Performance of Self Adaptive Cuckoo Search Algorithm in Optimal Power Flow Problems

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Abstract - *Optimal power flow (OPF) problem is an important task in power system operation and planning. An efficient algorithm is necessary for solving the OPF problem as it is highly nonlinear in nature. In this paper, self adaptive cuckoo search based metaheuristic algorithm (SACSA) is proposed to solve different optimal power flow problems. To prove the effectiveness of the proposed method, it has been demonstrated on standard IEEE 30-bus test system for four different objectives that are related to fuel cost minimization of generators with convex or non-convex fuel cost characteristics. The results obtained by using the proposed method are compared with those obtained by other different methods followed in the literature. It is evident from the comparison that the cuckoo based algorithm performs better and found to be encouraging.*

***Key Words*: Optimal power flow, cuckoo search algorithm, power system optimization**

1. INTRODUCTION

The vast majority of the tools for optimization of power system operation and control are appropriately formulated as some sort of optimization problem [1]. OPF is the basic tool that has been widely used since its introduction [2, 3]. The term OPF was first introduced by Dommel and Tinney in 1968 [4] as discussed in [1]. OPF problem is a large-scale highly constrained non-linear non-convex optimization problem [5]. There are numerous OPF models are developed and utilized to formulate different types of optimization problems using different sets of controls variables and under different types of constraints [7].

The OPF problem has been rigorously analyzed in the past few decades, and many optimization techniques have emerged and been applied to solve this problem [8]. In the past, many conventional optimization techniques have been successfully applied for OPF problems. Some of those methods were gradient-based methods, Newton-based method, the simplex method, sequential linear programming, sequential quadratic programming, and interior point methods [9]–[12]. Even though some of these techniques have excellent convergence behaviour, they suffer from some shortcomings. Some of the drawbacks are that they cannot ensure global optimality [1], [12].

The recent rapid developments in computational intelligence tools have motivated research in the area of metaheuristic optimization methods [1]. Most of these techniques have been applied to OPF problems, such as the genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), bacterial foraging algorithms (BFAs), biogeography-based optimization (BBO), simulated annealing (SA), and tabu search (TS). These methods are known for their capabilities of finding global best solutions and avoiding being trapped into local ones and their ability of fast searching of large solution spaces. References [1],[13] review some of these optimization techniques applied to solve the OPF problem.

The cuckoo search algorithm, is a new optimization algorithm based on the food foraging behaviour of cuckoo [15]. This method is suitable for nonlinear problems with bounded variables. Owing to its characteristics and performances, the algorithm has been gaining attention and been extended and applied in many works, with most reporting its promising performance [15].

The following sections are as follows: section-2 formulates the OPF, section-3 is devoted for the CSA and its implementation for OPF problem. Next, the CSA is applied to solve the OPF problem to optimize the power system operating conditions in section-4. Finally, in section-5, some final remarks and points concluded.

2. OPF PROBLEM FORMULATION

OPF is a type of power flow problem that gives the optimal values of the control variables for a given amount of load by optimizing a preset objective function while satisfying some constraints. Hence, the OPF problem can be mathematically formulated as a non-linear constrained optimization problem as follows [16]–[18].

$$\min imize \quad f\left(x,u\right)$$
$$subject\ to$$
$$g\left(x,u\right)=0$$
$$and$$
$$h\left(x,u\right)\leq 0$$

where f (**x**,**u**) is the objective function, g (**x**,**u**) is the set of equality constraints, h (**x**,**u**) is the set of inequality constraints, **u** is the vector of independent variables or control variables and **x** is the vector of dependent variables or state variables respectively. Four different objectives are considered here for the OPF problem. These four cases are discussed below.

2.1Case 1: Minimization of fuel cost (FC)

It represents the smooth or the quadratic cost function whose objective function is expressed as follows:

$$f_1 = FC = \sum_{i=1}^{ng}\left(a_i + b_i P_{gi} + c_i P_{gi}^2\right) \quad (1)$$

where FC is the total fuel cost; ai; bi and ci are fuel cost coefficients of the ith unit.

2.2Case 2: Minimization of valve point effect cost (VPC)

The effect of valve point is considered here to determine the exact cost of power generation using the following equation:

$$f_2 = VPC = \sum_{i=1}^{ng}\left\{\begin{array}{l}\left(a_i + b_i P_{gi} + c_i P_{gi}^2\right)\\ + \left|d_i \sin\left(e_i\left(P_{gi}^{\min} - P_{gi}\right)\right)\right|\end{array}\right\} \quad (2)$$

where VPC is the fuel cost; ai; bi and ci are fuel cost coefficients of the ith unit.

2.3Case 3: Minimization of piecewise fuel cost (PWC)

In the IEEE-30 bus system, generators 1 and 2 can be run from two different fuels and cost of power generation is also different. The fuel cost is calculated considering the fuel used that is fuel 1 or fuel 2.

$$f_3 = PWC = \left(a_{ik} + b_{ik} P_{gi} + c_{ik} P_{gi}^2\right) \quad (3)$$

where **k** is the fuel option. In this study, generators only 1 and 2 have two fuel options (**k** = 2).

2.4Case 4: Minimization of emission (EmC)

To minimize the pollution, emission from the thermal generators should be minimized by taking this objective.

$$f_4 = EmC = \sum_{i=1}^{ng}\left(\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \xi_i e^{\lambda_i P_{gi}}\right) \quad (4)$$

where EmC is the total emission cost (ton/h), a_i, b_i and c_i are the emission coefficients of the i^{th} unit.

2.1. Constraints

2.1.1. Equality constraints

In the below terms, g is the equality the equality constraints, illustrating typical load flow equations:

$$P_{Gi} - P_{Di} - \sum_{k=1}^{N_B} V_i V_j Y_{ij}\cos\left(\delta_{ij} + \gamma_j - \gamma_i\right) = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} - \sum_{k=1}^{N_B} V_i V_j Y_{ij}\sin\left(\delta_{ij} + \gamma_j - \gamma_i\right) = 0 \quad (6)$$

where N_B is the number of buses, P_{Gi} is the active power generation, Q_{Gi} is the reactive power generation, P_{Di} is the active load demand, Q_{Di} is the reactive load demand, Y_{ij} is the admittance of line connected between buses I and j.

2.1.2. Inequality constraints

h is the inequality constraints that include:
Inequality constraints
Voltage Constraint:

$$V_i^{\min} \le V_i \le V_i^{\max} \;; i \in N_B \quad (7)$$

Transformer tap constraint:

$$T_i^{\min} \le T_i \le T_i^{\max} \;; i \in N_T \quad (8)$$

Shunt VAR constraint:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \;; i \in N_C \quad (9)$$

Transmission line flow limit:

$$S_i \le S_i^{\max}; \quad i \in N_L \quad (10)$$

Where $V_i^{\min}$, $V_i^{\max}$, $Q_{Ci}^{\min}$ $Q_{Ci}^{\max}$, $T_i^{\min}$ and $T_i^{\max}$ are the minimum and maximum values of the all load buses, shunt compensating reactive devices and transformer tap settings respectively.

$S_i^{\max}$ is the maximum loadablity of the transmission lines. N_B, N_T N_C and N_L are the number of buses, transformers, shunt compensating devices and total number of transmission lines of the system respectively.

3. SELF-ADAPTIVE CUCKOO SEARCH ALGORITHM (SACSA)

3.1 Overview

Cuckoo Search Algorithm (CSA) is a swarm intelligence based metaheuristic optimization algorithm developed by Yang and Deb [19]. CSA mimics the breeding behaviour of few cuckoo species and Levy flight behaviour of some birds and fruit flies.
To trap the behaviour of cuckoos in nature and adapt it to be suitable for using as an algorithm, there are three basic rules:

(i) each cuckoo lays one egg at a time in a nest and dumps it in a randomly chosen nest
(ii) the best nests which resemble the closest to the host's eggs (high quality eggs) are carried to the further generations
(iii) The number of available host nests is fixed and any egg laid by a cuckoo may be discovered by the host bird with a probability Pa ∈ [0,1].

In the first step, parameters of CSA are set consisting of the number of nests, the step size control parameter 'α' and shifting parameter 'Pa'. Initial locations of the nests are determined by a randomly assigned set to each decision variable. As can be seen from the algorithm in the flowchart, new cuckoos are generated by Levy flights using the equations of local random walk equation 11(intended primarily for exploitation of the current solutions) and global random walk equation 12 (intended primarily for exploration of the search space defined in the function).

Local random walk is performed using the Pa parameter is expressed as,

$$nest_i^{new} = nest_i^{cur} + \alpha \otimes H\left(Pa - rand\right) \otimes \left(nest_j^{cur} - nest_k^{cur}\right) \quad (11)$$

Global random walk (Eq. 12) is performed by using the α (step length) and the best nest using Levy-Flight

$$nest_i^{new} = nest_i^{cur} + \alpha * f\left(best, \beta\right) \quad (12)$$

Here f is a function of current best nest and levy-flight parameter β.

The generating new cuckoos and discovering alien eggs steps are alternately performed until the termination criteria (i.e., till the algorithm reaches the maximum function evaluations [FEval]) is satisfied. The performance of this algorithm is sensitive to two main parameters, i.e. step size control parameter 'α' and discovering probability parameter 'Pa'. These two parameters govern the exploration and exploitation ability of the algorithm. To solve this problem, a self-adaptive version of this algorithm is proposed.

SACSA attempts to dynamically update the values of both the step size (α) and discovering probability parameter (Pa) as the algorithm proceeds, as shown in equation 13 and equation 12 .

$$\alpha\left(i\right) = \left(\frac{1}{t}\right)^{\left(\frac{F_{ideal} - F_i}{F_{ideal} - F_{anti\ ideal}}\right)} \quad (13)$$

Here α- alpha, i - nest number, t – iteration number, F_{ideal}- Fitness value of best nest, $F_{anti-ideal}$ - Fitness value of worst nest

$$Pa\left(t\right) = Pa\max * e^{t/time} \quad (14)$$

Here *Pamax* – Maximum value of the discovering probability parameter (assumed 0.9), t –iteration number, time – maximum number of iterations.

This enhancement enables the algorithm to search in larger search space, initially and as the iteration increases, the search space also decreases enabling a better convergence rate com- pared to original cuckoo search. As a result, two out of the three parameters are self-adapted and easy to set.

3.2Implementation of CS algorithm

Step-1: Assume the NP host nests $nest_i$ (i= 1, 2,..NP) and maximum number of iteration.

Step-2: Check for maximum number of iterations and select a cuckoo randomly by levy flights evaluate the fitness or cost function (f_i).

Step-3: Select a nest among NP on random basis, say (j).

Step-4: Compare if f_i is less than f_j replace j by the new solution.

Step-5: Best nests are maintained. A fraction (Pa) of worst nests is abandoned and new ones are built.

Step-6: Rank the nests based on their quality and find the current best.

Step-7: Repeat this in all the iterations and end when the maximum iterations are reached.

Step-8: Print the results.

4. RESULTS AND DISCUSSIONS

To examine the effectiveness of the proposed SACSA method, it is applied to solve the OPF problems with different objectives is tested on the standard IEEE 30 bus system. To exhibit the improvements made using the SACSA based method, the results are presented along with those of the other methods for the test case.

The developed SACSA based algorithm is coded using the MATLAB 7.9b computing environment, on a 2.20-GHz i5 PC with 4 GB of RAM The parameters of the SACSA are selected as follows: the number of nest NP = 50, probability for an alien egg to be discovered Pa = 0.5, maximum number of iterations = 500, For obtaining the optimal solution, the algorithm is performed 30 independent runs.

IEEE 30 bus system is a medium size test case. It has 24 load buses and 6 generator buses and 41 transmission lines in its configuration [20]. The control variables in OPF problems are: real power generation from generators, generator bus voltages, transformer tap settings and VAR outputs from shunt compensators. Figure shows the one-line diagram of the IEEE 30 bus test case.

4.1 Case 1: Minimization of generator fuel cost

The quadratic cost function is used in this case for calculation of total generation cost. The proposed algorithm is applied for minimizing the total fuel cost. The best control variable values corresponding to minimum fuel cost is tabulated in table 1.

The cost reported by the SACSA based method is compared with the other algorithms like BBO, IEM and RBBO in the table. It is evident that the proposed algorithm minimizes the fuel cost in a better way.

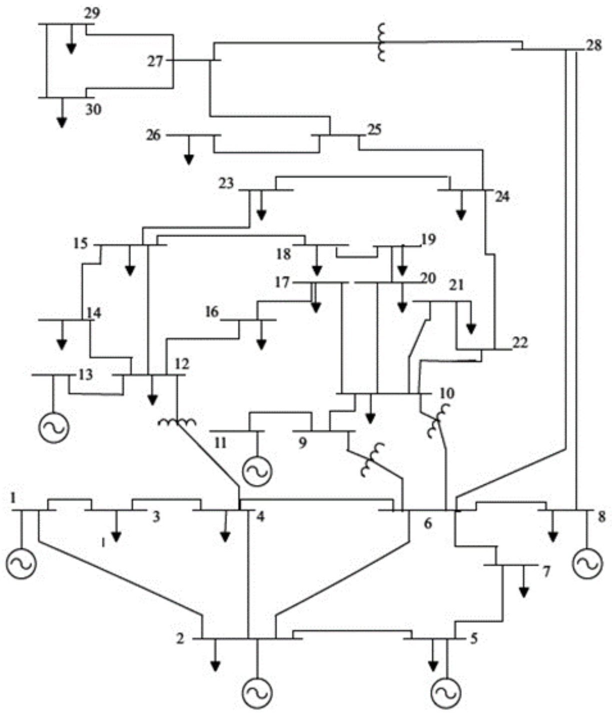

Figure.1 One line diagram of IEEE 30 bus system

Table 1. Best control variables in minimization of fuel cost

Variable	SACSA	BBO [21]	IEM [22]	RBBO [23]
P_{g1}	175.2680	177.0177	174.4387	177.1590
P_{g2}	47.4494	48.6410	48.1710	48.5610
P_{g5}	21.2466	21.2390	20.8907	21.4289
P_{g8}	20.6761	21.1360	20.5925	21.2958
P_{g11}	12.5242	11.9440	13.4993	11.9803
P_{g13}	12.0587	12.0540	14.4318	12.0004
V_{g1}	1.1000	1.1000	1.0908	1.0851
Vg2	1.0823	1.0876	1.0788	1.0651
V_{g5}	1.0543	1.0614	1.0520	1.0331
V_{g8}	1.0624	1.0695	1.0604	1.0384
V_{g11}	1.0986	1.0982	1.0853	1.1000
V_{g13}	1.1000	1.0998	1.0845	1.0408
T_{11}	1.0215	1.0500	1.0359	1.0974
T_{12}	0.9041	0.9000	0.9227	0.9006
T_{15}	0.9794	0.9900	1.0049	0.9663
T_{36}	0.9640	0.9700	0.9814	0.9760
Q_{c10}	4.6993	5.0000	3.6724	2.2567
Q_{c12}	4.4397	5.0000	4.4120	4.2353
Q_{c15}	3.9944	5.0000	3.9357	4.2998
Q_{c17}	2.6044	5.0000	4.4873	4.9446
Q_{c20}	3.9043	5.0000	4.5202	3.7381
Q_{c21}	4.8652	5.0000	3.7935	4.9901
Q_{c23}	5.0000	4.0000	3.9689	2.6502

Q_{c24}	4.7552	5.0000	4.5687	5.0000
Q_{c29}	2.0956	3.0000	3.3512	2.3967
FC ($/hr)	**799.0603**	799.1116	800.0781	800.5159

The algorithm is run for 500 iterations in optimizing the fuel cost the results are converged in 450 iterations. The convergence quality of algorithm is proved in the figure 2.

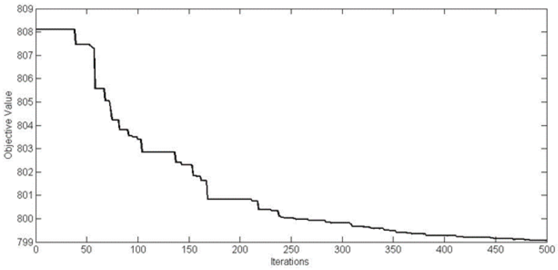

Figure. 2 Convergence quality of CSA in quadratic fuel cost minimization

4.2Case 2: Minimization of valve point cost

In this case, the valve point effects are taken in to account in cost calculations. For performance comparison, TLBO, GSA and BBO algorithms are taken. The results are compared in table 2 for understanding the strength of the proposed algorithm. The valve point effect cost reported by SACSA is 920.3103, which much less than the cost reported by the other algorithms in the table.

Table 2. Best control variables in minimization of valve point effect cost

Variable	SACSA	TLBO [24]	GSA [25]	BBO [26]
P_{g1}	196.222	194.1673	199.59943	197.426
P_{g2}	20.0000	44.3449	51.94640	52.037
P_{g5}	23.9881	20.6902	15.00000	15.000
P_{g8}	19.4821	13.1553	10.00000	10.000
P_{g11}	15.9055	10.0000	10.00000	10.001
P_{g13}	13.6247	12.0000	12.00000	12.000
V_{g1}	1.0870	1.0500	1.099002	1.0371
Vg2	1.0708	1.0287	1.099002	1.0130
V_{g5}	1.0478	1.0024	1.018042	0.9648
V_{g8}	1.0681	1.0163	1.052247	1.0320
V_{g11}	1.1000	1.0999	0.950000	1.0982
V_{g13}	1.0873	1.1000	0.963430	1.0890
T_{11}	0.9175	1.0065	0.950702	1.0969
T_{12}	1.0884	0.9073	0.918200	1.0909
T_{15}	1.0292	0.9936	0.909096	1.0991
T_{36}	1.0044	0.9485	0.945975	1.0021
Q_{c10}	2.8915	0.0000	-	-
Q_{c12}	0.2075	0.0000	-	-
Q_{c15}	2.4165	0.0000	-	-
Q_{c17}	4.8092	0.0000	-	-
Q_{c20}	3.7203	0.0000	-	-
Q_{c21}	2.8520	0.0000	-	-
Q_{c23}	2.6239	0.0000	-	-
Q_{c24}	0.6967	0.0000	-	-
Q_{c29}	3.9760	0.0000	-	-
VPC	**920.3103**	923.414	929.7240	930.793

Taking 375 iterations, the algorithm has converged to the global best results showing the better reliability of the algorithm. The convergence behaviour of the SACSA in valve point effect cost minimization is depicted in figure 3.

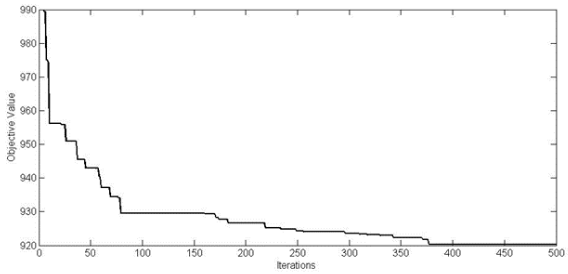

Figure. 3 Convergence quality of CSA in valve point effect fuel cost minimization

4.3Case 3: Minimization of piecewise cost

When multi type fuels are used in a generator, the fuel cost is different for different fuels. This cost function is the piecewise cost function which is used here for calculation of generation cost. BBO, PSO and MDE algorithms are taken for comparison of the performance of SACSA. It is clear from the table 3 that the cost reported by the proposed CSA is less than the cost reported by the other algorithms taken for comparison.

Table 3. Best control variables in minimization of piecewise quadratic fuel cost

Variable	CSA	BBO [21]	PSO [21]	MDE [21]
P_{g1}	136.479	140.0000	140.0000	140.000
P_{g2}	54.7591	55.0000	55.0000	55.0000
P_{g5}	32.5433	24.1500	24.1257	24.0000
P_{g8}	32.5787	18.5100	35.0000	34.9890
P_{g11}	10.0000	35.0000	18.6600	18.0440
P_{g13}	22.8620	17.7900	17.6810	18.4620
V_{g1}	0.9932	1.0500	1.0500	1.0500
Vg2	0.9689	1.0412	1.0396	1.0400

V_{g5}	0.9751	1.0170	1.0133	1.0139
V_{g8}	0.9192	1.0282	1.0225	1.0259
V_{g11}	0.9097	1.0910	1.0722	1.0940
V_{g13}	1.0238	1.0876	1.0866	1.0773
T_{11}	0.9000	1.0192	1.0060	0.9714
T_{12}	1.0996	0.9573	0.9000	1.0046
T_{15}	0.9966	1.0120	0.9645	0.9902
T_{36}	0.9000	0.9505	0.9305	0.9494
Q_{c10}	2.7397	-	-	-
Q_{c12}	1.1946	-	-	-
Q_{c15}	0.3887	-	-	-
Q_{c17}	3.5836	-	-	-
Q_{c20}	5.0000	-	-	-
Q_{c21}	3.3025	-	-	-
Q_{c23}	0.2000	-	-	-
Q_{c24}	2.4263	-	-	-
Q_{c29}	0.5560	-	-	-
PWC ($/hr)	**446.5340**	647.69	647.7437	647.846

The algorithm convergences to the best results in about 375 iterations in piecewise cost minimization and this is shown in figure 4.

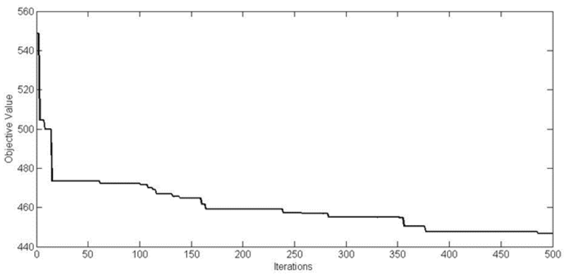

Figure. 4 Convergence quality of CSA in piecewise quadratic fuel cost minimization

4.4Case 4: Minimization of emission

The quality of the algorithm is tested in emission minimization. The emission reported is 0.2048 which is less than the emission level reported by the other algorithms compared in the table 4. Moreover, the VAR supplied by the shunt compensators for achieving this emission level is low indicating more reactive power reserve or system security.

Table 4. Best control variables in minimization of emission

Variable	CSA	IPSO [26]	IPSO [26]	BSO [27]
P_{g1}	66.6800	67.1300	67.0400	112.918
P_{g2}	67.5447	68.9400	68.1400	59.3719
P_{g5}	50.0000	49.8600	50.0000	27.6576
P_{g8}	35.0000	34.8900	35.0000	34.9989
P_{g11}	29.9999	29.6700	30.0000	27.0652
P_{g13}	39.9975	39.9400	40.0000	26.4502
V_{g1}	1.0792	1.0287	1.0351	1.1000
Vg2	1.0742	1.0341	1.0273	1.0855
V_{g5}	1.0567	1.0387	1.0417	1.0606
V_{g8}	1.0592	1.0254	1.0248	1.0757
V_{g11}	1.0987	1.0317	1.0321	1.1000
V_{g13}	1.0994	1.0395	1.0410	1.1000
T_{11}	0.9810	1.0300	1.0300	1.0000
T_{12}	0.9016	1.0200	1.0100	0.9500
T_{15}	0.9568	1.0500	1.0600	1.0000
T_{36}	0.9455	0.9900	0.9900	0.9625
Q_{c10}	1.5556	11.8500	12.5300	3.4844
Q_{c12}	3.5945	8.2510	8.7410	4.5129
Q_{c15}	4.8219	77.1300	76.6700	4.7990
Q_{c17}	1.6543	70.6700	66.5600	4.9965
Q_{c20}	4.9593	67.1300	67.0400	3.9809
Q_{c21}	3.8209	68.9400	68.1400	4.7684
Q_{c23}	2.7699	49.8600	50.0000	3.8535
Q_{c24}	4.9996	34.8900	35.0000	4.2332
Q_{c29}	0.6613	29.6700	30.0000	1.6339
Emission	0.2048	0.2063	0.2058	0.2425

Figure 5 shows that the SACSA algorithm is quick in convergence in emission minimization and produces the lowest level of emission. In this case also, the convergence strength of the algorithm is excellent.

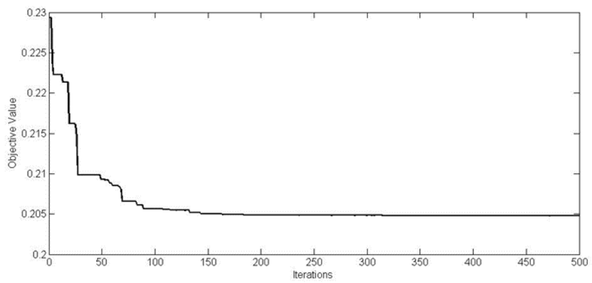

Figure. 5 Convergence quality of CSA in emission minimization

5. CONCLUSIONS

In this paper, the recently developed improved metaheuristic algorithm of self adaptive cuckoo search algorithm is employed and successfully tested in solving different OPF problems in the standard IEEE 30 bus system. The outperforming characteristics of the algorithm in four different optimization objectives is really encouraging. The simulation results demonstrate the effectiveness and robustness of the proposed method.

Moreover, the results obtained using the SACSA method have been compared with those obtained from the other methods previously reported in the literature. The comparison shows the superiority of the proposed SACSA method over many other methods used for solving the OPF in terms of results quality. The results obtained are promising and implementing a multi-objective SACSA is a possible extension of the current work.

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