Optimal Reactive Power Scheduling Using Cuckoo Search Algorithm

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Article Info

ABSTRACT

This paper solves an optimal reactive power scheduling problem in the deregulated power system using the evolutionary based Cuckoo Search Algorithm (CSA). Reactive power scheduling is a very important problem in the power system operation, which is a nonlinear and mixed integer programming problem. It optimizes a specific objective function while satisfying all the equality and inequality constraints. In this paper, CSA is used to determine the optimal settings of control variables such as generator voltages, transformer tap positions and the amount of reactive compensation required to optimize the certain objective functions. The CSA algorithm has been developed from the inspiration that the obligate brood parasitism of some Cuckoo species lay their eggs in nests of other host birds which are of other species. The performance of CSA for solving the proposed optimal reactive power scheduling problem is examined on standard Ward Hale 6 bus, IEEE 30 bus, 57 bus, 118 bus and 300 bus test systems. The simulation results show that the proposed approach is more suitable, effective and efficient compared to other optimization techniques presented in the literature.

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1.   INTRODUCTION

The demand for electricity is growing rapidly in recent years. Because of the limited transmission capabilities for handling these additional demands, the optimal reactive power scheduling and dispatch has become an important issue for the electrical power utility company. Any changes to the system load demand or system configuration may result in lower or higher voltage profiles to the system. To maintain the acceptable levels of voltages and reactive power flow under various system configurations and operating conditions, the system operators (SOs) may use a number of control tools like changing generator voltages, switching VAR sources, and/or adjusting the tap settings of transformer [1]. Hence, the reactive power scheduling problem can be stated as the determination of optimal settings of various controls, so that the total system transmission losses are optimized [2].

The optimal reactive power scheduling is a major issue in the optimal operation of electrical power systems. It is a mixed integer and nonlinear problem, which finds the optimal control variables settings for the reactive power producers to optimize a specific objective function while satisfying all the technical constraints. Voltage is an important indicator for the safety and economy of power system operation. It directly reflects the balance and distribution performance of reactive power of the power system. If the system reactive power is insufficient or unreasonable distribution, which will lead to lower voltage,

instability, abnormal operation of electrical equipments, can also cause serious problems such as voltage collapse. When the network structure, the system voltage and the active power transmitted is determined, the system power loss depends entirely on the reactive power distribution, transmission and management. The rational allocation and optimal operation of reactive power equipment can effectively improves the voltage quality, guarantees the system voltage stability and reduces the network loss, which in turn improves the safety and economy of power system operation [3].

Real world optimization problems involve complex and non-linear interactions among the variables, and the search space usually contains more than one optimal solution. Classical algorithms are designed to solve a specific type of optimization problem may not be efficient in solving other type of problems. Further, the classical optimization techniques are not efficient in handling the problems with discrete search space [4-5]. Difficulties arise in the classical approach, as it assumes all variables to be continuous during the optimization and there after a value close to the obtained solution is recommended for a discrete variable. Complex real world optimization problems can now be easily solved with the parallel computing systems. Most classical algorithms use point-by-point approaches, where in one iteration; one solution is updated using the previous solution. Therefore, the advantage of parallel computing cannot be exploited fully [6-7].

The above discussion reveals that classical optimization algorithms may face difficulties in solving the practical real world optimization problems. Evolutionary algorithms find applications in solving various optimization problems including science, commerce and engineering [8]. Different classes of evolutionary algorithms include Evolutionary Programming (EP), Evolution Strategies (ES), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), etc. All these methods are inspired by nature's evolution. All these optimization approaches share a common conceptual base of simulating the evolution of individual structures.

In the literature, a number of classical optimization algorithms have been presented to solve the reactive power scheduling problem. These techniques include the Non-linear programming, Gradient method, Linear programming, Quadratic programming and Interior point method [9]. Although these methods have been applied successfully for the solution of optimal reactive power scheduling problem, still there are some difficulties associated with them. One is the multimodal characteristics of problems to be handled. Also, because of the non-linearity, non-differential and non-convex nature of the reactive power scheduling problem, majority of these algorithms converge to a local optimum [10]. Nowadays, many evolutionary/ meta-heuristic based optimization algorithms such as GA [11], EP [12] and Biogeography Based Optimization (BBO) [13] have been applied successfully to solve the optimal scheduling problem.

Reference [14] presents different conventional and evolutionary based computational approaches for solving the optimal reactive power dispatch problem. A Quantum Stirred Cuckoo Search Algorithm (QS-CSA) for solving the optimal reactive power dispatch problem is presented in [15]. In recent years, the meta-heuristic techniques have been closely concerned and widely used in the global optimization problem. Therefore, Tabu Search (TS), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Improved PSO, Harmony Search (HS), Differential Evolution (DE) and Artificial Immune Algorithm (AIA), etc. have been used widely in the reactive power optimization of power system. However, the main shortcomings of these algorithms are the premature convergence and the convergence speed. Recently, a new meta-heuristic technique proposed by X.S. Yang and S. Deb in 2009 [16] i.e., Cuckoo Search Algorithm (CSA) has been used to overcome the above mentioned short comings. The proposed approach is inspired from the life of the family of cuckoo. Recent studies show that the CSA is more efficient than the GA and PSO [17-18]. The number of parameters to be tuned in the CSA is less than the GA and PSO, and hence it is more generic to adapt to a wider class of optimization problems. In this paper, CSA is proposed for solving the reactive power scheduling optimization. The proposed CSA approach is examined on the Ward-Hale 6 bus, 30 bus, 57 bus, 118 bus and 300 bus systems, and the results obtained are compared with many other optimization algorithms presented in the literature.

The rest of the paper is outlined as follows. Section 2 presents the detailed formulation of reactive power scheduling problem. The description of Cuckoo Search Algorithm (CSA) is described in Section 3. The simulation results on different test systems and the comparison of results with previous algorithms presented in the literature are provided in Section 4. Finally, the contributions with the concluding remarks are presented in Section 5.

2. REACTIVE POWER SCHEDULING: PROBLEM FORMULATION

For the reactive power scheduling problem, the minimization of system transmission losses is selected as the objective function. Transmission loss in each line is calculated from the power flow solution. The converged power flow solution gives the bus voltage magnitudes and phase angles. Using these, the active power flow through the transmission lines can be evaluated. The total power loss is the sum of power

losses in each transmission line. In this paper, the generator bus voltage magnitudes, transformer tap limits and the limits on switchable shunt VAR sources are considered as the control variables. The objective of reactive power scheduling problem is to determine the optimal settings of various controls which minimizes the power losses during the control and operation of a network. The power loss is a nonlinear function of bus voltages and phase angles which are implicitly the functions of control variables. The real power loss (P_{loss}) is represented as [19].

$$P_{loss} = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} G_{ij} \left[V_i^2 + V_j^2 - 2V_iV_j cos(\delta_i - \delta_j) \right] \tag{1}$$

where G_{ij} is conductance of a transmission line connected between the buses i and j. N is the total number of buses in the system. V_i and δ_i are the voltage magnitude and phase angle at bus i, respectively.

2.1. Problem constraints
2.1.1. Equality constraints:
These constraints include the typical power flow equations, and they are represented as,

$$P_i = P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N} V_j \left[G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij} \right] = 0 \tag{2}$$

$$Q_i = Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N} V_j \left[G_{ij} sin\delta_{ij} - B_{ij} cos\delta_{ij} \right] = 0 \tag{3}$$

In the above equations, i =1,2,3,.....,N. P_{Gi} and Q_{Gi} are the active and reactive power generations at bus-i, P_{Di} and Q_{Di} are the corresponding active and reactive load demands.

2.1.2. Inequality Constraints
These constraints represent operating limits of the power system.
Generator Constraints: Generator Voltage magnitudes (V_{Gi}), Generator active power outputs (P_{Gi}) and reactive power generation (Q_{Gi}) are limited by their lower and upper limits. They are represented as,

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_G \tag{4}$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_G \tag{5}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_G \tag{6}$$

Transformer Constraints: Transformer taps have lower and upper settings. They are expressed as,

$$T_i^{min} \leq T_i \leq T_i^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_T \tag{7}$$

Switchable VAR sources: The sources have limitations as,

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_C \tag{8}$$

Security constraints: These constraints include the limits on load bus voltage magnitudes and transmission line flows.

$$V_{Di}^{min} \leq V_{Di} \leq V_{Di}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_D \tag{9}$$

$$S_{Li} \leq S_{Li}^{max} \qquad\qquad i = 1,2,3,\dots\dots,N_{line} \tag{10}$$

3.   CUCKOO SEARCH ALGORITHM (CSA)
The CSA is a novel evolutionary technique which is nature-inspired by Cuckoos' search for their nests where they could lay their eggs. Cuckoo Search Algorithm (CSA) [20-22] is one of the recent optimization approaches and it developed from the inspiration from obligate brood parasitism of some the cuckoo species lay their eggs in nests of other host birds which are of other species. This technique was proposed by X.S. Yang and S. Deb [16], they optimized 10 standard test functions and then gave the working principle of CSA. Reference [17] presents the extension of Reference [16], it uses the standard test functions

as well as the stochastic functions for testing the efficiency of the algorithm. This CSA is developed based on the following principles [20-21]:

1. Each Cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest.
2. Best nests with high quality of eggs will carry over to the next iterations/ generations.
3. The number of available host nests is fixed and the egg laid by a Cuckoo is identified by the host bird with a probability in the range between 0 and 1. In this situation, the host bird can throw the egg away or abandon the entire nest, and build a completely new nest.

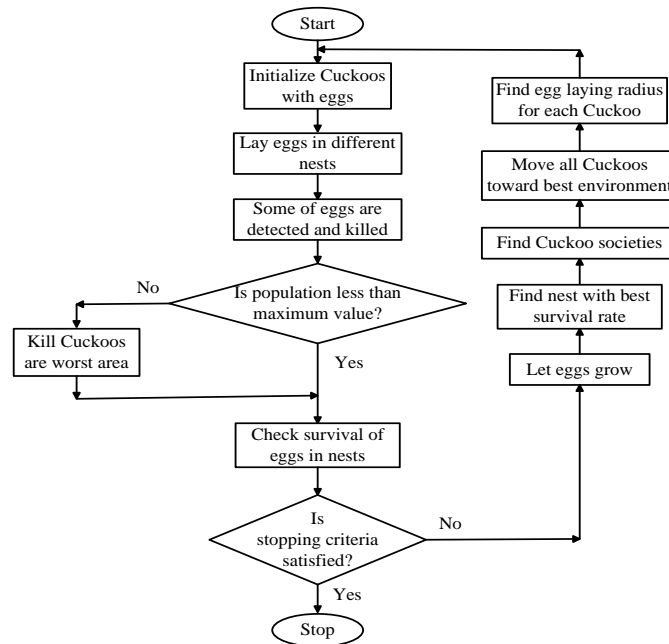Based on these principles, the flow chart of CSA is depicted in Figure 1.

Figure 1. Flow Chart of Cuckoo Search Algorithm (CSA).

The steps to implement the CSA can be described as follows [20-23]:

Step 1: Initialize the population size (*n* host nests i.e., x_i (i=1,2,3,...,n)) and maximum number of iterations/ generations.

Step 2: Determine the objective function, i.e., J(x). Where x=($x_1,x_2,x_3,.....,x_n$).

Step 3: Find the current best solution (i.e., determine the best nest) and set the current generation number/count as 1.

Step 4: For each generation count, generate the new solutions and store the current best.

Step 5: Update the generation count. Generation count = Generation count + 1.

Step 6: If the number of generations is more than or equal to the maximum number of generations. Then, go to Step 7, otherwise go to Step 2.

Step 7: The best objective obtained so far is the best nest, and it is the optimal solution.

4.   RESULTS AND ANALYSIS

The performance of the proposed reactive power scheduling approach using CSA has been examined on Ward Hale 6 bus, IEEE 30 bus, 57 bus, 118 and 300 bus test systems. The simulation results obtained with the proposed CSA are also compared with other optimization techniques reported in the literature. In this paper, the generator voltage magnitudes are considered as the continuous control variables and the transformer tap settings, switchable shunt VAR sources limits are considered as the discrete control variables. All the optimization programs are coded in MATLAB R20016a and executed in a PC Core i7 with 8 GB of RAM. Thirty runs have been performed for the each optimization program. The reported results are the best solution obtained over these 30 runs.

4.1. Simulation Results on Ward Hale 6 bus system

The system data for Ward Hale 6 bus test system is taken from Reference [2]. The minimum and maximum limits of transformer tap settings are 0.9 p.u. and 1.1 p.u., respectively. Table 1 presents the optimum control variables settings and the optimum loss obtained for the Ward Hale 6 bus system using the CSA and other optimization algorithms reported in the literature.

Table 1. Optimum control variables and loss for Ward Hale 6 bus system.

Variables	Non fuzzy Approach [24]	Fuzzy Approach [24]	GA [24]	PSO [2]	Improved PSO [2]	CSA
V_1 (p.u.)	1.09	1.1	1.0225	1.023	1.023	1.1
V_2 (p.u.)	1.15	1.15	1.1	1.1	1.1	1.1
V_3 (p.u.)	1.00	1.01	0.99	1.0	1.0	1.0486
V_4 (p.u.)	1.00	1.01	0.917	0.9185	0.918	1.0359
V_5 (p.u.)	1.00	1.01	0.969	0.9696	0.9696	0.9914
V_6 (p.u.)	0.98	0.994	0.90	0.9019	0.9019	0.9903
Q_1 (MVAR)	36.3	35.3	42.3	19.3	92.7	50.12
Q_2 (MVAR)	19.3	19.4	37.8	56.1	57.9	36.70
Q_4 (MVAR)	5	5	5	5	5	5
Q_6 (MVAR)	5.5	5.5	5.5	5.5	5.5	5.5
$T_{6,5}$ (p.u.)	0.96	0.98	0.9	0.9	0.9	0.9250
$T_{4,3}$ (p.u.)	0.98	0.99	0.9	0.9	0.9	0.9750
P_{Loss} (MW)	**8.93**	**8.77**	**8.1746**	**8.1745**	**8.1745**	**8.1534**

In Table 1, the optimum loss obtained with the non-fuzzy approach [24], fuzzy approach [24], GA [24], PSO [2] and Improve PSO [2] are compared with the optimum loss obtained with the CSA. From this Table, it can be observed that the optimum transmission loss obtained using GSA (i.e., 8.1534 MW) is optimum compared to all other optimization algorithms reported in the literature.

4.2 Simulation Results on IEEE 30 bus test system

IEEE 30 bus test system consists of 6 generating units, 21 load demands and 41 transmission lines, of which 4 lines are the transformer tap setting branches. The generation, load demand and the network parameters of the system are taken from Reference [25]. The network buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 have been selected as the shunt compensation buses. The active and reactive power load demands in this system are 283.4MW and 126.2MVAr, respectively. The transformer tap settings have lower and upper tap settings of 0.9p.u. and 1.1 p.u., respectively. Switchable shunt VAR compensators have minimum and maximum limits of 0 MVAR and 5 MVAR, respectively. Generator bus voltage magnitudes have minimum and maximum limits of 0.95p.u. and 1.1p.u., whereas the load bus voltage magnitudes have minimum and maximum limits of 0.95p.u. and 1.05p.u., respectively. The thermal flow limits of lines are presented in [26].

Table 2. Optimum control variables and loss for IEEE 30 bus system.

Control Variables	GA [2]	PSO [2]	Improved PSO [2]	DE [27]	OGSA [28]	FA [29]	GSA [30]	CSA
V_{G1} (p.u.)	1.0	1.018	1.015	1.1	1.05	1.1	1.07165	1.0851
V_{G2} (p.u.)	0.999	1.012	1.0048	1.0944	1.041	1.0644	1.02219	1.0388
V_{G5} (p.u.)	0.974	1.013	1.0017	1.0749	1.0154	1.0745	1.04	1.0512
V_{G8} (p.u.)	1.007	0.994	0.99	1.0768	1.0267	1.0869	1.0507	1.0476
V_{G11} (p.u.)	1.0894	1.04	1.0019	1.0999	1.0082	1.0916	0.97712	1.0950
V_{G13} (p.u.)	1.088	1.016	0.993	1.0999	1.05	1.099	0.96765	1.0566
T_{6-9} (p.u.)	NA	NA	NA	1.0465	1.0585	1.0	1.0984	1.075
T_{6-10} (p.u.)	NA	NA	NA	0.9097	0.9089	0.94	0.9824	0.9875
T_{4-12} (p.u.)	NA	NA	NA	0.9867	1.0141	1.0	1.0959	1.0215
T_{28-27} (p.u.)	NA	NA	NA	0.9689	1.0182	0.97	1.0593	1.025
Q_{C10} (MVAR)	NA	NA	NA	5.0	3.30	3.0	1.6537	4.0
Q_{C12} (MVAR)	NA	NA	NA	5.0	2.49	4.0	4.3722	5.0
Q_{C15} (MVAR)	NA	NA	NA	5.0	1.77	3.3	0.1199	4.0
Q_{C17} (MVAR)	NA	NA	NA	5.0	5.0	3.5	2.0876	5.0
Q_{C20} (MVAR)	NA	NA	NA	4.406	3.34	3.9	0.3577	5.0
Q_{C21} (MVAR)	NA	NA	NA	5.0	4.03	3.2	0.2602	3.0
Q_{C23} (MVAR)	NA	NA	NA	2.8004	2.69	1.3	0.0	4.0
Q_{C24} (MVAR)	NA	NA	NA	5.0	5.0	3.5	1.3839	2.0
Q_{C29} (MVAR)	NA	NA	NA	2.5979	1.94	1.42	0.0003	5.0
P_{Loss} (MW)	**4.2716**	**4.1501**	**4.1396**	**4.555**	**4.4984**	**4.5691**	**4.5143**	**4.1066**

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Table 2 presents the optimum control variables and optimum loss values using the different optimization algorithms presented in the literature. From this Table, it can be observed that the optimum transmission losses obtained using the CSA (i.e., 4.1066 MW) is better than all other optimization algorithms presented in the literature i.e., GA [2], PSO [2], Improved PSO [2], DE [27], Opposition-based Gravitational Search Algorithm (OGSA) [28], Firely Algorithm (FA) [29] and Gravitational Search Algorithm [30].

4.3. Simulation Results on IEEE 57 bus test system

IEEE 57 bus system [25] consists of 7 generating units, 80 transmission lines and 15 branches with transformer tap settings. The reactive power sources are considered at the buses 18, 25 and 53 [31]. The total active and reactive power demands in the system are 1250.8 MW and 336.4 MVAR, respectively. The system bus data and line data is given in [25]. The generator data of IEEE 57 bus system is given in Table 3. The optimum loss obtained using different optimization algorithms i.e., Comprehensive Learning PSO (CLPSO) [32], DE [31], Gravitational Search Algorithm (GSA) [31], Opposition-based GSA (OGSA) [33], Seeker Optimization Algorithm (SOA) [32], Quasi-Oppositional DE [31] and CSA techniques is presented in Table 4. From this Table, it can be observed that the optimum loss obtained using the CSA is better than the algorithms reported in the literature.

Table 3. Generation data of IEEE 57 bus test system.

Generator Number	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	Q_{Gi}^{max} (MVAR)	Q_{Gi}^{min} (MVAR)
1	20	50	0	0
2	15	90	50	-17
3	10	500	60	-10
4	10	50	25	-8
5	12	50	200	-140
6	10	360	9	-3
7	50	550	155	-50

Table 4. Comparison of optimum loss obtained for IEEE 57 bus system using different optimization algorithms.

	CLPSO [32]	DE [31]	GSA [31]	OGSA [33]	SOA [32]	QODE [31]	CSA
P_{Loss} (MW)	24.5152	16.7857	23.4611	23.43	24.2654	15.8473	15.5149

4.4. Simulation Results on IEEE 118 bus test system

This test system consists of 54 generating units, 64 load demands, 9 tap setting transformers and 14 switchable shunt VAR compensators. This test system data including lower and upper limits of reactive power sources and transformer tap settings are presented in [31]. The total active and reactive power demands are 4242 MW and 1438 MVAR, respectively [34]. As mentioned earlier, the generator voltage magnitudes, transformer taps and switchable VAR sources are considered as the control variables. Hence, the totals of 77 control variables are required to be optimized. Table 5 presents the optimum power loss obtained using the CSA and various optimization algorithms reported in the literature i.e., PSO [31], Comprehensive Learning PSO (CLPSO) [34], Gravitational Search Algorithm (GSA) [34], Opposition-based GSA [31], DE [31], Gray Wolf Optimizer (GWO) [34], Quasi-oppositional DE (QODE) [31] and CSA techniques. From this Table, it can be observed that the total transmission loss obtained by using the CSA is superior to the other algorithms reported in the literature.

Table 5. Comparison of optimum loss obtained for IEEE 118 bus system using different optimization algorithms.

	PSO [31]	CLPSO [34]	GSA [34]	OGSA [31]	DE [31]	GWO [34]	QODE [31]	CSA
P_{Loss} (MW)	131.99	130.96	127.76	126.99	82.2473	120.65	80.9257	80.5864

4.5. Simulation Results on IEEE 300 bus test system

This test system [25] consists of 69 generating units, and 411 transmission lines, of which 62 lines are the transformer tap setting branches, and 12 buses have been considered as the shunt compensation buses [35]. The system generation, load and line data is given in [25]. Table 6 presents the optimum objective

function values obtained using the Enhanced GA (EGA) [35], Efficient Evolutionary Algorithm (EEA) [35] and the proposed CSA. From this Table, it can be observed that the optimum loss obtained using CSA is superior to the other algorithms reported in the literature.

Table 6. Comparison of optimum transmission losses obtained for IEEE 300 bus test system using different optimization algorithms.

	EGA [35]	EEA [35]	CSA
P_{Loss} (MW)	646.2998	650.6027	635.8942

5. CONCLUSION

This paper presented a meta-heuristic based Cuckoo Search Algorithm (CSA) for solving the optimal reactive power scheduling problem considering the generator voltages, transformer tap settings and switchable shunt VAR sources as the control variables for achieving the optimum transmission losses. The problem is formulated as the minimization of transmission losses by controlling the control variables. It is formulated as a non-linear constrained optimization problem with continuous and discrete variables. This paper proposes a very effective and robust optimization algorithm based on the manner on which Cuckoos' search their nests for laying their eggs. This Cuckoo Search Algorithm (CSA) is used for the solution of optimal reactive power scheduling problem. The performance of the CSA is examined on Ward Hale 6 bus, IEEE 30 bus, 57 bus, 118 bus and 300 bus test systems. The simulation results obtained using the proposed CSA have been compared with other optimization techniques reported in the literature. This algorithm is effective for reactive power scheduling problem, it has good theoretical as well as practical value. The scope for the future study is to improve the efficiency of CSA.

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