Multiobjective Deterministic Economic-Emission Load Dispatch Optimization Problem using Firefly Algorithm

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Abstract: Environmental pollution is on the increase due to industrial advancement. Due to the environmental concerns that arise from the emissions produced by fossil-fueled electric power plants, the classical economic dispatch, which operates electric power systems so as to minimize only the total fuel cost, can no longer be considered alone. Thus, by environmental dispatch, emissions can be reduced by dispatch of power generation to minimize emissions. The economic-emission load dispatch problem has been most commonly solved using a deterministic approach. However, power generated, system loads, fuel cost and emission coefficients are subjected to inaccuracies and uncertainties in real-world situations. This paper describe and Introduce a new nature Inspired Artificial Intelligence method called Firefly Algorithm(FA). The Firefly Algorithm is a stochastic Meta heuristic approach based on the idealized behavior of the flashing characteristics of fireflies. The aim is to minimize NOx emission and the generating unit's combined fuel cost having quadratic cost characteristics subjected to limits on generator real power output & transmission losses. This paper presents an application of the FA to EELD for different Test Case system. The obtained solution quality and computation efficiency is compared to another artificial intelligence technique, called Genetic algorithm (GA) . The simulation results show that the proposed algorithm outperforms previous artificial intelligence method.

Keywords: Economic Emission Dispatch, Firefly Algorithm, Genetic Algorithm

I. INTRODUCTION

The classical economic dispatch problem is to operate electric power systems so as to minimize the total fuel cost. This single objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil fueled electric power plants. In fact, the Clean Air Act Amendments have been applied to reduce SO_2 and NO_x emissions from such power plants. Accordingly, emissions can be reduced by dispatch of power generation to minimize emissions instead of or as a supplement to the usual cost objective of economic dispatch.

Environmental/economic dispatch is a multi-objective problem with conflicting objectives because pollution is conflicting with minimum cost of generation. Various techniques have been proposed to solve this multi-objective problem whereby most researchers have concentrated on the deterministic problem.

For solving this knowledge-based or Artificial Intelligence techniques are used increasingly as alternatives to more classical techniques to model environmental systems. Artificial Intelligence (AI) could be defined as the ability of computer software and hardware to do those things that we, as humans, recognize as intelligent behavior.

A new algorithm that belongs in the category of nature inspired algorithms is the firefly algorithm, which was developed by Dr. Xin-She Yang at Cambridge University in 2007, shows its superiority over some traditional algorithms [5], [8]. Firefly algorithm 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[9-12]. In the firefly algorithm, the objective function of a given problem is associated with 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, the firefly algorithm is used to solve the multiobjective EELD problem.

For the efficiency and validation of this algorithm, hear using as an example, two case study system of 3 generators and 6 generators, and compare the solutions obtained with the ones obtained by alternative optimization techniques that have been successfully applied by many researchers in order to solve these types of problems, such as the Genetic algorithm[6][7].

II. ECONOMIC EMISSION LOAD DISPATCH

The economic emission load dispatch involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The deterministic problem is formulated as described below.

2.1 Objective Functions

Fuel Cost Objective. The classical economic dispatch problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the total required demand can be mathematically stated as follows [26]:

$$C = \sum_{i=1}^{n} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) \text{Rs/hr} \quad ....(1)$$

where
C: total fuel cost Rs/hr),
a_i, b_i, c_i: fuel cost coefficients of generator i,
P_{Gi}: power generated (p.u.) by generator i, and
n: number of generators.

NOx Emission Objective. The minimum emission dispatch optimizes the above classical economic dispatch including NO_x emission objective, which can be modeled using second order polynomial functions [15]:

$$E_{NO_x} = \sum_{i=1}^{n} \left(a_{iN} + b_{iN} P_{Gi} + c_{iN} P_{Gi}^2 + d_{iN} \sin\left(e_{iN} P_{Gi} \right) \right) \text{ton/hr} \quad ....(2)$$

2.2 Constraints

The optimization problem is bounded by the following constraints:

Power balance constraint. The total power generated must supply the total load demand and the transmission losses.

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_L = 0 \quad ....(3)$$

where
P_D: total load demand (p.u.), and
P_L: transmission losses (p.u.).
The transmission losses is given by

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} P_i P_j \quad ....(4)$$

where, B_{ij} are the elements of the loss coefficient matrix B and P_i and P_j are the out powers of the ith and j^{th} generator; respectively.

Maximum and minimum limits of power generation. The power generated P_{Gi} by each generator is constrained between its minimum and maximum limits, i.e.,

$$P_{Gi\,min} \leq P_{Gi} \leq P_{Gi\,max} \quad ....(5)$$

where
P_{Gimin}: minimum power generated, and
P_{Gimax}: maximum power generated.

2.3 Multiobjective Formulation

The multiobjective deterministic environmental/economic dispatch optimization problem is therefore formulated as:

Minimize [C, E_{NO_x}]

subject to:

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_L = 0 \quad \text{(power balance), and} \quad ....(6)$$

$$P_{Gi\,min} \leq P_{Gi} \leq P_{Gi\,max} \quad \text{(generation limits)} \quad .... (7)$$

III. THE GENETIC ALGORITHM

Genetic algorithms were formally introduced in the United States in the 1970s by John Holland at University of Michigan. Genetic algorithm is based on the mechanics of natural selection and natural genetics [7].Its fundamental principle is that *the fittest member of* population *has the highest probability for survival.* The genetic algorithm, works only with objective function information in a search for an optimal parameter set. In particular, genetic algorithms work very well on mixed (continuous and discrete), combinatorial problems. They are less susceptible to getting 'stuck' at local optima than gradient search methods. But they tend to be computationally expensive. To use a genetic algorithm, it must represent a solution to your problem as a genome (or chromosome)[6] The genetic algorithm then creates a population of solutions and applies genetic operators such as mutation and crossover to evolve the solutions in order to find the best one(s) which is shown in Fig:2, as no of iteration increased the value of fitness function(objective function) improves.
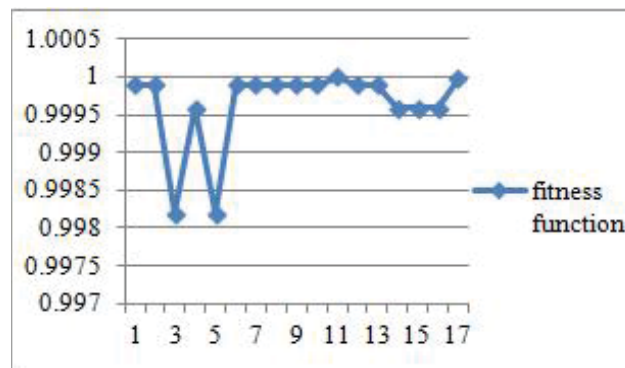

Fig. 2. fitness function of GA Versus no of iterations.

IV. PROPOSED METHOD: THE FIREFLY ALGORITHM

4.1. Description

This algorithm (FA) is based on the social (flashing) behavior of fireflies, or lighting bugs [3][11]. 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. Although the firefly algorithm has many similarities with other algorithms which are based on the swarm intelligence, such as the Particle Swarm Optimization (PSO), Artificial Bee Colony optimization (ABC), and Bacterial

Foraging (BFA) algorithms, it is indubitably much simpler both in concept and implementation[13][4][11].Moreover, according to recent bibliography, the algorithm is very efficient and can perform better than 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 [4][11].The main advantage of FA is that it uses mainly real random numbers, and it is based on the global communication among the swarming particles (i.e., the fireflies).

The firefly algorithm has three idealized rules which are based on some of the major flashing characteristics of

real fireflies [3][8].

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

4) the objective function of a given problem. For maximization problems, the light intensity is proportional to the value of the objective function.

4.2 Attractiveness

In the firefly algorithm, the form of attractiveness function of a firefly is the following monotonically decreasing function [6][7][8][10]:

$$\beta(r) = \beta_o * \exp(-\gamma r^m) \quad m \geq 1, \quad \ldots\ldots (8)$$

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.

4.3 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 [6][7][10]:

$$r_{ij} = \left\| x_i - x_j \right\| \quad \ldots\ldots\ldots\ldots (9)$$

$$r_{ij} = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad \ldots\ldots\ldots(10)$$

where $x_{i,k}$ is the kth component of the spatial coordinate x_i of the ith firefly and d is the number of dimensions , for d =2,

4.4. 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][8][10]:

$$x_i = x_i + \beta_o * \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (rand - 0.5) \quad \ldots\ldots\ldots(11)$$

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 α is a coefficient of randomization parameter, while rand is a random number generator uniformly distributed in the space [0,1]. Hear $\beta_0 = 1.0$, α =[0, 1] and the attractiveness or absorption coefficient γ =1.0, which guarantees a quick convergence of the algorithm to the optimal solution.

The basic steps of the FA can be summarized as the pseudo code for Firefly Algorithm as follows.

Pseudocode for proposed Firefly algorithm:

Input: $\alpha, \gamma, \beta_0, n$, Maximum Generation, B, cost- coefficients Output: P_{Gi} for $i = 1, \ldots 6$, $f(X), f_1(X), f_2(X)$

Begin of algorithm:

Define the objective function: max $-f(P_{Gi})$, with $i = 1, \ldots$, no of generators.

Generate initial population of fireflies $n = 1, \ldots, 12$ (generate $n =12$ initial solutions)

Light Intensity of firefly n is determined by objective function, $In = f(P_{Gi})$

Define $\alpha = 0.2$, $\beta_0 =1.0$ and $\gamma =1.0$ %necessary algorithm's parameters

While ($t \leq$ MaxGeneration =50)

For $i = 1 : 12$ (for all fireflies (solutions)) For $j = 1 : 12$ (for all fireflies (solutions)) If ($I_i < I_j$)

Then move firefly i towards firefly j (move towards brighter one)

Attractiveness varies with distance r_{ij} via $\exp(-\gamma r_{ij})$ Generate and evaluate new solutions and update Light Intensity

End for j loop End for i loop

Check the ranges of the given solutions and update them as appropriate

Rank the fireflies, find and display the current best %max solution for each iteration

End of while loop

% Post-process results and visualization

Find the firefly with the highest Light Intensity among all fireflies %optimal solution

End of algorithm

As shown in Fig:3 as no of iteration increased the value of light intensity(objective function) improves.
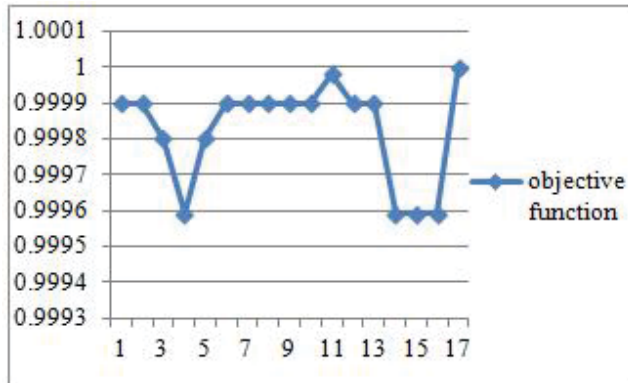
V. SIMULATION RESULTS AND DISCUSSION

To solve the EELD problem, this paper implement the FA in MATLAB 2008 and it was run on a portable computer with an Intel Core2 Duo (1.8GHz) processor, 2GB RAM memory and MS Windows 7 as an operating system. Mathematical calculations and comparisons can be done very quickly and effectively with MATLAB and that is the reason that the proposed Firefly algorithm was implemented in MATLAB programming environment. In this proposed method, each firefly represent and associate 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 10. 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 transmission losses are considered as outputs of the proposed Firefly algorithm. Initially, the objective function of the given problem is formulated and it is associated with the light intensity of the swarm of the fireflies.

The FA has been proposed for two case studies (3 and 6 generators) systems. In this system GA & FA Algorithms were used in EELD. In table 2, results obtained from proposed FA method has been compared with other method. According to the result obtained using the FA for EELD is more advantageous then Genetic Algorithm.

5.1. Case Study I: Three-Unit System

This case study consists of three thermal units.

The Input and cost coefficients are shown in Tables 1 . In this case, the load demand expected to be determined is PD = 850 MW.

Table 1. Data for the three thermal units of generating unit capacity and coefficients.

Unit	$P_i$min	$P_i$max	a	b	c	d	e
1	100	600	0.0016	7.92	561	300	0.032
2	50	200	0.0048	7.92	78	150	0.063
3	100	400	0.0019	7.85	310	200	0.042

5.2. Case Study II: Six-Unit System

This case study consists of six thermal units.

The Input and cost coefficients are shown in Tables 2. In this case, the load demand expected to be determined is PD = 1263 MW.

Table 2. Data for the six thermal units of generating unit capacity and coefficients.

Unit	$P_i$min	$P_i$max	a	b	c	d	e
1	100	500	0.0070	7.0	240	300	0.035
2	50	200	0.0095	10.0	200	200	0.042
3	80	300	0.0090	8.5	220	200	0.042
4	50	150	0.0090	11.0	200	150	0.063
5	50	200	0.0080	10.5	220	150	0.063
6	50	120	0.0075	12.0	190	150	0.063

Table 3. Comparison table showing simulation results of various algorithms for three-unit system.

	FA(Proposed Algorithm)	GA
PG1(MW)	297.25	297.27
PG2(MW)	186.25	186.32
PG3(MW)	367.56	367.63
Total power	851.09	851.22
Fuel cost(INR.)	8543.5	8543.9
Ploss(MW)	1.2001	1.2005

Table 4. Comparison table showing simulation results of various algorithms for six-unit system.

	FA(Proposed Algorithm)	GA
PG1(MW)	473.27	485.56
PG2(MW)	145.19	181.09
PG3(MW)	295.29	244.61
PG4(MW)	96.356	77.126
PG5(MW)	164.98	196.72
PG6(MW)	93.342	92.451
Total power	1268.4	1277.5
Fuel cost(INR.)	16200	16251
Ploss(MW)	13.731	14.569

VI. CONCLUSION

The proposed FA to solve Economic emission Load Dispatch of generation by considering the practical constraints has been presented in this paper. The feasibility of the proposed method for solving the non-smooth economic emission load dispatch problem is demonstrated using three and six units test system. Algorithm for economic emission dispatch, is developed for FA and GA in MATLAB. From the comparison Fig 4 and Fig 5, it is observed that the proposed algorithm exhibits a comparative performance with respect to other population based technique(GA). It is clear from the results that Firefly algorithm is capable of obtaining higher quality solution with better computation efficiency and stable convergence characteristic. The effectiveness of FA was demonstrated and

tested. From the simulations, it can be seen that FA gave the best result of total cost minimization and reduced fuel cost and Power loss compared to the other method.
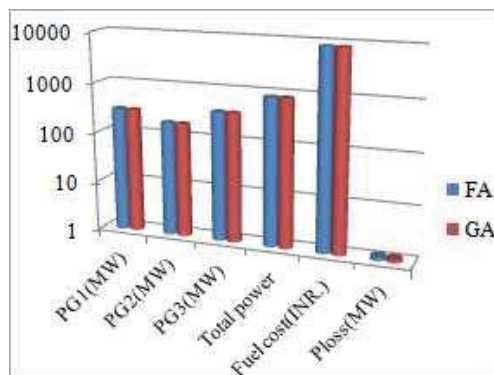

Fig. 4. Comparison graph showing simulation results of various algorithms for three-unit system.
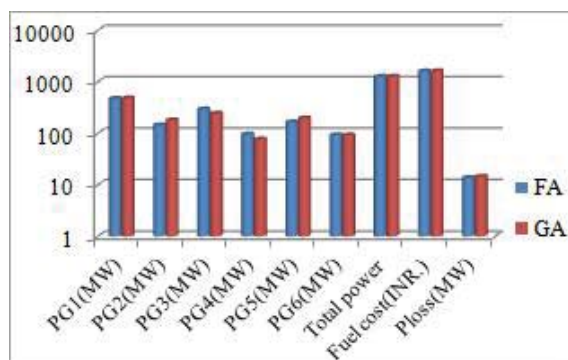

Fig. 5. Comparison graph showing simulation results of various algorithms for six-unit system.

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