

Imperialist Competitive Algorithm for Optimal Reactive Power Dispatch Problem: A Comparative Study

Mojtaba Ghasemi*, Ali Reza Roosta

Department of Electronics and Electrical Engineering, Shiraz University of Technology,
Shiraz, Iran

*Corresponding's Email: M.Noabad@sutech.ac.ir

Abstract – In this paper, imperialist competitive algorithm (ICA) is applied to solve the optimal reactive power dispatch (ORPD) problem. The ORPD problem is a key instrument to achieve secure and economic operation of power systems. Due to complex characteristics of ORPD, heuristic optimization has become an effective solver. Based on the IEEE 14- and 30- bus systems, ICA is compared with some basic algorithms. Simulation results show that ICA is a suitable algorithm for ORPD and should deserve more attention.

Keywords: Optimal Reactive Power Dispatch (ORPD), Heuristic Optimization.

INTRODUCTION

The optimal reactive power dispatch (ORPD) plays an important role in optimal operation of electric power systems. The optimal reactive power dispatch problem is a non-linear optimization problem with many uncertainties. The optimal reactive power dispatch is an effective method to improve voltage level, decrease network losses and maintain the power system running under normal conditions. The main objective of the ORPD is to minimize the system real power loss. Generally, the control variables of ORPD consist of transformer tap positions, generator set points (either reactive power injection or voltage), and reactive power compensations [1, 2].

In recent years, some new algorithms based on artificial intelligence have been proposed to solve the reactive power optimization, for examples: fuzzy logic (FL), expert system, artificial neural network (ANN), genetic algorithm (GA) [3], gravitational search algorithm (GSA) [4], differential evolution (DE) [5], tabu search (TS) [6], particle swarm optimization (PSO) [7], ant colony optimization (ACO) [8], evolutionary programming (EP) [9], bacterial foraging optimization (BFO) [10], etc.. These algorithms could treat discrete and non-convex nonlinear problems effectively. The global optimal solution could be gained easier by new algorithms than by conventional ones. So these algorithms have been widely applied to the reactive power optimization.

In this paper, ICA is applied for solving the ORPD problem. In the process of solving, ORPD problem is formulated as a nonlinear constrained single-objective optimization problem where the real power loss is to be

ORIGINAL ARTICLE

minimized. Simulations have been done using MATLAB program. The proposed algorithm is tested on IEEE 14- and 30- bus systems for evolution of effectiveness of it. Results obtained from ICA are compared with other heuristic methods. Results show that proposed algorithm is more effective and powerful than other algorithms in solution of ORPD problem.

PROBLEM FORMULATION

The objective of the ORPD problem is to minimize the system real power losses by setting generator bus voltages, VAR (volt amp reactive) compensators and transformer taps. Objective function minimized in this paper and constraints are formulated taking from (1, 9) and shown as follows.

1. Minimization of Real Power Loss

The real power loss is a non-linear function of bus voltages, which are functions of control variables. This is mathematically stated as follows:

Minimize:

$$P_{loss} = \sum_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j) \right] \quad (1)$$

Where P_{loss} is the total active power losses of the transmission network, nl is the number of transmission lines, g_k is the conductance of branch k th, V_i and V_j are voltage magnitude at buses i and j of the k th, and δ_i and δ_j are the voltage phase angle at the end buses i and j .

2. System Constraints

In the reactive power optimization mathematical model, some problem constraints which one is equality and others are inequality had to be met.

2.1. Load Flow Equality Constraints

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \begin{bmatrix} G_{ij} \cos(\delta_i - \delta_j) \\ + B_{ij} \sin(\delta_i - \delta_j) \end{bmatrix} = 0 \quad (2)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \begin{bmatrix} G_{ij} \sin(\delta_i - \delta_j) \\ - B_{ij} \cos(\delta_i - \delta_j) \end{bmatrix} = 0 \quad (3)$$

Where $i=1, \dots, NB$; NB is the number of buses, P_G is the active power generated, Q_G is the reactive power generated, P_D is the load active power, Q_D is the load reactive power, G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j , respectively.

2.2. Inequality constraints

These constraints include:

• **Generator constraints:** generator voltages and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max}, \quad i = 1, \dots, NG \quad (4)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, \quad i = 1, \dots, NG \quad (5)$$

• **Transformer constraints:** transformer tap settings are bounded as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad i = 1, \dots, NT \quad (6)$$

• **Shunt VAR constraints:** shunt VAR compensations are restricted by their limits as follows:

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max}, \quad i = 1, \dots, NC \quad (7)$$

• **Security constraints:** these include the constraints of voltages at load buses and transmission line loadings as follows:

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}, \quad i = 1, \dots, NL \quad (8)$$

$$S_{li} \leq S_{li}^{\max}, \quad i = 1, \dots, nl \quad (9)$$

Where NG is the number of the generator-bus, NL is the number of bus bars, NT is the number of the transformer taps, NC is the member of shunt compensations and nl is total number of transmission lines.

IMPERIALIST COMPETITIVE ALGORITHM

Imperialist competitive algorithm (ICA) [11] is introduced for general searching that is inspired from imperialist competition. Fig.1 shows the flowchart of the ICA. In sum, this algorithm starts with an initial population. Each individual of the population is called a 'country'. Some of the countries in the population with the minimum cost (equal with elites in GA) are selected to be the imperialist states and the rest form the colonies of these imperialists. Imperialistic competitions among these empires form the basis of the ICA. The imperialist states together with their colonies form some empires. Imperialistic competitions converge to a state in which there exists only one empire and its colonies are in the same position and have the same cost as the imperialist.

The power of each country is inversely proportional to its cost.

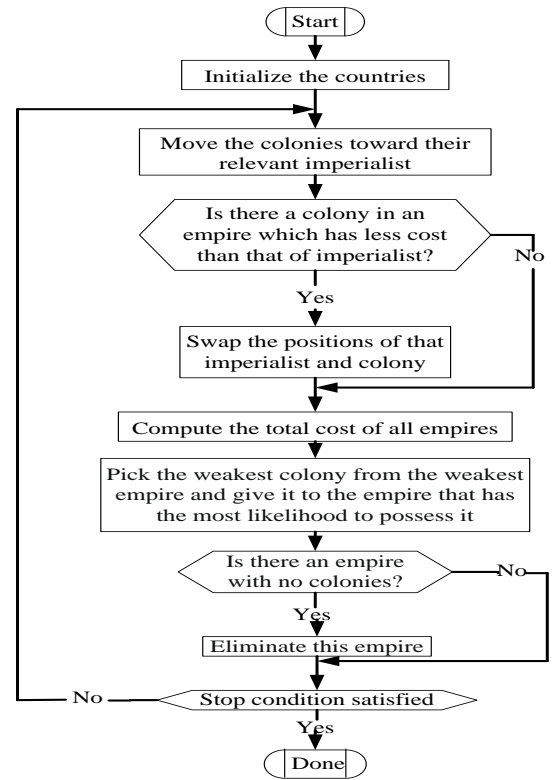


Fig. 1- Flowchart of the ICA

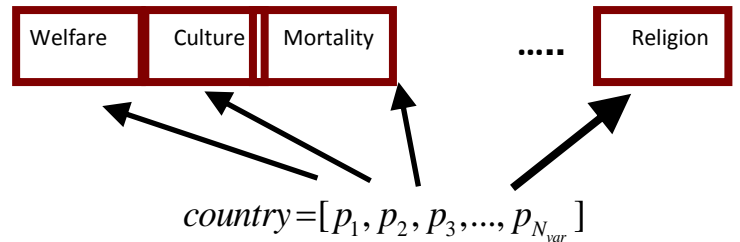


Fig. 2- Interpretation of country using some of socio-political characteristics

1. Generating Initial Empires

The objective of optimization is to attain an optimal solution in terms of the variables of the problem. Algorithm-user forms an array of variable values to be optimized. In the ICA terminology, this array is called 'country' (equal with 'chromosome' in GA). When solving a N_{var} dimensional optimization problem, a country is a $1 \times N_{var}$ array. This country is defined as follow:

$$country = [P_1, P_2, P_3, \dots, P_{N_{var}}] \quad (10)$$

Where P_i s are considered as the variables that should be optimized.

The candidate solutions of the problem, called country, consist of a combination of some socio-political characteristics such as, welfare, culture, religion and

mortality. Fig. 2 shows the interpretation of country using some of socio-political characteristics.

When the problem was optimized, the optimal solution is going to be finding which the one with the minimum cost value is. By evaluating the cost function, f , for variables $(P_1, P_2, P_3, \dots, P_{N_{var}})$, the cost of a country will be found (Equation (11)):

$$\text{cost}_i = f(\text{country}) = f(P_1, P_2, P_3, \dots, P_{N_{var}}) \quad (11)$$

To begin the ICA algorithm, initial population of size $N_{country}$ is produced. We select N_{imp} of the strongest population to form the empires. The remaining N_{col} of the population will be the colonies each of which belongs to an imperialist. We give some of these colonies to each imperialist for dividing the early colonies among the imperialist accordance with their power. To proportionally divide the colonies among imperialists, the normalized cost of an imperialist is defined by:

$$C_n = \max_i \{c_i\} - c_n \quad (12)$$

In the above equation, c_n is the cost of n th imperialist and C_n is its normalized cost. When the normalized costs of all imperialists are gathering, the normalized power of each imperialist is evaluate according to the following equation:

$$P_n = \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \quad (13)$$

The initial colonies are divided among empires based on their power. Then, the initial number of colonies of the n th empire will be:

$$N.C._n = \text{round} \{ P_n . N_{col} \} \quad (14)$$

Where $N.C._n$ is initial number of empire's colonies and N_{col} is the total number of existing colonies countries in the initial countries crowds.

2. Absorption Policy Modeling

As mentioned earlier, imperialist states made their colonies to move toward themselves along different socio-political axis such as welfare, culture and religion. In fact this central government tries to close colony country to its self by applying attraction policy, in different political and social dimensions, with considering showing manner of country in solving optimization problem. This movement is shown in Fig. 3 in which a colony moves toward the imperialist by units.

In Fig. 3, distance between imperialist and colony is shown by d and x is accidental number with steady distribution.

It means for x , we have:

$$x \sim U(0, \beta \times d) \quad (15)$$

Where β is a number greater than one and nears to two. A good selection can be $\beta=2$. To increase the ability of searching more area around the imperialist, a random amount of deviation is added to the direction of movement. In Fig.3, θ is a parameter with uniform distribution. Then:

$$\theta \sim U(-\gamma, +\gamma) \quad (16)$$

Where γ is ideal parameter that it's increasing causes increasing searching around imperialist and its decreasing cause's colonies close possibly to the vector of connecting colony to the imperialist. The value of γ is arbitrary, in most of implementations, a value of about $\pi/4$ (Rad).

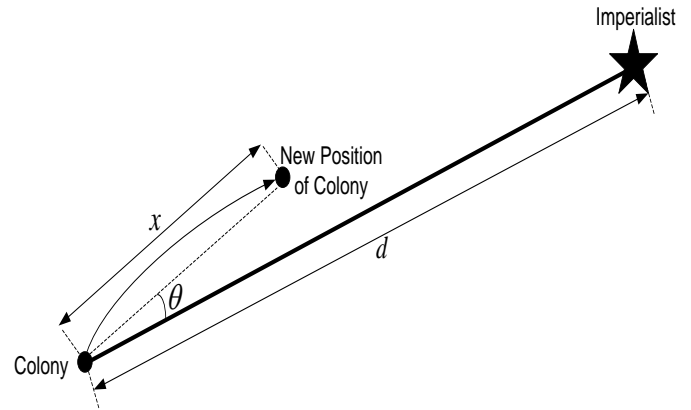


Fig. 3 - Giving a move to the colonies toward their corresponding imperialist in an accidental deviated orientation

3. Position Displacement of Colony and Imperialist

While moving toward the imperialist, if a colony reaches a better point than an imperialist, they will be replaced by each other. After that, the algorithm continues with imperialist country in new location and this time it is the new imperialist country in which begins to applying assimilation policy for its colonies.

4. Total power of an Empire

Sum power of an empire is mostly affected by the power of imperialist country. Howbeit, the power of the colonies of an empire has an effect, albeit negligible, on the sum power of that empire. In this case the sum cost of an empire calculates as follow:

$$T.C._n = \text{Cost}(\text{imperialist}_n) + \xi \text{mean}\{\text{Cost}(\text{colonies of empire}_n)\} \quad (17)$$

Where $T.C._n$ is the total cost of the n th empire and ξ is a positive number that is usually between zero and one and near to zero. A low value for ξ causes the total power of the empire to be determined by just the imperialist and increasing it will increase to the role of the colonies in determining the total power of an empire. The value of 0.15 for ξ has shown good results in most of the implementations.

5. Imperialistic Competitions

There has always been a competition among the empires to take control and possess each other's colonies. The imperialistic competition is modeled by just picking some (usually one) of the weakest colonies of the weakest empire and making a competition among all empires to possess these (this) colonies. Based on their total power, in this competition, each of the empires will have a likelihood of taking possession of the mentioned colonies. These weakest colonies will not definitely be possessed by the most powerful empires, but these empires will be more likely to possess them.

For modeling the competition between the empires for possessing these colonies, first of all, the weakest empire is chosen and then the possession probability of each empire is estimated. The possession probability P_p is proportionate to the total power of the empire. The normalized total cost of an empire is simply obtained by:

$$N.T.C._n = \max_i \{T.C._i\} - T.C._n \quad (18)$$

Where $T.C._n$ is total cost of n th empire and $N.T.C._n$ is normalized cost of that n th empire. Having the normalized total cost, the possession probability of each empire is defined by:

$$P_{p_n} = \frac{N.T.C._n}{\sum_{i=1}^{N_{imp}} N.T.C._i} \quad (19)$$

We divide the mentioned colonies accidentally between the empires, but with related probability to ownership probability of each empire. In order to divide the given colonies among the empires, vector P is formed as follows:

$$P = [P_{p_1}, P_{p_2}, P_{p_3}, \dots, P_{p_{N_{imp}}}] \quad (20)$$

After that, the vector R should be defined with the same size of vector P . The arrays of this vector are accidental number with the same distribution in $[0, 1]$.

$$R = [r_1, r_2, r_3, \dots, r_{N_{imp}}] \quad (21)$$

Then, vector D is constructed by subtracting R from P .

$$D = P - R = [D_1, D_2, D_3, \dots, D_{N_{imp}}] \quad (22)$$

$$= [P_{p_1} - r_1, P_{p_2} - r_2, P_{p_3} - r_3, \dots, P_{p_{N_{imp}}} - r_{N_{imp}}]$$

We give the mentioned colonies to the empires with having vector D so that related index in vector D is bigger than others.

The imperialistic competition will gradually result in an increase in the power of great empires and a decrease in the power of weaker ones. The weak empires will slowly lose their power and getting weakened by the time.

SIMULATION RESULTS

In order to verify the proposed approach, ICA is applied to IEEE 14-bus and IEEE 30-bus power systems. The topology and data of these two systems can be found in [12, 13]. In all case studies, as decision variables, generator voltages, transformers tap settings, and reactive power compensators are chosen. In this paper, these variables are considered to be continuous [14]. For the two test cases, the performance of ICA is compared with the following algorithms.

1. PSO [7];
2. GA [3];
3. Invasive weed optimization (IWO) [15];
4. Shuffled frog leaping algorithm (SFLA) [16];

All programs were implemented in MATLAB R2010a. Because the most time-consuming parts in these methods are the repeated power flow calculations and the number of such calculations is fixed, the computational time of all algorithms is not significantly different. The comparison in this paper will be based on quality of the final results.

1. IEEE 14-Bus System

The IEEE 14-bus system consists of five generators, 20 lines where 3 of which are equipped with ULTC (under-load tap changer) transformers. The one line diagram of IEEE 14-bus system is shown in Fig. 4. The lower and upper limits of voltage magnitude at all buses are 0.95 and 1.10 p.u., respectively, while the transformer tap settings are varied between 0.9 and 1.1 p.u. Shunt reactive power compensator is connected to bus 9. The susceptances of capacitor banks are within the interval $[0, 0.3]$ p.u.. In the IEEE 14-bus system, totally 9 control variables are taken for optimal reactive power dispatch.

The line parameters and the loads are taken from [12] and the initial transmission line loss is 13.393 MW for the IEEE 14-bus system. The network loads are given as follows: $P_D = 259$ MW and $Q_D = 73.5$ MVar.

The values of parameters and limits of generators for system case1 are given in Table 1. Five algorithms of PSO, GA, IWO, SFLA and ICA for solving objective reactive power optimization problem are shown in Fig. 5. From the optimal value of the convergence curve, ICA algorithm is fast at the beginning of generations decline, showing that the algorithm optimizing the effectiveness and superiority of the system; In the iteration 10, it have been able to very close to the optimal solution, but PSO algorithm to 50 iterations to achieve the optimal solution. GA, IWO and SFLA should be about 80, 180 and 100 iterations to achieve the optimal solution, respectively. So, ICA is better than PSO, GA, IWO and SFLA. The algorithm proposed in this paper has better convergence and accuracy. Table 2 shows the optimized algorithms the optimal value of the control variables.

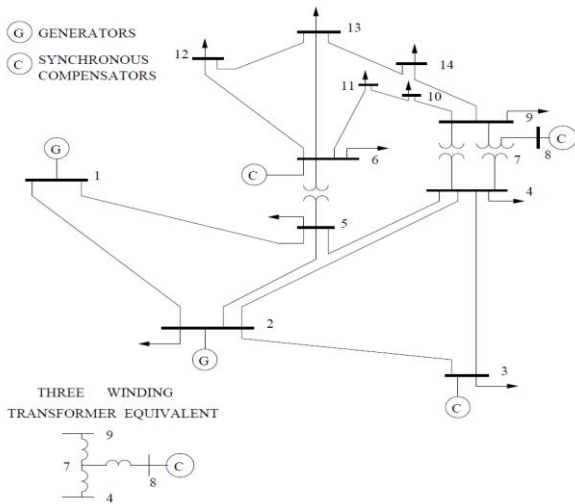


Fig. 4 - Single line diagram of IEEE 14-bus test system [12]

TABLE 1
Generator Data of IEEE 14-Bus System

Bus	P_G (MW)	Q_{Gmax} (MVar)	Q_{Gmin} (MVar)
1	232.4	10	0
2	40	50	-40
3	0	40	0
6	0	24	-6
8	0	24	-6

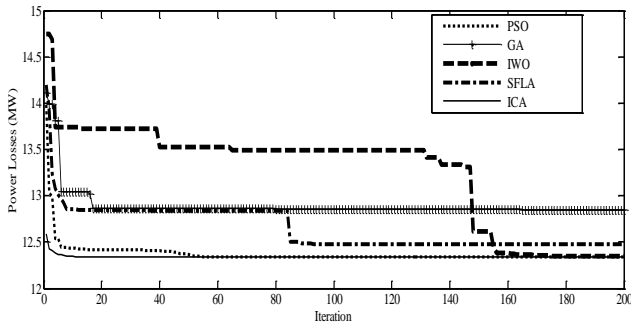


Fig.5 - Convergence characteristics of IEEE 14-bus system

TABLE 2
Best Control Variables for IEEE 14-Bus System ($p.u.$)

Variables	Algorithms				
	PSO	GA	IWO	SFLA	ICA
V_{G1}	1.1000	1.0857	1.1000	1.0990	1.1000
V_{G2}	1.0759	1.0613	1.0760	1.0726	1.0759
V_{G3}	1.0463	1.0325	1.0463	1.0353	1.0464
V_{G6}	1.1000	1.0252	1.0968	1.0536	1.1000
V_{G8}	1.0754	1.0176	1.0685	1.0567	1.0759
T_{4-7}	1.0206	1.0294	1.0333	1.0258	1.0143
T_{4-9}	0.9045	0.9666	0.9039	1.0035	0.9169
T_{5-6}	0.9729	1.0097	0.9719	1.0097	0.9724
B_9	0.29688	0.20220	0.29630	0.21077	0.30000
$P_{loss}(MW)$	12.3397	12.8498	12.3450	12.4758	12.3399
Time(sec)	13.32	16.65	17.39	18.46	12.54

Table 3 shows the statistical comparison of results obtained by PSO, GA, IWO, SFLA and ICA algorithms as regards to the objective function of minimizing real power loss only, the ICA algorithm is better than GA, IWO and SFLA, even as the average and maximum values of ICA algorithm are better of PSO algorithm. Fig. 6 shows the voltage magnitudes of all the bus bars as calculated from the ORPD solution by the different methods. It can be seen that all the bus voltages obtained by the proposed method are within the limits.

TABLE 3
Comparison of Best, Worst and Average Values for Different Algorithms for IEEE 14-Bus System

	Algorithms				
	PSO	GA	IWO	SFLA	ICA
Minimum	12.3397	12.8498	12.3450	12.4758	12.3399
Average	12.3787	13.0356	12.3791	12.6082	12.3431
Maximum	12.7673	13.2497	12.4620	12.8970	12.3498

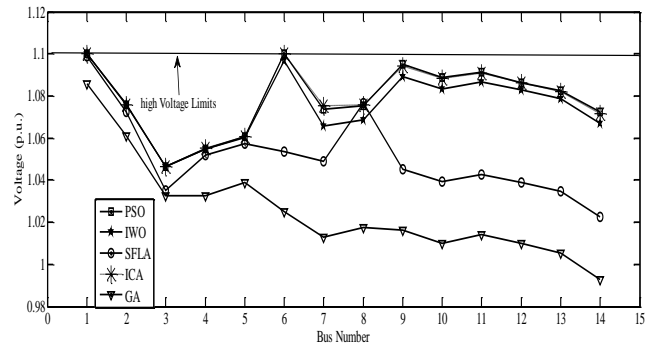


Fig. 6 - Voltage profiles of IEEE 14-bus system

2. IEEE 30-Bus System

The network consists of 6 generators; 41 lines; 4 transformers and 2 capacitor banks. The one line diagram of IEEE 30-bus system is shown in Fig. 7. In the transformer tests, tap settings are considered within the interval [0.9, 1.1]. The susceptances of capacitor banks are within the interval [0, 0.3] p.u., and they are connected to buses 10 and 24. Voltages are considered within the range of [0.95, 1.1]. In this case, the decision space has 12 dimensions, namely, the 6 generator voltages, 4 transformer taps, and 2 capacitor banks.

In order to validate the proposed approach, it is tested with two test systems having non-linear characteristics.

2.1. System Case 1

The system loads and power losses are given as follows:

$$P_D=283.4MW, Q_D=126.2MVar, P_{loss}=17.557MW.$$

The values of parameters and limits of generators for system case 1 are given in Table 4. Also, Fig. 8 shows the performances of GA, PSO, IWO, SFLA and ICA during reactive power optimization.

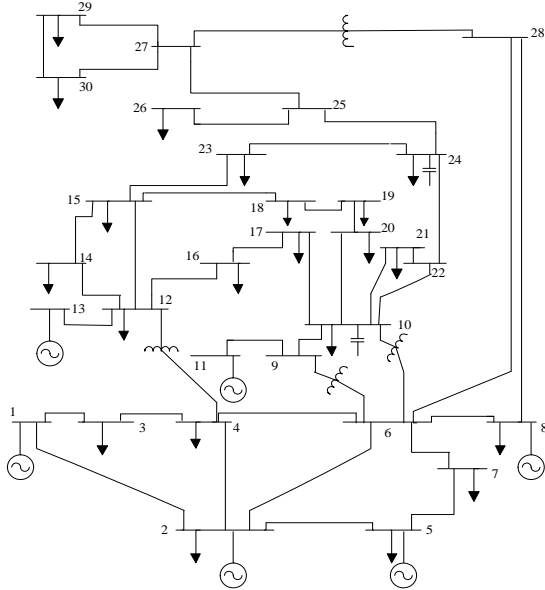


Fig. 7 - Single line diagram of IEEE 30-bus test system

TABLE 4
Generator data for IEEE 30-Bus System for Case 1

Bus	$P_G(MW)$	$Q_{Gmax}(MVar)$	$Q_{Gmin}(MVar)$
1	260.2	10	0
2	40	50	-40
5	0	40	-40
8	0	40	-10
11	0	24	-6
13	0	24	-6

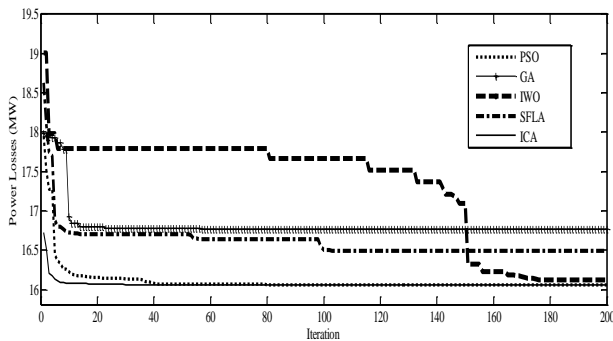


Fig. 8 - Convergence characteristics for IEEE 30-bus system for case 1

As shown in Fig. 8, by using the ICA algorithm, the iterations for convergence can be reduced greatly. The optimum has been obtained after iterating about 10 generations by ICA, whereas 40 generations by standard PSO algorithm, 180 generations by IWO, 95 generations by GA and 100 generations by SFLA. Table 5 gives the optimal settings of decision variables in *p.u.* for the reactive control of IEEE 30-bus system as proposed by competitors and the ICA.

TABLE 5
Best Control Variables for IEEE 30-Bus System for Case 1(*p.u.*)

Variables	Algorithms				
	PSO	GA	IWO	SFLA	ICA
V_{G1}	1.1000	1.0854	1.1000	1.0921	1.1000
V_{G2}	1.0741	1.0606	1.0745	1.0650	1.0741
V_{G5}	1.0421	1.0227	1.0358	1.0308	1.0419
V_{G8}	1.0480	1.0274	1.0460	1.0360	1.0479
V_{G11}	1.0999	1.0340	1.0896	1.0540	1.1000
V_{G13}	1.1000	1.0436	1.1000	1.0591	1.1000
T_{6-9}	1.0849	0.9957	0.9607	1.0200	1.0862
T_{6-10}	0.9000	1.0367	1.0570	1.0158	0.9000
T_{4-12}	0.9576	1.0135	0.9771	1.0134	0.9599
T_{27-28}	0.9458	0.9660	0.9588	0.9958	0.9463
B_{10}	0.30000	0.14130	0.29875	0.13180	0.30000
B_{24}	0.10307	0.10784	0.05747	0.15431	0.10250
$P_{loss}(MW)$	16.0637	16.7637	16.1181	16.4899	16.0638
Time(sec)	20.14	26.47	29.36	30.58	19.47

Table 6 shows that comparison of best, worst and average values for different methods. Due to probabilistic characteristic of heuristic algorithms, results reported here correspond to average from 30 trials. From Table 6 we can see: the best value, worst value and average value found by the ICA algorithm are apparently better than those obtained by GA, IWO and SFLA. Hence, the conclusion can be drawn that ICA algorithm is better than, or comparable to, all the other listed algorithms in terms of global and local search. As shown in the table, the average global value, the best solution and the worst solution obtained by the proposed algorithm is much better than those of obtained by the others. Also the algorithm converges to global solution in 19 times while the PSO, GA, IWO and SFLA reach to the best solution in 15, 5, 12, and 8 times, respectively. We can conclude that the ICA algorithm is robust.

TABLE 6
Comparison of Best, Worst and Average Values for Different Algorithms

	Algorithms				
	PSO	GA	IWO	SFLA	ICA
Minimum	16.0637	16.7637	16.1181	16.4899	16.0638
Average	16.0643	16.9172	16.1492	16.6025	16.0641
Maximum	16.0732	17.1156	16.3007	16.7555	16.0673

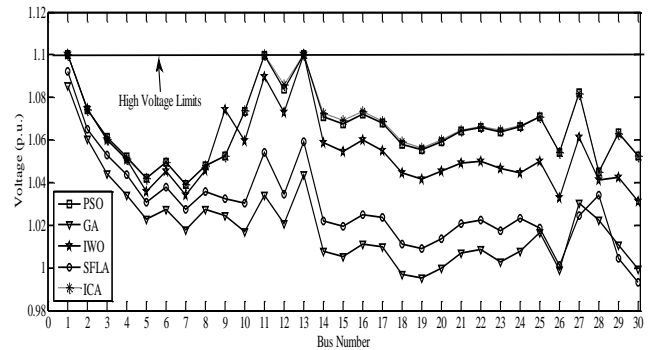


Fig. 9 - Voltage profiles of IEEE 30-bus system for case 1

After the ORPD result given by each method, power flow is calculated to determine bus voltages as shown in

Fig. 9. It is shown that all bus voltages can be maintained within the limits. These voltage profiles confirm the merits of ORPD in achieving reduced power losses.

2.2. System Case 2

The system loads and power losses are given as follows: $P_D=283.4MW$, $Q_D=126.2MVar$, $P_{loss}=3.829MW$.

The values of parameters and limits of generators for system case 2 are given in Table 7. The convergence of active power losses averaged from 30 independent trials of different algorithms is shown in Fig. 10. In terms of the convergence characteristic, ICA is the very good. The optimum control parameter settings of proposed approach are given in Table 8. The best power loss obtained from proposed approach is 3.1775 MW. Statistical results are shown in Table 9. In this test case, minimum, average and maximum of power losses from ICA are the lowest among all methods. Only minimum amount of PSO algorithm is equal with ICA.

TABLE 7
Generator Data for IEEE 30-Bus System for Case 2

Bus	P_G (MW)	Q_{Gmax} (MVar)	Q_{Gmin} (MVar)
1	260.200	10	0
2	60.140	50	-40
5	49.532	40	-40
8	34.743	40	-10
1	30.000	24	-6
13	39.740	24	-6

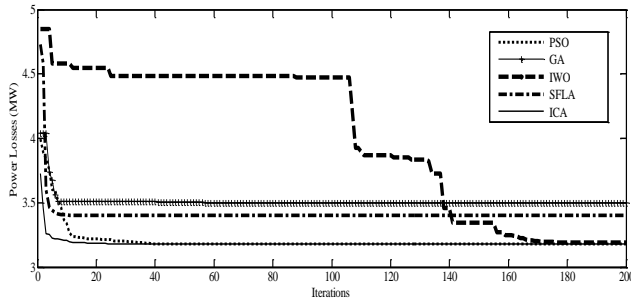


Fig. 10 - Convergence characteristics for IEEE 30-bus system for case 2

TABLE 8

Best Control Variables for IEEE 30-Bus System for Case 2 (p.u.)

Variables	Algorithms				
	PSO	GA	IWO	SFLA	ICA
V_{G1}	1.1000	1.0625	1.1000	1.0720	1.1000
V_{G2}	1.0911	1.0535	1.0909	1.0631	1.0910
V_{G5}	1.0734	1.0334	1.0718	1.0385	1.0736
V_{G8}	1.0807	1.0441	1.0797	1.0505	1.0809
V_{G11}	1.1000	1.0425	1.0672	1.0762	1.1000
V_{G13}	1.1000	1.0395	1.1000	1.0669	1.1000
T_{6-9}	1.0792	1.0214	1.0753	0.9739	1.0806
T_{6-10}	0.9004	1.0069	0.9368	1.0163	0.9000
T_{4-12}	0.9582	0.9889	0.9697	0.9695	0.9588
T_{27-28}	0.9595	0.9849	0.9692	0.9609	0.9594
B_{10}	0.24283	0.16374	0.29974	0.22552	0.24701
B_{24}	0.09945	0.13372	0.11413	0.14273	0.09997
$P_{loss}(MW)$	3.1775	3.5005	3.1892	3.4003	3.1775
Time(sec)	22.78	29.35	31.66	34.89	21.50

TABLE 9
Comparison of Best, Worst and Average Values for Different Algorithms

	Algorithms				
	PSO	GA	IWO	SFLA	ICA
Minimum	3.1775	3.5005	3.1892	3.4003	3.1775
Average	3.1789	3.5415	3.2489	3.4393	3.1777
Maximum	3.1840	3.5799	3.3381	3.5601	3.1779

Fig. 11 shows the voltage profiles at load buses resulting from all methods. Again, all optimization algorithms can maintain all bus voltages within the limits.

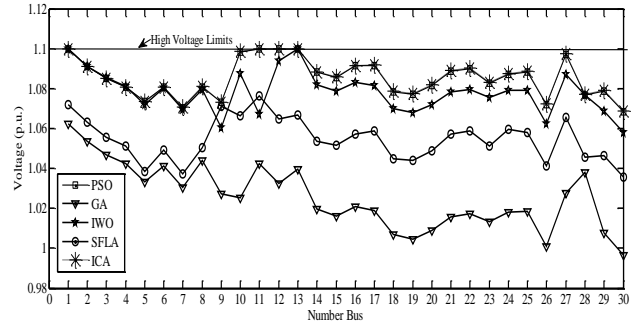


Fig. 11 - Voltage profiles of IEEE 30-bus system for case 2

CONCLUSIONS

The optimal reactive power dispatch is a global optimization problem of a non-continuous nonlinear function arising from large-scale industrial power systems. ICA algorithm for optimal reactive power dispatch problem is presented by this study in the first time. According to the simulation results, it is seen that this method is very effective and quite efficient for solving ORPD. From the simulation results, it has been seen that ICA algorithm converges to the global optimum. The optimization strategy is general and can be used to other power system optimization problems as well. The simulation results indicate the effectiveness and robustness of the proposed algorithm to solve optimal reactive power dispatch problem in test systems.

REFERENCES

- [1] W. Nakawiro, I. Erlich, and J.L. Rueda, "A novel optimization algorithm for optimal reactive power dispatch: a comparative study," In: Proceedings of the IEEE Germany electric utility deregulation and restructuring and power technologies (DRPT) conference, 2011, pp. 1555 – 1561.
- [2] P. Subbaraj, and P.N. Rajnarayanan, "Hybrid particle swarm optimization based optimal reactive power dispatch," In: *J. of Computer Applications* 1, 2010, pp. 65-70.
- [3] Z. Hu, X. Wang, and H. Chen, "Volt/Var control in distribution systems using a time-interval based approach," *IEE Proc. -Gener. Transm. Distrib.*, 2003, 150, pp. 548-554.
- [4] S. Duman, Y. Sonmez, U. Guvenc, and N. Yorukeren, "Application of gravitational search algorithm for optimal reactive power dispatch problem," In: Proceedings of the IEEE Turkey innovations in intelligent systems and applications (INISTA), 2011, pp. 519 – 523.

- [5] A.A. Abou El Ela, M.A. Abido, and S.R. Spea, "Differential evolution algorithm for optimal reactive power dispatch," *Electr. Power Syst. Res* 81, 2011, pp. 458-464.
- [6] E.S. Wen, and C.S Chang, "Tabu search approach to alarm processing in power systems," *IEE Proc. -Gener. Transm. Distrib* 144, 1997, pp. 31-38.
- [7] V. Miranda, and N. Fonseca, "EPSO-evolutionary particle swarm optimization, a new algorithm with applications in power systems," In: Proceedings of the IEEE Brazil transmission and distribution conference 2, 2002, pp. 745-750.
- [8] M. Dorigo, V. Maniezzo, and A. Colomi, "Ant system: optimization by a colony of cooperating agents," *IEEE Trans. Syst. Man and Cybernetics. Part B* 26, 1996, pp. 29-41.
- [9] Q.H. Wu, J.T. Ma, "Power system optimal reactive power dispatch using evolutionary programming," *IEEE Trans. Power Syst* 10, 1995, pp. 1243-1249.
- [10] M. Tripathy, and S. Mishra, "Bacteria foraging-based solution to optimize both real power loss and voltage stability limit," *IEEE Trans. Power Syst* 22, 2007, pp. 240-248.
- [11] A. Khabbazi, E. Atashpaz-Gargari, and C. Lucas, "Imperialist competitive algorithm for minimum bit error rate beamforming," *Int. J. Bio-Inspired Computation* 1, 2009, pp. 125-133.
- [12] The IEEE 14-Bus Test System [online]. Available at: http://www.ee.washington.edu/research/pstca/pf14/pg_tca14bus.htm
- [13] The IEEE 30-Bus Test System [online]. Available at: http://www.ee.washington.edu/research/pstca/pf30/pg_tca30bus.htm
- [14] J.G. Vlachogiannis, and K.Y. Lee, "A comparative study on particle swarm optimization for optimal steady-state, performance of power Systems," *IEEE Trans. Power Syst* 21, 2006, pp. 1718-1728.
- [15] H. Hajimirsadeghi, A. Ghazanfari, A. Rahimi-Kian, and C. Lucas, "Cooperative coevolutionary invasive weed optimization and its application to nash equilibrium search in electricity markets," In: Proceedings of the IEEE Iran nature & biologically inspired computing conference, 2009, pp. 1532-1535.
- [16] M. Nayeripour, M.R. Narimani, and T. Niknam, "Application of modified shuffled frog leaping algorithm on optimal power flow incorporating unified power flow controller", *Int. J. of Modeling and Optimization* 1, 2011, pp. 191-198.