MODIFIED CUCKOO SEARCH ALGORITHM FOR SOLVING OPTIMAL POWER FLOW PROBLEM

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ABSTRACT

Optimal power flow (OPF) is known as one of the most important planning and scheduling tools in electrical power systems. The OPF problem is a non-convex optimization problem, therefore, the applications of meta-heuristic algorithms in the OPF problem have been gained more attentions in recent years. In this paper, a modified cuckoo search algorithm (MCSA) is proposed to solve OPF problem. The proposed method has been developed on the original cuckoo search algorithm to improve the quality of the optimal solutions. Modifications include additional information exchanges between the top eggs, or the best solutions. The new algorithm is implemented to the OPF problem so as to minimize the total generation cost when considering the equality and inequality constraints. In order to validate of the proposed algorithm, it is applied to the standard IEEE 30-bus and IEEE 57-bus test systems. The results show that the proposed technique provides better solutions than other heuristic techniques reported in literature.

Keywords: *Modified cuckoo search algorithm, Optimization, Optimal power flow, Power system*

1. INTRODUCTION

Modern power system consists of a set of connections in which the energy can be transmitted from generators to load. In an interconnected power system, the objective function is to find the real and reactive power scheduling of each power plant in such a way as to minimize the operating cost. The optimal power flow (OPF) problem has become an essential for operation, planning and control of power systems. It was proosed first time in 1968 by Dommel and Tinney [1]. The main goal of OPF problem is to optimize a selected objective function such as fuel cost, power loss etc. In solving OPF problem, objective function is optimized by adjusting system control variable while satisfying the equality constraints and inequality constraints. The equality constraints normally power flow equations and inequality constraints which are limits on control variables and limits of power system dependent variables. Many conventional techniques such as gradient-based method, Newton method, linear programming, and quadratic programming have been employed for the solution of OPF problem [2-4]. But these methods cannot find a global optimization solution in OPF problems which have nonlinear constraints and objective function. Recently, numerous heuristic algorithms have been developed and have been implemented to successfully generate OPF solution such as tabu search (TS) [5], genetic algorithm (GA) [6-8], evolutionary programming (EP) [9], artificial bee colony (ABC) algorithm [10-12], differential evolution (DE) [13-16], teaching learning-based optimization (TLBO) [17-19], biogeography-based optimization (BBO) [20-22], particle swarm optimization (PSO) [23-25], and gravitational search algorithm (GSA) [26].

In cuckoo search algorithm (CSA) the Lévy flight was used to achieve good optimization performance [27, 28]. Although the optimization performance of CSA is good based on the Lévy flight some complicated mathematical operations should be used to realize the Lévy flight such as trigonometric function, gamma function and exponential functions, which limited the application of the cuckoo search algorithm especially there is high requirement about computation complex like the realization in the embedded systems. Hence the Lévy flight function can be replaced and some other techniques can be used to improve the optimization performance. In this paper, a modified cuckoo search algorithm (MCSA) which in an improved version of CSA has been applied to solve the OPF problems. The performance of the proposed approach has been demonstrated on the standard IEEE 30-bus and IEEE 57-bus test systems. Simulation results demonstrate that the proposed method provides better results than other heuristic optimization techniques.

The remainder of this paper is structured as follows. Section 2 describes the preliminary knowledge about cuckoo search algorithm. The MCSA is presented in Section 3. Simulation results are presented in Section 4 and Section 5 provides a conclusion.

2. PROBLEM FORMULATION

The optimal power flow problem solution aims to optimize a selected objective function via optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. Generally, the OPF problem can be mathematically written as follows:

$$\text{Min } J(x,u) \tag{1}$$

Subject to

$$g(x,u)=0$$
$$h(x,u)\le 0 \tag{2}$$

where J is objective function to be minimized, g is the equality constraints represent typical load flow equations, h is the inequality constraints represent the system operating constraints, x is the vector of dependent variables or state vector consisting of:

(1) Active power of generators at slack bus P_{G1}.
(2) Load bus voltage V_L.
(3) Generator reactive power output Q_G.
(4) Transmission line loading (line flow) S_l.

Hence, x can be expressed as:

$$x^T=[P_{G1},V_{L1}\cdots V_{LNL},Q_{G1}\cdots Q_{GNG},S_{l1}\cdots S_{lnl}] \tag{3}$$

where NG, NL, and nl are the number of generators, number of load buses, and number of transmission lines, respectively. u is the vector of independent variables or control variables consisting of:

(1) Generator voltage V_G at PV bus.
(2) Generator real power output P_G at PV buses except at the slack bus P_{G1}.
(3) Transformer tap setting T.
(4) Shunt VAR compensation (or reactive power of switchable VAR sources) Q_c.

Hence, u can be expressed as:

$$u^T=[P_{G2}\cdots P_{GNG},V_{G1}\cdots V_{GNG},Q_{c1}\cdots Q_{cNc},T_1\cdots T_{NT}] \tag{4}$$

where NT and NC are the number of the regulating transformer and VAR compensators, respectively.

2.1 Objective Function

The objective function for the OPF reflects the cost associated with generating in power system. The objective function for the whole power system can then be written as the sum of the fuel cost model for each generator:

$$J=\sum_{i=1}^{NG}F_i \tag{5}$$

where F_i indicate the fuel cost of the i-th generator.

The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator as:

$$F_i=a_i+b_iP_{Gi}+c_iP_{Gi}^2 \tag{6}$$

where a_i, b_i, and c_i are the cost coefficient of the i-th generator, P_{Gi} is the power generated by the i-th unit and NG is the number of generators.

2.2 Equality Constraints

These constraints are specific load flow equations which can be described as follows:

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{NB}V_j\left[G_{ij}\cos(\delta_i-\delta_j)+B_{ij}\sin(\delta_i-\delta_j)\right]=0 \tag{7}$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{NB}V_j\left[G_{ij}\sin(\delta_i-\delta_j)-B_{ij}\cos(\delta_i-\delta_j)\right]=0 \tag{8}$$

where, i=1,…, NB, NB is the number of buses; P_G is the active power generated, Q_G is the reactive power generated, P_D is the load active power, Q_D is the load reactive power, G_{ij} and B_{ij} respectively indicate the real part and imaginary part of the ij-th element of the node admittance matrix.

2.3 Inequality constraints

These constraints reflect the system operating limits as follows:

1. Generator constraints: generator voltages, real power outputs, and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{Gi}^{\min}\le V_{Gi}\le V_{Gi}^{\max},\ i=1,\dots,NG \tag{9}$$
$$P_{Gi}^{\min}\le P_{Gi}\le P_{Gi}^{\max},\ i=1,\dots,NG \tag{10}$$
$$Q_{Gi}^{\min}\le Q_{Gi}\le Q_{Gi}^{\max},\ i=1,\dots,NG \tag{11}$$

2. The transformer constraints: transformer tap settings are bounded as follows:

$$T_i^{\min}\le T_i\le T_i^{\max},\ i=1,\dots,NT \tag{12}$$

3. Shunt VAR constraints: shunt VAR compensations are qualified by their limits as follows:

$$Q_{ci}^{\min}\le Q_{ci}\le Q_{ci}^{\max},\ i=1,\dots,NC \tag{13}$$

4. Security constraints: these include the constraints of voltages at load busses and transmission line loadings as follows:

$$V_{Li}^{\min}\le V_{Li}\le V_{Li}^{\max},\ i=1,\dots,NL \tag{14}$$
$$S_{li}\le S_{li}^{\max},\ i=1,\dots,nl \tag{15}$$

3. CUCKOO SEARCH ALGORITHM

Cuckoo search algorithm (CSA) is inspired by some species of a bird family called cuckoo because of their special lifestyle and aggressive reproduction strategy. This algorithm was proposed by Yang and Deb [27]. The CSA is an optimization algorithm based on the brood parasitism of cuckoo species by laying their eggs in the communal nests of other host birds, though they may remove others' eggs to increase the hatching probability of their own eggs. Some host birds do not behave friendly against intruders and engage in direct conflict with them. If a host bird discovers the eggs are not their own, it will either throw these foreign eggs away or simply abandon its nest and build a new nest elsewhere [27, 28].

The CSA is based on three idealized rules [28]:

- Each cuckoo lays one egg (a design solution) at a time, and dumps its egg in a randomly chosen nest among the fixed number of available host nests;
- The best nests with high quality of eggs (better solution) will be carried over to the next generation;
- The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability of $p_a \in [0, 1]$. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

The later assumption can be approximated by the fraction p_a of the n nests which are replaced by new ones (with new random solutions).

The CSA contains a population of nests or eggs. Each egg in a nest represents a solution and a cuckoo egg represents a new solution. If the cuckoo egg is very similar to the host's, then this cuckoo egg is less likely to be discovered; thus, the fitness should be related to the difference in solutions. The better new solution (cuckoo) is replaced with a solution which is not so good in the nest. In the simplest form, each nest has one egg. When generating new solutions for $x^{(t+1)}$, say cuckoo i, a Lévy flight is performed:

$$x_i^{(t+1)} = x_i^t + \alpha L(s,\lambda) \quad (16)$$

where

$$L(s,\lambda) = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}},\ (s >> s_0 > 0) \quad (17)$$

In equation (16), the term $L(s, \lambda)$ determines the characteristic scale and $\alpha > 0$ denotes a scaling factor of the step size s, which should be related to the scales of the problem of interest. The characteristic scale L depends on the problem to be solved. For instance, the $\alpha=O(L/10)$ is suitable when the dimensionality of the problem is small. In contrast, when the dimensionality of the problem is large, the $\alpha=O(L/100)$ is more appropriate.

Based on these three rules, the basic steps of the CSA can be summarized as the pseudo-code shown in Figure 1.

Objective function $f(x), x = (x_1, \cdots, x_d)^T$
Initial a population of n host nests x_i (i=1, 2, …, n);
while (t < MaxGeneration) or (stop criterion);
  Get a cuckoo (say i) randomly by Lévy flights;
  Evaluate its quality/fitness F_i;
  Choose a nest among n (say j) randomly;
  if ($F_i > F_j$);
    Replace j by the new solution;
  end
  Abandon a fraction (p_a) of worse bests;
    [and build new ones at new location via Lévy flights];
  Keep the best solutions (or nests with quality solutions);
  Rank the solutions and find the current best;
end while
Postprocess results and visualization;

Figure 1: Pseudo-code of CSA [28]

4. MODIFIED CUCKOO SEARCH ALGORITHM

Given enough computation, the CSA will always find the optimum solution, but as the search relies entirely on random walks, a fast convergence cannot be guaranteed. Presented here, two modifications to the method are made with the aim of increasing the convergence rate, thus making the method more practical for a wide range of application but without losing the attractive features of the original method.

The first modification is made to the Lévy flight step size α. In CSA, the value of α is 1 and is constant, whereas in MCSA if the number of generations increase the value of α is reduced. In the MCSA, a portion of the eggs with the best fitness (quality) are put into a group of top eggs [29]. Initially, the value of Lévy flight step size A = 1 was selected and, at each generation, a new value of Lévy flight step size is calculated by using $\alpha = A/\sqrt{G}$, where G is the generation number. This exploratory search is carried out only on the fraction of nests to be abandoned. The second modification is to add information exchange between the eggs in an attempt to speed up convergence to a minimum. In the CSA, there is no information exchange between individuals and, essentially, the searches are performed independently. In the MCSA, a fraction of the eggs with the best fitness are put into a group of top eggs. For each of the top eggs, a second egg in this group is picked at random and a new egg is then generated on the line connected these two top eggs.

The distance along line at which the new egg is located and calculated using the inverse of the golden ratio φ=(1+√5)/2, such that it is closer to the egg with the best fitness. In the case that both eggs have the same fitness, the new egg is generated at the midpoint. Whilst developing the method a random fraction was used in the place of the golden ration, it was found that the golden ratio showed significantly greater performance than a random fraction. There is a possibility that, in this step, the same egg is picked twice. In this case, a local Lévy flight search is performed from the randomly picked nest with step size $\alpha = A/G^2$. There are two parameters, the fraction of nests to be abandoned and the fraction of nests to make up the top nests, which need to be adjusted in the MCSA [29].

Computational steps for MCSA can be summarized as the pseudo-code shown bellows:

Step 1: Initialize the population of cuckoo with eggs.

Step 2: Calculate the fitness of function $F_i = f(x_i)$, i=1, 2, ..., n, for each generation until the number of objective evaluation is less than the maximum number of evaluation.

Step 3: Arrange all the fitness function values in the order of their fitness.

Step 4: After the evaluation, calculate the number of nests to be abandoned.

Step 5: Calculate the Lévy flight step size by using $\alpha = A/\sqrt{G}$. Generate a new egg by performing the Lévy flight from a randomly selected position of an egg. If the generated new egg is better than the other randomly selected egg than this egg is moved to new position.

Step 6: The random search of Lévy flight is controlled by multiplying it with α and now $\alpha = A/G^2$ is to explore the abandoned nests.

Step 7: The new generated egg is randomly chosen. The egg having the best fitness are grouped in one and from these a second egg is randomly taken and a new egg is generated along the distance which is calculated using,

$$dx = \left| x_i - x_j \right| / \varphi \tag{18}$$

The distance is such calculated that the nest is moved towards the worst to the best position of an egg.

Step 8: The best nest is being selected as the best objective value so far.

5. SIMULATION RESULTS

In order to validate the feasibility and effectiveness of the proposed method, the algorithm was tested on the standard IEEE 30-bus and IEEE 57-bus test systems. The proposed algorithm is implemented on MATLAB R2016a using a Pentium IV PC, 3.6 GHz Processor and 4 GB RAM. The MCSA parameters used for the simulation are as follow: the population size (N_p), maximum number of iterations, and the value of probability p_a have been selected 40, 100, and 0.7, respectively.

5.1 IEEE 30-Bus Test System

The proposed MCSA technique has been tested on the standard IEEE 30-bus test system is shown in Figure 2. The system consists of 41 transmission lines, 6 generating unit and 4 tap-changing transformers. The complete system data is given in [30, 31]. The upper and lower active power generating limits and the fuel cost coefficients of all generators of the standard IEEE 30-bus test system are presented in Table 1. The voltage magnitude limits are between 0.95 and 1.05 pu for all load buses, while it is between 0.95 and 1.1 pu for all generator buses. Tap setting of all transformer taps are between 0.9 and 1.1 pu. The total system demand was chosen 283.4 MW.

Optimal values of control variables are given in Table 2. The total fuel cost obtained by proposed technique is 800.3856 $/h. Figure 3 show the cost convergence characteristic of MCSA for IEEE 57-bus test system. Table 3 shows a comparison between the results of fuel cost and power losses obtained from the proposed approach and those reported in the literature. The comparison is performed with the same control variable limits, initial conditions, and other system data. It is clear from the Table 3 that the proposed MCSA technique outperforms TS, TLBO, BBO, ABC, and GA techniques.

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Table 1: Generator data and fuel cost coefficients

Bus	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	a_i (\$/h)	b_i (\$/MW.h)	c_i (\$/MW^2.h)
1	50	200	0.00	2.00	0.00375
2	20	80	0.00	1.75	0.01750
5	15	50	0.00	1.00	0.06250
8	10	35	0.00	3.25	0.00834
11	10	30	0.00	3.00	0.02500
13	12	40	0.00	3.00	0.02500

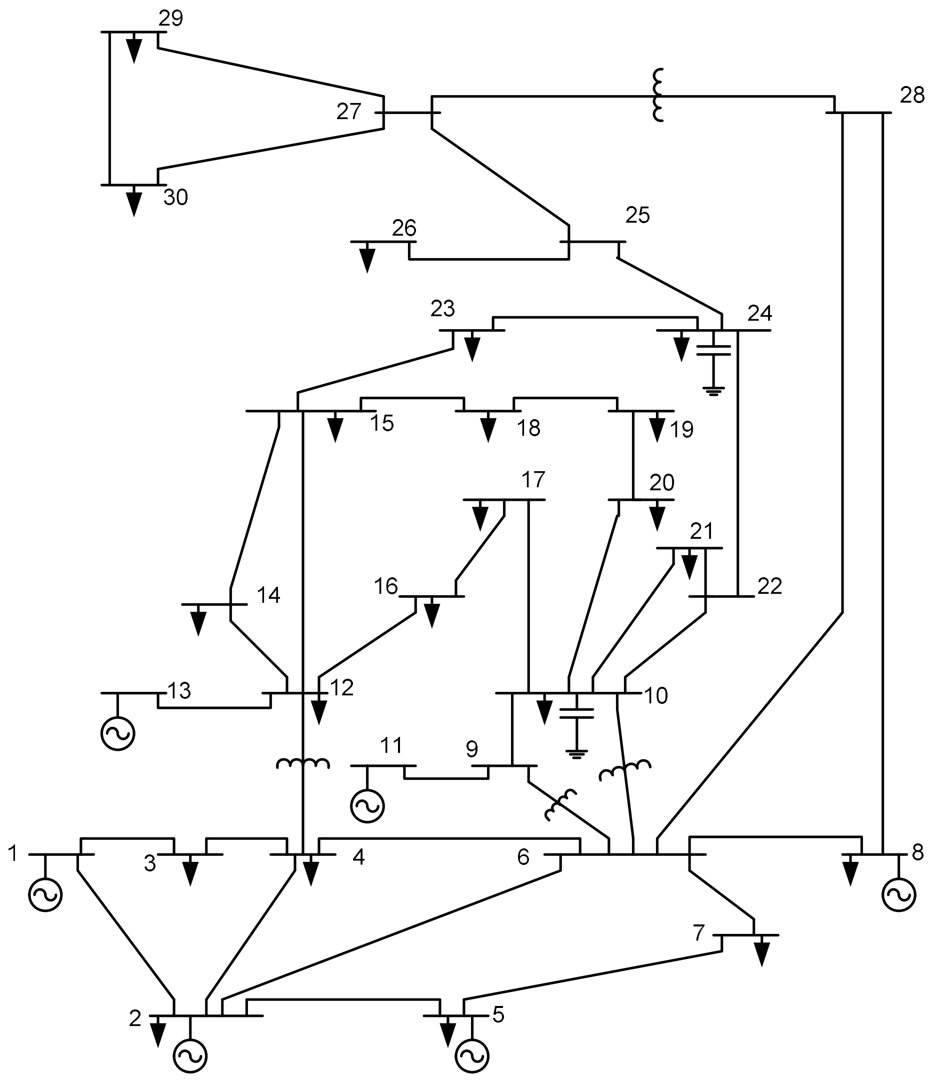

Figure 2: Single Line Diagram of IEEE 30-Bus Test System

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Table 2: Optimal Values of Control Variables

Variables	Limit		Result
	Lower	Upper	(Best solution)
P_{G1} (MW)	50	200	177.2375
P_{G2} (MW)	20	80	48.8705
P_{G5} (MW)	15	50	21.7325
P_{G8} (MW)	10	35	19.5596
P_{G11} (MW)	10	30	12.7538
P_{G13} (MW)	12	40	12.2368
V_{G1} (pu)	0.95	1.10	1.0999
V_{G2} (pu)	0.95	1.10	1.0848
V_{G5} (pu)	0.95	1.10	1.0555
V_{G8} (pu)	0.95	1.10	1.0651
V_{G11} (pu)	0.95	1.10	1.0002
V_{G13} (pu)	0.95	1.10	1.0459
T_{11}	0.90	1.10	0.9745
T_{12}	0.90	1.10	1.0585
T_{15}	0.90	1.10	1.0999
T_{36}	0.90	1.10	1.0212
Fuel cost ($/h)	800.3856		
Ploss (MW)	8.9910		

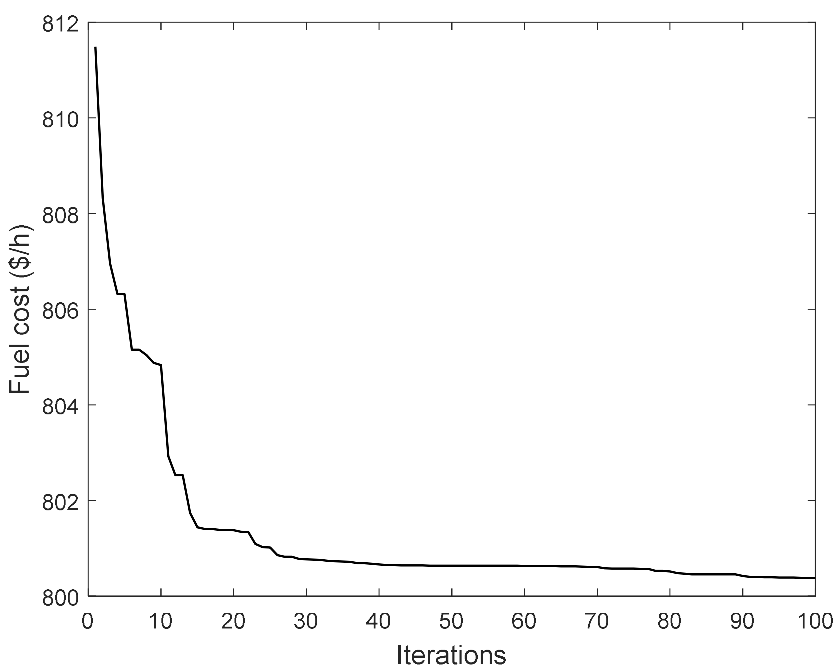

Figure 3: Cost Convergence Characteristics for IEEE 30-Bus Test System

Table 3: Results of minimum fuel cost for IEEE 30-bus system

Variables	TS [5]	TLBO [19]	BBO [22]	ABC [22]	GA [22]	MCSA
P_{G1} (MW)	176.04	176.94	171.9231	180.5218	177.28	177.2375
P_{G2} (MW)	48.75	49.02	48.8394	48.7845	48.817	48.8705
P_{G5} (MW)	21.56	21.53	21.4391	21.2598	21.529	21.7325
P_{G8} (MW)	22.05	21.81	21.7629	18.6469	21.81	19.5596
P_{G11} (MW)	12.44	12.20	12.1831	11.8145	11.325	12.7538
P_{G13} (MW)	12.00	11.41	16.5588	12.1011	12.087	12.2368
Fuel cost ($/h)	802.29	802.45	802.717	802.1649	802.0012	800.3856
Power loss (MW)	-	9.525	9.3064	9.7286	9.4563	8.9910

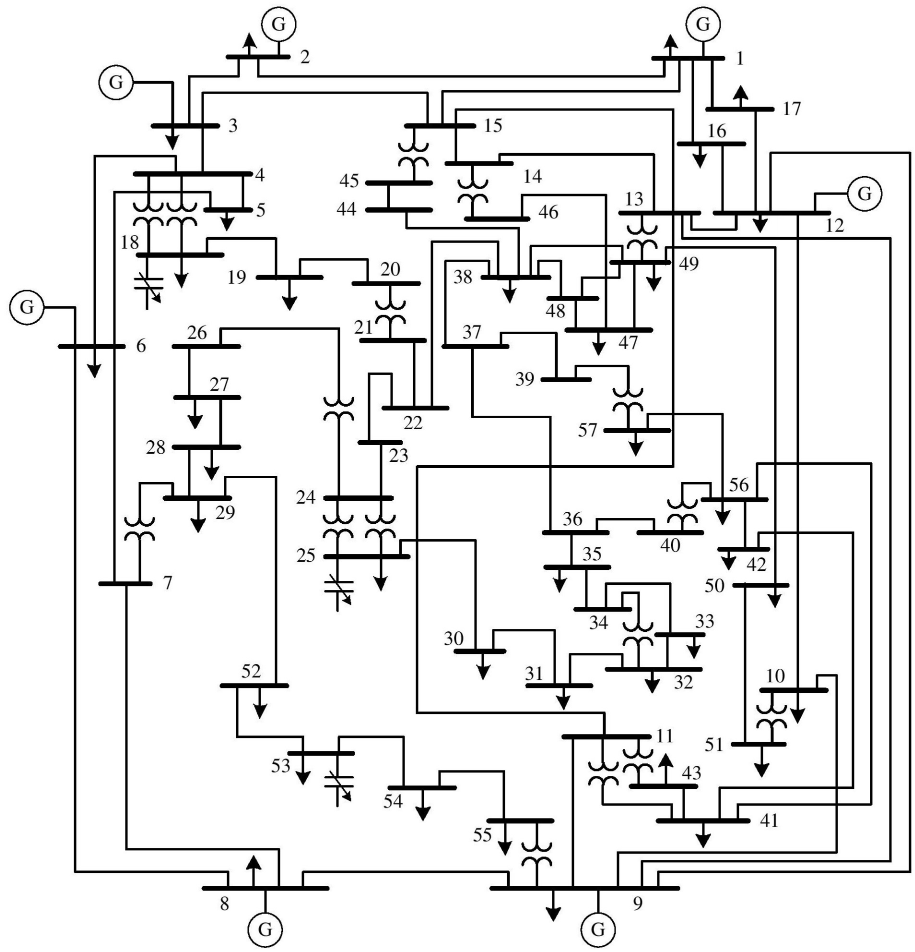

Figure 4: Single Line Diagram of IEEE 57-Bus Test System

5.2 IEEE 57-Bus Test System

To evaluate the efectiveness and efficiency of the proposed MCSA approach in solving larger power system, a standard IEEE 57-bus test system is considered as shown in Figure 4. The standard test system consist of 80 transmission lines, seven gnerators at the buses 1, 2, 3, 6, 8, 9, and 12, and 15 branches under load tap setting transformer branches. The shunt reactive power sources are considered at buses 18, 25, and 53. The total load demand of system is 1250.8 MW and 336.4 MVAR. The bus data and the line data are taken from [30, 31]. The minimum and maximum active power generating limits and the fuel cost coefficients of all generators of the standard IEEE 57-bus test system are presented in Table 4. The maximum and minimum values for voltages of all gnerator buses and tap setting transformer control variables are considered to be 1.1-0.9 in p.u. The maximum and minimum values of shunt reactive power sources are 0.0 and 0.3 in p.u. The maximum and minimum values for voltages of all load buses are 1.06 and 0.94 in p.u, respectively.

Best control variables settings are given in Table 5. The total fuel cost obtained by proposed technique is 41835.9919 \$/h and total active power loss is 18.6180 MW. Table 6 shows a comparison between the results of fuel cost obtained from the proposed approach and those reported in the literature. The comparison is performed with the same control variable limits, initial conditions, and other system data. It is clear from the Table 6 that the proposed MCSA technique outperforms Shuffled Frog Leaping Algorithm (SFLA) and Grey Wolf Optimizer (GWO) techniques. Figure 5 show the cost convergence characteristic of MCSA for IEEE 57-bus test system.

Table 4: Generator Data and Fuel Cost Coefficients

Bus	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW^{2}h)
1	0	575.88	0.00	20	0.07758
2	0	100	0.00	40	0.01000
3	0	140	0.00	20	0.25000
6	0	100	0.00	40	0.01000
8	0	550	0.00	20	0.022222
9	0	100	0.00	40	0.01000
12	0	410	0.00	20	0.032258

Table 5: Best Control Variables Settings for IEEE57-Bus Test System

Control variables	Best result	Control variables	Best result
P_{G1} (MW)	144.1184	$T_{24\text{-}25}$ (pu)	1.0988
P_{G2} (MW)	91.1478	$T_{24\text{-}25}$ (pu)	0.9077
P_{G3} (MW)	45.0011	$T_{24\text{-}26}$ (pu)	0.9137
P_{G6} (MW)	75.9760	$T_{7\text{-}29}$ (pu)	1.0088
P_{G8} (MW)	455.2431	$T_{34\text{-}32}$ (pu)	0.9596
P_{G9} (MW)	93.7208	$T_{11\text{-}41}$ (pu)	1.0531
P_{G12} (MW)	364.2109	$T_{11\text{-}43}$ (pu)	0.9540
V_{G1} (pu)	1.0753	$T_{15\text{-}45}$ (pu)	0.9955
V_{G2} (pu)	1.0669	$T_{14\text{-}46}$ (pu)	1.0237
V_{G3} (pu)	1.0640	$T_{10\text{-}51}$ (pu)	1.0046
V_{G6} (pu)	1.0688	$T_{13\text{-}49}$ (pu)	0.9779
V_{G8} (pu)	1.0897	$T_{9\text{-}55}$ (pu)	1.0727
V_{G9} (pu)	1.0524	$T_{40\text{-}56}$ (pu)	0.9156
V_{G12} (pu)	1.0628	$T_{39\text{-}57}$ (pu)	0.9801
$T_{4\text{-}18}$ (pu)	0.9958	Q_{c18} (pu)	0.0930
$T_{4\text{-}18}$ (pu)	1.0020	Q_{c25} (pu)	0.1886
$T_{21\text{-}20}$ (pu)	1.0980	Q_{c53} (pu)	0.1334
Fuel cost (\$/h) = 41835.9919; Ploss (MW) = 18.6180			

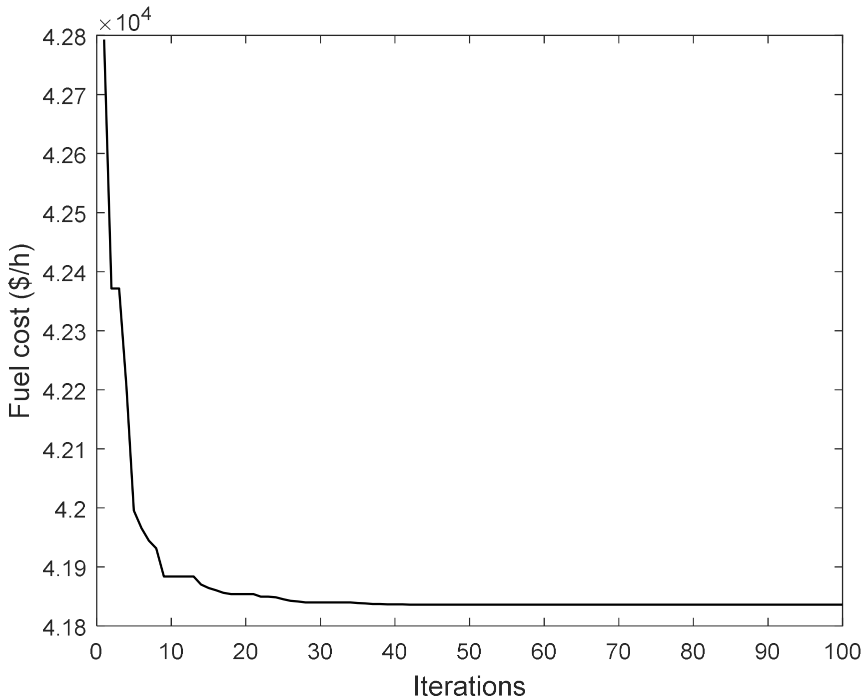

Figure 5: Cost Convergence Characteristics for IEEE 57-Bus Test System

Table 6: Results of Minimum Fuel Cost for IEEE 57-Bus System

Variables	SFLA [32]	GWO [32]	MCSA
P_{G1} (MW)	144.856	145.42	144.1184
P_{G2} (MW)	93.0378	95.66	91.1478
P_{G3} (MW)	45.209	45.02	45.0011
P_{G6} (MW)	68.2624	67.57	75.9760
P_{G8} (MW)	457.0264	454.28	455.2431
P_{G9} (MW)	95.8565	94.11	93.7208
P_{G12} (MW)	365.9573	367.95	364.2109
Fuel cost ($/h)	41872.9	41873.188	41835.9919

6. CONCLUSION

In this paper, an application of MCSA method for OPF problem is employed to get faster and better optimization performance. The problem of the present work is formulated as a nonlinear optimization problem with equality and inequality constraints of the power system. The feasibility of the proposed technique for solving OPF problems is demonstrated by using the standard IEEE 30-bus and IEEE 57-bus test systems. Results obtained are compared to those other well established techniques in the literature recently. It is revealed that among all the techniques, the proposed method gives better results in terms of finding the minimum fuel cost for all the test system of the OPF problem. The superior performance of the MCSA is due to its ability to simultaneously refine a local search, while still searching globally. It can do this because of the information exchange between the top eggs and the exploration globally due to the abandoning of nests and search via Lévy flights. On the other hand, the MCSA has the advantage of being very simple to implement and only having two parameters to adjust.

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