An Efficient Meta Heuristic Algorithm to Solve Economic Load Dispatch Problems

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Abstract: The Economic Load Dispatch (ELD) problems in power generation systems are to reduce the fuel cost by reducing the total cost for the generation of electric power. This paper presents an efficient Modified Firefly Algorithm (MFA), for solving ELD Problem. The main objective of the problems is to minimize the total fuel cost of the generating units having quadratic cost functions subjected to limits on generator true power output and transmission losses. The MFA is a stochastic, Meta heuristic approach based on the idealized behaviour of the flashing characteristics of fireflies. This paper presents an application of MFA to ELD for six generator test case system. MFA is applied to ELD problem and compared its solution quality and computation efficiency to Genetic algorithm (GA), Differential Evolution (DE), Particle swarm optimization (PSO), Artificial Bee Colony optimization (ABC), Biogeography-Based Optimization (BBO), Bacterial Foraging optimization (BFO), Firefly Algorithm (FA) techniques. The simulation result shows that the proposed algorithm outperforms previous optimization methods.

Keywords: Artificial Bee Colony optimization, Biogeography-Based Optimization, Economic Load Dispatch, Firefly Algorithm, Genetic algorithm, Particle swarm optimization.

1 Introduction

Electrical power industry restructuring has created highly vibrant and competitive market that altered many aspects of the power industry. In this changed scenario, scarcity of energy resources, increasing power generation cost, environment concern, ever growing demand for electrical energy necessitate optimal dispatch.Economic Load Dispatch (ELD) [1], is one of the important optimization problem in power systems that have the objective of dividing the power demand among the online generators economically while satisfying various constraints. Since the cost of the power generation is exorbitant, an optimum dispatch saves a considerable amount of money. Optimal generation dispatch is one of the most important problems in power system engineering, being a technique commonly used by operators in every day system operations. Optimal generation seeks to allocate the real and reactive power throughout power system obtaining optimal operating state that reduces cost and improves overall system efficiency. The ELD problem reduces the system cost by allocating the real power among online generating units.

In the ELD problem the classical formulation presents deficiencies due to simplicity of models. Here, the power system modelled through the power balance equation and generators are modelled with smooth quadratic cost functions and generator output constraints.

To improve power system studies, new models are continuously being developed that result in a more efficient system operations. Cost functions that consider valve point loadings, fuel switching, and prohibited operating zones as well as constraints that provide more accurate representation of system such as: emission, ramp rate limits, line flow limits, spinning reserve requirement and system voltage profile. The improved models generally increase the level of complexity of the optimization problem due to the non-linearity associated with them.

Traditional algorithms like lambda iteration, base point participation factor, gradient method, and Newton method can solve the ELD problems effectively if and only if the fuel-cost curves of the generating units are piece-wise linear and monotonically increasing. The basic ELD considers the power balance constraint apart from the generating capacity limits. However, a practical ELD must take ramp rate limits, prohibited operating zones, valve point effects, and multi fuel options into consideration to provide the completeness for the ELD formulation. The resulting ELD is a non-convex optimization problem, which is a challenging one and cannot be solved by the traditional methods. Practical ELD problems have nonlinear, non-convex type objective function with intense equality and inequality constraints. Recent advances in computation and the search for better results of complex optimization problems have fomented the development of techniques known as Evolutionary Algorithms. Evolutionary Algorithms are stochastic based optimization techniques that search for the solution of problems using a simplified model of the evolutionary process. These algorithms provide an alternative for obtaining global optimal solutions, especially in the presence of non-continuous, non-convex, highly solution spaces. These algorithms are population based techniques which explore the solution space randomly by using several candidate solutions instead of the single solution estimate used by many classical techniques. The success of evolutionary algorithms lies in the capability of finding solutions with random exploration of the feasible region rather than exploring the complete region. This result in a faster optimization process with lesser computational resources while maintaining the capability of finding global optima.The conventional optimization method is not able to solve such problems due to local optimum solution convergence. Meta-heuristic optimization techniques especially Genetic Algorithms (GA) [7], Particle Swarm Optimization (PSO) [9], and Differential Evaluation (DE) [14], gained an incredible recognition as the solution algorithm for such type of ELD problems in last decade.

Notations

ai, bi, ci : fuel cost coefficient of i^{th} generator, $\$/MW^2 h$, \$/MW h, \$/h

Fi (Pi) : fuel cost of i^{th} generator, \$/ht; total fuel cost, \$/h n : number of generators

Pi max : maximum generation limit of ith generator, MW

Pi min : minimum generation limit of ith generator, MW

P_L : total system transmission loss, MW

P_d : system power demand, MW

B_{mn} : transmission loss coefficients, 1/MW

2 Problem Formulation

The classical ELD problem is an optimization problem that determines the power output of each online generator that will result in a least cost system operating state. The objective of the classical economic dispatch is to minimize the total system cost where the total system cost is a function composed by the sum of the cost functions of each generator. This power allocation is done considering system balance between generation and loads, and feasible regions of operation for each generating unit.

The objective of the classical ELD is to minimize the total fuel cost by adjusting the power output of each of the generators connected to the grid. The total fuel cost is modelled as the sum of the cost function of each generator.

The basic economic dispatch problem can be described mathematically as a minimization of problem.

$$\text{Minimize Ft} = \sum_{i=1}^{n} F_i(P_i) \qquad (1)$$

Where F_i (P_i) is the fuel cost equation of the ith plant. It is the variation of fuel cost in \$ with generated Power (MW).

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \qquad (2)$$

The total fuel cost is to be minimized subject to the following constraints.

$$\sum_{i=1}^{n} P_i = P_d + P_l \tag{3}$$

$$P_l = \sum_{i}^{n} \sum_{j}^{j} P_i B_{ij} P_j \tag{4}$$

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{5}$$

3 The Firefly Algorithm

The Firefly Algorithm (FA) [10], 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. 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) [9], and Artificial Bee Colony optimization (ABC) [11], algorithms it is indeed much simpler both in concept and implementation. The main advantage is that it uses mainly real random numbers, and it is based on the global communication among the swarm 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. They are

- All fireflies are unisex, and they will move towards more attractive and brighter ones regardless their sex.
- 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.

- 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.

3.1 Algorithm

Step 1: Read the system data such as cost coefficients, minimum and maximum power limits of all generator units, power demand and B-coefficients.

Step 2: Initialize the parameters and constants of Firefly Algorithm. They are **noff, α_{max}, α_{min}, β_0, γ_{min}, γ_{max} and itermax** (maximum number of iterations).

Step 3: Generate **noff** number of fireflies randomly between λ_{min} and λ_{max}.

Step 4: Set iteration count to 1.

Step 5: Calculate the fitness values corresponding to **noff** number of fireflies.

Step 6: Obtain the best fitness value **GbestFV** by comparing all the fitness values and also obtain the best firefly values **GbestFF corresponding** to the best fitness value **GbestFV**.

Step 7: Determine alpha (**α**) value of current iteration using the following equation: **α (iter)** = αmax - ((αmax - αmin) (current Iteration number)/ **itermax**)

Step 8: Determine the r_{ij} values of each firefly using the following equation: r_{ij}= **GbestFV -FV** r_{ij} is obtained by finding the difference between the best fitness value **GbestFV** (**GbestFV** is the best fitness value i.e., j^{th} firefly) and fitness value **FV** of the i^{th} firefly.

Step 9: New xi values are calculated for all the fireflies using the following equation:

$$xi_{new}=xi_{old} + \beta_0 * \exp(-\gamma\, r_{ij}^2 * (x_j - x_i) + \alpha(iter) * (rand - \tfrac{1}{2}) \qquad (6)$$

In equation (6), β_0 is the initial attractiveness γ is the absorption co-efficient r_{ij} is the difference between the best fitness value **GbestFV** and fitness value **FV** of the ith firefly. **α(iter)** is the randomization parameter (In this work, **α (iter)** is set to 0.2) rand is the random number between 0 and 1.In this work, $x \rightarrow \lambda$

Step 10: Iteration count is incremented and if iteration count is not reached maximum then go to step 5

Step 11: **GbestFF** gives the optimal solution of the Economic Load Dispatch problem and the results are printed.

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

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3.2 Pseudo Code

Objective function f(x), $x = (x_1,\ldots,x_d)T$

Generate initial population of fireflies xi (i=1, 2.., n)

Light intensity Ii at xi is determined by $f(x_i)$

Define light absorption coefficient γ

while (t < MaxGeneration)

for i = 1: n all n fireflies

for j = 1: i all n fireflies if (Ij > Ii), More firefly i towards j in d-dimension; end if

Attractiveness varies with distance r via exp $[-\gamma_r]$

Evaluate new solutions and update light intensity

end for j

end for i

Rank the fireflies and find the current best

end while

Post process results and visualization.

4 Modified Firefly Algorithm

The modified firefly algorithm MFA was proposed in this paper to improve the exploration of the searching optimum solution. Two modifications have been done. Firstly, instead of using Cartesian distance of r_{ij}, the modification was done by finding the minimum variation distance between fireflies *i* and secondly, to improve the exploration or diversity of the candidate of solution, the simple mutation corresponds to α is adopted in the FA process. Thus it will enhance the optimum results in solving ELD. The proposed modifications can be summarized as the pseudo code given below.

4.1 Pseudo Code

Objective function f(x) $\mathbf{x} = (x_1,\ldots,x_d)^T$

Generate initial population of fireflies x_i (i=1, 2…, n)

Light intensity I_i at x_i is determined by f (x_i)

Define light absorption coefficient γ

while (t < MaxGeneration)

for i = 1: n all n fireflies

for j = 1: i all n fireflies

if ($I_j > I_i$), More firefly i towards j in d-dimension; end if

Find the minimum variation distance of all

fireflies r = min((firefly i –firefly j))

Attractiveness varies with distance r via exp[-γ_r] Evaluate new solutions and update light intensity

end for j

end for i

randnum

Mutation if randnum < probability of mutation

Rank the fireflies and find the current best end while

Post process results and visualization.

5 Simulation Results

To solve the ELD problem, the MFA is coded with MATLAB programming and it was run on a computer with an Intel Core2 Duo processor, windows operating system. Mathematical calculations and comparisons can be done very quickly and effectively with MATLAB. 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 100. 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 MFA 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 MFA has been proposed for IEEE - 30 Bus with six generator test system from the references. This power system is connected through 41 transmission lines and the demand is 1263MW. The input and the cost coefficients for 3-generator and 6-generator test system are given in table 1 and table 2. In this system GA [4], [7], PSO [9], DE [14], ABC [11], BBO [6], BFO [8], FA [10], [12] and MFA [13] Algorithms were used for solving ELD. In the table 3, table 4 and table 5, the loss coefficient matrix and the results obtained from the proposed MFA method has been compared with other methods for 3 and 6- generator systems respectively. Figure 1and Figure 3 shows the generator output for various algorithms of 3 and 6 generator systems and Figure 2 shows the comparison chart of 6-generator system. According to the result obtained, the MFA for ELD is more advantageous than all other Algorithms. From the simulation results of six generator test system for ELD using MFA method, the total fuel cost and total line losses are decreased than all other algorithms.

Table 1 Generating unit capacity and Fuel cost co-efficient for 3- generator unit.

Unit	$P_{i\,min}$ (MW)	$P_{i\,max}$ (MW)	c_i	b_i	a_i
1	150	600	561	7.92	0.001562
2	100	400	310	7.85	0.00194
3	50	200	78	7.97	0.00482

Table 2 Generating unit capacity and Fuel cost co-efficient for 6- generator unit.

Unit	$P_{i\,min}$ (MW)	$P_{i\,max}$ (MW)	c_i	b_i	a_i
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 3 Loss Co-Efficient Matrix

$$B_{mn}= \begin{pmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{pmatrix}$$

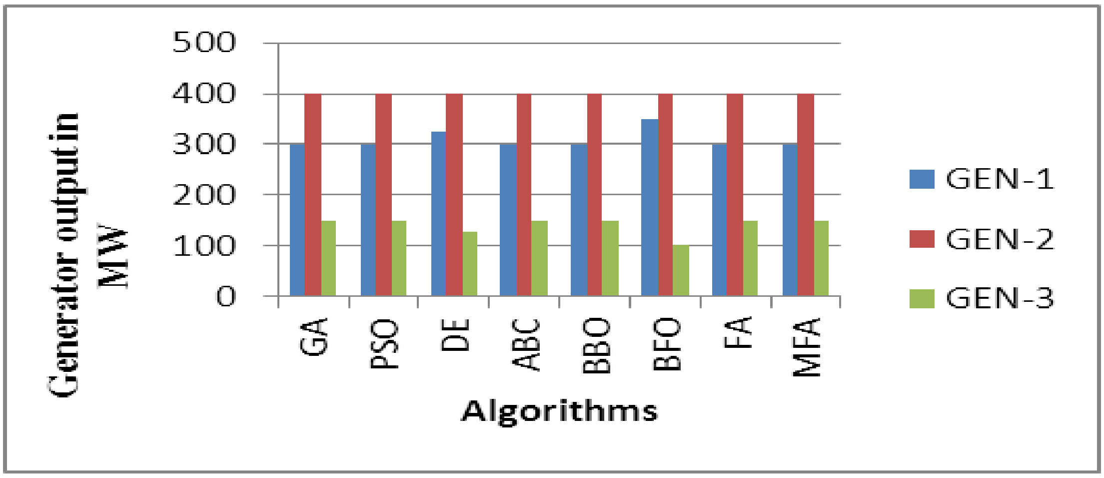

Figure 1 Output graph of 3 generator system for Various Algorithms

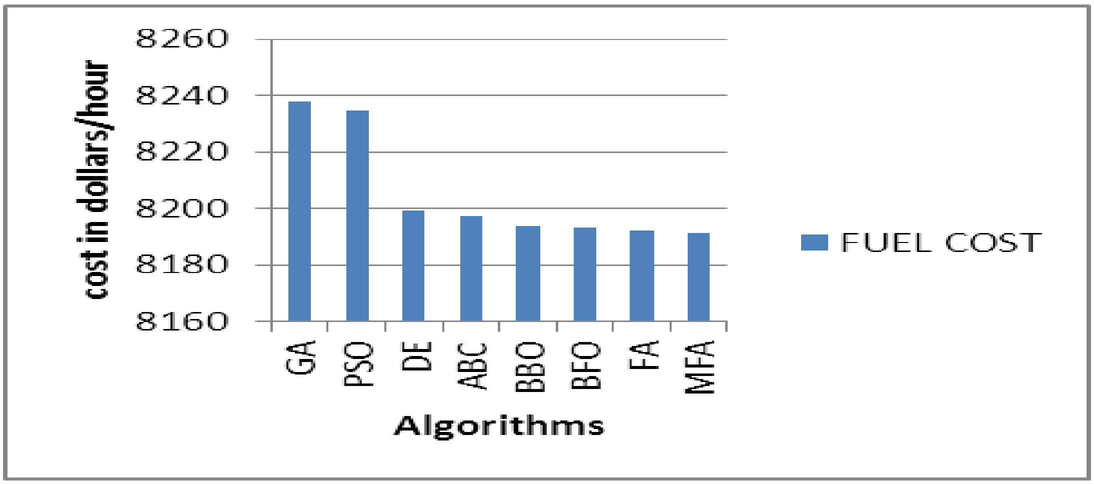

Figure 2 Fuel cost graph of 3 generator system for various Algorithms

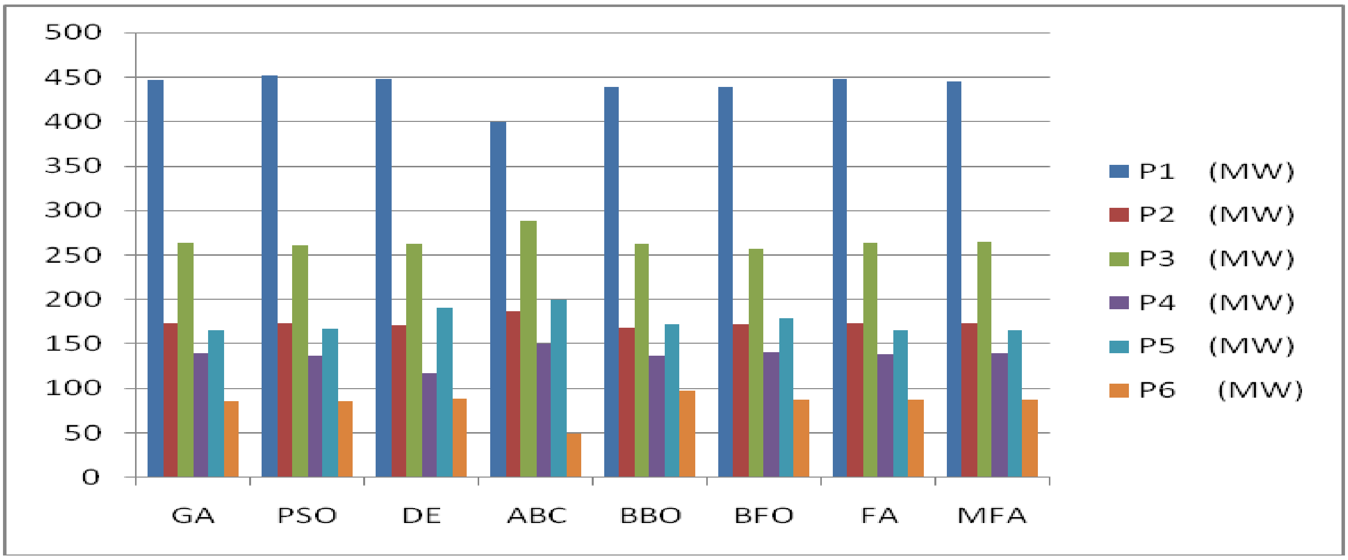

Figure 3 Comparison Chart Showing Total Power Output, Power Loss, Fuel Cost and Total Line Losses of 6-generator system for various Algorithms

Table 4 Comparison Table Showing Simulation Result Of 3-generator unit for GA, PSO, DE, ABC, BBO, BFO, FA and MFA Algorithms

Sl.No	Description	GA	PSO	DE	ABC	BBO	BFO	FA	MFA
1.	P_1 (MW)	300.00	300.27	324.40	300.25	300.28	349.46	300.00	300.00
2.	P_2 (MW)	400.00	400.00	399.19	399.98	399.99	399.19	400.00	400.00
3.	P_3 (MW)	150.00	149.73	126.41	149.77	149.73	101.35	150.00	150.00
4.	Power Output (MW)	850.00	850.00	850.00	850.00	850.00	850.00	850.00	850.00
5.	Fuel cost **($/h)**	8237.60	8234.72	8199.29	8197.39	8194.07	8193.44	8192.32	8191.13

Table 5 Comparison Table Showing Simulation Result of 6-generator unit for GA, PSO, DE, ABC, BBO, BFO, FA and MFA Algorithms

Sl.no	Description	GA	PSO	DE	ABC	BBO	BFO	FA	MFA
1.	**P_1 (MW)**	447.08	451.97	447.50	400.00	438.65	438.21	445.08	**447.39**
2.	**P_2 (MW)**	173.18	173.16	170.52	186.55	167.90	172.58	173.08	**173.24**
3.	**P_3 (MW)**	263.92	261.16	261.90	289.00	262.82	257.42	264.42	**263.32**
4.	**P_4 (MW)**	139.06	136.85	116.91	150.00	136.77	141.09	139.59	**138.00**
5.	**P_5 (MW)**	165.58	166.70	190.41	200.00	171.76	179.37	166.02	**165.41**
6.	**P_6 (MW)**	86.63	85.68	88.49	50.00	97.67	86.88	87.21	**87.80**
7.	**Power Output MW)**	1275.47	1275.52	1275.73	1275.55	1275.57	1275.73	1275.40	**1275.50**
8.	**P_{loss} (MW)**	12.47	12.52	12.73	12.55	12.52	12.55	12.40	**12.50**
9.	**Fuel cost ($/h)**	15466.00	15458.00	15456.56	15452.00	15445.90	15446.00	15443.00	**15442.90**
10.	**Execution time(sec.)**	62.02	58.18	54.09	6.20	2.82	4.23	8.52	**11.02**

6 Conclusion

The proposed MFA to solve ELD problem by considering the practical constraints has been presented in this paper. From the comparison table it is observed that the proposed algorithm exhibits a better performance with respect to all other techniques. The effectiveness of MFA was demonstrated and tested in this research. From the simulations, it can be seen that MFA gave the best result of total cost minimization compared to all other optimization methods. In future, the proposed MFA can be used to solve ELD considering the valve point loading effects.

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