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Optimal Reactive Power Dispatch using Crow Search Algorithm

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ABSTRACT

The optimal reactive power dispatch is a kind of optimization problem that plays a very important role in the operation and control of the power system. This work presents a meta-heuristic based approach to solve the optimal reactive power dispatch problem. The proposed approach employs Crow Search algorithm to find the values for optimal setting of optimal reactive power dispatch control variables. The proposed way of approach is scrutinized and further being tested on the standard IEEE 30-bus, 57-bus and 118-bus test system with different objectives which includes the minimization of real power losses, total voltage deviation and also the enhancement of voltage stability. The simulation results procured thus indicates the supremacy of the proposed approach over the other approaches cited in the literature.

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1. INTRODUCTION

Optimal Reactive Power Dispatch (ORPD) enhances system security and helps in proper planning of reactive power and its dispatch in the system. The ORPD problem, which is a non-linear multi-objective optimization problem aims at minimizing the objectives such as real power loss, total voltage deviation and enhancing voltage stability by optimal setting of the control variables such as voltages of generator, transformer Tap set values and the reactive power output obtained from shunt capacitors in an optimal way which has to meet the required equality and inequality constraints. Over the last few decades, the ORPD problems were solved using various traditional methods like Newton's approach, linear programming, interior point method, etc. [1]-[4]. There are certain disadvantages also pertaining to the traditional methodologies, which are difficulties in finding a global optimal solution, insecure convergence, complexity and bad initial termination.

In order to overcome the above illustrated drawbacks, heuristic methodologies have been under research for solving ORPD problem. In the past few decades, heuristic algorithms such as Genetic Algorithm [5]-[9], Evolutionary Programming [10], [11], Particle Swarm Optimization [12]-[15], Ant Colony Optimization [16], [17], Bacterial Foraging Optimization [18], Seeker Optimization Algorithm [19], Differential Evolution [20], Gravitational Search Algorithm [21], Cuckoo Search Algorithm [22] were used for solving ORPD problem. The above stated heuristic algorithms have overcome the drawbacks in the traditional methods, but also have certain limitations, that is they easily get trapped in the local optima and premature convergence would occur . In this paper, a CSA [23] based approach is being proposed to solve the ORPD problem. The problem is formulated as a nonlinear optimization problem with both equality and inequality constraints. In this study, different objectives are considered such as minimizing the power losses, improving the voltage profile and enhancing power system voltage stability. The proposed way of approach has been examined and tested on the standard IEEE 30-bus, 57-bus and 118-bus test system [24]-[26]. The prospective and effectiveness of the proposed approach is demonstrated and the results are compared with those cited in the literature.

2. ORPD PROBLEM FORMULATION

In the present work the ORPD problem is formulated as a multi-objective optimization problem which is listed below:

2.1. Minimization of real power loss

The objective of ORPD problem is minimization of real power loss while satisfying its various equality and inequality constraints.

$$\text{Minimize} \quad F_1 = \sum_{i=1}^{N_L} g_k [(V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j))] \tag{1}$$

where N_L represents the number of transmission lines, g_k is the conductance of i^{th} transmission line, V_i and V_j is the voltage magnitudes of i^{th} and j^{th} buses, δ_i and δ_j is the voltage phase angle of i^{th} and j^{th} buses. The state variables for ORPD problem are,

$$x^T = [P_{G1}, V_{L1} \ldots V_{LN_{PQ}}, Q_{G1} \ldots Q_{GN_G}] \tag{2}$$

where P_{G1} denotes the slack bus power, V_L denotes the load bus voltages, Q_G denote the reactive power output of the generators, N_G denotes the number of voltage controlled buses, N_{PQ} denotes the number of load buses. The control variables for ORPD problem are,

$$u^T = [V_{G1} \ldots V_{GN_G}, Q_{C1} \ldots Q_{CN_C}, T_1 \ldots T_{N_T}] \tag{3}$$

where N_T and N_C denotes the number of tap changing transformers and shunt VAR compensators. V_G denotes the voltages of voltage controlled bus and T denotes the transformer tap ratio and Q_C denotes the reactive power output of shunt VAR compensators.

2.2. Minimization of total voltage deviation

The minimization of voltage deviation improves the voltage profile of the system, thereby enhancing the security and quality of the system. The objective function is given as,

$$\text{Minimize} \quad F_2 = \sum_{i \in N_{PQ}} |V_i - V_i^{ref}| \tag{4}$$

where V_i^{ref} is the reference value of i^{th} bus voltage magnitude which is usually 1.0p.u.

2.3. Enhancement of voltage stability

Voltage stability is the ability of the system to maintain its voltages within its permissible limits. Voltage instability occurs only when a system is subjected to disturbances in the system. Voltage stability can be improvised by minimizing the voltage stability indicator L-index at all buses. L-index is usually in the range of 0 to 1 for all load buses. The L-index at a bus denotes the chances of the voltage collapse condition of that bus. L-index L_j of the j^{th} bus is given as,

$$L_j = \left| 1 - \sum_{i=1}^{N_{PV}} F_{ji} \frac{V_i}{V_j} \right| \qquad \text{Where } j = 1, \ldots, N_{PQ} \tag{5}$$

$$F_{ji} = -[Y_1]^{-1}[Y_2] \tag{6}$$

where N_{PV} denotes number of PV buses. Y_1 and Y_2 are the sub-matrices that are obtained after separating PQ and PV bus parameters,

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \tag{7}$$

3. L-index is calculated for all *PQ* buses. The L-index value can be described as,

$$L_{\max} = \max(L_j), \quad \text{where } j = 1,..., N_{PQ} \tag{8}$$

A lower value of L denotes a stable system. In order to improve the voltage stability and to move the system from voltage collapse point, the objective can be described as,

$$Minimize \quad F_3 = L_{\max} \tag{9}$$

where *Lmax* is the maximum value of L-index.

2.4. Constraints

The objective functions are subject to both Equality and Inequality constraints as below:

2.4.1. Equality constraints

$$P_{Gi} - P_{Di} - \sum_{j=1}^{Nb} V_i V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad i = 1, 2, \cdots, Nb \tag{10}$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{Nb} V_i V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad i = 1, 2, \cdots, Nb \tag{11}$$

where N_B is the number of buses, P_{Gi} and Q_{Gi} are generated active and reactive power, P_{Di} and Q_{Di} are active and reactive power of load, G_{ij} is the transfer conductance and B_{ij} is the transfer susceptance between i^{th} and j^{th} bus.

2.4.2. Generator constraints

Generator voltages and reactive power output have to be within its permissible limits described as follows,

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \qquad i = 1,...,N_G \tag{12}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \qquad i=1,...,N_G \tag{13}$$

2.4.3. Transformer constraints

The transformer tap settings have to be within its lower and upper limits as follows,

$$T_i^{\min} \le T_i \le T_i^{\max}, \qquad i=1,..., N_T \tag{14}$$

2.4.4. Shunt VAR compensator constraints

Shunt VAR compensators should be within its lower and upper limits as follows,

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \qquad i=1,..., N_C \tag{15}$$

2.4.5. Security constraints

The load bus voltages and transmission line loadings have to be within its prescribed limits,

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \quad i = 1,...,N_{PQ} \tag{16}$$

$$S_{Li}^{\min} \leq S_{Li}^{\max} \qquad i=1,...,N_L \tag{17}$$

Thus the generalized objective function can be formulated as,

$$Min \quad Obj = F_{obj} + \lambda_V \sum_{i=1}^{NPQ} (V_{Li} - V_{Li}^{\lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \lambda_L \sum_{i=1}^{NL} (S_{Li}^{\max} - S_{Li}^{\min})^2 \tag{18}$$

where F_{obj} is the objective function, λ_V, λ_L and λ_Q are the penalty factors.

3. CROW SEARCH ALGORITHM

Crows or Corvids are intellectual omnivores; natural history books remain to be an evidence for it. Crows have remarkable abilities like problem-solving skills, communication skills and adaptability. Crows are known for its excellence in memory, certain vital researches show that crows don't forget a face and hence alerts other crows how to identify the individuals. Certain behavior of crows is enlisted [23],

a. Crows live in groups
b. Crows have excellent memory on their position of hidden places
c. Crows follows each other to perform acts of thievishness
d. Crows hide their collectives that have been theft

Crow Search Algorithm (CSA) is developed based on the above nature and behavior of crows. The algorithm has d-dimensional environment with N number of crows and the position of crows (X_i^k) which can be specified by a vector,

$$X_i^k = [X_i^{k,1}, X_i^{k,2}, ..., X_i^{k,d}] \tag{19}$$

where $i = 1, 2, ..., N$; $k = 1, 2, ..., iter^{\max}$; $iter^{\max}$ is the maximum number of iterations

In accordance with its memory capacity, the algorithm proceeds as, at k^{th} iteration, the position of hiding place of i^{th} crow is given by, M_i^k. For better illustration, assume that j^{th} crow wants to visit its hiding place at k^{th} iteration, at this instant of iteration, i^{th} crow follows j^{th} crow to know its hidden place, here there are two possibilities,

Possibility 1: The crow *j* being unaware of crow *i*, shows its hidden place, hence at this instant the new position of crow *i* become,

$$X_i^{iter+1} = X_i^{iter} + r_i \times fl_i^{iter} \times (M_i^{iter} - X_i^{iter}) \tag{20}$$

where r_i is a random number with uniform distribution between 0 and 1, fl_i^{iter} denotes the flight length of crow *i* at iteration *iter*. The value of *fl* has great impact on the search space of the algorithm, if *fl* is a smaller value than it results in local search and if *fl* is a larger value it results in global search.

Possibility 2: The crow *j* aware of crow *i* that it is following it, in order, hence to protect its collect from crow *i*, crow *j* will move to another position to divert crow *j*, then the new position is thus given by,

$$X_i^{iter+1} = \begin{cases} X_i^{iter} + r_i \times fl_i^{iter} \times (M_j^{iter} - X_i^{iter}) r_j \geq AP_j^{iter} \\ a \quad random \quad position \quad otherwise \end{cases} \tag{21}$$

where AP_j^{iter} denotes the awareness probability of crow *j* at iteration *iter*. This factor decides whether the search space is intensified or diversified. When *AP* is increased, the search space gets increased thereby, results in global optimal and vice versa.

4. APPLICATION OF CROW SEARCH ALGORITHM FOR ORPD PROBLEM

The sequence of steps that ought to be followed in the implementation of the CSA is given in this section.

Step 1: Initialization of algorithm parameters and constraints

The algorithm parameters comprises of population size (*N*), maximum number of iterations ($iter^{max}$), flight length (*fl*) and awareness probability (*AP*) and the constraints include power balance equality constraints, line flow and voltage constraints.

Step 2: Initialization of the position and memory of crows

The *N* population of crows is randomly positioned in a *d*-dimensional search space. Each crow denotes a possibility of feasible solution of the problem and *d* is the number of control variables which includes generator voltages, transformer tap settings and reactive power output of shunt capacitor. The memory of each crow is initialized. At the beginning of iteration *iter*, it is assumed that the crows have hidden their foods at their initial positions.

Step 3: Evaluate fitness (objective) function

For each crow, the position is determined by fitting the control variable values into the objective function (minimization of real power loss, total voltage deviation and voltage stability indicator).

Step 4: Generate new position

Crows finds a new position in the *d*-dimensional search space by as follows: suppose crow *i* wants to find a new position. For this, the crow randomly selects one of the crows, let that be crow *j* and follows it to discover the Position of collecting hidden by this crow (m_j). The new position of crow *i* is given by Equations (20) and (21).

Step 5: Check the feasibility of new positions

The viability of the new position of each crow thus obtained is checked and the position is updated based on it. If the new position, thus obtained is not viable, then the crowd stays in the current position and does not move to the new position found.

Step 6: Evaluate the fitness function of new positions

The fitness function i.e. objective function value for the new position of each crow is evaluated.

Step 7: Update memory

The crows update their memory as follows:

$$m^{i,iter+1} = \begin{cases} x^{i,iter+1} f(x^{i,iter+1}) \quad is \quad better \quad than \quad f(m^{i,iter}) \\ \qquad\qquad m^{i,iter} \quad otherwise \end{cases} \tag{22}$$

where f_{obj} denotes the objective function value.

It is seen that if the fitness function value of the new position of a crow is better than the fitness function value of the memorized position, the crow updates its memory by the new position.

Step 8: Check termination criterion

Steps 4 to 7 are repeated until maximum iteration is reached. When the termination criterion is met, the best position of the memory in terms of the objective function value is reported as the solution of the optimization problem.

5. RESULTS AND DISCUSSION

The present work is being tested on standard IEEE-30, 57 and 118 bus systems and the results are obtained. The description of these studied test systems is depicted below. The software is written in MATLAB R2015 computing environment. The various algorithm parameters are initialized and are set to be as: The value of flock size (population) is set to 75, the awareness probability index determines whether the search space is intensified or diversified and is set to 0.5, the flight length is assumed to be 2 and the maximum number of iterations performed is set to 200 for all the test cases considered. The results of interest are boldfaced in the respective tables to indicate the optimization capability of the proposed algorithm.

5.1. Case-1: Minimization real power loss

In this case, the proposed algorithm is executed considering the minimization of real power loss alone as the objective function. The convergence characteristic of the algorithm considering the real power loss is shown in Figure 1, which indicates fast and smooth convergence of CSA. The superiority of the aforesaid CSA based approach for solving ORPD problem can be witnessed from the comparison made between other optimization techniques from Table 1, Table 2 and Table 3. The best power loss obtained using CSA for IEEE 30, 57 and 118 bus systems are 2.8507 MW, 15.1934 MW and 76.7783 MW respectively, which is lesser than result reported in [12], [14], [19], [21].

Table 1. Comparison of results for minimization of active power loss for IEEE-30 bus system

Methodology	CSA	CLPSO [14]	GSA [21]
Power loss (MW)	2.8507	4.5615	4.5143

Table 2. Comparison of results for IEEE 57-bus system

Methodology	CSA	CLPSO [14]	SOA [19]	GSA [21]
Power loss (MW)	15.1934	24.5152	24.2654	23.4611

Table 3. Comparison of results for IEEE 118-bus system

Methodology	CSA	PSO [12]	SOA [19]	GSA [21]
Power loss (MW)	76.7783	131.99	114.9501	127.7603

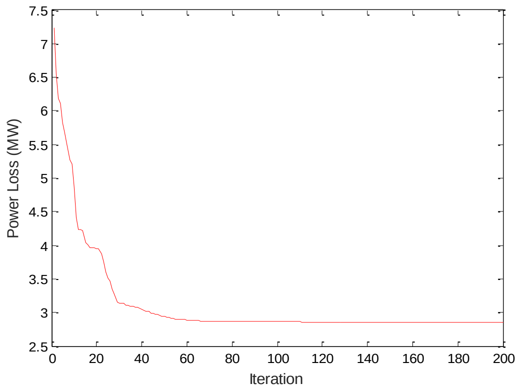

Figure 1. Convergence characteristics considering the real power loss as objective

5.2. Case-2: Minimization of total voltage deviation

The proposed CSA approach is also applied for minimization of total voltage deviation of IEEE-30 bus test network and the result yielded from this approach is illustrated in Table 4 and are compared with those reported in the literature. The minimum total voltage deviation obtained by the proposed method is 0.0907, which is lesser than results reported in [12], [14]. The convergence characteristic of voltage deviation versus number of iterations is depicted in Figure 2.

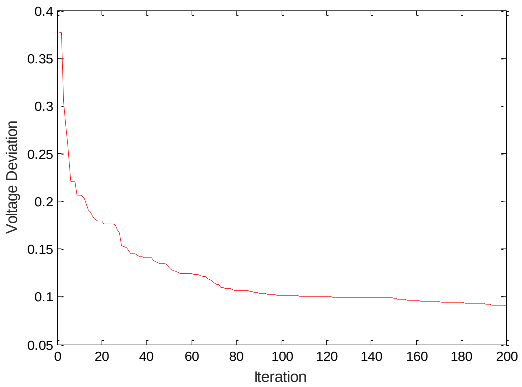

Figure 2. Convergence characteristics considering voltage deviation as objective

Table 4. Comparisons of results for voltage profile improvement IEEE-30 bus system

Methodology	CSA	PSO [12]	CLPSO [14]
Σ Voltage deviation (p.u)	0.0907	0.2450	0.2577

5.3. Case-3: Enhancement of voltage stability

In this case the enhancement of voltage Stability is taken as objective function. The solution obtained by the proposed method and reported in literature by other methods is illustrated in Table 5. The voltage stability indicator obtained by the CSA is 0.1180, which is lesser than results reported in [20], [21] and which is proving the excellence of the aforesaid CSA algorithm over other optimization techniques. The convergence characteristic of L-index versus number of iterations are depicted in Figure 3, which shows fast and smooth convergence characteristics of CSA.

Table 5. Comparison of results for enhancement of voltage stability IEEE-30 bus system

Methodology	CSA	DE [20]	GSA [21]
L-index (p.u)	0.1180	0.1246	0.1368

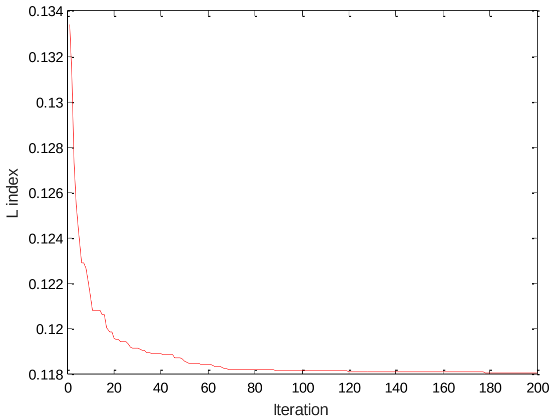

Figure 3. Convergence characteristics considering voltage stability indicator as objective

The optimal setting of the control variables for the IEEE-30 bus system is illustrated in Table 6. The optimal control variable setting for IEEE-57 and IEEE-118 bus system for case-1 (minimization of real power loss) is illustrated in Table 7 and Table 8 respectively.

Table 6. Control variable settings for IEEE-30 Bus System

Control variable	Case-1	Case-2	Case-3
V_{G1} (p.u)	1.1000	1.0152	1.1000
V_{G2} (p.u)	1.0975	1.0006	1.0882
V_{G5} (p.u)	1.0796	1.0173	1.1000
V_{G8} (p.u)	1.0867	1.0027	1.0885
V_{G11} (p.u)	1.1000	1.0736	1.1000
V_{G13} (p.u)	1.1000	1.0172	1.1000
T_{6-9}	1.0665	1.0961	1.0025
T_{6-10}	0.9000	0.9000	0.9000
T_{4-12}	0.9880	0.9972	0.9675
T_{28-27}	0.9738	0.9692	0.9078
Q_{C10} (MVAR)	5.0000	4.0381	5.0000
Q_{C12} (MVAR)	5.0000	4.7556	5.0000
Q_{C15} (MVAR)	5.0000	4.9998	4.3599
Q_{C17} (MVAR)	5.0000	0.0006	4.9892
Q_{C20} (MVAR)	4.0451	4.9979	4.8982
Q_{C21} (MVAR)	5.0000	4.9785	0
Q_{C23} (MVAR)	2.6117	5.0000	0
Q_{C24} (MVAR)	5.0000	5.0000	0
Q_{C29} (MVAR)	2.2796	2.8054	0
Power loss (MW)	2.8507	10.3406	9.0087
Σ Voltage deviation	2.0447	0.0907	2.3063
L-index	0.1261	0.1489	0.1180

Table 7. Optimal settings of control variables for IEEE 57-bus system

Control variables	Value	Control variables	Value	Control variables	Value	Control variables	Value	Control variables	Value
V_{G1} (p.u)	1.0468	V_{G13} (p.u)	1.0290	Q_{C3} (MVAR)	13.8328	T_{11-41}	0.9001	T_{11-43}	0.9564
V_{G2} (p.u)	1.0457	T_{4-18}	0.9964	T_{24-25}	1.1000	T_{15-45}	0.9634	T_{40-56}	0.9874
V_{G3} (p.u)	1.0423	T_{4-18}	0.9708	T_{24-25}	0.9922	T_{14-46}	0.9573	T_{39-57}	0.9801
V_{G6} (p.u)	1.0550	T_{21-20}	1.0018	T_{24-26}	1.0281	T_{10-51}	0.9667	T_{9-55}	0.9987
V_{G8} (p.u)	1.0638	Q_{C1} (MVAR)	9.0156	T_{7-29}	0.9924	T_{13-49}	0.9239		
V_{G9} (p.u)	1.0346	Q_{C2} (MVAR)	17.3349	T_{34-32}	0.9705	Power loss (MW)		15.1934	

Table 8. Optimal settings of control variables for IEEE 118-bus system

Control variables	Value	Control variable	Value	Control variables	Value	Control variables	Value	Control variables	Value
V_{G1} (p.u)	1.0238	V_{G34} (p.u)	1.0175	V_{G70} (p.u)	1.0259	V_{G103} (p.u)	1.0307	Q_{C79} (MVAR)	39.3480
V_{G4} (p.u)	1.0380	V_{G36} (p.u)	1.0143	V_{G72} (p.u)	1.0332	V_{G104} (p.u)	1.0160	Q_{C82} (MVAR)	31.2706
V_{G6} (p.u)	1.0287	V_{G40} (p.u)	1.0098	V_{G73} (p.u)	1.0250	V_{G105} (p.u)	1.0154	Q_{C83} (MVAR)	8.6446
V_{G8} (p.u)	1.0764	V_{G42} (p.u)	1.0149	V_{G74} (p.u)	1.0146	V_{G107} (p.u)	1.0114	Q_{C105} (MVAR)	0.6263
V_{G10} (p.u)	1.0946	V_{G46} (p.u)	1.0262	V_{G76} (p.u)	1.0121	V_{G110} (p.u)	1.0181	Q_{C107} (MVAR)	26.8462
V_{G12} (p.u)	1.0247	V_{G49} (p.u)	1.0410	V_{G77} (p.u)	1.0314	V_{G111} (p.u)	1.0246	Q_{C110} (MVAR)	13.4358
V_{G15} (p.u)	1.0207	V_{G54} (p.u)	1.0237	V_{G80} (p.u)	1.0452	V_{G112} (p.u)	1.0145	T_{5-8}	1.0150
V_{G18} (p.u)	1.0239	V_{G55} (p.u)	1.0249	V_{G85} (p.u)	1.0564	V_{G113}(p.u)	1.0322	T_{25-26}	1.0500
V_{G19} (p.u)	1.0181	V_{G56} (p.u)	1.0234	V_{G87} (p.u)	1.0581	V_{G116} (p.u)	1.0299	T_{17-30}	1.0354
V_{G24} (p.u)	1.0474	V_{G59} (p.u)	1.0413	V_{G89} (p.u)	1.0722	Q_{C34} (MVAR)	6.8484	T_{37-38}	1.0137
V_{G25} (p.u)	1.0765	V_{G61} (p.u)	1.0345	V_{G90} (p.u)	1.0479	Q_{C44} (MVAR)	2.2374	T_{59-63}	0.9791
V_{G26} (p.u)	1.1000	V_{G62} (p.u)	1.0327	V_{G91} (p.u)	1.0465	Q_{C45} (MVAR)	23.4731	T_{61-64}	0.9991
V_{G27} (p.u)	1.0345	V_{G65} (p.u)	1.0354	V_{G92} (p.u)	1.0550	Q_{C46} (MVAR)	0	T_{65-66}	0.9668
V_{G31} (p.u)	1.0221	V_{G66} (p.u)	1.0517	V_{G99} (p.u)	1.0368	Q_{C48} (MVAR)	9.6476	T_{68-69}	0.9380
V_{G32} (p.u)	1.0296	V_{G69} (p.u)	1.0546	V_{G100} (p.u)	1.0411	Q_{C74} (MVAR)	11.7550	T_{80-81}	0.9742
P_L (MW)			76.7783						

6. CONCLUSION

In this work, the CSA algorithm was proposed for solving optimal reactive power dispatch problem and successfully implemented in IEEE 30, 57 and 118 bus systems. The results obtained from the CSA approach were compared with those reported in recent literature and hence the CSA algorithm proves its capability of solving ORPD more efficiently in terms of its search capability and robustness. The supremacy of CSA over the other approaches was observed. In accordance with the results obtained, the CSA algorithm has a simple structure and quick convergence characteristics and therefore can be used to solve ORPD in large scale power systems and may be recommended as a very promising algorithm for solving complex engineering optimization problems.

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