Scientific Journal Impact Factor (SJIF): 1.711
International Journal of Modern Trends in Engineering and Research
IJMTER
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

A Hybrid Biogeography Based Optimization with Differential Evolution for Solving Power System Problem

G.Srikanth [1], A.Lumani[2]
[1,2] *PG Scholar,GIT*

Abstract - Power System has many problems in operation point of view, in which Economic load dispatch (ELD) problem is important. By having an optical operation for the problem power system can be operated without losses. In this paper a hybrid BBO with DE, namely BBO/DE is proposed is presented for the economic load dispatch problem. Biogeography based Optimization (BBO) is a new biogeography inspired algorithm, which uses the biogeography based migration operator to share the information among solutions. Differential Evolution, a fast and robust evolutionary algorithm used for global optimization. The proposed technique combines the exploitation of BBO with the exploration of DE effectively, and this leads to the generation of promising candidate solutions. The results have been demonstrated for ELD of standard 3-generator and 6-generator Performance of our proposed technique is verified and compared with BBO and GA Technique.

Keywords- Optimization, hybridization, Differential Evolution, Biogeography Based Optimization, Economic Load Dispatch, power system

I. INTRODUCTION

With the increase in global economy, the demand for electric power increases rapidly, which forces the electric utilities to meet the same by increasing their production. The electric power transmitted between two areas in a transmission network is limited by numerous transfer limits such as voltage limits, stability limits and thermal limits. Ensuring the operation of power system within its limits is very important to maintain the security of power system, failing which results in extensive damages with potentially rigorous social and economic consequences. The Economic Dispatch (ED) problem, one of the nonlinear optimization problems in electrical power systems, has an important place in the economical operation of the power system [1]. In solving the ED problem, the objective is to minimize the total fuel cost, while satisfying the various physical and operational constraints. In the traditional ED problem, the fuel cost function of a generator is performed as quadratic function. The economic load dispatch (ELD) of power generating units has always occupied an important position in the electric power industry. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost. For the purpose of optimum economic operation of this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings.

The Economic Dispatch Problems (EDPs) is to determine the optimal combination of power outputs of all generating units to minimize the total fuel cost while satisfying the load demand and operational constraints [2].ELD focuses upon coordinating the production cost at all power plants operating on the system. Many Intelligent methods are iterative techniques that can search not only local optimal solutions but also a global optimal solution. Among these methods, some of them are Particle swarm optimization (PSO) [3] and [4], evolutionary programming (EP) [5], Tabu search [6], neural Network (NN) [7], GA [8], Gravitational Search Algorithm [9], Ant colony optimization [10] and SA [11].

Nowadays, hybridization of EAs is becoming trendy due to their capabilities in managing numerous real-world problems. A hybrid BBO with DE, referred to as BBO/DE is projected in this paper to solve the economic load dispatch problem. The proposed hybrid migration operator combines the exploitation of BBO with the exploration of DE efficiently which requires less computation time and memory and the results are compared with the iteration methods GA and BBO.

II. EVOLUTIONARY ALGORITHMS

A. *Genetic Algorithm (GA)*

Genetic Algorithm (GA) was invented by John Holland in the 1960s and was developed by Goldberg later. Genetic Algorithm (GA) is a search heuristic method that mimics the process of natural evolution. This heuristics is routinely used to generate useful solutions to optimization and search problems. Genetic Algorithm (GA) belongs to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution. The Genetic Algorithm (GA) has four principle components; they are the chromosomes, the fitness function, the crossover operator and the mutation operator. The candidate solutions are represented by chromosomes. New candidate solutions are produced from parent chromosomes by the crossover operator. The parent chromosomes can be selected by the roulette wheel technique. The mutation operator will then be applied to the population and at this point a generation or iteration is completed. The new chromosomes in a population are rated by their fitness measure according to a fitness function. When a chromosome with the desires fitness is formed, it will be taken as the optimum solution and the optimization process is terminated. This process is repeated until the maximum number of generations is reached or the fittest chromosome so far formed is taken to the optimum solution. The advantages of GA are the ease with which it can handle arbitrary kinds of constraints or objective function and adaptability to any kind of optimization problems.

B. *Particle Swarm Optimization (PSO)*

PSO is originally attributed to Kennedy, Eberhart and Shi and was first intended for simulating social behavior, as a stylized representation of the movement of organisms in a bird flock or fish school. Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO is a meta-heuristic that makes few or no assumptions about the problem being optimized and can reach very large spaces of candidate solutions. (PSO) doesn't require the optimization problem be differentiable. PSO optimizes a problem by having a population of candidate solutions, here said as particles. PSO has no evolution operators such as crossover and mutation. Here the particles fly through the problem space by following the current optimal particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. The fitness value is also stored. This value is called pbest. Another best value that is tracked by the PSO is the best value, obtained so far by any particle in the neighbors of the particle. This location is called lbest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest. In PSO concept at each time step, changing the velocity of (accelerating) each particle towards its pbest and lbest location. Acceleration is weighted by a random term, which separate random numbers being generated for acceleration towards pbest and lbest locations. This is expected to move the swarm towards the best solution. The advantages of PSO are that it is attractive as there are few parameters to adjust and requires less computation time and memory.

C. *Differential Evolution (DE)*

Differential Evolution (DE), proposed by Price and Storn in 1997 is a powerful population based, simple, direct search algorithm, which uses generation-and-test feature for global optimization problems with real-valued parameters. The information on distance and direction from the existing population is used by DE to direct the further exploration. The advantages of DE are its uncomplicated structure, speed, robustness and ease of use. The first working principle of DE was proposed by Price and Storn in 1997 with single scheme. Later on, ten different schemes of DE was recommended by Price and Storn in 2005 and 2008. DE is superior at exploring the search space and locating the area of local optimum, but it is slow in exploitation of the solutions. DE shows poor performance in locating the global optimum with limited number of fitness function evaluations (NFFEs).

D. *Biogeography Based Optimization (BBO)*

Biogeography based optimization (BBO) is a new optimization algorithm, proposed by Simon and developed from the theory of biogeography. The study of the geographical distribution of biological organisms is known as Biogeography. Similar to Genetic Algorithms (GAs), BBO is a stochastic global optimizer based on the population of individuals. In original BBO algorithm, the solution of a set of population is represented as a vector of integers. Similar to other biology based algorithms, such as GAs and PSO, the Migration operator of BBO helps in sharing information between solutions. Because of this feature, BBO finds its application in the problems which uses GAs and PSO. However, apart from the above mentioned common features of BBO, it has certain unique features compared with other biology based algorithms, like maintaining its set of best solution throughout the iteration process. BBO was compared with seven state-of-the-art EAs by Simon. The results declare that BBO has good exploitation ability and performs well compared to other biology based algorithms.

III. PRAPOSED APPROACH: A HYBRID BBO WITH DE

As pointed out earlier, DE is good at exploring the search space and locating the area of global minimum. However, it is slow exploiting of the solution. On the other hand, BBO has a good exploitation for global optimization. Based on these considerations, in order to balance the exploration and the exploitation of DE, in this work, we propose a hybrid DE approach, called BBO/DE, which combines the exploration of DE with the exploitation of BBO effectively.

A. Hybrid Migration Operator

The key work of BBO/DE is carried out by the hybrid migration operator, which hybridizes the migration operator of BBO with the DE operator, described in Algorithm 1. The core scheme of the projected hybrid migration operator is based on the following two considerations. First, the destruction of good solutions would be less, while poor solutions can inherit a lot of new characteristics from good solutions. In this sense, the existing inhabitants can be exploited adequately. Second, the mutation operator of DE is able to explore the new search space and build the algorithm to be healthier. From the analysis of the results obtained, it can be seen that the hybrid migration operator balances the exploitation of BBO and the searching of DE effectively.

Algorithm 1: Hybrid migration operator of BBO/DE

1: for i = 1 to NP
2: Select uniform randomly $r_1 \neq r_2 \neq r_3 \neq i$
3: $j_{rand} = rndint(1,D)$
4: for j = 1 to D do
5: if $rndreal(0, 1) < \lambda_i$ then
6: if $rndreal_j[0,1) < CR$ *or* $j == j_{rand}$ *then*
7: $U_i(j) = X_{r1}(j) + F(X_{r2}(j) - X_{r3}(j))$ {The original mutation operator of DE}
8: else
9: Select Xk with probability ∞ µk
10: Ui(j) = Xk(j)
11: end if
12: else
13: Ui(j) = Xj(j)
14: end if
15: end for
16: end for

B. Boundary Constraints

Title Trial parameters that go against the constraint limits should be returned back from the limit by the quantity of desecration to keep the solution of bound-constrained problems viable. In this work, the following repair rule is applied

$$X(i) = \begin{cases} l_i + rndreal_i[0,1] * (u_i - l_i) if\ X(i) < l_i \\ u_i + rndreal_i[0,1] * (u_i - l_i) if\ X(i) < u_i \end{cases} \quad (1)$$

where

$rndreal_i$ [0, 1] is the uniform random variable from [0,1] in each dimension i.

C. Main Procedure

The hybrid BBO with DE technique is formulated by incorporating the aforementioned hybrid migration operator into DE and is described in Algorithm 2. The BBO/DE Compared with the original DE algorithm, BBO/DE requires only a little amount of additional computational cost in sorting the inhabitants and calculating the migration rates. Besides, BBO/DE is capable of exploring the new search space with the mutation operator of DE and in exploiting the population information with the migration operator of BBO. This feature of BBO/DE has made it possible to overcome the deficit of exploitation in the original DE algorithm.

Algorithm 2: Procedure for BBO/DE

1: Generate the initial population P
2: Evaluate the fitness for each individual in P
3: If the halting criterion is not satisfied
4: Sort the Population from worst to best
5: For each individual, map the fitness to the number of species
6: Calculate the immigration rate λ_i and the emigration rate μ_i for each individual X_i
7: Modify the Population with the hybrid migration operator shown in algorithm 1
8: Evaluate the offspring Ui
9: If offspring is better than Parent vector, then replace the parent vector with the new offspring.

IV. ECONOMIC LOAD DISPATCH FORMULATION

The practical static ELD problem with generator nonlinearities such as prohibited operating zones are solved in this paper using PSO variants to find the optimal generation dispatch for different operating conditions. The objective of the economic dispatch problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints. The equality and inequality constraints are represented by (1) and (2) given by

$$\sum P_i - (P_d + P_1) = 0 \quad (2)$$

$$P_{imin} \leq P_i \leq P_{imax} \quad (3)$$

In the power balance criterion, an equality constraint must be satisfied, as shown in (2). The generated power should be the same as the total load demand plus total line losses. The generating power of each generator should lie between maximum and minimum limits represented by (3), where Pi is the power of it generator, n is the number of generators in the system; Pd is the system total demand; Pl represents the total line losses; and are, respectively, the output of the minimum and maximum operation of the generating unit. The total fuel cost function is formulated as follows:

$$MinF_T = \sum_{i=1}^{N} F_i(P_t) \quad (4)$$

where Fi is the total fuel cost for the ith generator (in $/h) which is defined by,

$$F_i(P_t) = (a_i P_t^2 + b_i P_i + c_i) \quad (5)$$

For a given total real load PD the system loss Pl is a function of active power generation at each generating unit. To calculate system losses, methods based on penalty factors and constant loss formula coefficients or B-coefficients are in use. The latter is adopted in this paper as per which transmission losses are expressed as

$$P_l = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (6)$$

V. SIMULATION RESULTS

The BBO algorithm has been proposed for solving i) A practical 3-generating unit ii) 6-generating unit .The simulations are carried out using MATLAB

Test case 1: -The system has 3-generating units. The cost data has been show in the in Table 1 and the load demand is 850 MW. The results obtained from proposed BBO algorithm have been compared with GA and PSO, It can be observed that population size 100, and M.R. =0.2 are best parameters of this case after 100 Trials, which is very close to global minima. The solutions of 100 trials of this case are plotted in Fig 1, fig 2 and compare the results in Table 2.

Table 1 Cost Coefficient data

No. of Units	Cost Coefficients			Real Power	
	a_i	b_i	c_i	Min	Max
1	0.001552	8.01	550	200	550
2	0.00182	7.89	280	150	350
3	0.00380	7.84	220	100	400
4	0.00254	7.91	165	50	200
5	0.00124	7.86	97	55	145
6	0.000089	7.96	70	40	160

Table 2 Performance Comparisons with different optimization techniques

Optimization method	GA Result	PSO Result	BBO Result	HBBO Result
P_1	324.112	324.101	324.011	325.000
P_2	301.215	301.124	305.201	306.000
P_3	89.623	88.523	89.564	90.231
P_4	54.232	54.200	53.258	54.151
P_5	50.294	51.350	50.236	48.285
P_6	30.524	30.702	27.73	26.333
Total Power (MW)	**850.00**	**850.00**	**850.00**	**850.00**
Total Cost (Rs/MWh)	**8191.986**	**8191.527**	**8191.256**	**8191.246**

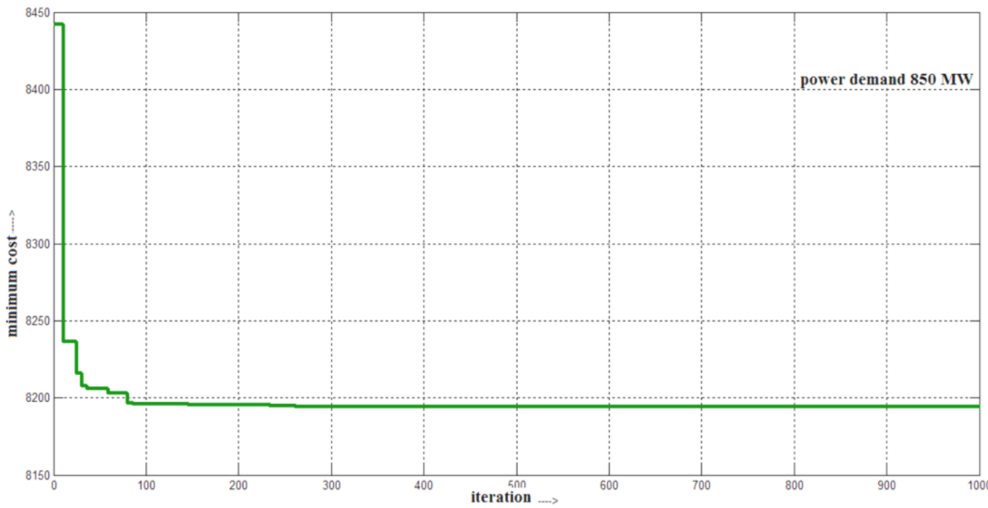

Fig 1 Best Results for the 3-Unit system for Population size =100 out of 100 trials, PD=850 MW

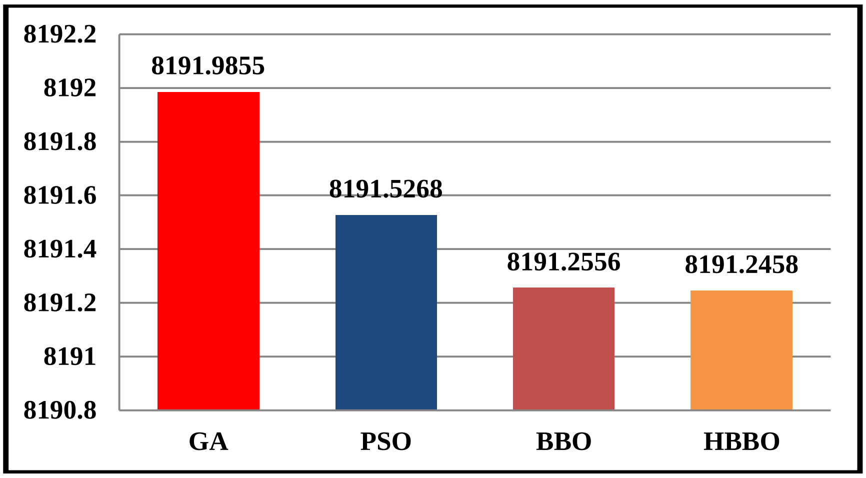

Fig 2 Comparison between different optimization techniques

Test case 2:-The system has 6-generating units. The cost data has been show in the in Table 3 and the load demand is 450 MW. The results obtained from proposed BBO algorithm have been compared with GA and found to match very closely, It can be observed that population size 100, and M.R. =0.2 are best parameters of this case after 100 Trials, which is very close to global minima. The solutions of 100 trials of this case are plotted in Fig 3, Fig 4 and compare result with GA ,PSO and BBO show in Table 4.

Table 1 Cost Coefficient data

No. of Units	Cost Coefficients			Real Power	
	a_i	b_i	c_i	Min	Max
1	0	3	150	15	95
2	0.01	3.01	200	15	85
3	0.015	2.95	300	25	75
4	0.010	0.95	180	50	200

Table 2 Performance Comparisons with different optimization techniques

Optimization method	GA Result	PSO Result	BBO Result	HBBO Result
P_1	105.298	180.356	174.985	175.000
P_2	158.659	110.124	128.265	120.000
P_3	98.658	85.659	78.659	105.000
P_4	87.385	73.861	68.091	50.000
Total Power (MW)	**850.00**	**850.00**	**850.00**	**850.00**
Total Cost (Rs/MWh)	**8191.986**	**8191.527**	**8191.256**	**8191.246**

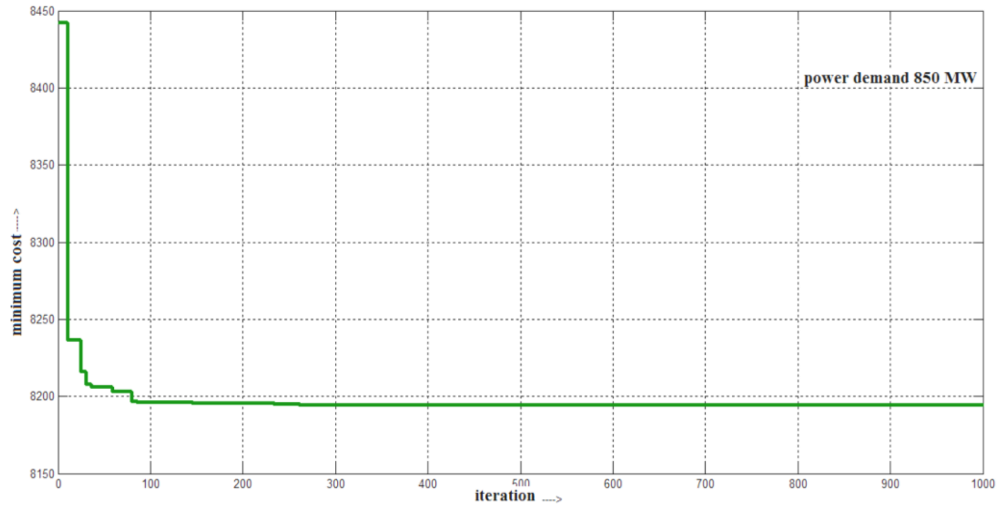

Fig 3 Best Results for the 6-Unit system for Population size =100 out of 100 trials, PD=450MW

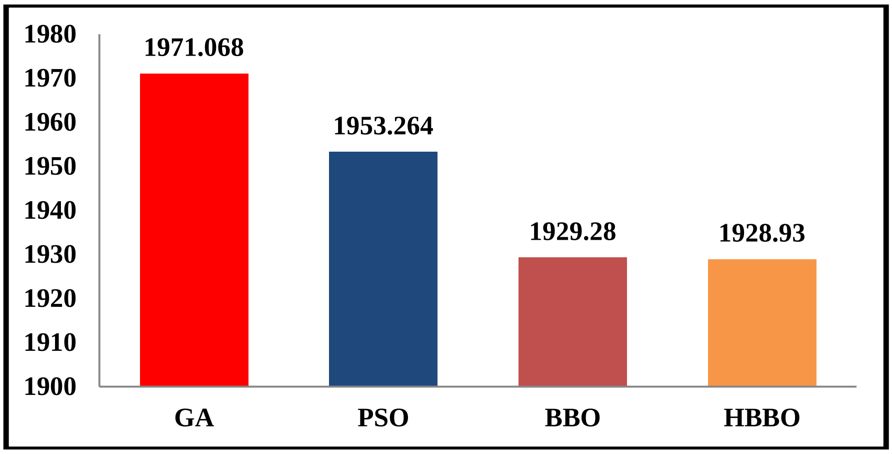

Fig 4 Comparison between different optimization techniques

VI. CONCLUSION

This paper presents an efficient and powerful approach for solving the economic load dispatch (ELD) problem of power system. This paper demonstrates with clarity, chronological development and successful application of HBBO technique to the solution of ELD. Two test systems 3-generator and 6-generator systems have been tested and the results are compared with different Optimization techniques. Overall, the HBBO algorithms have been shown to be very helpful in studying optimization problems in power systems. The proposed approach is relatively simple, reliable and efficient and suitable for practical applications of power system.

REFERENCE

[1] Wenyin Gong, Zhihua Cai and Charles X. Ling, "DE/BBO: a hybrid differential evolution with biogeography-based optimization for global numerical optimization, Springer Verlag 2010, DOI 10.1007/s00500-010-0591-1.

[2] M. Vanita and K. Thanushkodi, "An effective Biogeography Based Optimization Algorithm to solve Economic Load Dispatch problem, "Journal of Computer Science 8 (9): 1482 – 1486, 2012.

[3] Hardiansyah1, Junaidi2, Yohannes MS3, "Solving Economic Load Dispatch Problem Using Particle Swarm Optimization Technique" I.J. Intelligent Systems and Applications, 2012, 12, 12-18.

[4] Leandro dos Santos Coelho a,*, Chu-Sheng Lee b, "Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches" Electrical Power and Energy Systems 30 (2008) 297–307.

[5] Mohd Javed Khan1, Hemant Mahala2, "Particle Swarm Optimization by Natural Exponent Inertia Weight for Economic load Dispatch", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3, Issue 12, December 2014.

[6] Amita Mahor a*, Vishnu Prasad b,Saroj Rangnekar a,1, "Economic dispatch using particle swarm optimization: A review", Renewable and Sustainable Energy Reviews 13 (2009) 2134–2141

[7] K.P. wong & J. yuryevich, "Evolutionary based algorithm for environmentally constraints economic dispatch",IEEE transaction on power system , vol.13,no.2,1998,pp.301-306.
[8] W. M. Lin, F. S. Cheng, and M. T. Tsay. An Improved Tabu Search for Economic Dispatch with Multiple Minima, IEEE Trans. on Power Systems, 2002, 17(1): 108-112.
[9] K.Y. Lee, A. Sode-Yome and J.H. Park, Adaptive Hopfield neural network for economic Load dispatch, IEEE Trans. Power Syst. 13 (May (2)) (1998), pp. 519–526.
[10] Arunpreet Kaur1, Harinder Pal Singh2 and Abhishek Bhardwaj3, "Analysis of Economic Load Dispatch Using Genetic Algorithm", International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 3, Issue 3, March 2014.
[11] S. Duman1, U. Güvenç1, N. Yörükeren3, "Gravitational Search Algorithm for Economic Dispatch with Valve-Point Effects" International Review of Electrical Engineering (I.R.E.E.), Vol. 5, N. 6 November-December 2010.
[12] Gaurav Prasad Dixit, Hari Mohan Dubey, Manjaree Pandit, B.K.panigrahi, "Economic Load Dispatch using Arifitial Bee Colony Optimization", International conference on Advanced Computing, Communication and Networks,2011
[13] Kamlesh Kumar Vishwakarma1, Hari Mohan Dubey2* , Manjaree Pandit3 and B.K. Panigrahi4 "Simulated annealing approach for solving economic load dispatch problems with valve point loading effects", International Journal of Engineering, Science and Technology Vol. 4, No. 4, 2012, pp. 60-72.
[14] Dan Simon, "Biogeography-based optimization", IEEE Transaction on Evolutionary Computation, vol.12, No. 6, 2008, pp 702-713.
[15] Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay"Biogeography –Based Optimization for Different Economic Load Dispatch" IEEE Trans. Power System may 2010.
[16] A. Bhattacharya and P. K. Chattopadhyay "Biogeography-Based Optimization for Different Economic Load Dispatch Problems" IEEE Trans. Power Syst., Vol. 25, pp. 1064 –1077, 2010.