Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 4615 – 4623

doi:10.3906/elk-1703-159

Reactive power optimization in a power system network through metaheuristic algorithms

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Received: 13.03.2017 • **Accepted/Published Online:** 13.06.2017 • **Final Version:** 03.12.2017

Abstract: Reactive power optimization (RPO) in a power system is a rudimentary necessity for the reduction of the loss of power. For the requirement of a unity power factor in the RPO system, the reduction of the system losses is ensured. The pivotal requirements of a power system are inclusive of a perfect compensation technique and methodology for stable reactive power compensation. The proposed concept in this paper utilizes the different reactive power optimization algorithms and performs a comparison. The process is accomplished by the use of IEEE 6-bus, 14-bus, and 30-bus systems to test the optimization technique. The conclusive information reinforces the outperformance of the based optimization algorithm to the other algorithm, thereby providing high stability to the system. The algorithm ensures the confinement of the voltage profile of the system within the permissible limits.

Key words: Reactive power optimization, power loss minimization, optimization, voltage profile

1. Introduction

The stark factor that has seized the attention of a large number of researchers is the concerns in reactive power optimization (RPO) in a power system. In the necessity of the reduction of the system losses, the RPO is made to work towards the improvement of the power factor of the system. Due to the unity power factor in the system, the reduction of losses is obtained, resulting in the maintenance of stability in the system. The RPO is used for the maintenance of stability and safe operating zone in the system in addition to reduction of power loss. For the optimization of reactive power in a system, the optimization is done on the basis of the voltage profile of the bus bar and power factor. By various optimization techniques the minimization of loss of power in a system is achieved. Real power generation constraint and reactive power generation constraints are taken into account in the reduction of the power loss. The quantity of reactive power depends on the phase shift between the voltage and current wave. Reactive power improves voltage stability and avoids voltage collapse. By regulating the reactive power, voltage stability, system efficiency, energy cost, and power losses of a power system network can be controlled effectively. Over long distance power transmission, additional reactive power loss occurs due to the large reactive impedance. To avoid excessive reactive power transmission and consumption, it should be as close as possible to each other; if it is not compensated properly, then it will cause an inappropriate voltage profile.

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2. Related works

A multitude of proposals for the compensation of reactive power in the system have been composed in various papers. The utility of wind farms across the network with the New England 39-bus systems with 12 doubly fed induction generators is studied. Assessment of voltage security parameters is performed. The comparison of the loss of power and the reactive power generation of individual wind farms has been attained with and without the imposition of voltage stability constraints on the OPF solution. The constrained OPF increased active power losses in the network. Furthermore, the determination of the contribution to the reactive power by each wind farm and the optimization on the basis of selectivity is completed for the evaluation of contributions towards system active power losses by each individual wind farm [1]. Moreover, only by the use of wind farms with the least contribution to system active power losses can a reduction in the number of reactive power optimized wind farms be realized. There is another proposed solution applied for the multitude kinds of optimal reactive power flow problems that are constrained in operation.

The constraints like power balance, line flow, and V_b limits are revealed by Aniruddha Bhattacharya et al. [2] as the biogeography-based optimization (BBO) technique. The BBO technique for the global optimum is done by two steps: migration and mutation. Active power loss is reduced by BBO to obtain solutions for the optimal reactive power flow problems on standard IEEE 57-bus and IEEE 30-bus power systems. To optimize the reactive power, an avant-garde proposal put forth by Su et al. [3] is the improved cloud particle swarm optimization BP neural network [4]. It is easy to track the local minimum and the slow convergences in the distribution network reactive power optimization are the functions in cloud particle swarm optimization (CPSO).

The improvement of the cloud particle swarm optimization is done on the basis of cloud digital features, and local search and global search with the foundations from the solution space transform are pooled. The transference of the trial simulation was done in an IEEE 30-bus. The results of the simulation exhibit the attainment of a better global solution by the employment of an improved algorithm that further led to the acceleration and improvement of convergence speed and accuracy [5]. In an effort to achieve an evolutionary technique for placement of flexible AC transmission systems (FACTS) devices in interconnected power systems with an optimal approach [6], a genetic algorithm (GA) has been devised by Bhattacharyya et al. [7]. The parallel immune particle swarm optimization (PIPSO) algorithm was proposed by Yuan et al. [8].

In parallel optimization with PSO and discrete PSO (DPSO), the convergence capability of the system is improved. The efficient solution to the problem of local convergence is by the employment of the immune operator; however, the reasonable solution to the problem posed by complex coding is with a mixture obtained by the parallel optimization of discrete variables and continuous variables. Faster achievement of the convergence effect and increased stability have been observed by the results obtained from the simulation of IEEE 14-bus, IEEE 30-bus, and IEEE 118-bus systems, with parallel immune particle swarm optimization. It is also the preferred solution in large-scale power system reactive power optimization.

In order to improve the performance of the optimization problem, hybrid soft computing techniques have been proposed. In this respect, evolutionary programming and efficient particle swarm optimization (EP-EPSO) may prove to be very effective in solving a nonlinear problem. EP-EPSO has advanced quality, better optimal cost, and higher convergence rate [9]. Multiobjective functions assisted in the analysis of voltage control methodology carried out by Liang et al. [10] and Zhao et al. [11]. However, the aforementioned algorithms lacks in providing the best fit with respect to limited time duration. The work proposed here provides a comprehensive comparison of a series of optimization techniques that provide RPO.

3. Reactive power optimization

Minimization of the objective function given in Eq. (1) leads to better reactive power optimization [12]. Since the RPO is a factor related to the voltage profile and cosine angle between the two voltage systems, the main aim is to minimize the same [13].

3.1. Objective function

$$MinP_L = \sum G_K \left[V_i^2 + V_j^2 - 2V_iV_j \cos\left(\alpha i - \alpha j\right)\right] \tag{1}$$

The number of lines in the given network is denoted by K. The minimization of the above function is imperiled by a number of limitations [14]. Eq. (2) confers the power generation and demand limitation of the system.

$$0 = P_{gi} - P_{di} - V_i \sum V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{2}$$

Eq. (3) elucidates the reactive power demand and reactive power generation by the compensator scheme in the system.

$$0 = Q_{gi} - Q_{di} - V_i \sum V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}\right) \tag{3}$$

$$Q_{ci} \min < Q_{ci} < Q_{ci} \max_{i \in n_c}$$

$$Q_{gi} \min < Q_{ci} < Q_{ci} \max_{i \in n_g}$$

$$T_k \min < T_k < T_k \max_{k \in n_t}$$

$$V_i \min < V_i < V_i \max_{i \in n}$$

The system is considered to operate with the particular zone as given in Eq. (1).

4. Interactive artificial bee colony (IABC)

4.1. Flowchart for IABC algorithm

4.2. Constraints

In order to validate the proposed optimization techniques for the RPO problem, it is tested with 6-, 14-, and 30-bus systems. The performance of accuracy is compared using the following measures: control variable data, voltage profile, real power loss, number of iterations, and CPU time. In general, the ABC algorithm affords better results of the objective function. The relation between the employed bees is deliberated by the original design of the employed bees [15]. The relationship between the employed bee and onlooker bee is selected by the roulette wheel selection. Therefore, it is not strong enough to maximize the exploitation capacity, i.e. chance of finding the food sources is minimum. An interactive ABC algorithm is anticipated based on the skeleton of the ABC algorithm [16]. The flowchart for the proposed IABC algorithm is exemplified in Figure 1.

5. Simulation results and discussion

The algorithm is validated in an IEEE 14-bus system. The results produced by the proposed IABCO are compared with the results of other optimization methods. Tables 1 and 2 give the control variables comparison of the RPO problem for different approaches and also show that the minimum real power loss achieved by IABCO is the least of all other methods, emphasizing its superior quality of solution.

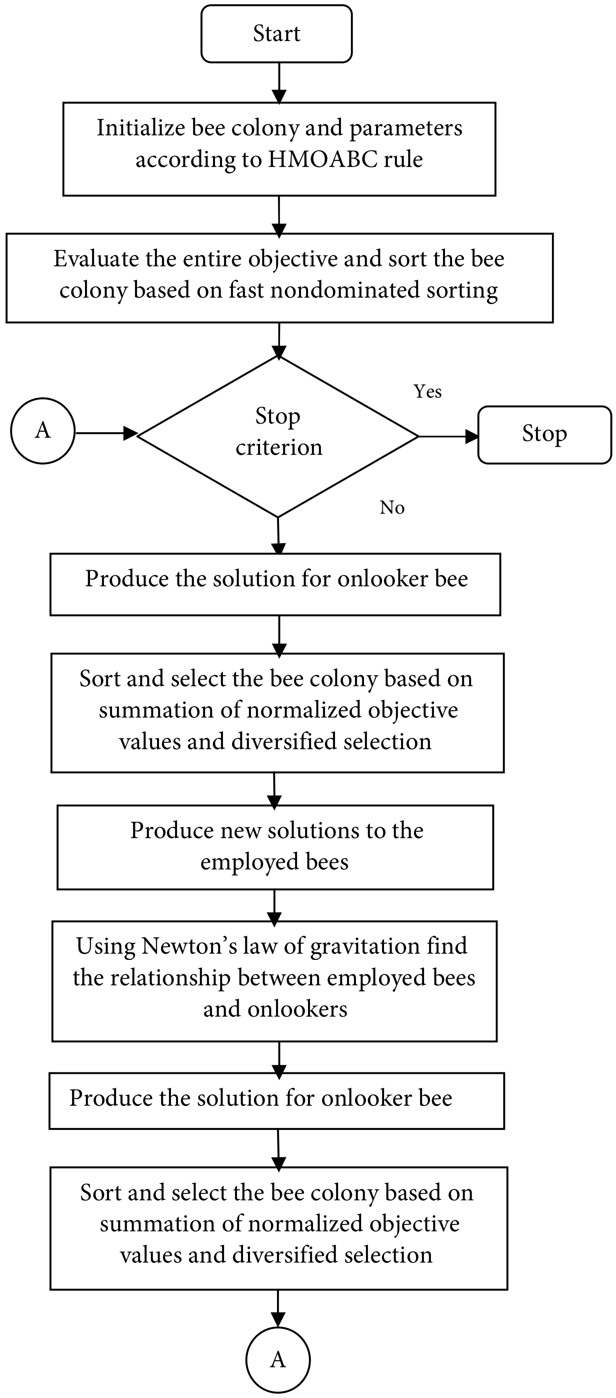

Figure 1. Flowchart for the proposed IABC algorithm.

Figures 2 and 3 elucidate the voltage profile compared among the different proposed approaches, namely improved particle swarm optimization (IPSO), quantum particle swarm optimization (QPSO), artificial bee colony optimization (ABCO), and interactive artificial bee colony optimization (IABCO) are shown using the bar charts for every measure individually. Table 3 illustrates the comparison of the different methods for 30-bus systems.

Table 1. Comparison among different methods for 6-bus system.

Control variable	Classical PSO [17]	Improved PSO [18]	Quantum PSO [19]	ABCO (Proposed method 1)	IABCO (Proposed method 2)
V_1	1.07	1.02	0.97	1.05	1.07
V_2	1.12	1.05	1.00	1.07	1.10
V_3	0.97	1.00	1.00	1.02	1.05
V_4	1.01	1.02	0.95	1.05	1.07
V_5	1.00	1.00	0.97	1.02	1.05
V_6	0.95	0.97	0.95	1.01	1.05
Q_1	0.192	0.934	0.916	0.895	0.872
Q_2	0.601	0.598	0.523	0.510	0.504
Q_4	0.05	0.05	0.05	0.05	0.05
Q_6	0.055	0.055	0.055	0.055	0.055
T_{65}	0.9	0.9	0.95	0.9	0.9
T_{43}	0.9	0.9	0.8	0.8	0.8
P_{loss} (MW)	8.17452	8.10955	8.02703	7.83640	7.40791

Table 2. Comparison among different methods for 14-bus system.

Control variable	Classical PSO [17]	Improved PSO [18]	Quantum PSO [19]	ABCO (Proposed method 1)	IABCO (Proposed method 2)
V_1	1.100	0.96	0.95	1.06	1.05
V_2	1.087	0.96	0.96	1.03	1.05
V_3	1.056	0.96	0.96	0.98	1.03
V_6	1.046	0.94	0.94	1.05	1.05
V_8	1.002	0.96	0.95	1.00	1.04
Q_9	0.172	0.151	0.148	0.139	0.132
T_{56}	0.957	1.013	0.985	0.979	0.960
T_{47}	0.918	0.996	0.955	0.950	0.950
T_{49}	1.027	1.033	1.020	1.014	1.007
P_{loss} (MW)	8.10706	7.05077	6.83213	5.92892	5.50031

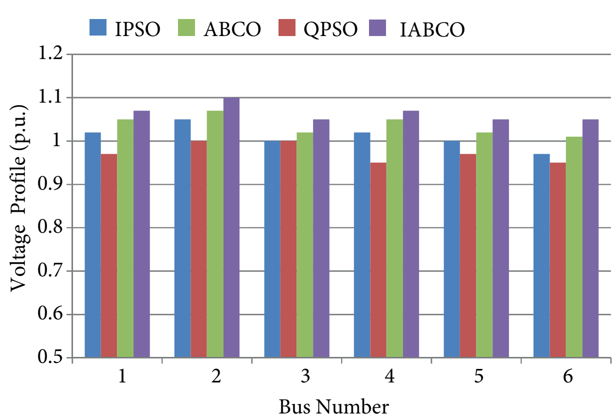

Figure 2. Voltage profile comparison chart of proposed techniques for 6-bus system.

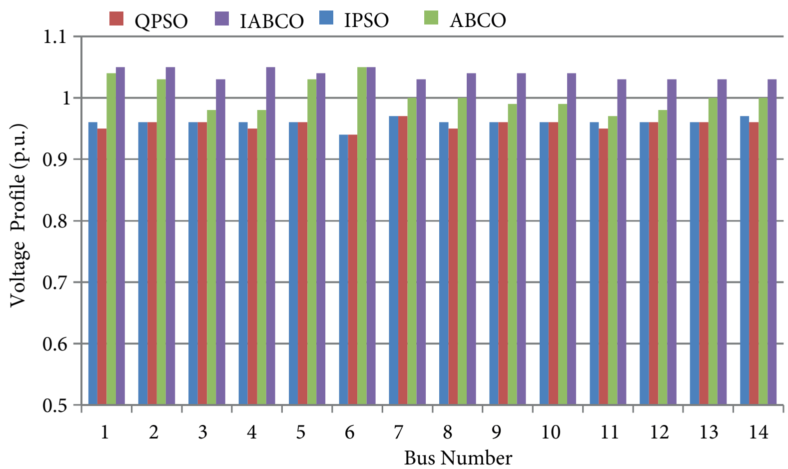

Figure 3. Voltage profile comparison chart of proposed techniques for 14-bus system.

IABCO is one of the intelligent random search optimization algorithms of evolutionary computing; the results obtained with different random inputs may be different because different random inputs will generate different random number sequences, and different random number sequences will lead to the artificial agents searching in different locations in the solution space. This will lead to a global optimum solution for complex problems. According to the results obtained by IABCO, ABCO, QPSO, IPSO, and PSO the performance of the IABCO method used in the case study of IEEE 6-bus, 14-bus, and 30-bus systems has proved superior to the earlier methods as illustrated in the comparison tables, and the IABCO method provides a global solution, nourishing the constraints with very high probability with a tolerable computation time and improving the quality of solution and convergence speed. From Tables 1–3 it is clear that the IABCO method has a better optimal solution for power loss than the ABCO, QPSO, IPSO, and PSO methods. Computational results reveal that the proposed technique is superior to the ABCO, QPSO, IPSO, and PSO approaches in computational requirement.

Table 3. Comparison among different methods for 30-bus system.

Control variable	Classical PSO [17]	Improved PSO [18]	Quantum PSO [19]	ABCO (Proposed method 1)	IABCO (Proposed method 2)
V_1	1.03	1.01	1.01	1.08	1.13
V_2	1.04	1.01	1.01	1.07	1.13
V_5	1.05	1.03	1.03	1.06	1.13
V_8	1.04	1.04	1.04	1.08	1.13
V_{11}	1.06	1.07	1.07	1.10	1.14
V_{13}	1.01	1.06	1.06	1.08	1.13
Q_{10}	0.0428	0.0425	0.0406	0.0391	0.0385
Q_{24}	0.0500	0.0500	0.0500	0.0500	0.0500
T_{11}	0.9587	0.9514	0.9409	0.9397	0.9465
T_{12}	1.0543	0.9758	0.9681	0.9624	0.9580
T_{15}	1.0024	1.0006	1.0000	0.9831	0.9762
T_{36}	0.9755	0.9809	0.9614	0.9509	0.9433
Ploss (MW)	5.09894	4.83205	4.66748	4.26950	4.01399

In view of the excellence of the results and convergence speed gained, this method seems to be a hopeful alternative approach for solving the RPO problem in practical power systems. The average number of iterations to reach the optimum solutions is 30–40 in all the 50 experimental runs. The convergence characteristics of the IPSO, QPSO, ABCO, and IABCO methods for IEEE 6-bus, 14-bus, and 30-bus systems are shown in Figures 2–4 and Tables 1–3, respectively. Figures 5–7 illustrate the complexity analysis of the optimization technique. The IABCO proposes minimal computational complexity when compared to other algorithms in the

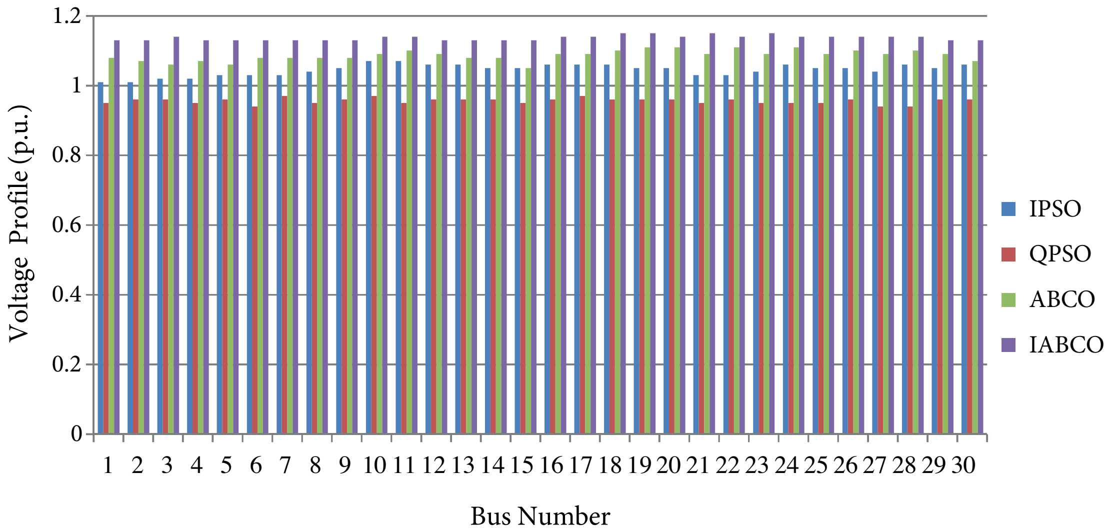

Figure 4. Voltage profile comparison chart of proposed techniques for 30-bus system.

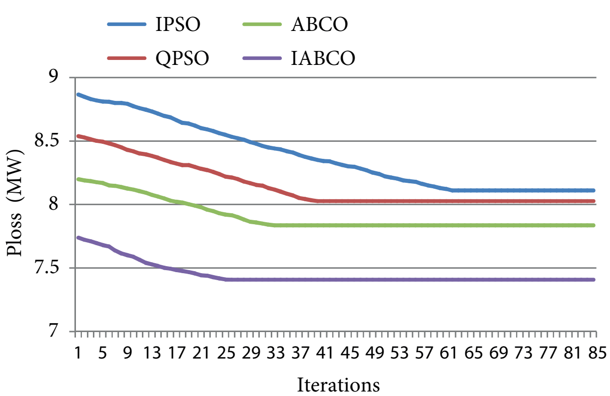

Figure 5. Power loss convergence characteristics of proposed techniques for 6-bus system.

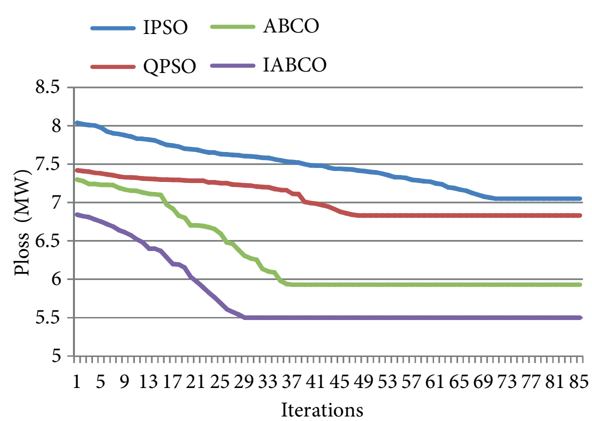

Figure 6. Power loss convergence characteristics of proposed techniques for 14-bus system.

Table 4. Final state of Ward–Hale 6-bus system.

Variable	IPSO	QPSO	ABCO	IABCO
Voltage (p.u.)	0.97	0.95	1.01	1.05
No. of iterations	63	40	33	26
Time taken (s)	8.76	4.17	3.77	3.25
Power loss (MW)	8.10955	8.02703	7.83640	7.40791

case of IEEE 6-bus, 14-bus, and 30-bus systems. Tables 4–6 provide the power loss of the system; the IABCO algorithm provides better results when compared to the other algorithms. Table 4 illustrates the power loss of the optimization techniques. The IABCO shows improved results when compared to the IPSO, QPSO, and ABCO algorithms.

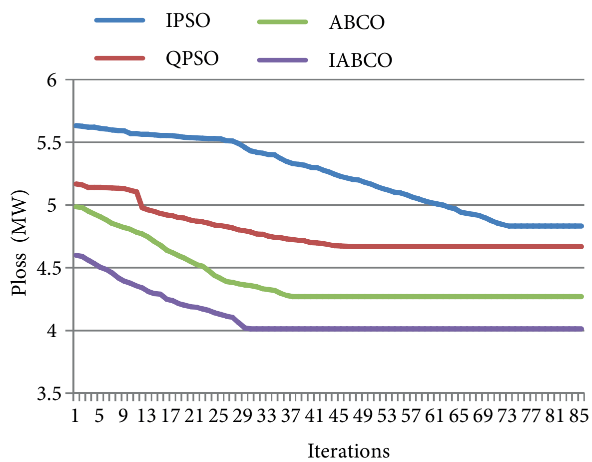

Figure 7. Power loss convergence characteristics of proposed techniques for 30-bus system.

Table 5. Final state of IEEE 14-bus system.

Variable	IPSO	QPSO	ABCO	IABCO
Voltage (p.u.)	0.97	0.97	1.04	1.05
No. of iterations	71	48	37	29
Time taken (s)	9.02	4.52	3.97	3.46
Power loss (MW)	7.05077	6.83213	5.92892	5.50031

Table 6. Final state of IEEE 30-bus system.

Variable	IPSO	QPSO	ABCO	IABCO
Voltage (p.u.)	1.02	0.97	1.11	1.15
No. of iterations	73	49	37	30
Time taken (s)	21.79	18.25	14.33	12.54
Power loss (MW)	4.83205	4.66748	4.26950	4.01399

6. Conclusion

Graphical illustrations and a multitude of optimization methods have been used to solve RPO problems, and the analysis and comparison performed on this basis. They have been carried out with the iterations of the power loss in MW and voltage profile in p.u. To obtain reactive power optimization the implementation of algorithms has been carried out on the IEEE 6-bus, 14-bus, and 30-bus systems. IABCO was one among various optimization methods that produces better results. Maintenance of voltage profile, reduction of power loss, and optimization of reactive power have been facilitated by the algorithm. Comparison was done on the results obtained from IPSO, QPSO, ABCO, and IABCO. In IABCO, the particle was made to perform studies on every other individual particle considered in the system and also on itself.

References

[1] Meegahapola G, Vittal E, Keane A, Flynn D. Voltage security constrained reactive power optimization incorporating wind generation. IEEE Int Conf Pow Sys Tech 2012; 1-5.

[2] Bhattacharya A, Chattopadhyay PK. Solution of Optimal Reactive Power Flow using Biogeography-Based Optimization. International Journal of Electrical and Electronics Engineering 2010; 4: 621-629.

[3] Su H, Zhang P. Research of distribution network reactive power optimization based on improved cloud particle swarm optimization BP neural network. International Journal of Computer and Electrical Engineering 2013; 5: 164-168.

[4] Kennedy J, Eberhart R. Swarm Intelligence. 1st ed. San Francisco, CA, USA: Academic Press, 2001.

[5] Sujin PR, Prakash T, Mary Linda M. Particle swarm optimization based reactive power optimization. J Comp 2010; 2: 73-78.

[6] Platel MD, Schliebs S, Kasabov N. Quantum-inspired evolutionary algorithm: a multimodal EDA. IEEE T Evol Comp 2009; 13: 1218-1232.

[7] Bhattacharyya B, Gupta VK. Fuzzy based evolutionary algorithm for reactive power optimization with FACTS devices. Elec Pow Ener Sys 2014; 61: 39-47.

[8] Yuan G, Zhu L, Tong Yu. Reactive power optimization based on parallel immune particle swarm optimization. J Comp 2014; 9: 2198-2205.

[9] Muthu Vijaya Pandian S, Thanushkodi K. Considering transmission loss for an economic dispatch problem without valve-point loading using an EP-EPSO algorithm. Turk J Elec Eng & Comp Sci 2012; 20: 1259-1267.

[10] Sun L, Jian X, Yuan W. The application and practice of the voltage reactive power optimization automatic control system (AVC) in the power grid of Wuhu Region. International Journal of Online Engineering 2016; 12: 10-15.

[11] Zhao H, Luan Z, Han GC. Multi-objective reactive power optimization of distribution network with distributed generation. MATEC Web of Conf 2016; 1-6.

[12] Miller TJE. Reactive Power Control in Electric Systems. 1st ed. India, Wiley, 2012.

[13] Valle Y, GaneshKumar V, Mohagheghi S. Particle swarm optimization: basic concepts variants and applications in power systems. IEEE T Evol Comp 2008; 12: 171-194.

[14] Wei Z, Cui Z, Zeng J. Social cognitive optimization algorithm with reactive power optimization of power system. IEE Int Conf on Comp Asp of Soc Net 2010; 11-14.

[15] Kaur A, Goyal S. A survey on the applications of bee colony optimization techniques. International Journal of Computer and Electrical Engineering 2011; 3: 3037-3046.

[16] Karaboga D, Basturk B. Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems. IFSA Springer 2007; 4529: 789-798.

[17] Mahadevan K, Kannan PS. Comprehensive learning particle swarm optimization for reactive power dispatch. App Soft Comput 2010; 10: 641-652.

[18] Chandragupta Mauryan KS, Thanushkodi K. Reactive power optimization using quantum particle swarm optimization. J Comp Sci 2012; 8: 1644-1648.

[19] Chandragupta Mauryan KS, Thanushkodi K. Optimization of reactive power based on improved particle swarm algorithm. Euro J Sci Res 2012; 72: 608-617.