Oppositional Biogeography-Based Optimization for Solving Economic Dispatch Problems: An Efficient Method

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ABSTRACT
In this paper, Oppositional biogeography-based optimization (OBBO) technique based on opposition-based learning (OBL) concept has been presented for solving the economic dispatch (ED) problems. The OBBO technique has been applied on two test systems, one consisting of three generators and the other of six generators. The results obtained have been compared with the conventional Lagrange multiplier method, particle swarm optimization (PSO) and biogeography-based optimization (BBO) methods. The results show that the presented OBBO technique has good convergence characteristics and 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, Oppositional Biogeography-Based Optimization, Opposition-Based Learning

1. INTRODUCTION
In the present complex power system, economic, reliable and environment friendly operation of the power plants is very important. The soft computing methods are finding a great place in providing the optimal solution of such complex systems' problems. Recently many powerful modern power system optimization techniques have been applied to power systems [1]. Evolutionary algorithms based computations have emerged as the latest solver systems and in general, they are applied to solve optimization problems as well as multi-objective problems that may not be solved by other tools.

Economic Dispatch (ED) is considered as one of the most important and influential issues in the field of 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) [7-8,28], 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 its 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, for which source of inspiration comes from the social behavior of bird flocking or fish schooling, has enabled solution of nonlinear optimization problems more effectively. Therefore, PSO and its hybrids have been tried by numerous researchers for solving ED problems [12-13, 23, 27]. Among various new-generation AI techniques, DE is considered a prominent one and is very much reliable and efficient for solving nonlinear and constrained optimization problems [16].

Biogeography-based optimization (BBO) [17] is a latest evolutionary algorithm (EA) that has been developed to enhance the global search capability and results from generalization of biogeography to EA. Biogeography can be defined as the study of the geographical distribution of biological organisms. Mathematical models of biogeography describe how the biological organisms or species, to be more specific, travel from island to island, how birth of new species take place, and how these species die out. Any geographically isolated habitat with respect to other habitats defines an island [17]. The concept of BBO is based on the migration and mutation operations.

In this research paper, the concept of opposition-based learning (OBL) [18, 19] has been applied for the solution of ED problems. The OBL algorithm has been applied to the BBO method in order to improve its performance and the algorithm is named oppositional BBO (OBBO) [19]. Application of OBL to EAs results in an accelerated convergence speed whereby the fitness of a given solution is compared to its opposite and the fitter one being kept in the population. In the past few years it has been shown that, as compared to opposite points, convergence rate of quasi-opposite points is better [20].

Few authors applied BBO [24, 25] and OBBO [22] for some test systems of plants. In this paper work has been extended and applied to two different test systems and an extensive analysis has been carried out. Further the performance of presented method (OBBO) has been compared with Lagrange Multiplier, BBO and PSO based solutions.

In order to show the effectiveness of the OBBO algorithm, two test systems have been taken. The first test system consists of three generators [1] and the second one comprises six generating units [11].

2. PROBLEM DESCRIPTION

ED problem is aimed at determining the allocation of optimal active power output P_{gk} (MW) of each of the generators for a total load demand of P_D (MW). Total fuel cost F_{fuel} ($/hr) for N_{Gen} number of generators is minimized subject to the certain equality and the inequality constraints.

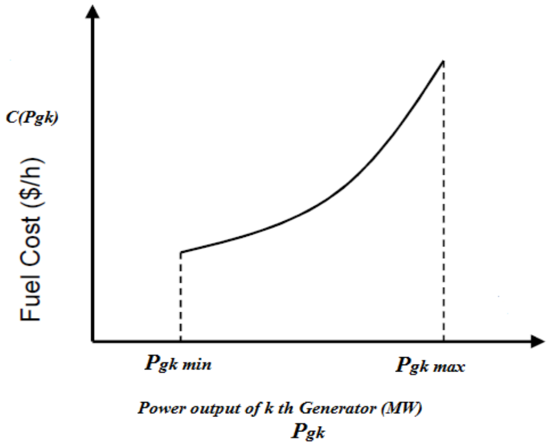

Figure 1: The fuel cost curve of the kth Generator

The fuel cost curve is approximated as a quadratic function of the active power output from the generators and is represented as [1]:

$$C(P_{gk}) = \alpha_k P_{gk}^2 + \beta_k P_{gk} + \gamma_k \tag{1}$$

Where,

$\alpha_k, \beta_k, \gamma_k$ are the fuel cost coefficients of the k_{th} generator.

The fuel cost curve of the k_{th} generator [1] based on the equation (1) can be presented as shown in the Figure (1). This fuel cost curve has been accepted and referred by a larger section of the research community [1].

The ED problem can be defined by the equation as below:

Minimize

$$F_{fuel} = \sum_{k=1}^{N_{Gen}} C(P_{gk}) \tag{2}$$

Subject to the following two constraints given as:

(1) The equality constraint –

$$\sum_{k=1}^{N_{Gen}} P_{gk} = P_D + P_L \tag{3.1}$$

and

(2) The inequality constraint –

$$P_{gk\min} \le P_{gk} \le P_{gk\max} \tag{3.2}$$

Where,

$P_{gk\min}$ is minimum power output limit of the k_{th} generator in MW

$P_{gk\max}$ is maximum power output limit of the k_{th} generator in MW

The total transmission losses, P_L (MW) depend upon power outputs from the generators and can be expressed using B-coefficients as [1]:

$$P_L = \sum_{k=1}^{N_{Gen}} \sum_{l=1}^{N_{Gen}} P_k B_{kl} P_l + \sum_{k=1}^{N_{Gen}} P_k B_{0k} + B_{00} \tag{4}$$

3. BIOGEOGRAPHY-BASED OPTIMIZATION

In this section the BBO technique has been discussed in brief. The concept of BBO is mainly dependent on the migration and mutation operations. The migration and mutation operations with their basic concept and mathematical formulation are discussed below in short [17, 24, 25, 26]:

3.1 Migration

In BBO, the migration operation refers to the process of either entering (immigration) or leaving (emigration) of the species into or from an island. The BBO algorithm operates by considering each real number in the given population 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 total generation cost of a generator. A superior solution corresponds to a high HIS value whereas an inferior solution indicates a low HSI value.

Although the immigration and emigration curves could be complex but for the sake of simplicity these have been shown to be straight lines as in Figure 2.

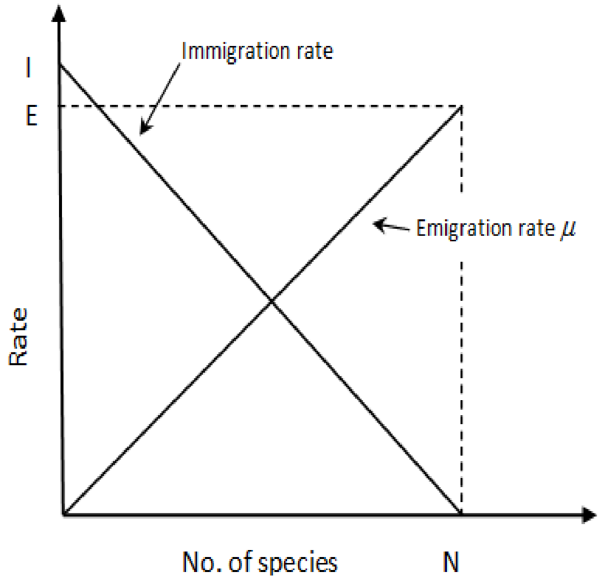

Figure 2: Linear migration rates

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

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

$$\mu_n = \frac{En}{N} \quad (6)$$

Where,

I and E are the maximum immigration and emigration rates, respectively

N is maximum acceptable species count of a habitat

3.2 Mutation

Cataclysmic events can have adverse effects on the HSI of a habitat that may result in the species count of that habitat to vary from its value at equilibrium. Such a process, in BBO, is modeled as SIV mutation and the mutation rates of the habitats are calculated using the species count probabilities [17] given below:

$$P_n = \begin{cases} -(\lambda_n+\mu_n)P_n+\mu_{n+1}P_{n+1}, & n=0 \\ -(\lambda_n+\mu_n)P_n+\lambda_{n-1}P_{n-1}+\mu_{n+1}P_{n+1}, & 1 \le n \le N\text{-}1 \\ -(\lambda_n+\mu_n)P_n+\lambda_{n-1}P_{n-1}, & n=N \end{cases} \quad (7)$$

Where,

P_n is the probability of the habitat to contain exactly n species

In order to calculate the mutation rate of each set of solution species count probability is employed and these two are related using the equation given below [17]:

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

Where,

$m(n)$ is habitat's mutation rate that contains exactly n species

$m_{\max}$ is user defined parameter

$P_{\max}$ is largest of all the P_n values

The mutation scheme described above results in an increased diversity in the population. In ED problem, the mutation operation is performed simply by replacing a selected solution with a randomly generated solution which satisfies the constraints given by (3). For details refer [17].

4. OPPOSITION-BASED LEARNING

Opposition-based learning (OBL) was proposed by Tizhoosh [18]. Neural networks first utilized the OBL concept to improve learning and back propagation [21]. OBL considers natural learning time consuming as it has been modeled considering a very slow process. A simulation model inspired from 'social revolutions' [18] may result in improvement of the learning process since revolutions are fast compared to changes that are fundamental whether it may be any field such as politics, economics or any other. In OBL, the 'social revolutions' theory is mapped to machine learning and opposite numbers are employed instead of random numbers so that the population may be evolved quickly and efficiently.

OBL employs the basic principle i.e. utilization of opposite numbers to approach a solution. Studies carried out on OBL emphasize on the fact that the probability of a number's opposite being closer to a solution is more than a random number. Thus, comparison of a number with its opposite reduces the need of a large search space and hence, a smaller search space may be enough to converge to an optimal solution.

4.1 Opposite, Quasi-Opposite and Quasi-Reflected points

This section defines the opposite, quasi-opposite and quasi-reflected points as given by [20].

Definition 1: Assuming z be any real number in the range $[m,n]$. Its opposite, z_0, is defined as

$$z_0 = m+n-z$$

Definition 2: Assuming z be any real number in the range $[m,n]$. Its quasi-opposite point, z_{q0} is defined as

$$z_{q0} = rand(s, z_0)$$

Where s is the center of the interval $[m,n]$ and is calculated as $(m+n)/2$ and $rand(s, z_0)$ is a uniform random number between s and z_0.

Definition 3: Assuming z be any real number in the range $[m,n]$. Its quasi-reflected point, z_{qr} is defined as

$$z_{qr} = rand(s, z)$$

Where $rand(s,z)$ is a uniform random number between s and z.

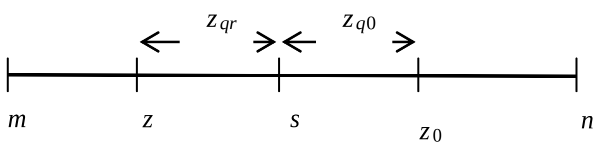

Figure 3: Opposite points defined in domain $[m,n]$

5. OBBO ALGORITHM APPLIED TO ED PROBLEM

The OBBO algorithm presented in [18-19] gained wider popularity in the various engineering problems and subsequently applied to ED problem [22] has been summarized for the ready reference and understanding of the readers. Following are the major computational steps based on OBBO technique:

Step 1: Initialization of parameters: Choose the number of generators i.e. number of SIVs, number of habitats i.e. population size, power demand, loss coefficients. Also BBO parameters are initialized i.e. 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, jumping rate (J_r) = 0.3

Step 2: Initialization of SIVs: Initialize each SIV of a habitat randomly while satisfying the constraints of (3) and thus representing a potential solution for a specific problem.

Step 3: Calculation of HSIs: HSI for each habitat is calculated for given immigration and emigration rates. HSI corresponds to the fuel cost of the generators.

Step 4: Calculation of quasi-reflected habitat set: Quasi-reflected habitat set is calculated using algorithm given in [19].

Step 5: Forming new habitat set: A new habitat set is formed by sorting out best HSIs from the old habitat set and the quasi-reflected habitat set.

Step 6: Identification of elite habitats: Identification of elite habitats is done based on the HSI values. In this process those habitats for which the fuel cost is minimum, are selected from the newly formed habitat set.

Step 7: Performing migration operation: For each of the non-elite habitats, migration operation is performed. HSI for each habitat is recomputed. SIVs obtained after migration must satisfy the constraints of (3).

Step 8: Performing opposite habitat jumping: Opposite habitat jumping process is performed based on the algorithm given in [19]. Elite habitats are restored in the so formed habitat set.

Step 9: Stopping criterion: Go to step 5 for next iteration. If the predefined number of iterations is reached, stop the process.

6. NUMERICAL EXAMPLE AND RESULTS

The presented OBBO algorithm has been applied to two different test systems. First test system comprises three generators [1] with a load demand of 300 MW and the second test system comprises six generating units [11] with a load demand of 1263 MW. Results for this test system have been obtained by neglecting the losses and the effects of prohibited operating zones and ramp rate limits.

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, BBO and OBBO methods. Convergence characteristics of PSO, BBO and OBBO are shown in Figure 4. For this test system, it has been observed that convergence characteristics of the proposed method are better and also total generation/fuel cost obtained is lowest as compared. Thus, economic solution is obtained.

Table 1: Total generation cost and power output of each generator for three generator system

Power Output (MW)	Lagrange Multiplier	PSO	BBO	OBBO
P1	184.148	189.978	182.664	178.296
P2	45.448	39.419	42.409	48.964
P3	70.402	70.602	74.829	72.460
Total Generation Cost ($/hr)	**3482.315**	**3482.867**	**3482.025**	**3480.184**

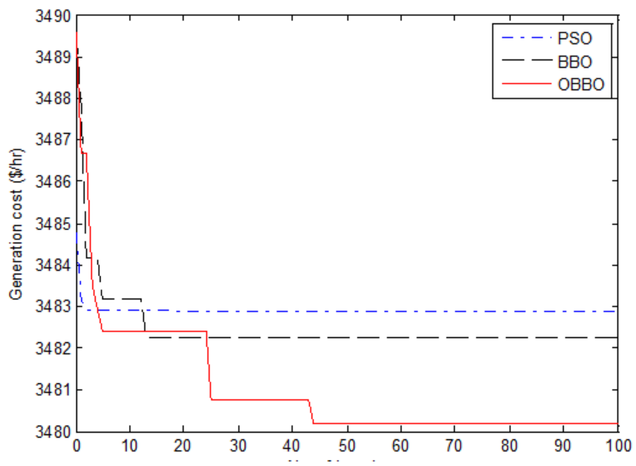

Figure 4: Convergence characteristics of PSO, BBO and OBBO (three generator system)

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, BBO and OBBO methods. Convergence characteristics of PSO, BBO and OBBO are shown in Figure 5. For this test system also, it is found that convergence characteristics of the presented method are comparatively better and also total generation cost computed is lowest as compared to other methods.

Table 2: Total generation cost and power output of each generator for six generator system

Power Output (MW)	Lagrange Multiplier	PSO	BBO	OBBO
P1	446.707	446.706	436.150	469.547
P2	171.257	171.258	177.708	159.799
P3	264.105	264.105	269.735	247.806
P4	125.216	125.217	127.812	139.719
P5	172.118	172.119	167.760	158.870
P6	83.593	83.593	83.319	87.258
Total Generation Cost ($/hr)	**15275.931**	**15275.930**	**15270.803**	**15269.133**

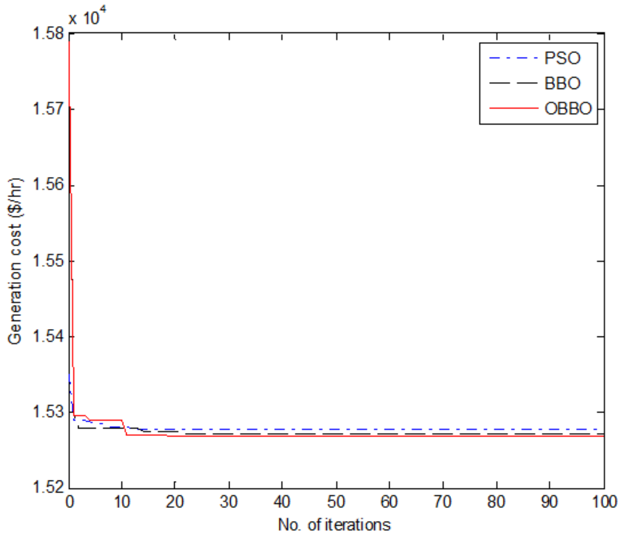

Figure 5: Convergence characteristics of PSO, BBO and OBBO (six generator system)

7. CONCLUSION

In this paper, a newly developed algorithm known as OBBO is presented for economic solution of the load dispatch problems and its performance has been compared with Lagrange multiplier, PSO and BBO methods. The OBBO algorithm has been successfully implemented on two different test systems. The results exhibit that the optimal cost obtained using OBBO technique is comparatively lesser as compared to other methods. Hence, it can be concluded that OBBO has the ability to find a better quality solution and exhibits better convergence characteristics than the Lagrange multiplier, PSO and BBO methods. Also using OBBO avoids premature convergence and thus enhances the global search capability. Owing to all these properties, the OBBO technique can be used to solve complex optimization problems in power systems.

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