

Reduction of Real Power Loss by using Enhanced Particle Swarm Optimization Algorithm

*Mr.K.Lenin[1], Dr.B.Ravindhranath Reddy[2], Dr.M.Surya Kalavathi[3]
1, Research Scholar, JNTU, Hyderabad 500 085 India,
2, Deputy executive engineer, JNTU, Hyderabad 500 085 India,
3, Professor of Electrical and Electronics Engineering, JNTU, Hyderabad 500 085, India.

Abstract
In this paper, an Enhancedparticle swarm optimization algorithm (EPSO) has been proposed to solve the reactive power problem. Particle Swarm Optimization (PSO) is swarm intelligence based exploration and optimization algorithm which is used to solve global optimization problems. But due to deficiency of population diversity and early convergence it is often stuck into local optima. We can upsurge diversity and avoid premature convergence by using evolutionary operators in PSO. In this paper the intermingling crossover operator is used to upsurge the exploration capability of the swarm in the exploration space .Particle Swarm Optimization uses this crossover method to converge optimum solution in quick manner .Thus the intermingling crossover operator is united with particle swarm optimization to augment the performance and possess the diversity which guides the particles to the global optimum powerfully. The proposedEnhanced particle swarm optimization algorithm (EPSO) has been tested in standard IEEE 30, 57,118 bus test systems and simulation results shows clearly the improved performance of the projected algorithm in reducing the real power loss and control variables are well within the limits.
Keywords: Optimal Reactive Power, Transmission loss, intermingling crossover operator

1. Introduction

The main objective of optimal reactive power dispatch (ORPD) problem is to minimize both the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. The problem of voltage stability and collapse play a vital role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. In [12, 13], Hybrid differential evolution algorithm and Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14, 15], an improved fuzzy based method and evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16,17], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method and pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18, 19] a two-step approach and a programming based approach is used to solve the optimal reactive power dispatch problem. In [20] a probabilistic algorithm is utilized for optimal reactive power provision in hybrid electricity markets with uncertain loads.Particle Swarm Optimization (PSO) [21] has been used efficaciously in solving many optimization problems, for its simplicity and fast convergence rate. Swarm intelligence is the subdivision of artificial intelligence and based on collective behaviour of self-organized system [22, 23]. The optimize value of the function using Particle Swarm Optimization Algorithm is hang on in the exploration and exploitation of the particles during searching in the exploration space [24].There are also problem in PSO like when it applies to various global optimization problems it may get held in the local optimization due to early convergence because the diversity shrinkages with the time for a large population[25] , So we apply various evolutionary operator to get the global optimal solution[26-31].The intermingling crossover is a crossover operator which is applied in basic PSO to discover the exploration area . The intermingling crossover operator is improved crossover operator, which is apply to the PSO to optimize the function**.**The proposed EPSO algorithm has been evaluated in standard IEEE 30, 57,118 bus test systems. The simulation results show that our proposed methodology outperforms all the entitled reported algorithms in minimization of real power loss.

2. Problem Formulation

2.1 Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \qquad (1)$$

or

$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d$ (2)

Where g_k is the conductance of branch between nodes i and j, Nbr is the total number of transmission lines in power systems. P_d is the total active power demand, P_{gi} is the generator active power of unit i, and P_{gsalck} is the generator active power of slack bus.

2.2 Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$F = PL + \omega_v \times VD$ (3)

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$VD = \sum_{i=1}^{Npq} |V_i - 1|$ (4)

2.3 Equality Constraint

The equality constraint of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$P_G = P_D + P_L$ (5)

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

2.4 Inequality Constraints

The inequality constraints reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max}$ (6)

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g$ (7)

Upper and lower bounds on the bus voltage magnitudes:

$V_i^{min} \leq V_i \leq V_i^{max}, i \in N$ (8)

Upper and lower bounds on the transformers tap ratios:

$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T$ (9)

Upper and lower bounds on the compensators reactive powers:

$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C$ (10)

Where N is the total number of buses, N_T is the total number of Transformers; $N_c$is the total number of shunt reactive compensators.

3. Particle Swarm Optimization (PSO)

PSO is a population based optimization tool, where the system is initialized with a population of random particles and the algorithm searches for optima by updating generations. Suppose that the search space is *D*-dimensional. The position of the *i*-th particle can be represented by a *D*-dimensional vector $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ and the velocity of this particle is $V_i = (v_{i1}, v_{i2}, .., v_{iD})$.The best previously visited position of the *i*-th particle is represented by $P_i = (p_{i1}, p_{i2}, .., p_{iD})$ and the global best position of the swarm found so far is denoted by$P_g = (p_{g1}, p_{g2}, .., p_{gD})$. The fitness of each particle can be evaluated through putting its position into a designated objective function. The particle's velocity and its new position are updated as follows:

$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{id}^t)$ (11)

$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$ (12)

Where $d \in \{1,2, .., D\}, i \in \{1,2, .., N\}$$N$ is the population size, the superscript *t* denotes the iteration number, ω

is the inertia weight, r_1 and r_2 are two random values in the range [0,1],c_1 and c_2 are the cognitive and social scaling parameters which are positive constants.

These both equations are used to update the velocity and position of a particle in the exploration space .The equation (11) is used to balance the search abilities of the particle in the search space. The equation (12) uses the velocity obtained in first equation to get the new position of the particle.

Crossover is a Genetic operator which is used after selection in Genetic Algorithm to get the new children using two or more than two parent .It is used to get the healthier solution than current solution. There are various improved version of crossover available to get the value of new-fangled species. Intermingling crossover is also aimproved operator which is used to get the new healthier child by using current parent. This operator is applied in PSO to optimize the multi-dimensional function and upsurge the probingcapability of the PSO, So that Particle Swarm Optimization optimizes the functions efficiently and did not jammed in the local optima.

4. Proposed EPSO Algorithm

Although the crossover operator is a conception of Genetic Algorithm but apart from genetic algorithm it has been used in many algorithms with some alterations .The crossover operator takes two or more than two parent and produce one or more than one child .The produced new child after crossover is superior to their parents. There are various improved crossover technique, The intermingling crossover operator is one of the improved crossover operator in which two particles are used to create a minimum and maximum range values which lies in the function's bounded region and the new particle is produced within the calculated minimum and maximum range values, Then we compute the fitness value of that new particle and compare it with the current particle and modernize the N_POP of the population of the particles.

Intermingling Crossover:

Start
Select two arbitrary particles from N_POP x_1 and x_2
Compute $x_{new}=(x_1-x_2)$
Compute $k_1=\min(x_1, x_2)$
Compute $k_2=\max(x_1, x_2)$
$k_{min}=k_1 - b*x_{new}$;
$k_{max}=k_2+b*x_{new}$;
Where "b" is an arbitrary selected integer within range
Now select an arbitrary particle from the range
N_new=$(k_{max}-k_{min})$ *rand +k_{min}
Now compute the fitness of newly produced particle N_new
End

EPSO algorithm for solving reactive power problem

Start
Initialize particle with Arbitrary Position and Velocity
Set P_best$_i$=X$_i$,g_best=min(P_best$_i$)
Initialize Generation as g=0; While $(g < \max\_generation)$
For (i=1 to N_POP)
For (j=1 to D_POP)
Computev_{id}^{t+1} using equation (11)
Computex_{id}^{t+1}using equation (12)
If $v_{id}^{t+1}$and $x_{id}^{t+1}$are in exploration range then;
Calculate fitness for corresponding particle x_i;
Apply intermingling crossover to compute the new particle N_new
Compute fitness value for newlyproduced particle
Compare the fitness value for $x_i$and N_new;
If Fitness (N_new) is superior than x_i then
Modernize the particle in N_POP g=g+1;
End for
End for
End of while
Print the value of g_best.
End

6. Simulation Results

At first EPSO algorithm has been verified in IEEE 30-bus, 41 branch system. It has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is slack bus and 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. Control variables limits are listed in Table 1.

Table 1: Preliminary Variable Limits (PU)

Variables	Min. Value	Max. Value	Type
Generator Bus	0.92	1.12	Continuous
Load Bus	0.94	1.04	Continuous
Transformer-Tap	0.94	1.04	Discrete
Shunt Reactive Compensator	-0.11	0.30	Discrete

The power limits generators buses are represented in Table2. Generators buses (PV) 2,5,8,11,13 and slack bus is 1.

Table 2: Generators Power Limits

Bus	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3: Values of Control Variables after Optimization

Control Variables	EPSO
V1	1.0628
V2	1.0452
V5	1.0289
V8	1.0290
V11	1.0779
V13	1.0572
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.90
Q10	0.12
Q24	0.12
Real power loss	4.2898
Voltage deviation	0.9080

Table 3 shows the proposed approach succeeds in keeping the control variables within limits.
Table 4 summarizes the results of the optimal solution obtained by various methods.

Table 4: Comparison Results

Methods	Real power loss (MW)
SGA (32)	4.98
PSO (33)	4.9262
LP (34)	5.988
EP (34)	4.963
CGA (34)	4.980
AGA (34)	4.926
CLPSO (34)	4.7208
HSA (35)	4.7624
BB-BC (36)	4.690
EPSO	4.2898

Secondly the proposed hybrid EPSO algorithm is tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 5.

The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load}= 12.422p.u. Q_{load} = 3.339p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.7729p.u. $\sum Q_G$ = 3.4559p.u.

P_{loss}= 0.27450p.u. Q_{loss} = -1.2249p.u.

Table 6 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after EPSO based optimization which are within the acceptable limits. In Table 7, shows the comparison of optimum results obtained from proposed EPSO with other optimization techniques. These results indicate the robustness of proposed EPSO approach for providing better optimal solution in case of IEEE-57 bus system.

Table 5: Variable limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	vgmax	vpqmin	vpqmax	tkmin	tkmax
0.5	1.0	0.91	1.01	0.5	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

Table 6: control variables obtained after optimization

Control Variables	EPSO
V1	1.1
V2	1.058
V3	1.042
V6	1.028
V8	1.041
V9	1.025
V12	1.026
Qc18	0.0768
Qc25	0.232
Qc53	0.0579
T4-18	1.010
T21-20	1.069
T24-25	0.971
T24-26	0.932
T7-29	1.081
T34-32	0.942
T11-41	1.010
T15-45	1.047
T14-46	0.910
T10-51	1.028
T13-49	1.062
T11-43	0.911
T40-56	0.901
T39-57	0.950
T9-55	0.958

Table 7: comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [37]	0.25902	0.30854	0.27858
2	CGA [37]	0.25244	0.27507	0.26293
3	AGA [37]	0.24564	0.26671	0.25127
4	PSO-w [37]	0.24270	0.26152	0.24725
5	PSO-cf [37]	0.24280	0.26032	0.24698
6	CLPSO [37]	0.24515	0.24780	0.24673
7	SPSO-07 [37]	0.24430	0.25457	0.24752
8	L-DE [37]	0.27812	0.41909	0.33177
9	L-SACP-DE [37]	0.27915	0.36978	0.31032
10	L-SaDE [37]	0.24267	0.24391	0.24311
11	SOA [37]	0.24265	0.24280	0.24270
12	LM [38]	0.2484	0.2922	0.2641
13	MBEP1 [38]	0.2474	0.2848	0.2643
14	MBEP2 [38]	0.2482	0.283	0.2592
15	BES100 [38]	0.2438	0.263	0.2541
16	BES200 [38]	0.3417	0.2486	0.2443
17	Proposed EPSO	0.22252	0.23120	0.23101

Then EPSO has been tested in standard IEEE 118-bus test system [39] .The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95,-1.1 per-unit., and on load buses are 0.95,-1.05 per-unit. The limit of transformer rate is 0.9,-1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 8, with the change in step of 0.01.

Table 8: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 9 and the results clearly show the better performance of proposed algorithm.

Table 9: Comparison results

Active power loss (p.u)	BBO [40]	ILSBBO/ strategy1 [40]	ILSBBO/ strategy1 [40]	Proposed EPSO
min	128.77	126.98	124.78	119.96
max	132.64	137.34	132.39	123.65
Average	130.21	130.37	129.22	120.99

7.Conclusion

Enhanced particle swarm optimization algorithm (EPSO) has been productively applied for Optimal Reactive Power dispatch problem.Enhanced particle swarm optimization algorithm (EPSO) based optimal reactive power problem has been tested in standard IEEE30, 57,118 bus systems. Performance comparisons with standard population-based algorithms have given exciting results. Real power loss has been considerablycurtailed and control variables are well within the limits.Enhanced particle swarm optimization algorithm (EPSO) ascendspowerfully to find noble solutions when compared to that of other algorithms. The simulation results presented in earlier section demonstrate the competence ofEnhanced particle swarm optimization algorithm (EPSO) toreach at near global optimal solution.

References

1. O.Alsac,and B. Scott, “Optimal load flow with steady state security”,IEEE Transaction. PAS -1973, pp. 745-751.

2. Lee K Y ,Paru Y M , Oritz J L –A united approach to optimal real and reactive power dispatch , IEEE Transactions on power Apparatus and systems 1985: PAS-104 : 1147-1153
3. A.Monticelli , M .V.F Pereira ,and S. Granville , “Security constrained optimal power flow with post contingency corrective rescheduling” , IEEE Transactions on Power Systems :PWRS-2, No. 1, pp.175-182.,1987.
4. DeebN ,Shahidehpur S.M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2) : 428-435
5. E. Hobson ,’Network consrained reactive power control using linear programming, ‘ IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980
6. K.Y Lee ,Y.M Park , and J.L Oritz, “Fuel –cost optimization for both real and reactive power dispatches” , IEE Proc; 131C,(3), pp.85-93.
7. M.K. Mangoli, and K.Y. Lee, “Optimal real and reactive power control using linear programming” , Electr.PowerSyst.Res, Vol.26, pp.1-10,1993.
8. C.A. Canizares , A.C.Z.de Souza and V.H. Quintana , “ Comparison of performance indices for detection of proximity to voltage collapse ,” vol. 11. no.3 , pp.1441-1450, Aug 1996 .
9. S.R.Paranjothi ,andK.Anburaja, “Optimal power flow using refined genetic algorithm”, Electr.PowerCompon.Syst , Vol. 30, 1055-1063,2002.
10. D. Devaraj, and B. Yeganarayana, “Genetic algorithm based optimal power flow for security enhancement”, IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.
11. A. Berizzi, C. Bovo, M. Merlo, and M. Delfanti, “A ga approach to compare orpf objective functions including secondary voltage regulation,” Electric Power Systems Research, vol. 84, no. 1, pp. 187 – 194, 2012.
12. C.-F. Yang, G. G. Lai, C.-H. Lee, C.-T. Su, and G. W. Chang, “Optimal setting of reactive compensation devices with an improved voltage stability index for voltage stability enhancement,” International Journal of Electrical Power and Energy Systems, vol. 37, no. 1, pp. 50 – 57, 2012.
13. P. Roy, S. Ghoshal, and S. Thakur, “Optimal var control for improvements in voltage profiles and for real power loss minimization using biogeography based optimization,” International Journal of Electrical Power and Energy Systems, vol. 43, no. 1, pp. 830 – 838, 2012.
14. B. Venkatesh, G. Sadasivam, and M. Khan, “A new optimal reactive power scheduling method for loss minimization and voltage stability margin maximization using successive multi-objective fuzzy lp technique,” IEEE Transactions on Power Systems, vol. 15, no. 2, pp. 844 – 851, may 2000.
15. W. Yan, S. Lu, and D. Yu, “A novel optimal reactive power dispatch method based on an improved hybrid evolutionary programming technique,” IEEE Transactions on Power Systems, vol. 19, no. 2, pp. 913 – 918, may 2004.
16. W. Yan, F. Liu, C. Chung, and K. Wong, “A hybrid genetic algorithminterior point method for optimal reactive power flow,” IEEE Transactions on Power Systems, vol. 21, no. 3, pp. 1163 –1169, aug. 2006.
17. J. Yu, W. Yan, W. Li, C. Chung, and K. Wong, “An unfixed piecewiseoptimal reactive power-flow model and its algorithm for ac-dc systems,” IEEE Transactions on Power Systems, vol. 23, no. 1, pp. 170 –176, feb. 2008.
18. F. Capitanescu, “Assessing reactive power reserves with respect to operating constraints and voltage stability,” IEEE Transactions on Power Systems, vol. 26, no. 4, pp. 2224–2234, nov. 2011.
19. Z. Hu, X. Wang, and G. Taylor, “Stochastic optimal reactive power dispatch: Formulation and solution method,” International Journal of Electrical Power and Energy Systems, vol. 32, no. 6, pp. 615 – 621, 2010.
20. A. Kargarian, M. Raoofat, and M. Mohammadi, “Probabilistic reactive power procurement in hybrid electricity markets with uncertain loads,” Electric Power Systems Research, vol. 82, no. 1, pp. 68 – 80, 2012.
21. Kennedy J, EberhartR. Particle swarm optimization. Proceedings of the IEEE international conference on neural networks (Perth, Australia), 1942–1948. Piscataway, NJ: IEEE Service Center; 1995.
22. Beni, G., Wang, J. Swarm Intelligence in Cellular Robotic Systems, Proceed. NATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy, June 26–30 (1989).
23. P.N.Suganathan, N.Hansen, J.J.Liang, K.Dev,Y.PChen, A.Auger,S.Tiwari,Problems Definition and Evolution Criteria for the CEC 2005 Special Session on Real-Parameter Optimization.
24. Pant, Millie, RadhaThangaraj, and Ajith Abraham. "A new pso algorithm with crossover operator for global optimization problems." Innovations in Hybrid Intelligent Systems. Springer Berlin Heidelberg, 2007. 215-222.
25. Pant, Millie, RadhaThangaraj, and V. P. Singh. "Particle swarm optimization with crossover operator and its engineering applications." IAENG International Journal of Computer Science 36.2 (2009): 112-121.
26. Zhang, Jian. "Particle swarm optimization using crossover operator." Journal of Convergence Information Technology 7.4 (2012): 287-295.
27. Yu-hui Shi and Russell Eberhart,” A modified particle swarm optimizer,” in proceedings of IEEE world

Congress on Computation intelligence,pp.69-73,1998.
28. Takahashi, Masato, and Hajime Kita. “A crossover operator using independent component analysis for real-coded genetic algorithms." Evolutionary Computation, 2001. Proceedings of the 2001 Congress on. Vol. 1. IEEE, 2001.
29. Zhi-Feng Hao,Zhi-Gang Wang,HanHuang,A Particle Swarm Optimization Algorithm With Crossover Operator Proceedings of the 6th international conference on Machine Learning and Cybernatics ,Hong Kong ,19-22 August 2007.
30. Chen, Stephen. "Particle swarm optimization with pbestcrossover."Evolutionary Computation (CEC), 2012 IEEE Congress on. IEEE, 2012.
31. Qinghai bai, China”Analysis of Particle Optimization Algorithm”computer and information science (CCSE), Vol. 3, No. 1, Februry 2010.
32. Q.H. Wu, Y.J.Cao, and J.Y. Wen. Optimal reactive power dispatch using an adaptive genetic algorithm. Int. J. Elect. Power Energy Syst. Vol 20. Pp. 563-569; Aug 1998.
33. B. Zhao, C. X. Guo, and Y.J. CAO. Multiagent-based particle swarm optimization approach for optimal reactive power dispatch. IEEE Trans. Power Syst. Vol. 20, no. 2, pp. 1070-1078, May 2005.
34. Mahadevan. K, Kannan P. S. “Comprehensive Learning Particle Swarm Optimization for Reactive Power Dispatch”, Applied Soft Computing, Vol. 10, No. 2, pp. 641–52, March 2010.
35. A.H. Khazali, M. Kalantar, “Optimal Reactive Power Dispatch based on Harmony Search Algorithm”, Electrical Power and Energy Systems, Vol. 33, No. 3, pp. 684–692, March 2011.
36. S. Sakthivel, M. Gayathri, V. Manimozhi, “A Nature Inspired Optimization Algorithm for Reactive Power Control in a Power System”, International Journal of Recent Technology and Engineering (IJRTE) ,pp29-33 Volume-2, Issue-1, March 2013.
37. Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang, “Seeker optimization algorithm for optimal reactive power dispatch,” IEEE Trans. Power Systems, Vol. 24, No. 3, August 2009, pp. 1218-1231.
38. J. R. Gomes and 0. R. Saavedra, “Optimal reactive power dispatch using evolutionary computation: Extended algorithms,” IEE Proc.-Gener. Transm. Distrib.. Vol. 146, No. 6. Nov. 1999.
39. IEEE, “The IEEE 30-bus test system and the IEEE 118-test system”, (1993), http://www.ee.washington.edu/trsearch/pstca/.
40. Jiangtao Cao, Fuli Wang and Ping Li, “ An Improved Biogeography-based Optimization Algorithm for Optimal Reactive Power Flow” International Journal of Control and Automation Vol.7, No.3 (2014), pp.161-176.