Economic Load Dispatch Problem with Ramp Rate Limit Using BBO

Neetu Agrawal, Shilpy Agrawal, K. K. Swarnkar, S. Wadhwani, and A. K. Wadhwani

***Abstract*—This paper presents an efficient and reliable biogeography–based optimization (BBO) algorithm to solve both convex and nonconvex Economic load dispatch problem (ELD) with Ramp rate limit of thermal power plants. Economic load dispatch (ELD) is a method to schedule the power generator outputs with respect to the load demands, and to operate the power system most economically. The objective of ELD is that the sharing of power demand among the online generators keeping minimum cost of generation as a constraint. This paper mainly focuses on minimizing the total fuel cost of all generators of the power system. BBO is a biology inspired optimization technique developed by Dan Simon in 2008 and is inspired by mathematical models of biogeography by Robert MacArthur and Edward Wilson. BBO is based on the science of biogeography. This paper presents an application of the BBO algorithm to economic load dispatch problem with ramp rate limit for 13 & 18 generator test case system. Economic load dispatch problems are applied and compared its solution quality and computation efficiency to Genetic algorithm (GA) and other optimization techniques. The simulation results show that the proposed algorithm outperforms previous optimization methods.**

***Index Terms*—Biogeography, economic load dispatch, *ramp rate limit* genetic algorithm, particle swarm optimization, mutation, migration.**

I. Introduction

Economic load dispatch is one of the key functions of modern energy management system. The economic load dispatch (ELD) problem is one of the non-linear optimization problems in electrical power systems in which the main objective is to reduce the total power generation cost, while satisfying various equality and inequality constraints. The ELD seeks 'the best' generation schedules for the generate plants to supply the essential the total coupled power demand plus transmission losses at least production cost [1]. Economic load dispatch (ELD) is the online dispatch which is used for the distribution of load among the generating units. The cost of power generation, particularly in fossil fuel plants, is very high and ELD helps in economy a considerable amount of profits. The Economic load dispatch is the name given to the process of apportioning the total load on a system between the various generating plants to achieve the greatest economy of operation [2] economic operation is very important for a power system to return a profit on the capital invested. Various investigation on ELD have been undertaken until date, as better clarification would result in major economical profit. Earlier, a number of derivatives–based approach like lambda iteration, based point input factor, gradient method and include lagrangian multiplier method have been apply to solve ELD problems There methods involve that incremental cost curves through quadratic or piecewise monotonically increasing in nature [3].But in apply the input output character of new generating units are extremely non linear because of valve–point loadings, ramp–rate limits, prohibited operating zones and multi–fuel option etc. their nature have to be about to meet to supplies of typical dispatch algorithms. Wood and Wollenberg proposed dynamic programming [3], which does not impose any restriction on the nature of the cost curves and solves both convex and non-convex ELD problems. But this method suffers from the curse of dimensionality, and simulation time increases rapidly with the increase of system size. More interests have been focused on the application of artificial intelligence technology for solution of ELD problems. Several methods, such as genetic algorithm (GA) [4]; artificial neural networks [5]; simulated annealing (SA), Tabu search; evolutionary programming [6]; particle swarm optimization (PSO) [7]; ant colony optimization; differential evolution (DE) [8] and etc. have been developed and applied successfully to ELD problems. Minimizing the total fuel cost of the thermal power plants while satisfying the demand power and power system constraints aims at overcoming the ELD problem.

The fuel cost effect is shown in Fig. 1.

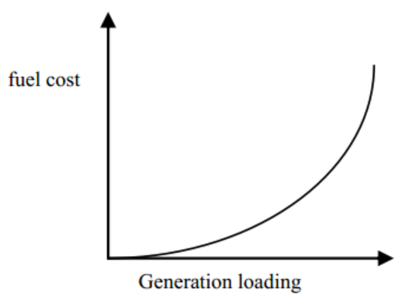

Fig. 1. Fuel cost effect

In ELD research, a number of study have focused upon the economical accepts of the problem above the statement that unit generation output can be adjusted instantaneously. Even though this assumption simplifies the problem, it does not reflect the actual operating processes of the generating unit. Ramp rate or power response rate is described as the power

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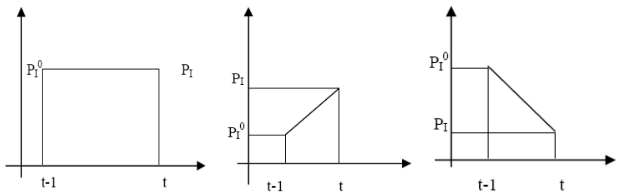
response capability of the unit in terms of accommodating power changes in specified time interval. The operating range of all on-line units is restricted by their ramp rate limits.

Fig. 2 shows three possible situations when a unit is on-line from hour t–1 to hour t. Fig. 2 (a) shows that the unit is in a steady operating status.

Fig. 2 (b) shows that the unit is in an increasing power generation status. Fig. 2 (c) shows that the unit is in a decreasing power generation status.



(a) (b) (c)

Fig. 2. Three possible situations of an on-line unit.

Artificial immune system (AIS) [9] is another population based or network-based soft computing technique in the field of optimization that has been successfully implemented in various power system optimization problems.

In each iteration of AIS, many operations like affinity calculation, cloning, hyper mutation, and selection are performed. During cloning, operation size of population also increases. Due to increase in number of operations, and larger size of population, convergence speed of AIS is much slower than DE or PSO.

Inspired from the mechanism of the survival of bacteria, e.g., E. coli, an optimization algorithm, called bacterial foraging algorithm (BFA) [10], has been developed. Chemo taxis, reproduction and dispersion are the three processes with the help of which global searching capability of this algorithm has been achieved. These properties have helped BFA to be applied successfully in several kinds of power system optimization problems. But constraints satisfaction creates little trouble in BFA.

Very recently, a new optimization concept, based on biogeography, has been proposed by Simon [11]. Biogeography is the nature's way of distributing species. Let us consider an optimization problem with some trial solutions of it. In biogeography-based optimization (BBO) technique, a good solution is analogous to an island with a high habitat suitability index (*HSI*), and a poor solution represents an island with a low *HSI*. High *HSI* solutions resist change more than low *HSI* solutions. Low *HSI* solutions tend to copy good features from high HIS solutions. The shared features remain in the high *HSI* solutions, while at the same time appearing as new features in the low *HIS* solutions. This is as if some representatives of a species migrating to a habitat, while other representatives remain in their original habitat. Poor solutions accept a lot of new features from good solutions.

This addition of new features to low *HSI* solutions may raise the quality of those solutions. This new approach to solve a problem is known as biogeography-based optimization (BBO) [11].These versatile properties of this new algorithm encouraged the authors to apply this newly developed algorithm to solve non convex complex ELD problems. This paper considers two types of non-convex ELD problems, namely, ELD with quadratic cost function and transmission loss, ELD with Ramp rate limit of thermal power plants. Section II of the paper provides a brief description and mathematical formulation of different types of ELD problems. The concept of biogeography is discussed in Section III. The original BBO approach is described in Section IV along with a short description of the algorithm used in this test system. The parameter settings for the test system to evaluate the performance of BBO and the simulation studies are discussed are discussed in Section V. The conclusion is drawn in Section VI.

II. Problem Formulation

The ELD may be formulated as a nonlinear constrained problem. Both convex and non-convex ELD problems have been modeled in this paper. The convex ELD problem assumes quadratic cost function along with system power demand and operational limit constraints. The practical non-convex ELD problem, in addition, considers generator nonlinearities *Ramp rate limit*.

A. ELD with Quadratic Cost Function and Without Transmission Loss

The objective function F_T of ELD problem may be written as

$$F_T = \text{MIN} \left(\textstyle\sum_{K=1}^{n} F_1 F_K(P_K) \right) \tag{1}$$

$$F_T = \text{MIN} \left(\textstyle\sum_{K=1}^{n} a_1\, a_k + b_k P_k + c_k P_k^2 \right) \tag{2}$$

$$F_K(P_K) = a_K + b_K P_K + c_k P_K^2 \tag{3}$$

where $F_K(P_K)$ is the kth generator's cost function and is usually expressed as a quadratic polynomial; a_k, b_k, and c_k are the cost coefficients of the kth generator; n is the number of commited generators to the power system; P_k is the power output of the kth generator.

The ELD problem consists in minimizing subject to the following constraints:

1) Real power balance constraint:

$$\textstyle\sum_{k=1}^{n} P_{\text{k}} - P_D = 0 \tag{4}$$

where P_D is the demand of power.

2) Generator Capacity Constraints: The power generated by each generator shall be within their lower operating limit and upper operating limit.

So that,

$$P_k^{\min} \leqslant P_k \leqslant P_k^{\max} \tag{5}$$

B. ELD with Quadratic Cost Function With Transmission Loss

The objective function F_T of ELD problem may be written as:

$$F_T = \text{MIN}\left(\textstyle\sum_{K=1}^{n} F_1 F_K(P_K) \right) \tag{6}$$

$$F_T = \text{MIN}\left(\textstyle\sum_{K=1}^{n} a_1\, a_k + b_k P_k + c_k P_k^2 \right) \tag{7}$$

$$F_K(P_K) = a_K + b_K P_K + \text{c}_\text{k} P_K^2 \tag{8}$$

The ELD problem consists in minimizing subject to the following constraints:

1) Real Power Balance Constraint:

$$\textstyle\sum_{k=1}^{n} P_{\text{k}} - (P_D + P_L) = 0. \tag{9}$$

2) Generator Capacity Constraints: The power generated by each generator shall be within their lower operating limit and upper operating limit.
So that,

$$P_k^{\min} \leqslant P_k \leqslant P_k^{\max} \tag{10}$$

C. ELD with Quadratic Cost Function With Ramp Rate Constraint

The objective function FT of ELD problem may be written as

$$F_T\text{=MIN } (\textstyle\sum_{K=1}^{n} F_1 F_K(P_K)) \tag{11}$$

$$F_T = \text{MIN } (\textstyle\sum_{K=1}^{n} a_1\ a_k + b_k P_k + c_k P_k^2) \tag{12}$$

$$F_K(P_K) = a_K + b_K P_K + c_k P_K^2 \tag{13}$$

The ELD problem consists in minimizing subject to the following constraints:

1) Real Power Balance Constraint:

$$\textstyle\sum_{k=1}^{n} P_k - (P_D + P_L) = 0. \tag{14}$$

2) Generator Capacity Constraints: the power generated by each generator shall be within their lower operating limit and upper operating limit.
So that,

$$\text{Pkmin} \leqslant \text{Pk} \leqslant \text{Pkmax} \tag{15}$$

3) Ramp rate limit constraint: The power generated, P_{i0} by the *i*th generator in certain interval may not exceed that of previous interval P_{i0} by more than a certain amount UR_i , the up-ramp rate limit and neither may it be less than that of the previous interval by more than some amount DR_i the down-ramp rate limit of the generator .These give rise to the following constraints.

As generation increases

$$P_i - P_{i0} \leqslant UR_i \tag{16}$$

As generation decreases

$$P_{i0} - P_i \leqslant DR_i \tag{17}$$

and

$$\max (P_i^{\min}, P_{i0} - DR_i) \leqslant P_i \leqslant \min(P_i^{\max}, P_{i0} + UR_i) \tag{18}$$

III. Biogeography-Based Optimization

BBO [11] has been developed based on the theory of Biogeography. BBO is a novel evolutionary algorithm that is based on the mathematics of biogeography. Biogeography is the study of the geographical distribution of biological species. In the BBO model, problem solutions are represented as islands, and the sharing of features between solutions is represented as immigration and emigration between the islands. BBO has some features that are in common with other biology-based optimization methods, like genetic algorithms (GAs) and particle swarm optimization (PSO).Biogeography is nature's way of distributing species. Fig. 3. describes a model of species abundance in a habitat [12]. The immigration curve of Fig. 3. shows that immigration rate to the habitat is maximum (I), when there are zero species in the habitat. As the number of species increases, the habitat becomes more crowded, fewer species are able to successfully survive immigration to the habitat, and the immigration rate decreases.

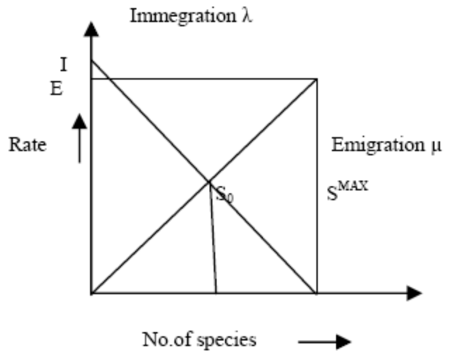


Fig. 3. Species model of a single habitat

The largest possible number of species that the habitat can support is Smax, at which point the immigration rate becomes zero. The emigration curve of Fig. 3. depicts that if there is no species in the habitat, the emigration rate will be zero. As the number of species increases, the habitat becomes more crowded, more species are able to leave the habitat to explore other possible residences and the emigration rate increases. The maximum emigration rate is *E*, which occurs when the habitat contains the largest number of species (S_{max}). The equilibrium number of species is S_0, at which point the immigration and emigration rates are equal. The immigration and emigration curves in Fig. 2 are shown as straight lines but, in general, they might be more complicated curves. Nevertheless, this simple model gives us a general description of the process of immigration and emigration. From Fig. 3, immigration rateλ_s and the emigration rate μ_s for *S* number of species may be formulated as follows:

$$\lambda_s = \text{ I [1-s\textbackslash s}_{\max}] \tag{19}$$

$$\mu_s = \text{E.S/S}_{\max} \tag{20}$$

Mathematically the concept of emigration and immigration can be represented by a probabilistic model. *Ps* is the probability of the habitat that contains exactly *S* species. Ps changes from time t to time $t + \Delta t$ as follows [12]:

$$p_s(t+\Delta t)=P_s(1-\lambda_s\Delta t-\mu_s\Delta t)+P_{s-1}\lambda_{s-1}\Delta t+P_{s+1}\lambda_{s+1}\Delta t \tag{21}$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the habitat. This equation holds because inorder to have *S* species at time $t + \Delta t$, one of the following conditions must hold:

1) There are *S* species at time *t*, and no immigration or emigration occurs between *t* and $t + \Delta t$;

2) There are ($S - 1$) species at time t, and one species immigrates;

3) There are ($S + 1$) species at time t, and one species

emigrates.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored then taking the limit of (16) as $\Delta t \rightarrow 0$ gives the following equation - :

$$P_{s} = \begin{cases} -(\lambda_s+\mu_s)\, P_s+\mu_{s+1}\, P_{s+1}, & S=0 \\ -(\lambda_s+\mu_s)\, P_s+\lambda_{s-1}P_{s+1}+\ \mu_{s+1}\, P_{s+1} & 1\leq S \leq S_{\max-1} \\ -(\lambda_s+\mu_s)\, P_s+\lambda_{s-1}P_{s+1}, & S= S_{\max} \end{cases} \qquad (22)$$

This algorithm searches for the global optimum mainly through two steps: migration and mutation. The concept and mathematical formulation of Migration and Mutation steps are given below

A. Migration

This BBO algorithm [11] is similar to other population based optimization techniques where population of candidate solutions can be represented as vectors of real numbers. Each real number in the vector is considered as one suitability index variable (SIV). Fitness (in BBO, a term called habitat suitability index (HSI)) of each candidate solution is evaluated using its SIVs.HSI represents the quality of each candidate solution. High HIS solution represents better quality solution and low HSI solution represents inferior solution in the optimization problem. The emigration and immigration rates of each solution are used to probabilistically share information between habitats. Immigration rate (λ_s) and emigration rate (μ_s) can be evaluated by the equations (14) and (15). Using Habitat Modification Probability each solution is modified based on other solutions. Immigration rate, λ_s of each solution is used to probabilistically decide whether or not to modify each SIV in that solution. If a SIV in a given solution is selected for modification, emigration rates, μ_s of other solutions are used to probabilistically select which of the solutions should migrate a randomly selected SIV to that solution. The main difference between recombination approach of evolutionary strategies (ES) and migration process of BBO is that in ES, global recombination process is used to create a completely new solution, while in BBO; migration is used to bring changes within the existing solutions. In order to prevent the best solutions from being corrupted by the immigration process, few elite solutions are kept in BBO algorithm.

B. Mutation

Due to some natural calamities or other events HSI of a natural habitat can change suddenly and it may deviate from its equilibrium value. In BBO, this event is represented by the mutation of SIV and species count probabilities are used to determine mutation rates. The species count probability can be calculated using the differential equation (17). Each population member has an associated probability, which indicates the likelihood that it exists as a solution for a given problem. If the probability of a given solution is very low then that solution is likely to mutate to some other solution. Similarly if the probability of some other solution is high then that solution has very little chance to mutate. Therefore, very high HSI solutions and very low HSI solutions are equally improbable for mutation i.e. they have less chances to produce more improved SIVs in the later stage. But medium HSI solutions have better chances to create much better solutions after mutation operation. Mutation rate of each set of solution can be calculated in terms of species count probability using the equation (18) [11]:

$$m(s) = m_{\max} 1\text{-}P_S/P_{\max} \qquad (23)$$

where

m (s) =the mutation rate for habitat containing S species,
$m_{\max}$ = maximum mutation rate,
$P_{\max}$ = maximum probability.

This mutation scheme tends to increase diversity among the populations. Without this modification, the highly probable solutions will tend to be more dominant in the population. This mutation approach makes both low and high HSI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier values. Few elite solutions are kept in mutation process to save the features of a solution, so if a solution becomes inferior after mutation process then previous solution (solution of that set before mutation) can revert back to that place again if needed. So, mutation operation is a high-risk process. It is normally applied to both poor and good solutions. Since medium quality solutions are in improving stage so it is better not to apply mutation on medium quality solutions. Here, mutation of a selected solution is performed simply by replacing it with randomly generated new solution set. Other than this any other mutation scheme that has been implemented for GA can also be implemented for BBO.

IV. The Proposed Solution Method

In this paper BBO algorithm has been employed to solve constrained ELD problem and to find optimal solutions satisfying both equality and inequality constraints. In BBO algorithm, applied to the ELD problem [12], each candidate solution (i.e. each habitat) is defined by a vector with m SIVs where each SIV represents the value of power output. If there are m independent variables, then the *i*-th individual habitat Hi can be defined as follows:

$$H^i = SIV^{iq} = \{ SIV^{1q}, SIV^{2q} \ \ldots\ldots SIV^{im} \} \qquad (24)$$

where: i =1, 2,..., n; q = 1, 2,...m

SIV^{iq} is the q-th independent variable of the i-th individual Hi. The dimension of the population is n ×m. All these components in each individual are real values. HSIi indicates the objective function of the i-th habitat containing m independent variables (SIVs) [13].The algorithm of the proposed method is as enumerated below.

Step 1: Initialization of the BBO parameters.

Step 2: The initial position of SIV of each habitat should be randomly selected while satisfying different equality and inequality constraints of ELD problems. Several numbers of habitats depending upon the population size are being generated. Each habitat represents a potential solution to the given problem.

Step 3: Calculate each HSIi i.e. value of objective function for each i-th habitat of the population set n for given emigration rate μs, immigration rate λs and species S.
Step 4: Based on the HSI values some elite habitats are identified.
Step 5: Each non-elite habitat is modified by performing probabilistically immigration and emigration operation as described in section III. A.
Step 6: Species count probability of each habitat is updated using. Mutation operation is performed on the non-elite habitat and HSI value of each new habitat is computed.
Step 7: Feasibility of a problem solution is verified i.e. each SIV should satisfy equality and inequality constraints.
Step 8: Go to step 3 for the next iteration.
Step 9: Stop iterations after a predefined number of iterations.

TABLE I: GENERATOR OPERATING LIMITS AND COST COEFFICIENTS OF THE TEST SYSTEM

Unit	P_{mini}	P_{maxi}	a_i	b_i	c_i
1	0	680	0.00028	8.10	550
2	0	360	0.00056	8.10	309
3	0	360	0.00056	8.10	307
4	60	180	0.00324	7.74	240
5	60	180	0.00324	7.74	240
6	60	180	0.00324	7.74	240
7	60	180	0.00324	7.74	240
8	60	180	0.00324	7.74	240
9	60	180	0.00324	7.74	240
10	40	120	0.00284	8.6	126
11	40	120	0.00284	8.6	126
12	55	120	0.00284	8.6	126
13	55	120	0.00284	8.6	126

TABLE II: GENERATOR LOADING AND FUEL COST DETERMINED BY THE PROPOSED METHOD

Generator	Generator production
Pg1	520,4830
Pg2	220,3566
Pg3	149,0664
Pg4	108,8725
Pg5	108,8681
Pg6	108,8595
Pg7	108,9365
Pg8	108,8521
Pg9	109,0274
Pg10	76,3590
Pg11	39,0014
$Pg12$	54,0102
$Pg13$	54,0553
$\sum Pgi$	1800MW
Total cost ($/h)	16865,4933

V. SIMULATION RESULTS

This test case consists of 13 generating units with quadratic cost function combined with the effects of valve point loading[14].The unit data (upper & lower bounds) along with the cost coefficients for the fuel cost (a, b, c, e and f) for the 13 generators with valve point loading are given.

A power system with 13 generators data is given in Table Ⅰ. In this power system, Economic dispatch is realized by using the CEP, FEP, MFEP, IFEP, PS and BBO methods. Economic dispatch results are given in Table Ⅲ. When economic dispatch is done by using the BBO, both in total fuel costs and reducing the total line losses significant gains can be achieved.

TABLE III: COMPARISON OF PROPOSED METHOD

Evolution method	**Total cost ($)**
CEP	18048.21
FEP	18018.00
MFEP	18028.09
IFEP	17994.07
PS	17969.07
BBO	17865.50

A power system with 18 generators data is given in Table Ⅳ. This power system is loaded with different load demands that are given in Table Ⅴ. In this power system, economic dispatch is made by using different methods and loads. Economic dispatch results are given in Table Ⅵ.The solution presented in this paper is based on a hybrid GA-PSO to solve various ED problems. If economic dispatch is done by using proposed method, total fuel costs significant gains can be achieved.

TABLE IV: GENERATOR OPERATING LIMITS AND COST COEFFICIENTS OF THE TEST SYSTEM.

Unit	P_{mini}	P_{maxi}	a_i	b_i	c_i
1	15,00	7	85,74158	22,45526	0,602842
2	45,00	7	85,74158	22,45526	0,602842
3	25,00	13	108,9837	22,52789	0,214263
4	25,00	16	49,06263	26,75263	0,077837
5	25,00	16	49,06263	26,75263	0,077837
6	14,75	3	677,73	80,39345	0,734763
7	14,75	3	677,73	80,39345	0,734763
8	12,28	3	44,39	13,19474	0,514474
9	12,28	3	44,39	13,19474	0,514474
10	12,28	3	44,39	13,19474	0,514474
11	12,28	3	44,39	13,19474	0,514474
12	24,00	3	574,9603	56,70947	0,657079
13	16,20	3	820,3776	84,67579	1,236474
14	36,20	3	603,0237	59,59026	0,394571
15	45,00	3	567,9363	56,70947	0,420789
16	37,00	3	567,9363	55,965	0,420789
17	45,00	3	567,9363	55,965	0,420789
18	16,20	3	820,3776	84,67579	1,236474

TABLE V: GENERATOR LOADING AND FUEL COST DETERMINED BY THE PROPOSED METHOD FOR DIFFERENT LOAD DEMAND.

Generator	POWER OUTPUT		
	80% P	70%P	365 MW
P_{g1}	13,9997	13,9997	13,9997
P_{g2}	43,9997	42,7577	43,8293
P_{g3}	23,9997	23,9997	23,9997
P_{g4}	23,9998	23,9997	23,9894
P_{g5}	24,9997	23,9997	24,9997
P_{g6}	2,9965	2,9996	4.6011
P_{g7}	2,2608	2,9996	5,1007
P_{g8}	11,2797	11,2500	11,2600
P_{g9}	11,2797	11,2500	11,2600
P_{g10}	11,2797	11,2500	11,2600
P_{g11}	11,2797	11,2500	11,2600
P_{g12}	19,6579	12,7110	19,8517
P_{g13}	1,9997	1,9997	2,3997
P_{g14}	29,0734	21,2345	30,9143
P_{g15}	29,7527	21,7578	35,1414
P_{g16}	32,5613	23,9047	35,2578
P_{g17}	32,9288	23,7224	35,3378
P_{g18}	1,1325	2,9996	3,3079
Total cost ($/h)	22748.0008	19278,2320	24343,4547

TABLE VI: COMPARISON OF PROPOSED METHOD FOR DIFFERENT LOAD DEMANDS.

Demand	y-iteration	GA	Real GA	BBO
80%P	23861,58	23980,24	23861,58	22648,0008
70%P	20393,43	20444,68	20396,39	19278,2320
365MW			25768,57	24343,4548

VI. CONCLUSION

In this paper, authors have successfully introduced Biogeography based optimization algorithm to solve Economic load dispatch problem and compared its results to those of other well established algorithms. It is observed that the proposed algorithm exhibits a comparative performance with respect to other population based techniques. It is clear from the results that Biogeography based optimization algorithm is capable of obtaining higher quality solution with better computation efficiency and stable convergence characteristics.

REFRENCES

[1] A. Bhattacharya, "Biogeography-Based Optimization for different Economic Load Dispatch Problems," in *Proc. of IEEE,* 2009.

[2] N. Agrawal and K. Swarnkar, "Economic load dispatch of thermal generator with Ramp rate limit using Biogeography based optimization," in *Proc.* IJEIT 2012.

[3] J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control,* 2nd ed. New York: Wiley, 1984.

[4] P. H. Chen and H. C. Chang, "Large-scale economic dispatch by genetic algorithm," *IEEE Trans. Power Syst.*, vol. 10, no. 4, pp. 1919–1926, Nov. 1995.

[5] C.-T. Su and C.-T. Lin, "New approach with a Hopfield modeling framework to economic dispatch," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 541, May 2000.

[6] T. Jayabarathi, G. Sadasivam, and V. Ramachandran, "Evolutionaryprogramming based economic dispatch of generators with prohibited operating zones," *Power Syst. Res.*, vol. 52, pp. 261–266, 1999.

[7] R. C. Eberhart and Y. Shi, "Comparison between genetic algorithms and particle swarm optimization," in *Proc. of IEEE Int. Conf. Evolutionary Computation*, pp. 611–616, May 1998.

[8] R. Storn and K. Price, "Differential Evolution—A Simple and Efficient Adaptive Scheme for Global Optimization Over Continuous Spaces," *International Computer Science Institute*, Berkeley: CA, Tech.Rep. TR-95–012, 1995.

[9] L. N. Castro and J. Timmis, *Artificial Immune Systems: A New Computational Intelligence Approach.* U.K.: Springer-Verlag, 1996.

[10] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," *IEEE Trans. Control Syst.*, vol. 22, no. 3, pp. 52–67, Jun. 2002.

[11] D. Simon, "Biogeography-based optimization," *IEEE Trans. Evol. Comput.*, vol. 12, no. 6, pp. 702–713, Dec. 2008.

[12] N. Agrawal and K. Swarnkar, "Economic load dispatch with Ramp rate limit using BBO," presented at International Conference on Agile Manufacturing Dayalbagh Agra, 2011.

[13] N. Agrawal and K. Swarnkar, "Economic load dispatch of *thermal* generator with Ramp rate limit using Biogeography based optimization," *IJEIT*, 2012.

[14] U. GAuvenc, S. Duman, B. Saracoglu, and A. Ozturk: "A hybrid GA-PSO approach based on similarity for various types of Economic Dispatch Problems," *Electronics and Electrical Engineering Elektronika ir elektrotechnik*a, no. 2 pp. 108, 2011.

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