

Performance of Hybrid Algorithm of Cuckoo Search and Particles Swarm in Optimal Power Flow Problem

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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 nonlinear in nature. In this paper, Hybrid algorithm of cuckoo search and particles swarm based meta heuristic algorithm is developed and 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 that has 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 hybrid cuckoo search and particles swarm based algorithm performs better and found to be encouraging.

KEYWORDS: optimal power flow, cuckoo search algorithm, power system optimization

I. 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]. Optimal power flow (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 meta heuristic optimization methods [1]. Most of these techniques have been applied to OPF problems, such as the genetic algorithm (GA), 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.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

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The hybrid algorithm of cuckoo search and particles swarm 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, section-4 is devoted PSO and its implementation Next, the CSA and PSO is applied to solve the OPF problem to optimize the power system operating conditions in section-5. Finally, in section-6, some final remarks and points concluded.

II. 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]:

$$\begin{aligned} &\text{minimize} && f(\mathbf{x}, \mathbf{u}), \\ &\text{Subject to} && g(\mathbf{x}, \mathbf{u}) = 0, \\ &\text{and} && h(\mathbf{x}, \mathbf{u}) \leq 0, \end{aligned}$$

where $f(\mathbf{x}, \mathbf{u})$ is the objective function, $g(\mathbf{x}, \mathbf{u})$ is the set of equality constraints, $h(\mathbf{x}, \mathbf{u})$ is the set of inequality constraints, \mathbf{u} is the vector of independent variables or control variables and \mathbf{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.

Case 1: Minimization of fuel cost (FC)

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

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

where FC is the total fuel cost; a_i ; b_i and c_i are fuel cost coefficients of the i th unit. The quadratic cost coefficients are obtained from Alsac et al. [19].

Case 2: Minimization of valve point effect cost (VPE)

$$f_2 = VPE = (a_i + b_i P_i + c_i P_i^2 + |d_i \sin \{e_i (P_i^{min} - P_i)\}|),$$

where FC is the total fuel cost; a_i ; b_i and c_i are fuel cost coefficients of the i th unit. The quadratic cost coefficients are obtained from Alsac et al. [20].

Case 3: Minimization of piecewise fuel cost (PWC)

$$f_3 = PWC = a_{ik} + b_{ik} P_{Gi} + c_{ik} P_{Gi}^2$$

The total generating fuel cost is given by,

$$f(\mathbf{x}, \mathbf{u}) = \sum_{i=1}^{Ng} f_i(\mathbf{x}, \mathbf{u})$$

where k is the fuel option. In this study, generators 1 and 2 have two fuel options ($k = 2$). [21]

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

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Case 4: Minimization of emission (EM)

$$f_4 = Em = \sum_{i=1}^{Ng} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \xi_i e^{\lambda_i P_{gi}})$$

where Em is the total emission cost (ton/h); α_i ; β_i ; γ_i ; ξ_i and λ_i are the emission coefficients of the i th unit. Its results are presented in the minimum emission obtained by ARCBBO is 0.2048 ton/h, which is better than that reported in [19].

III. CUCKOO SEARCH ALGORITHM

Cuckoo search algorithm (CSA) is a recent meta heuristic search algorithm [22-23] inspired by hatching behaviour of the cuckoo bird for solving optimization tasks. The basis of this algorithm is on the obligate brood parasitic behavior of some cuckoo species in combination with the Lévy flight behaviour. In nature, cuckoo birds usually lay their eggs in nests of the other bird species (host nests). There are some cases which can happen. The birds of host nests know the eggs of cuckoo birds (alien eggs) and they can reject it throw out their nests or they leave their nests and build new one. The birds of host nests do not know alien eggs and it will become cuckoo birds. Following cuckoo behavior, CSA described as three main steps.

A cuckoo lays one egg (a 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 a quality of egg will be carried over to the next generation; - A host bird can discover an alien egg in its nest with a probability of $p_a \in [0, 1]$. In this case, it can simply either throw the egg away or abandon the nest and find a new location to build a completely new one.

The Lévy flight distribution

In nature, animals can search for food in a random/quasi-random manner. Generally, the foraging path of an animal is effectively a random walk since the next move is based on the current location state and the transition probability to the next location. The chosen direction depends implicitly on a probability which can be mathematically modeled. Recent various studies have shown that the flight behavior of many animals and insects has demonstrated the typical characteristics of Lévy flights following step:

$$\text{Lévy} \sim u = t - \lambda, 1 < \lambda \leq 3$$

Implementation of CS algorithm

- Step-1: Assume the NP host nests X_i ($i = 1, 2, \dots, NP$) 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 (P_a) 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.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

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IV. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock with the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm. In PSO, individuals, referred to as particles, are “flown” through hyper dimensional search space. Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbors. The search behavior of a particle is thus affected by that of other particles within the swarm (PSO is therefore a kind of symbiotic cooperative algorithm). The consequence of modeling this social behavior is that the search process is such that particles stochastically return toward previously successful regions in the search space. The remainder of this chapter is organized as follows: An overview of the basic PSO, i.e. the first implementations of PSO, The very important concepts of social interaction and social networks are discussed Basic variations of the PSO are described in while more elaborate improvements are given A discussion of PSO parameters is given below.

The position of the particle is changed by adding a velocity, $v_i(t)$, to the current position,

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (16.1) \text{ with } x_i(0) \sim U(x_{\min}, x_{\max})$$

The velocity of particle i is calculated as

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 j(t) [y_{ij}(t) - x_{ij}(t)] + c_2 r_2 j(t) [p_{ij}(t) - x_{ij}(t)]$$

The personal best position at the next time step, $t+1$, is calculated as

$$y_i(t+1) = y_i(t) \text{ if } f(x_i(t+1)) \geq f(y_i(t)) \quad x_i(t+1) \text{ if } f(x_i(t+1)) < f(y_i(t))$$

The global best position can also be selected from the particles of the current swarm, in which case

$$y^*(t) = \min \{f(x_0(t)), \dots, f(x_n(t))\}$$

V. METHODOLOGY

HYBRIDIZATION OF CUCKOO SEARCH AND PARTICLE SWARM OPTIMIZATION

Cuckoo search and particle swarm optimization are two stochastic search optimization algorithm. In cuckoo search cuckoo bird lay their reproductive eggs in other birds nest though they may remove their eggs to improve the hatching probability of their own eggs for this strategy, CS refers to the fact that the problem initially searches for current best solution and then aim for global solution .In particle swarm optimization ,initially particles(birds) fly with a speed vector in solution space to find the best position for their food. Each particle has a memory to store its experience example its best position .Each particle maintains a distance from other particles and this process continues till each particles attains the best position so that the problem can be easily optimized .In our proposed algorithm we have replaced the behavior of cuckoo bird with the optimization technique of particles example birds of PSO.The main idea behind this hybridization of CS and PSO is that the search strategy for finding the nest for cuckoo bird in CS is replaced by the best position of the bird of PSO .In this way ,when cuckoo bird try to search for best position of nest to lay its egg, then search process would be completed by strategy of PSO. So the cuckoo egg would be at best optimized position by using PSO techniques. In this we can create a more optimized technique by integrating two best swarm optimization techniques. In this way the proposed algorithm can give a more optimized and efficient solution for the complex problems.

VI. RESULTS AND DISCUSSIONS

To examine the effectiveness of the proposed hybrid 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 CS and PSO based method, the results are presented along with those of the other methods for the test case.

The developed CS and PSO based algorithm is coded using the MATLAB 7.9b computing environment, on a 2.20-GHz i5 laptop with 4.00 GB of RAM The parameters of the CSA are selected as follows: the number of nest NP =

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

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50, probability for an alien egg to be discovered $P_a = 0.5$, maximum number of iterations = 300, For obtaining the optimal solution, the algorithm is performed 30 independent runs.

1) The IEEE 30-bus Test System

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 [24]. 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.

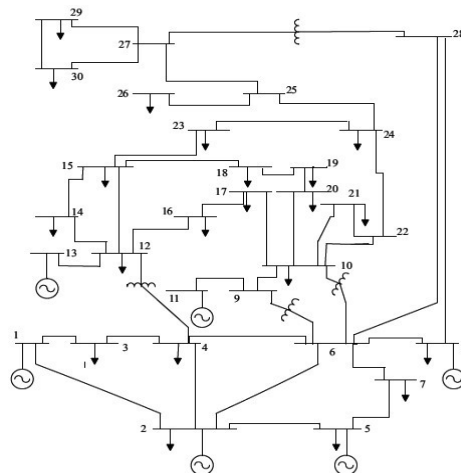


Figure.1 One line diagram of IEEE 30 bus system

Case 1: Minimization of Generation 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 CSA and PSO 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.

Table 1. Best control variables in minimization of fuel cost

Variable	CSPSO	CS	BBO [1]	IEM [2]	RBBO[2]
P_{g1}	177.0177	174.4387	177.0177	174.4387	177.1590
P_{g2}	48.8637	44.7481	48.6410	48.1710	48.5610
P_{g5}	21.4800	21.8910	21.2390	20.8907	21.4289
P_{g8}	19.6113	21.6733	21.1360	20.5925	21.2958
P_{g11}	12.1118	14.3571	11.9440	13.4993	11.9803
P_{g13}	12.2572	12.0000	12.0540	14.4318	12.0004
V_{g1}	1.1000	1.1000	1.1000	1.0908	1.0851
V_{g2}	1.0831	1.0801	1.0876	1.0788	1.0651
V_{g5}	1.0533	1.0434	1.0614	1.0520	1.0331
V_{g8}	1.0590	1.0532	1.0695	1.0604	1.0384
V_{g11}	1.0970	1.0572	1.0982	1.0853	1.1000

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V _{g13}	1.0612	1.0950	1.0998	1.0845	1.0408
T ₁₁	1.0932	0.9429	1.0500	1.0359	1.0974
T ₁₂	0.9000	0.9668	0.9000	0.9227	0.9006
T ₁₅	1.0232	1.0307	0.9900	1.0049	0.9663
T ₃₆	0.9643	0.9607	0.9700	0.9814	0.9760
Q _{e10}	4.6352	4.9651	5.0000	3.6724	2.2567
Q _{e12}	4.7331	4.8302	5.0000	4.4120	4.2353
Q _{e15}	0.2000	4.9097	5.0000	3.9357	4.2998
Q _{e17}	3.6370	1.8511	5.0000	4.4873	4.9446
Q _{e20}	0.2041	2.2640	5.0000	4.5202	3.7381
Q _{e21}	2.5009	1.1221	5.0000	3.7935	4.9901
Q _{e23}	2.2276	1.1733	4.0000	3.9689	2.6502
Q _{e24}	4.9274	3.8485	5.0000	4.5687	5.0000
Q _{e29}	1.4227	1.6592	3.0000	3.3512	2.3967
Fuel cost (\$/hr)	799.5575	800.0540	799.6776	800.0781	800.5159

The algorithm is run for 300 iterations in optimizing the fuel cost the results are converged in 250 iterations. The convergence quality of algorithm is proved in the figure 2.

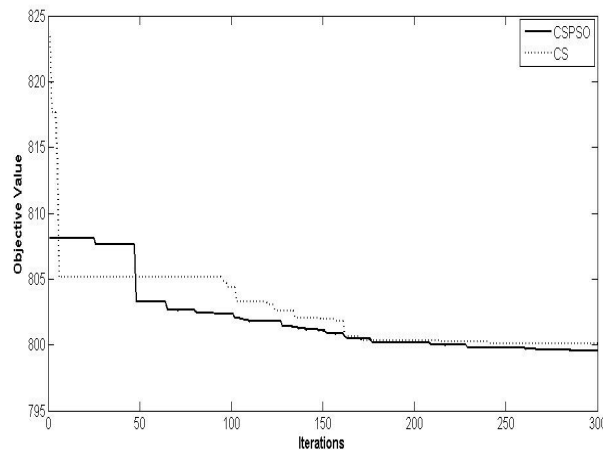


Figure. 2 Convergence quality of CS and PSO in fuel cost minimization

Case 2: Cost with valve point effect

In this case, the valve point effects are taken in to account in cost calculations. For performance comparison, TLBO, GSA and BBO are taken. The results are compared in table 2 for understanding the strength of the proposed algorithm. The valve point effect cost reported by CSA and PSO is **923.6487**, which much less than the cost reported by the other algorithms in the table.

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

Variable	CSPSO	CS	TLBO[3]	GSA [4]	BBO[4]
P _{g1}	194.1673	199.5994	194.1673	199.59943	197.426
P _{g2}	20.0029	20.0058	44.3449	51.94640	52.037
P _{g5}	20.3932	26.8304	20.6902	15.00000	15.000
P _{g8}	14.9784	21.4943	13.1553	10.00000	10.000
P _{g11}	16.9659	13.7485	10.0000	10.00000	10.001
P _{g13}	21.6399	12.1101	12.0000	12.00000	12.000
V _{g1}	1.1000	1.0890	1.0500	1.099002	1.0371
V _{g2}	1.0728	1.0568	1.0287	1.099002	1.0130
V _{g5}	1.0247	1.0091	1.0024	1.018042	0.9648
V _{g8}	1.0332	1.0107	1.0163	1.052247	1.0320
V _{g11}	0.9272	0.9549	1.0999	0.950000	1.0982
V _{g13}	1.0007	0.9941	1.1000	0.963430	1.0890
T ₁₁	1.0406	0.9152	1.0065	0.950702	1.0969
T ₁₂	1.0420	1.0925	0.9073	0.918200	1.0909
T ₁₅	1.0618	1.0396	0.9936	0.909096	1.0991
T ₃₆	1.0203	0.9987	0.9485	0.945975	1.0021
Q _{c10}	4.9780	3.3536	0.0000	-	-
Q _{c12}	4.3933	3.0376	0.0000	-	-
Q _{c15}	2.1228	0.2000	0.0000	-	-
Q _{c17}	4.8087	4.3627	0.0000	-	-
Q _{c20}	1.2375	1.0365	0.0000	-	-
Q _{c21}	0.4517	4.8766	0.0000	-	-
Q _{c23}	4.2138	4.3452	0.0000	-	-
Q _{c24}	1.8684	4.9581	0.0000	-	-
Q _{c29}	3.2183	0.2000	0.0000	-	-
VPE cost	923.5487	923.5854	924.414	929.7240472	930.793

Taking 275 iterations, the algorithm has converged to the global best results showing the better reliability of the algorithm. The convergence behaviour of the CSA and PSO in valve point effect cost minimization is depicted in figure 3.

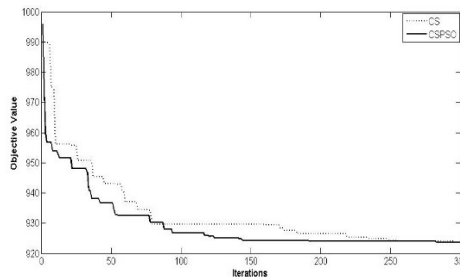


Figure. 3 Convergence quality of CS and PSO in valve point effect fuel cost minimization

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Case 3: Piecewise cost minimization

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 CSA. It is clear from the table 3 that the cost reported by the proposed CSA and PSO 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	CSPSO	CS	BBO[5]	PSO [5]	MDE[5]
P _{g1}	140.0000	140.0000	140.0000	140.0000	140.0000
P _{g2}	52.8476	54.7207	55.0000	55.0000	55.0000
P _{g5}	22.0641	26.0205	24.1500	24.1257	24.0000
P _{g8}	31.3625	32.2446	18.5100	35.0000	34.9890
P _{g11}	10.0000	12.1838	35.0000	18.6600	18.0440
P _{g13}	35.3819	28.6433	17.7900	17.6810	18.4620
V _{g1}	1.0997	0.9896	1.0500	1.0500	1.0500
V _{g2}	1.0550	0.9483	1.0412	1.0396	1.0400
V _{g5}	1.0439	0.9532	1.0170	1.0133	1.0139
V _{g8}	1.0283	0.9109	1.0282	1.0225	1.0259
V _{g11}	0.9909	0.9000	1.0910	1.0722	1.0940
V _{g13}	0.9812	0.9293	1.0876	1.0866	1.0773
T ₁₁	0.9784	1.0222	1.0192	1.0060	0.9714
T ₁₂	0.9745	1.0494	0.9573	0.9000	1.0046
T ₁₅	0.9016	1.0065	1.0120	0.9645	0.9902
T ₃₆	0.9660	0.9054	0.9505	0.9305	0.9494
Q _{c10}	2.5626	1.4609	-	-	-
Q _{c12}	3.8488	0.2000	-	-	-
Q _{c15}	1.2113	0.4979	-	-	-
Q _{c17}	3.0315	3.6293	-	-	-
Q _{c20}	5.0000	5.0000	-	-	-
Q _{c21}	4.9801	3.8444	-	-	-
Q _{c23}	3.3627	3.7713	-	-	-
Q _{c24}	2.5781	1.1218	-	-	-
Q _{c29}	2.0373	4.0315	-	-	-
Quadratic Fuel cost (\$/hr)	448.8471	455.1288	647.69	647.7437	647.846

The algorithm convergences to the best results in about 275 iterations in piecewise cost minimization and this is shown in figure 4.

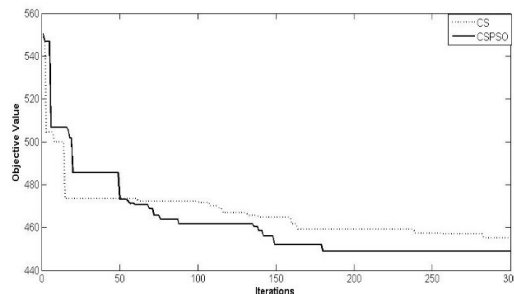


Figure. 4 Convergence quality of CS and PSO in piecewise quadratic fuel cost minimization

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Case 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	CSPSO	CS	IPSO[6]	IPSO[6]	BSO[7]
P _{g1}	67.1300	67.0400	67.1300	67.0400	112.9189
P _{g2}	68.0614	69.8545	68.9400	68.1400	59.3719
P _{g5}	50.0000	50.0000	49.8600	50.0000	27.6576
P _{g8}	35.0000	35.0000	34.8900	35.0000	34.9989
P _{g11}	29.9998	30.0000	29.6700	30.0000	27.0652
P _{g13}	39.9940	40.0000	39.9400	40.0000	26.4502
V _{g1}	1.0713	1.0225	1.0287	1.0351	1.1000
V _{g2}	1.0714	1.0023	1.0341	1.0273	1.0855
V _{g5}	1.0594	0.9662	1.0387	1.0417	1.0606
V _{g8}	1.0698	0.9850	1.0254	1.0248	1.0757
V _{g11}	1.0991	1.0076	1.0317	1.0321	1.1000
V _{g13}	1.0985	0.9942	1.0395	1.0410	1.1000
T ₁₁	0.9391	1.0508	1.0300	1.0300	1.0000
T ₁₂	1.0817	0.9204	1.0200	1.0100	0.9500
T ₁₅	0.9952	0.9633	1.0500	1.0600	1.0000
T ₃₆	0.9697	0.9452	0.9900	0.9900	0.9625
Q _{e10}	0.5132	4.9515	11.8500	12.5300	3.4844
Q _{e12}	1.2957	0.6408	8.2510	8.7410	4.5129
Q _{e15}	4.7201	4.9666	77.1300	76.6700	4.7990
Q _{e17}	4.9227	4.2820	70.6700	66.5600	4.9965
Q _{e20}	1.5026	3.3658	67.1300	67.0400	3.9809
Q _{e21}	2.3040	2.2994	68.9400	68.1400	4.7684
Q _{e23}	3.2825	1.2611	49.8600	50.0000	3.8535
Q _{e24}	4.9994	1.4715	34.8900	35.0000	4.2332
Q _{e29}	1.1481	3.5242	29.6700	30.0000	1.6339
Emission cost	0.2048	0.2051	0.2063	0.2058	0.2425

Figure 5 shows that the CSA and PSO 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

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Vol. 9, Issue 1, January 2020

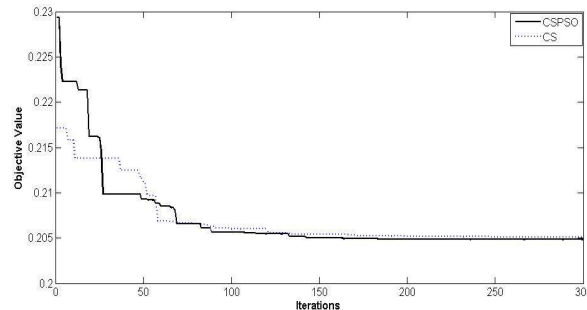


Figure. 5 Convergence quality of CS and PSO in emission minimization

VII. CONCLUSIONS

In this paper, the recently developed meta heuristic hybrid algorithm of cuckoo search and Particle swarm optimization algorithm is developed, employed and successfully tested in solving different OPF problems. The outperforming characteristic 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 CS and PSO method have been compared with those obtained from the other methods previously reported in the literature. The comparison shows the superiority of the proposed CS and PSO 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 CS and PSO is a possible extension of the current work.

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