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Economic Load Dispatch Problem with Reduce Power Losses using Firefly Algorithm

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Abstract

This paper presents an Efficient and Reliable Firefly Algorithm (FA) for solving Economic Load Dispatch Problem with Reduce Power Losses (ELD). The main objective is to minimize the total fuel cost of the generating units having quadratic cost characteristics subjected to limits on generator True power output & transmission losses. It has been achieved by using optimization techniques such as dynamic programming, integer programming, and mixed-integer non linear programming. On the other hand, a broad class of Meta heuristics has been developed for reliability-redundancy optimization. Recently, a new meta-heuristics called Firefly Algorithm (FA) algorithm has emerged. The FA is a stochastic Meta heuristic approach based on the idealized behavior of the flashing characteristics of fireflies. This paper presents an application of the Firefly Algorithm (FA) to ELD for different Test Case system. ELD is applied and compared its solution quality and computation efficiency to Genetic algorithm (GA), Particle swarm optimization (PSO), Artificial Bee Colony optimization (ABC), Biogeography-Based Optimization (BBO) and Bacterial Foraging algorithms (BFA) and other optimization techniques. The simulation results show that the proposed algorithm outperforms previous optimization methods.

Keywords: *Firefly Algorithm ; Economic load dispatch; Genetic algorithm; Particle swarm optimization; Artificial Bee Colony optimization; Biogeography-Based Optimization ; Bacterial Foraging algorithms.*

1 Introduction

Biology-inspired Meta heuristic algorithms have recently become the forefront of the current research as an efficient way to deal with many NP-hard combinatorial optimization problems and non-linear optimization constrained problems in general. These algorithms are based on a particular successful mechanism of a biological phenomenon of Mother Nature in order to achieve optimization, such as the family of honey-bee algorithms, where the finding of an optimal solution is based on the foraging and storing the maximum amount of flowers' nectar [1]. A new algorithm that belongs in this category of the so-called nature inspired algorithms is the firefly algorithm which is based on the flashing light of fireflies. Although the real purpose and the details of this complex biochemical process of producing this flashing light is still a debating issue in the scientific community, many researchers believe that it helps fireflies for finding mates, protecting themselves from their predators and attracting their potential prey [1–4]. In the firefly algorithm, the objective function of a given optimization problem is associated with this flashing light or light intensity which helps the swarm of fireflies to move to brighter and more attractive locations in order to obtain efficient optimal solutions.

In this research paper we will show how the recently developed firefly algorithm can be used to solve the famous ELD optimization problem. This hard optimization problem constitutes one of the key problems in power system operation and planning in which a direct Solution cannot be found and therefore Meta heuristic approaches, such as the firefly algorithm, have to be used to find the near optimal solutions.

This optimization problem deals with allocating loads to power generators of a plant for minimum total fuel cost while meeting the power demand and transmission losses constraints. this is numerous variation of this problem which model the one objective functions and the constraints in many different ways. Moreover, we will demonstrate how the firefly algorithm works and how this method can be easily adapted in order to solve this objective optimization problem. Therefore, we will discuss why this method is sufficiently accurate and easy to implement for real-time operation and control of power systems. For the efficiency and validation of this algorithm, we will use, as an example, a sample realistic test system having six power generators. We will also compare the solutions obtained with the ones obtained by alternative optimization techniques that have been successfully applied by many scientists in order to solve these types of problems, such as the goal attainment Genetic algorithm; Particle swarm optimization; Artificial Bee Colony optimization; Biogeography-Based Optimization ; Bacterial Foraging algorithms.

The remainder of this paper is organized as follows:

Section II of the paper provides a brief description and mathematical formulation of ELD problem. The concept of FA is discussed in Section III. The original FA 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 FA and the simulation studies are discussed are discussed in Section V. The conclusion, some suggestions and ideas for further research are drawn in Section VI.

2 Problem Formulation

The ELD may be formulated as a nonlinear constrained problem. The convex ELD problem assumes quadratic cost function along with system power demand and operational limit constraints.

II.1. - ELD with quadratic cost function without transmission loss. The objective function F_T of ELD problem may be written as:-

$$F_T = MIN(\sum_{k=1}^{n} F_k\,[P_k]) \qquad (1)$$

$$F_T = MIN\left(\sum_{k=1}^{n} a_k + b_k P_k + c_k P_k^2\right) \quad (2)$$

$$F_k(P_k) = a_k + b_k P_k + c_k P_k^2 \quad (3)$$

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

i. ***Real Power Balance Constraint:***

$$\sum_{k=1}^{n} P_k - (P_D) = 0 \quad (4)$$

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

So that,

$$P_k^{min} \le P_k \le P_k^{max} \quad (5)$$

II.2. - ELD with quadratic cost function with transmission loss. The objective function F_T of ELD problem may be written as:-

$$F_T = MIN\left(\sum_{k=1}^{n} F_k [P_k]\right) \quad (6)$$

$$F_T = MIN\left(\sum_{k=1}^{n} a_k + b_k P_k + c_k P_k^2\right) \quad (7)$$

$$F_k(P_k) = a_k + b_k P_k + c_k P_k^2 \quad (8)$$

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

i. ***Real Power Balance Constraint:***

$$\sum_{k=1}^{n} P_k - (P_D + P_L) = 0 \quad (9)$$

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

So that,

$$P_k^{min} \le P_k \le P_k^{max} \quad (10)$$

F_T = the total fuel cost, \$/hr.
P_k = the power output of k-th generator, MW.
a_k, b_k , c_k = the cost coefficient of k-th generator.
P_D = total load demand.
P_L = total transmission losses.
P_k^{min} = the power generated lower limit.
P_k^{max} = the power generated upper limit.

3 The Firefly Algorithm

The Firefly Algorithm [FA] is a Meta heuristic, nature-inspired, optimization algorithm which is based on the social flashing behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions[1–3, 20]. It was developed by Dr. Xin-She Yang at Cambridge University in 2007, and it is based on the swarm behavior such as fish, insects, or bird schooling in nature. In particular, although the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization [PSO], Artificial Bee Colony optimization [ABC], and Bacterial Foraging [BFA] algorithms, it is indeed much simpler both in concept and implementation [2–4,20]. Furthermore, according to recent bibliography, the algorithm is very efficient and can outperform other conventional algorithms, such as genetic algorithms, for solving many optimization problems; a fact that has been justified in a recent research, where the statistical performance of the firefly algorithm was measured against other well-known optimization algorithms using various standard stochastic test functions [1–3, 20]. Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles [i.e., the fireflies], and as a result, it seems more effective in optimization such as the ELD problem in our case.

The FA has three particular idealized rules which are based on some of the major flashing characteristics of real fireflies [_2–4, 20]. These are the following:

[1] All fireflies are unisex, and they will move towards more attractive and brighter ones regardless their sex.
[2] The degree of attractiveness of a firefly is proportional to its brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. If there is not a brighter or more attractive firefly than a particular one, it will then move randomly.
[3] The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem. For maximization problems, the light intensity is proportional to the value of the objective function.

III.1. Attractiveness **-** In the FA, the form of attractiveness function of a firefly is the following monotonically decreasing function [2, 3, and 20]:

$$\beta(r) = \beta_0^{=} \exp(\gamma r^{m}) \ \ with\ m \geq 1, \tag{11}$$

Where, r is the distance between any two fireflies, β_0 is the initial attractiveness at r =0, and γ is an absorption coefficient which controls the decrease of the light intensity.

III.2. Distance- The distance between any two fireflies i and j, at positions x_i and x_j, respectively, can be defined as a Cartesian or Euclidean distance as follows [2, 3, and 20]:

$$r_{ij} = \|xi - xj\| = \sqrt{\sum_{k=1}^{d}(xi,k - xj,k)^2} \quad (12)$$

Where $x_{i,k}$ is the k^{th} component of the spatial coordinate x_i of the *i*th firefly and *d* is the number of dimensions we have, for *d*= 2, we have

$$r_{ij} = ((xi - xj)^2 + (yi - yj)^2) \quad (13)$$

However, the calculation of distance *r* can also be defined using other distance metrics, based on the nature of the problem, such as Manhattan distance or Mahalanobis distance.

III.3. Movement - The movement of a firefly *i* which is attracted by a more attractive (i.e., brighter) firefly *j* is given by the following equation [2, 3, and 20]:

$$x_i = x_i + \beta0 * \exp(-\gamma r^2_{ij})*(x_j - x_i) + a*(\text{rand}-\tfrac{1}{2}) \quad (14)$$

Where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies, and the third term is used for the random movement of a firefly in case there are not any brighter ones. The coefficient α is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space (0, 1). As we will see in this implementation of the algorithm, we will use β_0 =1.0, $\alpha \in$ [0, 1] and the attractiveness or absorption coefficient γ [1.0], which guarantees a quick convergence of the algorithm to the optimal solution.

III.4. Convergence and Asymptotic Behavior - The convergence of the algorithm is achieved for any large number of fireflies *(n)* if *n*>> *m*, where *m* is the number of local optima of an optimization problem [1, 3]. In this case, the initial location of *n* fireflies is distributed uniformly in the entire search space. The convergence of the algorithm into all the local and global optima is achieved, as the iterations of the algorithm continue, by comparing the best solutions of each iteration with these optima. However, it is under research a formal proof of the convergence of the algorithm and particularly that the algorithm will approach global optima when $n \to \infty$ and $t >> 1$[3]. In practice, the algorithm converges very quickly in less than 80 iterations and less than 50 fireflies, as it is demonstrated in several research papers using some standard test functions [1–3, 20]. Indeed, the appropriate choice of the number of iterations together with the γ, β, α, and *n* parameters highly depends on the nature of the given optimization problem as this affects the convergence of the algorithm and the efficient find of both local and global optima. Note that the firefly algorithm has computational complexity of $O(n)^2$ where *n* is the population of fireflies. The larger population size becomes the greater the computational time is [1–3].

III.5. Special Cases - There are two important special cases of the firefly algorithm based on the absorption coefficient γ; that is, when $\gamma \to 0$ and $\gamma \to \infty$ [1, 3, 20]. When $\gamma \to 0$, the attractiveness coefficient is constant $\beta = \beta_0$, and the light intensity does not decrease as the distance *r* between two fireflies increases. Therefore, as the light of a firefly can be seen anywhere, a single local or global optimum can be easily reached. This limiting case corresponds to the standard Particle Swarm Optimization (PSO) algorithm.

On the other hand, when $\gamma \rightarrow \infty$, the attractiveness coefficient is the Dirac delta function $\beta(r) \rightarrow \delta(r)$.

In this limiting case, the attractiveness to light intensity is almost zero, and as a result, the fireflies cannot see each other, and they move completely randomly in a foggy place. Therefore, this method corresponds to a random search method.

III.6. Hybridization- In a recent bibliography, a new Meta heuristic algorithm has been developed and formulated based on the concept of hybridizing the firefly algorithm. In particular, the new Levy flight Firefly algorithm was developed by Dr. Xin-She Yang at Cambridge University in 2010 and it combines the firefly algorithm with the Levy flights as an efficient search strategy [4]. It combines the three idealized rules of the firefly algorithm together with the characteristics of Levy flights which simulate the flight behavior of many animals and insects. In this algorithm, the form of the attractiveness function and the calculation of distance between two fireflies are the same as in firefly algorithm, but in the movement function, the random step length is a combination of the randomization parameter together with a Levy flight. In particular, the movement of a firefly is a random walk, where the step length is drawn by the Levy distribution [4].

4 The Proposed Solution Method

In order to solve the ELD problem, we have implemented the FA in Mat lab 2009 and it was run on a computer with an Intel Core2 Duo (1.8GHz) processor, 3GB RAM memory and MS Windows XP as an operating system. Mathematical calculations and comparisons can be done very quickly and effectively with Mat lab and that is the reason that the proposed Firefly algorithm was implemented in Mat lab 2009 programming environment. In this proposed method, we represent and associate each firefly with a valid power output (i.e., potential solution) encoded as a real number for each power generator unit, while the fuel cost objective i.e., the objective function of the problem is associated and represented by the light intensity of the fireflies. In this simulation, the values of the control parameters are:

α = 0.2, γ =1.0, β_0 = 1.0, and n =12, and the maximum generation of fireflies (iterations) is 50. The values of the fuel cost, the power limits of each generator, the power loss coefficients, and the total power load demand are supplied as inputs to the firefly algorithm. The power output of each generator, the total system power, the fuel cost with/without transmission losses are considered as outputs of the proposed Firefly algorithm. Initially, the objective function of the given problem is formulated as defined in (1) and it is associated with the light intensity of the swarm of the fireflies. The initial solution of the given problem is generated based on the mathematical formulation given below:

$$x_j = \text{rand} *(\text{upper-range} - \text{lower-range}) + \text{lower-range}, \quad (15)$$

Where x_j is the new solution of j^{th} firefly, that is, created, rand is a random number generator uniformly distributed in the space [0, 1], while upper range and lower range are the upper range and lower range of the j^{th} firefly (variable), respectively.

After the evaluation of the initial population/generation (i.e., solution), the firefly algorithm enters its main loop which represents the maximum number of generations of the fireflies. This is actually the termination criterion that needs to be satisfied for the termination of the loop.

The generation of a new solution (i.e., the movement of a firefly) of the given problem is made based on the following mathematical formulation:

$$x_i = x_i + \beta_o * \exp(-\gamma * \sum_{ij=1}^{n} (xi - xj)^2 * (x_i - x) + a*(ran - ½) \quad (16)$$

Where x_i is the current solution of the i^{th} firefly and x_j is the current (optimal) solution of j^{th} firefly.

The values of the algorithm's control parameters is α =0.2, γ =1.0, β0= 1.0, and rand is a random number which is uniformly distributed in the space [0,1]. As we can see the distance between two fireflies is calculated using the Euclidean distance (Section II.2) and the generation of a new solution is actually a sum of the current solution (x_i), the metric of the evaluation of the current solution based on the current optimal solution (Euclidian metric), and a random step/move of the algorithm(Section III.3). After the generation of the new solutions, we have to apply the generator capacity constraints so as the new solutions are within the given operational power ranges. To avoid such violation, a repair process is applied to each solution (firefly) in order to guarantee that the generated power outputs are feasible. P_k, P_k min and P_k max denote the current, the minimum, and the maximum power outputs of the *i*th unit, which is associated with the *i*th firefly. Finally, it is notable that for each generation (iteration), the swarm of 12 fireflies is ranked based on their light intensity, and the firefly with the maximum light intensity (i.e., the solution with the higher objective function value) is chosen as the brighter one (i.e., it is a potential optimal solution), while the others are updated based on (16). In the final iteration, the firefly with the brighter light intensity among the swarm of 12 fireflies is chosen as the brightest one which represents the optimal solution of the problem.

5 Simulation Results

To solve the ELD problem, we have implemented the FA in Mat lab 2009 and it was run on a computer with an Intel Core2 Duo (1.8GHz) processor, 3GB RAM memory and MS Windows XP as an operating system. Mathematical calculations and comparisons can be done very quickly and effectively with Mat lab and that is the reason that the proposed Firefly algorithm was implemented in Mat lab 2009 programming environment. Since the performance of the proposed algorithm sometimes depends on input parameters, they should be carefully chosen. After several runs, the following input control parameters are found to be best for optimal performance of the proposed algorithm.

In this proposed method, we represent and associate each firefly with a valid power output (i.e., potential solution) encoded as a real number for each power generator unit, while the fuel cost objective i.e., the objective function of the problem is associated and represented by the light intensity of the fireflies. In this simulation, the values of the control parameters are:

α = 0.2, γ =1.0, β_0 = 1.0, and n =12, and the maximum generation of fireflies (iterations) is 50. The values of the fuel cost, the power limits of each generator, the power loss coefficients, and the total power load demand are supplied as inputs to the firefly algorithm. The power output of each generator, the total system power, the fuel cost with/without transmission losses are considered as outputs of the proposed Firefly algorithm. Initially, the objective function of the given problem is formulated as defined in (1) and it is associated with the light intensity of the swarm of the fireflies. The initial solution of the given problem is generated based on the mathematical formulation as defined in (15).

The FA has been proposed for IEEE - 30 Bus with six generator test system in the references. This power system is connected through 41 transmission lines and the demand 283.4 MW. The input data are given in [5]. The cost coefficient of IEEE - 30 Bus with six generator test system are given in tables 1-5. In this system GA, PSO, BBO, ABC, BFA & FA Algorithms were used in ELD. In table 7, results obtained from proposed FA method has been compared with PSO, GA and other methods. According top the result obtained using the FA for ELD is more advantageous then other Algorithms. In Power System with six generator test system, if ELD is realized by using the FA, a gain of Fuel costs can be achieved in total. Also a total line loss is decreased.

Table 1: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand by '*Pso*'

Unit	**a_k (\$/MWh^2)**	**b_k (\$/MWh)**	**c**	**P_{min} (MW)**	**P_{max} (MW)**	**PSO**
1	0.00375	2.00	0	50	200	175.6627
2	0.01750	1.75	0	20	80	48.6413
5	0.06250	1.00	0	15	50	21.4222
8	0.00834	3.25	0	10	35	22.6219
11	0.02500	3.00	0	10	30	12.3806
13	0.02500	3.00	0	12	40	12.000
Load Demand(MW)						283.400
Power Loss (MW)						9.3287
Total Generation(MW)						292.7287
Generation Cost($/h)						802.0138
CPU Time(Sec.)						26.59

Table 2: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand by '*Ga*'

Unit	**a_k ($/MWh^2)**	**b_k ($/MWh)**	**c**	**P_{min} (MW)**	**P_{max} (MW)**	**GA**
1	0.00375	2.00	0	50	200	175.727
2	0.01750	1.75	0	20	80	48.6812
5	0.06250	1.00	0	15	50	21.4232
8	0.00834	3.25	0	10	35	22.8313
11	0.02500	3.00	0	10	30	12.0667
13	0.02500	3.00	0	12	40	12.00
Load Demand(MW)						283.400
Power Loss (MW)						9.3349
Total Generation(MW)						292.7349
Generation Cost($/h)						802.0150
CPU Time(Sec.)						49.31

Table 3: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand by '*Abc*'

Unit	**a_k ($/MWh^2)**	**b_k ($/MWh)**	**c**	**P_{min} (MW)**	**P_{max} (MW)**	**ABC**
1	0.00375	2.00	0	50	200	173.8262
2	0.01750	1.75	0	20	80	48.998
5	0.06250	1.00	0	15	50	21.386
8	0.00834	3.25	0	10	35	22.63
11	0.02500	3.00	0	10	30	12.928
13	0.02500	3.00	0	12	40	12.00
Load Demand(MW)						283.400
Power Loss (MW)						8.3683
Total Generation(MW)						291.7683
Generation Cost($/h)						802.557
CPU Time(Sec.)						14.89

Table 4: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand By ‘Proposed *Fa*’

Unit	**a_k (\$/MWh^2)**	**b_k (\$/MWh)**	**c**	**P_{min} (MW)**	**P_{max} (MW)**	**Proposed FA**
1	0.00375	2.00	0	50	200	155.6326
2	0.01750	1.75	0	20	80	20.00
5	0.06250	1.00	0	15	50	42.00
8	0.00834	3.25	0	10	35	35.00
11	0.02500	3.00	0	10	30	25.00
13	0.02500	3.00	0	12	40	12.00
Load Demand(MW)						283.400
Power Loss (MW)						6.2326
Total Generation(MW)						289.6326
Generation Cost(\$/h)						801.7708
CPU Time(Sec.)						11.52

Table 5: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand By ‘ *Bfa*’

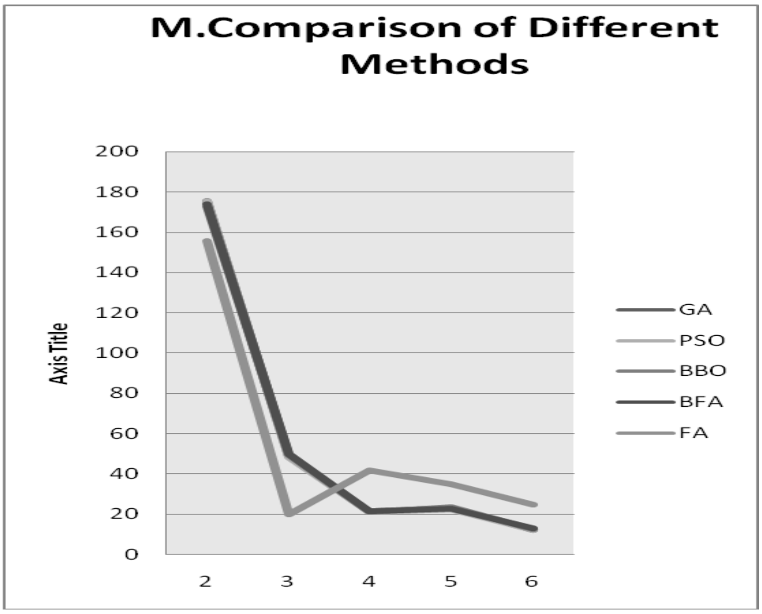
Unit	a_k (\$/MWh^2)	b_k (\$/MWh)	c	P_{min} (MW)	P_{max} (MW)	BFA
1	0.00375	2.00	0	50	200	173.848
2	0.01750	1.75	0	20	80	49.998
5	0.06250	1.00	0	15	50	21.386
8	0.00834	3.25	0	10	35	22.630
11	0.02500	3.00	0	10	30	12.928
13	0.02500	3.00	0	12	40	12.000
Load Demand(MW)						283.4
Power Loss (MW)						9.390
Total Generation(MW)						292.79
Generation Cost(\$/h)						802.62
CPU Time(Sec.)						14.7

Table 6: The Cost Coefficient, Minimum Power Dispatch, Total Cost with Load Demand By '*Bbo*'

Unit	**a_k (\$/MWh^2)**	**b_k (\$/MWh)**	**c**	**P_{min} (MW)**	**P_{max} (MW)**	**BBO**
1	0.00375	2.00	0	50	200	172.648
2	0.01750	1.75	0	20	80	49.378
5	0.06250	1.00	0	15	50	21.386
8	0.00834	3.25	0	10	35	23.630
11	0.02500	3.00	0	10	30	12.728
13	0.02500	3.00	0	12	40	13.580
Load Demand(MW)						283.4
Power Loss (MW)						8.390
Total Generation(MW)						292.79
Generation Cost($/h)						802.62
CPU Time(Sec.)						13.4

Table 7: Comparison of Different Methods

Unit	GA	PSO	BBO	BFA	FA (Proposed)
P_k1(MW)	175.727	175.662	172.648	173.84	155.632
P_k 2(MW)	48.6812	48.6413	49.378	49.998	20.00
P_k 3(MW)	21.4232	21.4222	21.386	21.386	42.00
P_k 4(MW)	22.8313	22.6219	23.630	22.630	35.00
P_k 5(MW)	12.0667	12.3806	12.728	12.928	25.00
P_k 6(MW)	12.00	12.000	13.580	12.000	12.00
Load Demand(MW)	283.400	283.400	283.4	283.4	283.400
Power Loss (MW)	9.3349	9.3287	8.390	9.390	6.2326
Total Generation(MW)	292.7349	292.728	292.79	292.79	289.632
Generation Cost($/h)	802.0150	802.013	802.62	802.62	801.770
CPU Time(Sec.)	49.31	26.59	13.4	14.7	11.52



6 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 characteristic.

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