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A Hybrid Firefly-DE Algorithm For Economic Load Dispatch

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Abstract- Economic load dispatch (ELD) is an important optimization task in power system. It is the process of allocating generation among the committed units such that the constraints imposed are satisfied and the energy requirements are minimized. There are three criteria in solving the economic load dispatch problem. They are minimizing the total generator operating cost, total emission cost and scheduling the generator units Economic Load Dispatch (ELD) problem in power systems has been solved by various optimization methods in the recent years, for efficient and reliable power generation. This paper introduces a solution to ELD problem using a new metaheuristic nature-inspired Hybrid algorithm called DE-Firefly Algorithm (FFA). The proposed approach has been applied to 3 unit test system. The results proved the efficiency and robustness of the proposed method when compared with the other Existed algorithm.

***Keywords* -** Economic Load Dispatch, Differential Evolution, Firefly Algorithm, Hybrid DE-Firefly Algorithm

1. INTRODUCTION

To manage with the increasing demand for electric power, the electric power industry has witnessed major changes i.e. deregulated electricity markets. These competitive markets reduce costs. The increased diffusion of non-dispatchable renewable sources, such as wind and solar, adds another degree of complexity to the scheduling of economic power dispatch. It becomes even more complex when more than one objective function is considered with various types of practical generators constraints. All these factors contribute to the increasing need for fast and reliable optimization methods, tools and software that can address both security and economic issues simultaneously in support of power system operation and control.

Economic Load Dispatch (ELD) seeks the best generation schedule for the generating plants to supply the required demand plus transmission loss with the minimum generation cost. Significant economical benefits can be achieved by finding a better solution to the ELD problem. So, a lot of researches have been done in this area. Previously a number of calculus-based approaches including Lagrangian Multiplier method have been applied to solve ELD problems. These methods require incremental cost curves to be monotonically increasing/piece-wise linear in nature. But the input-output characteristics of modern generating units are highly non-linear in nature, so some approximation is required to meet the requirements of classical dispatch algorithms. Therefore more interests have been focused on the application of artificial intelligence (AI) technology for solution of these problems. Several AI methods, such as Genetic Algorithm Artificial Neural Networks, Simulated Annealing, Tabu Search, Evolutionary Programming , Particle Swarm Optimization, Ant Colony Optimization, Differential Evolution, Harmony search Algorithm, Dynamic Programming, Biogeography based optimization, Intelligent water drop Algorithm have been developed and applied successfully to small and large systems to solve ELD problems in order to find much better results. Very recently, in the study of social insects behaviour, computer scientists have found a source of motivation for the design and execution of optimization algorithms.

2 ECONOMIC LOAD DISPATCH

A major challenge for all power utilities is to not only satisfy the consumer demand for power, but to do so at minimal cost. Any given power system can be comprised of multiple generating stations, each of which has its own characteristic operating parameters. The cost of operating these generators does not usually correlate proportionally with their outputs; therefore the challenge for power utilities is to try to balance the total load among generators that are running as efficiently as possible. In fig 2.1 the operating costs of a fossil fired generator is shown. The P_{gi}^{min} is the minimum loading limit below which the operating unit proves to be uneconomical (or may be technically infeasible) and P_{gi}^{max} is the maximum output limit.

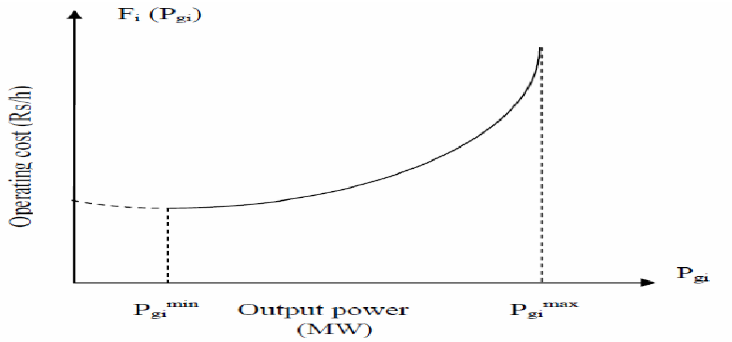

Fig 2.1 Operating costs of a fossil fired generator

2.1 Cost Function

Mathematically, economic dispatch problem considering valve point loading is defined as :

Minimize operating cost

$F(P_i) = \sum_{i=1}^{NG}(a_i * P_i^2 + b_i * P_i + c_i$ …. (2.1)

Subject to:-

Energy balance equation

$$\sum_{i=1}^{NG} P_i = P_D + P_L \quad ... (2.2)$$

The inequality constraints

$$P_i^{min} \le P_i \le P_i^{max} \qquad (i = 1,2, \dots, NG) \quad ...(2.3)$$

Where

a_i, b_i, c_i, d_i, e_i are cost coefficients of the i_{th} unit

P_D is load demand

P_i is real power generation and will act as decision variable

P_L is power transmission loss

NG is the number of generator buses.

2.2 Loss formula:-

One of the most important, simple but approximate method of expressing transmission loss as a function of generator power is through B-coefficients. This method uses the fact that under normal operating conditions, the transmission loss is quadratic in the injected bus real powers. The general form of the loss formula using B-coefficients is [31]

$$P_L = \sum_i^{NG} \sum_j^{NG} P_{gi} B_{ij}\, P_{gj}\; MW \qquad ...(2.4)$$

Where

P_{gi} and P_{gj} are the real power generations at the i_{th} and j_{th} buses

B_{ij} are the loss coefficients which are constant under certain assumed conditions.

NG is number of generation buses

The transmission loss formula of Eq. 2.4 is known as George's formula.

Another more accurate form of transmission loss expression given by Kron's loss formula is [31]

$$P_L = B_{00} \sum_i^{NG} B_{i0} P_{gj} + \sum_i^{NG} \sum_j^{NG} P_{gi} B_{ij}\, P_{gj}\; MW \qquad ...(2.5)$$

Where

B_{00}, B_{i0}, B_{ij} are the loss coefficients which are constant under certain assumed conditions NG is number of generation buses.

3 DIFFERENTIAL EVOLUTIONS

Differential Evolution (DE) is a type of evolutionary algorithm originally proposed by Price and Storn for optimization problems over a continuous domain. DE is exceptionally simple, significantly faster and robust. The basic idea of DE is to adapt the search during the evolutionary process. Differential Evolution (DE) is a parallel direct search method which utilizes NP D-dimensional parameter vectors $x_{i,g,}$ i = 1, 2, ...NP as a population for each generation G. NP does not change during the minimization process. The initial vector population is chosen randomly and should cover the entire parameter space. At the start of the evolution, the perturbations are large since parent populations are far away from each other. As the evolutionary process matures, the population converges to a small region and the perturbations adaptively become small. As a result, the evolutionary algorithm performs a global exploratory search during the early stages of the evolutionary process and local exploitation during the mature stage of the search. In DE the fittest of an offspring competes one-to-one with that of corresponding parent which is different from other evolutionary algorithms. This one-to-one competition gives rise to faster convergence rate. Price and Storn gave the working principle of DE with simple strategy in. Later on, they suggested ten different strategies of DE . The key parameters of control in DE are population size (NP), scaling or mutation factor (F) and crossover constant (CR). The optimization process in DE is carried out with three basic operations: mutation, crossover and selection. The DE algorithm is described as follows:

3.1 Initialization

The initial population comprises combinations of only the candidate dispatch solutions, which satisfy all the constraints and are feasible solutionsof economic dispatch. It consists of P_i^j $(i = 1,2,\dots,NG; j = 1,2,\dots,L)$ trail parent individuals. The elements of a parent are the combinations of power outputs of the generating units, which are chosen randomly by a random ranging over$[P_i^{min}, P_i^{max}]$ [10].

$$P_i^j = P_i^{min} + rand()\left(P_i^{max} - P_i^{min}\right)\ (i = 1,2,\dots,NG; j = 1,2,\dots,L)$$
... (3.1)

Where rand () is uniform random number ranging from over [0,1].

Where P_i^{max} is the upper bound of the n^{th} variable of the problem , P_i^{min} is the lower bound of the n^{th} variable of the problem, rand (0,1) is a uniformly distributed number within the limits(0,1). The elements of parent/offspring P_i^j may violate constraints Eq. (3.6). This violation is corrected by fixing them either at lower or upper limits as described below:

$$P_i^j = \begin{cases} P_i^{min}; \; P_i^j < P_i^{min} \\ P_i^{max}; \; P_i^j > P_i^{max} \\ P_i^j \,; \; P_i^{min} \leq P_i^j \leq P_i^{max} \end{cases} \qquad \ldots(3.1a)$$

$(i = 1,2, \ldots, NG; j = 1,2, \ldots, L)$

3.2 Evaluation of Objective Function

In order to satisfy the power balance constraints, a generator is arbitrarily selected as a dependent generator d. In this we are considering P_L=0 means transmission losses are neglected. Output of dependent or slack generator is given below

$$P_d^i = P_D - \sum_{\substack{k=1 \\ k \neq d}}^{NG} P_k^j \quad (j = 1,2, \ldots, L) \qquad \ldots(3.2)$$

Similarly, if the output of the dependent generator violates its limits . After limiting the value of the dependent generator as above, a penalty term is introduced in the objective function Eq. (3.4) to penalize its fitness value. When so introduced, Eq. (3.4) is changed to the following generalized form:

$$f^j = F\left(P_i^j\right) + \varphi^j \;\; (j = 1,2, \ldots, L) \qquad (3.3)$$

Where

Penalty factor is given by

$$\varphi^j = \begin{cases} (P_d^j - P_d^{min})^2 \;\; ; \;\; P_d^j < P_d^{min} \\ (P_d^{max} - P_d^j)^2 ; \;\; P_d^j > P_d^{max} \\ 0 \qquad ; \; P_d^{min} \leq P_d^j \leq P_d^{max} \end{cases} \qquad \ldots (3.3a)$$

3.3 Mutation

A new population named mutant population is generated whose size is same as that of the initial population (NG* L). Among the various strategies used for mutation in DE, the addition of the weighted difference vector between the two population members to the third member is adopted in this approach. Here three different members namely P_{r1} ,P_{r2} and P_{r3} are chosen from the current population .Then the difference between any two of these members is scaled by a scalar number F, which is then added to the third member. The value of F is usually in between 0.4 and 1. In each generation, a donor vector is created in order to change the population member vector. Therefore the j^{th} member of the donor vector Z_i(t) is expressed
as

$Z_{ij}^{(t+1)}$ = P_{r1}j(t) + F*(P_{r2}j(t) - P_{r3}j(t)) $(j = 1,2, \ldots, NG; j \neq d \,, i = 1,2, \ldots, L)$ ...(3.4)

3.4 Crossover

In order to increase the diversity of the perturbed parameter vectors, crossover is introduced. A new population is created by suitably combining the parent population and the mutant population. The process of crossover is based on the CR which is in between (0,1). Binomial crossover scheme is used which is performed on all D variables and can be expressed as:

U_{ij}(t) = Z_{ij}(t) if R_4(j) ≤ CR ...(3.5)
U_{ij}(t) = P_{ij}(t) else...

where U_{ij}(t) is the child which is obtained after crossover operation where j = 1,2, ... NG,
i= 1,2, ... L. Here, rand ensures that the newly generated vector is different for both Z_{ij}(t) and P_{ij}(t).

3.5 Selection

After calculating the objective function f^j using L number of variables for using initial and crossover population , a new population with the least objective function (minimum fuel cost) is formed for the next generation. This is given by

$$P_{ij}^{t+1} = \begin{cases} U_{ij}^{t+1} \;\; if \; f(\, U_i^{t+1}) < f(P_i^t) \quad (i = 1,2, \ldots, NG; i = 1,2, \ldots, L) \\ P_{ij}^t \;\; otherwise \end{cases} \qquad \ldots \quad (3.6)$$

The process is repeated until the maximum number of generations or no improvement is seen in the real power generation cost after many generations. The global optimum searching capability and the convergence speed of DE are very sensitive to the choice of control parameters L, F and CR. The crossover rate CR is between [0.3 , 0.9]. Mutation Factor (F) should not be smaller than a certain value to prevent premature convergence.

3.6 Stopping criterion

There are various criteria available to stop a stochastic optimization algorithm. In this
maximum number of iterations is chosen as the stopping criterion

4. FIREFLY ALGORITHM

The Firefly Algorithm (FA) is a Meta heuristics, nature-inspired, optimization algorithm which is based on the flashing behaviour of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions . Firefly Algorithm was developed by Dr. Xin-She Yang at Cambridge University in 2007, and it is based on the swarm behaviour such as insects or birds present in nature. The firefly algorithm is identical with other algorithms which are based on the so-called swarm intelligence, such as Particle Swarm Optimization (PSO), Artificial Bee Colony optimization (ABC), and Bacterial Foraging (BFA) algorithms, it is indeed much simpler both in concept and implementation Furthermore, according to recent bibliography, It is more 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 . 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.

4.1 The firefly algorithm has three rules which are based on some of the major flashing characteristics of real fireflies.

The characteristics are as follows: a) All fireflies are unisex and they will move towards more attractive and brighter ones regardless their sex.

b) The degree of attractiveness of a firefly is proportional to its brightness which decreases as the distance from the other firefly increases. This is 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.

c) 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.

4.2 Attractiveness:

In the firefly algorithm, the form of attractiveness function of a firefly is given by the following monotonically decreasing function

$$\beta(r) = \beta_0 * exp(-\gamma r_{ij}^{m}) \text{ with } m\geq 1 \qquad \ldots(4.1)$$

Where, r is the gap between two fireflies.

β_0 is the attractiveness in the starting when distance r=0

γ is an absorption coefficient which controls the decrease of light intensity.

4.3 Distance:

The distance between two fireflies i & j, at positions x_i *and* x_j.it can be defined as a Cartesian.

$$r_{ij} = \| x_i - x_{ji} \| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \qquad \ldots(4.2)$$

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 we have, for d=2 , we have

$$r_{ij} = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \qquad \ldots(4.3)$$

However, the calculation of a distance r can also be defined using other distance metrics, based on the nature of problem, such as manhattan distance.

4.4 Movement:

The movement of the firefly i which is attracted by a more attractive. Firefly j is given by is given by:

$x_i = x_i + \beta_0 * \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (rand - \frac{1}{2})$ ...(4.4)

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 third term is used for the random movement of fireflies in case there are no brighter ones. The coefficient α is a randomization parameter determined by the problem of interest. Rand is a random number generator uniformly in the distributed space [0,1].

5. HYBRID DIFFERENTIAL EVOLUTION (DE) & FIREFLY ALGORITHM

We have noticed that the meta-heuristic methods are very efficient for the search of global solution for complex problems better than deterministic methods. However their disadvantage is the time of convergence which is due the high number of the agents and iterations. To solve this problem we have developed a hybrid method with the combination of two algorithms, the firefly algorithm and the Differential Evolution with a lower number of ants and fireflies as possible, the explanation of computation procedure of hybrid method and its concept.

ALGORITHM

Step1: 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***, αmax, αmin, β0, γmin, γmax and ***itermax*** (maximum number of iterations).

Step 3: Generate ***noff*** number of fireflies (xi) randomly between λmin and λmax .

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 ***EbestFV*** by comparing all the fitness values and also obtain the best firefly values ***EbestFF*** corresponding to the best fitness value ***EbestFV***.

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 rij values of each firefly using the following equation:

rij= ***EbestFV*** **-FV**

rij is obtained by finding the difference between the best fitness value ***EbestFV*** (***EbestFV*** is the best fitness value i.e., jth firefly) and fitness value **FV** of the ith firefly.

Step 9: New xi values are calculated for all the fireflies using the equation(4.4)

Step 10: ***EbestFF*** gives the optimal solution of the Economic Load Dispatch problem and the results are printed. The E_{best} value of the Firefly Algorithm is given to the Differential Evolution as Input Value. Read the input Data

Step 11 : Generate an array of (Ng * L) of uniform random numbers. Set population counter , i=0 and increment the population counter to, i=i+1, set the generation counter, j=0 and increment the generation counter j=j+1.

Step 12**:** Compute P_{id} using Eq. (3.2), check limits and adjust using Eq. (3.1a). Then compute penalty factor, $\varphi_i and\ f_i$ using Eq. (3.3a) and (3.3).

Step 13: Generate an array of uniform random numbers and generate three different integer random numbers within the range 1 to L. . IF (j ≠ d) THEN compute $Z_{ij}{}^{t}$ using eq.(3.4)

Step 14: Compute $U_{ij}(t+1)$ using Eq. (3.6), check limits and adjust using Eq.

S.NO	a_n	b_n	c_n	p_{min}	p_{max}
1	1243.5311	38.30553	0.03546	35	210
2	1658.5696	36.32782	0.02111	130	325
3	1356.6592	38.27041	0.01799	125	315

(3.1a). Then compute penalty factor, $\varphi_i and\ f_i$ using Eq. (3.3a) and (3.3).

Step 15 After calculating the objective function f^j using L number of variables for using initial and crossover population , a new population with the least objective function (minimum fuel cost) is formed for the next generation. This is given by

$$P_{ij}^{t+1} = \begin{cases} U_{ij}^{t+1} \ if\ f(\,U_i^{t+1}) < f(P_i^t) \\ P_{ij}^t \ otherwise \end{cases} \qquad 5.7$$

Here $(i = 1,2, \dots, NG; i = 1,2, \dots, L)$

Step 16: The process is repeated until the maximum number of generations or no improvement is seen in the real power generation cost after many generations. The global optimum searching capability and the convergence speed of DE are very sensitive to the choice of control parameters L, F and CR.

Step 17: There are various criteria available to stop a stochastic optimization algorithm. In this maximum number of iterations is chosen as the stopping criterion

6. SIMULATION RESULTS

The effectiveness of the proposed firefly algorithm is tested with three unit system. Firstly the problem is solved by Firefly Algorithm and then the DE-FIREFLY Algorithm is used to solve the problem

6.1 Three-Unit System The generator cost coefficients, generation limits and B-coefficient matrix of three unit system are given below. Economic Load Dispatch solution for three unit system is solved using conventional Firefly Algorithm and DE-Firefly Hybrid algorithm method. Test results of DE-Firefly method are given in table 6.2.Test results of Firefly Algorithm are given in Table 6.3 Comparison of test results of DE-Firefly Hybrid and Firefly algorithm are shown in table 6.4.

Table 6.1: Cost Coefficients and Power limits of 3 Unit system

The loss Coefficients matrix of 3 Unit

$$B_{ij} = \begin{bmatrix} 0.000071 & 0.000030 & 0.000025 \\ 0.000030 & 0.000069 & 0.000032 \\ 0.000025 & 0.000032 & 0.000080 \end{bmatrix}$$

Table 6.2: Test results of DE-FIREFLY Algorithm for 3-Unit System

Sr. No	Power Demand(MW)	P1(MW)	P2(MW)	P3(MW)	P_{loss} (MW)	Fuel Cost(Rs/Hr)
1	350	64.093328	160.378922	126	.471	18383.601563
2	400	66.373126	187.517560	146.110058	.495	20487.569476
3	450	42.825634	191.521327	215.654036	0.5	22785.952605

4	500	64.499424	232.198943	203.302823	1	24974.465626
5	550	69.139309	209.381366	271.480796	1	27324.105080
6	600	71.333083	290.437160	238.230673	1.5	29641.525277
7	650	137.002425	298.971731	214.527763	1.7	31935.186230
8	700	141.852933	292.664739	266.484563	1.8	34273.731641

Table 6.3: Test results of FIREFLY Algorithm for 3-Unit system

Sr. No.	Power Demand(MW)	P1 (MW)	P2 (MW)	P3 (MW)	P_{loss} (MW)	Fuel Cost (RS/Hr)
1	350	43	159	149	1	18482.896615
2	400	36	216.668130	149.831467	1.25	20933.664547
3	450	43.074777	170.170286	238	1.245	23019.560655
4	500	93	209	199	1	25070.606105
5	550	210	173	168	1	27820.267310
6	600	190.244315	213.030429	196.726834	1.5	29751.569398
7	650	45.427961	308	298	1.65	32408.378730
8	700	160	276	266	2	34582.581876

Table4 : Comparison of test Results of Firefly Algorithm and DE-FIREFLY Algorithm for 3 unit System

Sr No.	Power Demand	Fuel Cost (Rs/Hr) Firefly Algorithm	Fuel Cost (Rs/Hr) DE-Firefly Algorithm
1	350	18482.896615	18383.601563
2	400	20933.664547	20487.569476
3	450	23019.560655	22785.952605
4	500	25070.606105	24974.465626
5	550	27820.267310	27380.105080
6	600	29751.569398	29641.525277
7	650	32408.378730	31935.186230
8	700	34582.581876	34273.731641

7. CONCLUSION

Economic Load Dispatch problem is solved by using Firefly Algorithm and DE-Firefly Hybrid Algorithm. The programs are written in MATLAB software package. The solution algorithm has been tested for three generating units. The results obtained from DE-Firefly Algorithm are compared with the results of Firefly Algorithm. Comparison of test results of both methods reveals that DE-Firefly Hybrid Algorithm is able to give more optimal solution than Firefly. Thus, it develops a simple tool to meet the load demand at minimum operating cost while satisfying all units and operational constraints of the power system.

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