Economic Load Dispatch Problem of Power Plant In Electric Generation System Using Firefly Algorithm

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Abstract- *In this paper work, we have applied the Firefly Algorithm (FA) for some non-linear benchmark functions to highlight the efficiency of algorithm. Global Economic Load Dispatch Problem (ELDP) of power plant in thermal electric generation system is discussed and implemented with Firefly Algorithm (FA) optimization technique. Then, we have included the a few renewable sources in ELDP problem, by estimating solar and wind power generation through probability density function including the underestimation and overestimation cost of solar and wind units. In this work we have assumed that the renewable source units are located near the load, hence we are neglecting the transmission losses by renewable sources and considering them only for the thermal units. The performance of the proposed method has been demonstrated under simulated conditions on 5-Generation units with and without inclusion of renewable sources along with different combinations of renewable sources and validated them with experimental approach. The simulation results show that the proposed algorithm outperforms previous optimization methods.*

I. INTRODUCTION

Today, as an engineer it is always in concern to obtain a product at a minimum cost by reducing either the product operating cost or by reducing the raw or input cost to the production unit. ELDP has a common meaning – the practice of operating a coordinated power system such that the lowest operating cost generators are used to the greatest extent and the highest operating cost generator are used to the lowest extent.

Several deterministic optimization approaches were proposed to solve the ELDP, including lambda iteration method, gradient method, linear programming, non-linear programming, dynamic programming and quadratic programming. But these methods require vast efforts in terms of computation. Due to complexities of computing, therefore developing efficient algorithm to find optimal solution viz. genetic algorithm, particle swarm optimization, evolutionary programming, artificial bee colony optimization, and biogeography based optimization; bacterial foraging and also their variants came into picture.

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 FA, 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 FA 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.
Wind power has vast possibility of expansion in India especially in the coastal plains.Winds in India are influenced by strong south-west summer monsoon in months of April to September where as are weakest in north-east winter monsoons. Total 1100 wind monitoring stations are established in India in 33 states/UTs, also it was estimated that 233 sites with annual average wind power density to be greater than 200 Watts/m^2. In future wind power growth in India is estimated to be around 1, 00,000 MW. Further there is a vast scope of the solar power generation in India due to the high solar irradiance index and also a very high estimated life of a solar power plant. Presently many projects are already in progress employing solar power generation in Rajasthan,

Gujarat and other regions of the country. India currently has a grid connected power capacity of around 10,000 MW. After allowing 100% FDI in wind sector and providing Generation Based Incentives (GBI), wind power sector has boosted [5].

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 ELDP. 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.

II. 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:-

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

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

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

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

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

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

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

So that,

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

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

$$F_T = MIN(\sum_{k=1}^{n} F_k\,[P_k]) \qquad (6)$$

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

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

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

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

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

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

So that,

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

II.3. - ELD with Renewable Energy Source. The objective function of the new ELD problem [6] with the renewable sources can be described as,

$$F_T = MIN\left\{(\sum_{k=1}^{n} F_k\,[P_k]) + \sum_{i=1}^{m} F_i[P_{wi}] + \sum_{j=1}^{s} F_j[P_{pvj}]\right\} \qquad (10\text{-i})$$

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

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

$$F_T - (P_D + P_L) = 0 \qquad (10\text{-ii})$$

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

So that,

$$P_k^{min} \le P_k \le P_k^{max} \quad (10\text{-iii})$$
$$0 \le P_{wi} \le P_{wi}^{max} \quad (10\text{-iv})$$
$$0 \le P_{pvj} \le P_{pvj}^{max} \quad (10\text{-v})$$

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

III. 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]:

$$\beta(r) = \beta_0^{m} \exp(\gamma r^{m}) \ with\ m \ge 1. \quad (11)$$

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]:

$$x_i = x_i + \beta 0 * \exp(-\gamma r^2_{ij})*(x_j - x_i) + a*(\text{rand} - \tfrac{1}{2}) \quad (14)$$

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 $\gamma \to \infty$, the attractiveness coefficient is the Dirac delta function $\beta(r) \to \delta(r)$. 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].

IV. 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:

$\alpha = 0.2$, $\gamma = 1.0$, $\beta_0 = 1.0$, 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 = rand *(upper-range − lower-range) + lower-range, (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:

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

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, $\beta 0$= 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.

V. 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 five generator test system in the references. In this work we are calculating only fuel cost of the thermal units, since the fuel cost of the renewable energy sources is zero and operating cost is only considered for the renewable farms. Further, the renewable sources are considered to be located near the loadcenter, so that the transmission loss are due to power transfer from thermal units to the load center is considered. In this case study we have each unit of 30 MW.

Table 1: Result of the ELD with Thermal units and renewable sources combined

S.No	Load demand (MW)	Thermal units			Wind units	Solar units	Fuel cost	Transmission loss	Elapsed (Sec.)
		P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	(Rs./Hr.)	P_L(MW)	
1.	**50**	10.90	13.33	11.14	7.36	8.48	755.94	0.21	2.66
2.	**100**	21.13	19.82	18.78	20.71	20.09	936.82	0.52	2.43
3.	**125**	23.19	30.96	26.07	21.52	24.16	1083.30	0.90	1.57
4.	**150**	34.08	40.66	28.39	23.46	24.87	1252.76	1.45	1.39
5.	**200**	47.63	61.01	42.06	25.09	27.01	1607.56	2.79	1.39

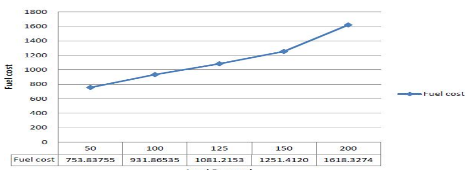

Figure 1 Fuel cost v/s Load Demand curve

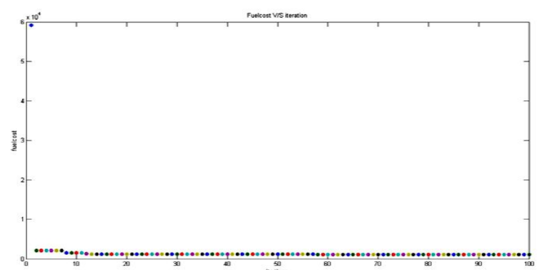

Figure 2 Fuel cost v/s iteration curve 125 MW

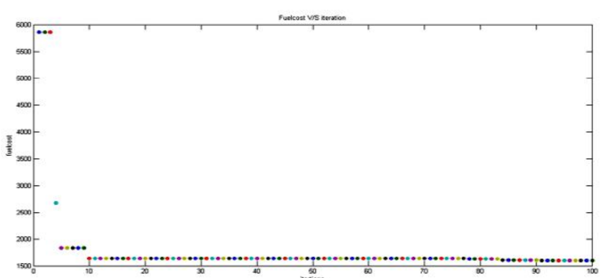

Figure 3 Fuel cost v/s iteration curve 200 MW

VI. CONCLUSION

The firefly algorithm developed by Yang works on the flashing behaviour of the fireflies and widely has been applied on different benchmark functions to find the accuracy and the efficiency of algorithm. For various load demands of four different test cases considered, simulations were performed to solve the constrained optimization ELD problem with and without inclusion of renewable sources of energy for obtaining optimal value of power generation. From the results it can inferred that firefly algorithm gives better optimal solution than lambda iteration techniques. From the simulations it was also seen that proper selection of population size, the number of iterations and the absorption coefficient for the convergence of the algorithm is important as this heavily depends on objective function of the problem.

With the inclusion of renewable sources of energy in the problem, the dispatching of load demand was simulated and it was concluded that the fuel cost of the thermal generating units and transmission losses (due to power transfer from thermal units to load centre) both reduces. This was due to the sharing of load demand by the renewable sources, the power generation by thermal units reduces and finally fuel cost reduces keeping the energy balance and other constraints within limits. A proper estimation of solar and wind probability density function should be made to determine actual probability of wind and solar power generation. The penalty cost and reserve cost coefficients however depend from state to state and country to country and their policies. These should be taken for the place for which the power estimation of wind and solar is to be made.

VII. FUTURE SCOPE

The results of firefly algorithm depend upon the best solution within a swarm. Therefore, improvising solution will be possible to improve the search power within the swarm. The binary coded firefly algorithm showed the application of firefly algorithm to problem with binary representation. Several variants of firefly algorithm viz. Gaussian, levy flight, chaos firefly algorithm, parallel firefly algorithm, can be used to improve the tuning of parameters and for higher converging rate. The hybridization of firefly algorithm with others can also made be possible to make local searches more pronounced. The solution of ELD problem with hybrid firefly algorithm may also provide better optimal solution with higher convergence rate and lower elapsed time.

In India renewable power generation has a vast scope in future, various renewable energies like tidal energy, geothermal, bio energy, hydro energy and many more can be used for power generation. Since majority of population depends on agricultural farming for their livelihood and large amount of agricultural waste is produced which can also be utilized to produce electrical energy which further can be dispatched to grids or to local load centres. Moreover, in rural areas the bio organic waste can also be used to produce power for their local power demand requirements. Moreover, power from other renewable sources like tidal, geothermal etc. can be dispatch to the grid, or can be directly consumed to full fill the load demands. Such practices may reduce the power generation from fossil fuel fired generating plants. The ELD problem with the inclusion of above mentioned resources of energy can be possible and then it will reduce the fuel cost of fossil fuel fired generating units and transmission losses due to power transfer from these units to the load centre.

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