases with 1500 iterations are plotted in Figs.10–11. Comparative distribution of the values of CS, DE and the proposed MCS-DE in the 30 trials for different objectives are presented in Fig.12–13. From these figures it may be observed that the convergence profile for the proposed MCS-DE approach for this test system is also promising one.

VI. Conclusion

In this paper, the hybrid MCS-DE algorithm has been proposed, and demonstrated successfully applied to solve nonlinear, non-convex ORPD problem. It is tested and examined with different objective functions such as minimization of active power losses and enhancement of voltage stability and voltage profile for standard IEEE 30-bus and 57-bus test systems. Statistical analysis confirms the high level of consistency and robustness of MCS-DE in solving ORPD problem of power systems. It is verified that the proposed MCS-DE approach is a global algorithm and has strong ability to jump out of local optimum. Furthermore, MCS-DE convergence speed than CS and DE algorithms and can discover higher quality solution for the problems studied in this paper with comparison other previously reported methods in the literature for power systems.

Acknowledgements

The authors would like to thank the editors and the reviewers for their constructive comments and suggestions. This work is supported by Chongqing University Innovation Team under Grant KJTD201312 and the National Natural Science Foundation of China (Nos. 51207064 and 61463014).

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