Application of Biogeography-based Optimization for Economic Dispatch Problems

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ABSTRACT

In this paper, Biogeography-based optimization (BBO) algorithm has been presented for solving the economic dispatch (ED) problems. An optimal short-term thermal generation schedule for 24 time intervals has been presented for the same purpose. The BBO algorithm has been applied to two different test systems, one consisting of three generators and the other of six generators. The results obtained are compared with the conventional Lagrange multiplier method and the particle swarm optimization (PSO) method. The results show that the presented BBOalgorithm provides comparatively better solutions in terms of total fuel cost as compared to other methods. Also, the global search capability is enhanced and premature convergence is avoided.

Keywords

Biogeography-based optimization, Economic Dispatch, Migration, Mutation

1. INTRODUCTION

Economic Dispatch (ED) is one of the most important issues in power system operation. The main aim of ED is to minimize the operating cost of units, while satisfying the load demand and certain constraints at the same time [1]. Many conventional methods have been developed in the previous years for solving the ED problem. Some of these methods include Lagrange multiplier method, direct search method, Newton-Raphson method, efficient method [1-3]. In these methods assumption is made that the incremental cost curves of the generators are monotonically increasing piece-wise linear. However, in practical case the cost curves of the generators are highly non-linear and hence, such an assumption may not give accurate results. The nonlinearities in the generator operation are due to valve-point loading effects, prohibited operating zones, etc. [1].

In recent years certain artificial intelligence (AI) techniques such as Fuzzy Logic (FL) [4], Artificial Neural Network (ANN) [5-6], Genetic Algorithm (GA) [7-8], Particle Swarm Optimization (PSO) [11-13], Bacteria Foraging Optimization (BFO) [14], Differential Evolution (DE) [15-16] etc. have been successfully applied to the ED problems for units having non-linear cost functions. Although the GA model has been employed successfully in various optimization problems, recent researches show some difficulties with implementation. GA shows quiet a large inefficiency when being implemented to objective functions in which the parameters to be optimized are highly correlated [9]. Also premature convergence is another problem that reduces its searching capability [10]. PSO, inspired by social behavior of bird flocking or fish schooling, has been found to be more robust in solving such nonlinear optimization problems.

Therefore, many researchers have tried PSO and its hybrids in solving ED problems [12-13]. DE is one of the most prominent new-generation AI techniques that exhibits consistent and reliable performance for solving nonlinear problems and has been found to be effective for constrained optimization problems [16].

In this paper a latest and newly developed Biogeography based optimization (BBO) [17] algorithm has been applied to the ED problems. The BBO algorithm was developed by D. Simon in the year 2008 from the theory of Biogeography as its base. To show the effectiveness of the BBO, the BBO algorithm has been applied to two different test systems, one comprising of three generating units and the other one comprising of six generating units. The results of BBO are compared with the conventional Lagrange multiplier method and PSO method and it has been found that the BBO algorithm shows superior performance. Till now, the BBO technique has been applied to various ED problems [18-19] only by a few researchers. In this paper, more exhaustive analysis is done taking a 24-hour short-term thermal generation schedule [20-21] for both the generating systems. Due to lack of space, the 24-hour generation schedule for the six generator system has only been presented.

2. PROBLEM DESCRIPTION

The objective of the ED problem is to determine the optimal active power output P_{gi} (MW) of each of the generator for a total load demand of P_D (MW). Total fuel cost C_{fuel} (\$/hr)for NG generators is minimized subject to the equality and the inequality constraints. The fuel cost curve is approximated as a quadratic function of the active power output from the generators and is represented as [1]:

$$C(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i \tag{1}$$

Where

 a_i, b_i, c_i are the fuel cost coefficients of the i_{th} generator. The ED problem can be defined by the following equation:

$$\begin{aligned} \text{Minimize} \\ C_{fuel} &= \sum_{i=1}^{NG} C(P_{gi}) \end{aligned} \tag{2}$$

subject to the constraints given as:

a) the equality constraint –

$$\sum_{i=1}^{NG} C(P_{qi}) = P_D + P_L \tag{3.1}$$

b) the inequality constraint –

$$P_{gimin} \leq P_{gi} \leq P_{gimax}$$
 (3.2)

Where.

 P_{gimin} - minimum power output limit of the i_{th} generator (MW)

 P_{gimax} - maximum power output limit of the i_{th} generator (MW)

The total transmission losses P_L (MW) is a function of unit power outputs that can be expressed using B-coefficients as [1]

$$P_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} P_i B_{0i} + B_{00}(4)$$

3. OVERVIEW OF BBO TECHNIQUE

The Biogeography-based optimization algorithm [17] has been developed from the theory of Biogeography as its base. Biogeography is the study of the geographical distribution of biological organisms. Mathematical models of biogeography describe how the biological organisms or species, to be more specific, migrate from one island to another, how new species arise, and how these species become extinct. An island can be defined as any habitat that is geographically isolated from other habitats. The concept of BBO is based on the migration and mutation operations. The concept and mathematical formulation of the migration and mutation operations are briefed below:

3.1 Migration

In BBO, the migration operation refers to the process of either entering or leaving of the species into or from an island. Like PSO and other population based search techniques, BBO also uses a population of candidate solutions for optimization purpose. Representation of each candidate solution is done as a vector of real numbers. Here each real number in the population is considered as one suitability index variable (SIV). In ED problem, these SIVs are analogous to the power output of the generators. The SIVs in one array are used to calculate the habitat suitability index (HSI) of a habitat. The HSI is analogous to the objective function as used in other techniques. In ED problem, the HSI is analogous to the generation cost of a generator. Solutions with high HSI represent a superior solution whereas solutions with low HSI represent an inferior solution.

The process of species entering a habitat is known as immigration whereas the process of leaving a habitat is known as emigration. The immigration rate, λ and the emigration rate, u of each habitat is used to probabilistically share information with other habitats/solutions. Each solution is modified according to probability P_{modify} , known as the habitat modification probability, based on other solutions. If a particular habitat is selected for modification, then its λ is used to probabilistically decide whether or not to modify each SIV of that habitat. If a particular SIV in a given habitat is selected for modification, then μ of other habitats are used to probabilistically decide which of the habitats should migrate a randomly selected SIV from those habitats to that particular habitat. Unlike other AI techniques where the recombination process is used to generate a completely new solution, the migration operation in BBO is used to bring changes within an existing solution. In order to prevent the best solutions from being changed by the migration process, few elite solutions are kept the same in the consequent iterations.

Immigration and emigration rate for habitat containing n species is given as [17]

$$\lambda_n = I(1 - \frac{n}{N}) \tag{5}$$

$$\mu_n = \frac{En}{N} \tag{6}$$

Where

I, E: the maximum immigration and emigration rates respectively

N: maximum number of species that a habitat can contain

3.2 Mutation

If some disastrous events happen, the HSI of a habitat can change drastically resulting in the species count to differ from its equilibrium value. In BBO this process is modeled as SIV mutation and the mutation rates of the habitats can be calculated using the species count probabilities [17] given below:

Where.

 \vec{P}_n : the probability of the habitat to contain exactly n species Each candidate solution of the population has a probability associated with it, which indicates whether that candidate exists as a solution or not. If the probability of a selected candidate is too low then that candidate is likely to mutate to some other solution. Similarly, if the probability of a given candidate is too high then it has got very little chances to mutate. Therefore, very high HSI solutions and very low HSI solutions are equally improbable to mutate. But medium HSI solutions have a high probability to create better solutions after mutation operation. Mutation rate of each set of solution is calculated in terms of species count probability using the equation given below [17]:

$$m(n) = m_{max} \left((1 - P_n) / P_{max} \right) \tag{8}$$

Where,

m(n): the mutation rate for habitat containing exactly n species

 m_{max} : user defined parameter

 P_{max} Largest of all the P_n values With the help of this mutation so

With the help of this mutation scheme diversity among the population is increased. Without the mutation operation, the solutions with high probability will try to become more dominant in the population. This mutation scheme helps low HSI solutions to mutate, hence giving them a chance to improve. It also makes high HSI solutions to mutate thereby giving them a chance of further improvement. An elitism approach is also used to save the features of the habitat that contains the best solution in the BBO process. If the HSI of that habitat is ruined due to mutation it can be reverted back to its previous HSI if needed. In ED problem, the mutation operation is performed simply by replacing a selected solution with a randomly generated solution that satisfies the constraints given by (3).

4. BBO ALGORITHM APPLIED TO ED PROBLEM

The BBO algorithm as applied to ED problem [18-19] has been summarized below.

Step 1: <u>Initialization of BBO parameters</u>: Choose the number of generators i.e. number of SIVs, number of habitats i.e. population size, power demand, loss coefficients, habitat modification probability $P_{modify} = 1$, mutation probability = 0.01, maximum mutation rate m_{max} , maximum immigration rate I = 1, maximum emigration rate E = 1, step size for numerical integration dt = 1, elitism parameter = 2.

Step 2: <u>Initialization of SIVs</u>: Each SIV of a habitat is initialized randomly while satisfying the constraints of (3). Each habitat represents a potential solution to the given problem.

Step 3: <u>Calculation of HSIs</u>: HSI for each habitat is calculated for given immigration and emigration rates. HSI represents the fuel cost of the generators.

Step 4: <u>Identification of elite habitats</u>: Based on the HSI values, elite habitats are identified i.e. those habitats for which the fuel cost is minimum, are selected.

Step 5: <u>Performing migration operation</u>: For each of the nonelite habitats, migration operation is performed. HSI for each habitat is recomputed. SIVs obtained after migration must satisfy the constraints of (3).

Step 6: <u>Performing mutation operation</u>: Species count probability of each habitat is updated using (7). Mutation operation is carried out on the non-elite habitats. HSI value of each new habitat set is recomputed.

Step 7: <u>Stopping criterion</u>: Go to step 3 for next iteration. If the predefined number of iterations is reached, stop the process.

5. TEST SYSTEMS AND RESULTS

In order to show the effectiveness of the BBO technique, two generating systems have been taken into consideration. The first test system consists of three generating units [1] with a load demand of 300 MW. The second test system has been taken from [11] that consists of six generating units with a load demand of 1263 MW. Losses and the effects of prohibited operating zones and ramp rate limits have been neglected in this case.

Case 1: Three Generator System

For this system, population size is 20. Maximum number of iterations is taken as 100.

PSO parameters used are [1]: Minimum inertia weight factor $w_{min} = 0.4$ Maximum inertia weight factor $w_{max} = 0.9$ Acceleration constants $c_1 = 2$, $c_2 = 2$ Table 1 shows the total generation cost and power output of each generator obtained by Lagrange multiplier, PSO and BBO methods. Convergence characteristics of PSO and BBO are shown in figure 1.

Table 1 ($P_D = 300 \text{ MW}$)							
Power Output (MW)	Lagrange Multiplier	PSO	ВВО				
P1	184.148	189.978	182.664				
P2	45.448	39.419	42.409				
Р3	70.402	70.602	74.829				
Cost (\$/hr)	3482.315	3482.867	3482.025				

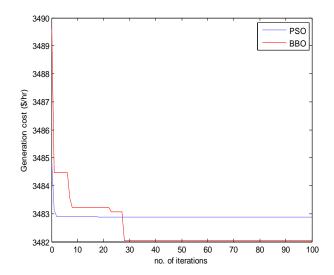


Figure 1: Convergence characteristics of PSO and BBO (three generator system)

Case 2: Six Generator System

For this system, population size is 30. Maximum number of iterations is taken as 100.

PSO parameters used are [1]:

Minimum inertia weight factor $w_{min} = 0.4$ Maximum inertia weight factor $w_{max} = 0.9$ Acceleration constants $c_1 = 2$, $c_2 = 2$

Table 2 shows the total generation cost and power output of each generator obtained by Lagrange multiplier, PSO and BBO methods. Convergence characteristics of PSO and BBO are shown in figure 2.

Table 2 ($P_D = 1263 \text{ MW}$)							
Power	Lagrange	PSO	BBO				
Output	Multiplier						
(MW)							
P1	446.707	446.706	436.150				
P2	171.257	171.258	177.708				
Р3	264.105	264.105	269.735				
P4	125.216	125.214	127.812				
P5	172.118	172.118	167.760				
P6	83.593	83.593	83.319				
Cost (\$/hr)	15275.931	15275.930	15270.803				

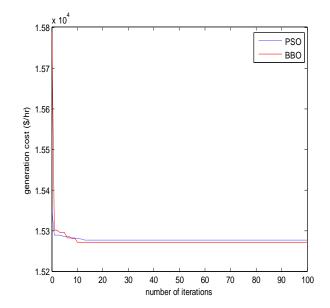


Figure 2: Convergence characteristics of PSO and BBO (six generator system)

The optimal thermal generation schedule for the six generator system is shown in table 3 for a peak demand of 1263 MW.

6. CONCLUSION

In this paper, the BBO algorithm has been applied to ED problems. The performance of this algorithm has been compared with the conventional Lagrange multiplier method and the PSO algorithm by employing two different test systems and it has been found that BBO algorithm obtains comparative results with respect to these methods. Results obtained through BBO clearly exhibit an improved solution quality and stable convergence characteristics. Global search capability is enhanced and premature convergence is avoided. Also, a 24-hour short-term thermal generation schedule has Been presented for the six generator system to further add to the effectiveness of the BBO algorithm. Table 2 shows the total generation cost and power output of each generator obtained by Lagrange multiplier, PSO and BBO methods. Convergence characteristics of PSO and BBO are shown in figure 2.

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Table 3:Short-term thermal generation scheduling for	or case 2 (Peak Demand = 1263 MW)
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Time	Load	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6	Generation
Interval	Demand (MW)						(MW)	Cost (\$/hr)
1	855	343.53	80.85	206.45	76.59	87.94	59.61	10132.67
2	868	321.23	65.63	236.24	84.49	110.23	50.18	10317.78
3	880	346.28	82.24	239.46	67.77	91.57	52.67	10439.79
4	891	348.11	70.32	208.31	55.81	154.93	53.52	10590.84
5	956	353.23	161.81	197.13	63.94	124.30	55.58	11367.33
6	970	384.61	120.81	188.12	96.00	119.24	61.23	11529.49
7	984	370.36	115.17	210.63	84.55	124.55	78.73	11707.67
8	1009	366.16	106.09	239.49	82.26	143.70	71.28	12024.84
9	1021	383.03	147.94	196.55	87.75	136.05	69.67	12167.59
10	1042	400.86	108.06	240.15	89.03	132.04	71.84	12430.29
11	1078	422.57	148.68	224.95	112.74	106.05	63.00	12886.18
12	1121	407.40	161.71	216.44	118.34	147.23	69.86	13432.79
13	1189	415.95	142.30	258.68	125.57	183.80	62.68	14312.44
14	1263	436.15	177.71	269.74	127.81	167.76	83.32	15270.80

15	1176	387.03	163.05	263.04	108.09	161.62	93.16	14152.62
16	1219	461.91	138.82	234.93	126.30	176.58	80.45	14712.28
17	1089	374.20	142.04	214.41	105.23	162.76	90.36	13041.52
18	1058	420.89	120.92	196.71	90.87	166.99	61.61	12642.95
19	1010	385.23	116.58	250.73	110.40	83.71	63.34	12046.74
20	986	362.83	100.45	213.85	106.04	140.55	62.28	11738.89
21	945	345.65	141.59	229.73	65.87	78.58	83.56	11253.35
22	910	400.69	105.53	198.86	80.05	74.31	50.54	10794.54
23	887	379.97	100.16	167.30	58.19	111.85	69.50	10526.95
24	855	343.53	80.85	206.45	76.59	87.94	59.61	10132.67

Load profile during 24-hour interval for the six generator system is shown in figure 3.

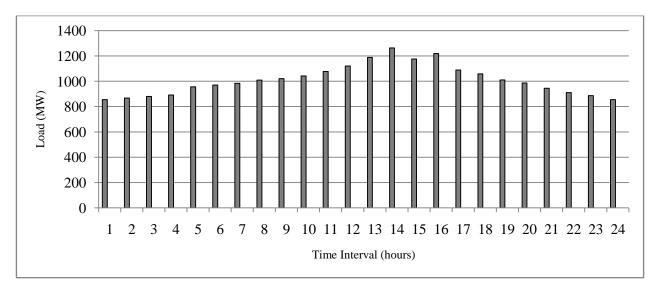


Figure 3: Load profile for 24-hour interval (six generator system)

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