Biogeography Based Optimization Technique for Multi-Constrained Economic Load Dispatch Problems

P. K. Roy 1, S. P. Ghoshal 2, S. S. Thakur 2
1 Dr. B. C. Roy Engineering College, Department of Electrical Engineering, Durgapur, West Bengal, India
Email: roy_provas@yahoo.com
2 National Institute of Technology, Department of Electrical Engineering, Durgapur, West Bengal, India
Email: {spghoshalnitdgp@gmail.com, sst_nit_ee@yahoo.co.in}

Abstract—This paper presents Biogeography-Based Optimization (BBO) technique for solving constrained economic dispatch problems in power system. Many nonlinear characteristics of generators, like valve point loading, ramp rate limits, prohibited zone, and multiple fuels cost functions are considered. The technique is applied to two Economic Load Dispatch (ELD) problems with different characteristics. Its solution quality and computation efficiency are compared to the same of Genetic algorithm (GA), Particle swarm optimization (PSO), and other optimization techniques. The simulation results show that the proposed algorithm outperforms other optimization methods.

Index Terms—Biogeography, Economic load dispatch, Genetic algorithm, Particle swarm optimization, Mutation, Migration.

I. INTRODUCTION

Economic load dispatch (ELD) problem is one of the major issues of power system operation, planning, and control. Its main objective is generation allocation to the power generators so as to meet the total load demand at minimum operating cost while satisfying all equality and inequality constraints. Several classical methods such as lambda iteration method (LIM), gradient methods etc. have been applied to solve economic load dispatch assuming monotonically increasing piecewise linear cost function. But unfortunately, these methods are infeasible in practical systems because of nonlinear characteristics like ramp rate limits, discontinuous prohibited operating zones, and non-smooth cost functions. Complex constrained ELD problems are solved by many population based optimization techniques in the recent years. Some of the population based optimization methods are genetic algorithm [1]-[2], simulated annealing [3], particle swarm optimization (PSO) [4]-[7], chaotic ant swarm optimization (CASO) [8], and Bacteria foraging optimization (BFO)[9].

Biogeography based optimization (BBO) [11] has some common features with other population based algorithms. Like GA, & PSO, BBO also shares information amongst the solutions but BBO does not involve in reproduction like GA. While GA solutions are lost at the end of each iteration, BBO maintains its set of solution from one iteration to next like PSO. But PSO solutions do not change directly; first their velocities are changed then positions (solutions) changes. However, BBO solutions are changed directly via migration from other solutions.

In this paper BBO algorithm, which is totally new in power system area is used to solve ELD problem.

II. MATHEMATICAL PROBLEM FORMULATION

A. Objective Function

The objective function of ELD is to minimize the generation cost while satisfying all the equality and inequality constraints.

Minimize \[ FC(P) = \sum_{i=1}^{n} FC_i(P_i) \] (1)

where \( FC_i(P_i) \) : fuel cost of generating unit \( i \),
\( P_i \) : generating power of unit \( i \),
\( n \) : number of generating units,
Subject to the following constraints:

\[ \sum_{i=1}^{n} P_i = P_D + P_L \] (2)

where \( P_D \) : Total Demand,
\( P_L \) : Transmission loss which is given by
\[ P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{ij} P_i + B_{00} \]  
\[ (3) \]

where \( B_{00}, B_{ij} & B_{ij} \) are loss coefficients.

b) \[ P_i^{\min} \leq P_i \leq P_i^{\max} \]  
\[ (4) \]

where \( P_i^{\min}, P_i^{\max} \) are minimum and maximum generation limit of i-th unit.

c) The power output of each unit is limited by ramp up/down rate at each hour as given below:
\[ \text{Max}(P_i^{\min}, P_i^{\max}, P_i^0 - DR_i, UDR_i) \leq P_i \leq \text{Min}(P_i^{\min}, P_i^{\max}, P_i^0 + UDR_i) \]  
\[ (5) \]

where \( P_i^0 \) : previous operating point of unit i,
\( DR_i, UDR_i \) : Downrate and Uprate limits of unit i.

d) Output generation of each unit must avoid operation in prohibited zones. The operating zone of unit \( i \) may be described as follows:
\[ P_i^{\min} \leq P_i \leq P_i^{l_{j-1}} \]
\[ P_i^{u_{j-1}} \leq P_i \leq P_i^{l_j}, \quad j = 2,3,\ldots, n_i \]  
\[ (6) \]

where \( n_i \) : number of prohibited zone of unit i,
\( P_i^{l_j} \) : Lower generation limit of prohibited zone \( j \) of unit i,
\( P_i^{u_{j-1}} \) : Upper generation limit of prohibited zone \( j-1 \) of unit i.

B. Cost Function

The cost function of ELD problem is defined as follows:

a) Cost function of generating units without valve point effect and multiple fuels is given by:
\[ FC(P) = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i) \]  
\[ (7) \]

Where \( a_i, b_i, & c_i \) are cost coefficients of i-th generator.

b) Cost function of generating units with valve point effect and multiple fuels is given by:
\[ FC(\delta P) = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i) \]
\[ \text{fuel} \text{min} \leq P_i \leq \text{fuel} \text{max} \]  
\[ (8) \]

where
\[ d_{ik}, \epsilon_{ik} \] : the fuel cost coefficients of fuel type k of the i-th generating unit reflecting the valve point loading.

III. OVERVIEW OF BBO TECHNIQUE

BBO [11] has been developed based on the theory of Biogeography. BBO concept is mainly based on Migration and Mutation. The concept and mathematical formulation of Migration and Mutation steps are given below:

A. Migration

This BBO algorithm [11] is similar to other population based optimization techniques where population of candidate solutions is represented as vector of real numbers. Each real number in the array is considered as one SIV. Fitness of each set of candidate solution is evaluated using SIV. In BBO a term HSI is used which is analogous to fitness function of other population-based techniques, to represent the quality of each candidate solution set. High HSI solutions represent better quality solution and low HSI solutions represent inferior solution in optimization problem.

The emigration and immigration rates of each solution are used to probabilistically share information between habitats. Using Habitat Modification Probability each solution is modified based on other solutions. Immigration rate \( \lambda \) of each solution is used to probabilistically decide whether or not to modify each suitability index variable (SIV) in that solution. After selecting the SIV for modification, immigration rates, \( \mu \) of other solutions are used to probabilistically select which solutions among the population set will migrate. The main difference between recombination approach of evolutionary strategies (ES) and migration process of BBO is that in ES, global recombination process is used to create a completely new solution, while in BBO, migration is used to bring changes within the existing solutions. In order to prevent the best solutions from being corrupted by the immigration process, few elite solutions are kept in BBO algorithm.

B. Mutation

Due to some natural calamities or other events HSI of a natural habitat can change suddenly and it may deviate from its equilibrium value. In BBO, this event is represented by the mutation of SIV and species count probabilities are used to determine mutation rates. The probability of each species count can be calculated using the differential equation (9) [11] given below:
\[ \dot{P}_s = \left\{ \begin{array}{ll}
- (\lambda_i + \mu_i) P_i + \lambda_i s \cdot P_{s,i} & \text{if } S = 0 \\
- (\lambda_i + \mu_i) P_i + \lambda_i s \cdot P_{s,i} - \mu_i s \cdot P_{s,i} & \text{if } 1 \leq S \leq S_{\text{max}} - 1 \\
- (\lambda_i + \mu_i) P_i + \lambda_i s \cdot P_{s,i} - \mu_i s \cdot P_{s,i} & \text{if } S = S_{\text{max}}
\end{array} \right. \]  
\[ (9) \]

where
The probability of habitat contains exactly $S$ species, $\lambda_s$, $\mu_s$. The immigration and emigration rate for habitat contains $S$ species. Immigration rate ($\lambda_s$) and emigration rate ($\mu_s$) can be evaluated by the equation (10) and (11) [11] given below:

$$\lambda_s = \frac{I}{1 - \frac{S}{S_{\text{max}}}} \quad (10)$$

$$\mu_s = \frac{ES}{S_{\text{max}}} \quad (11)$$

where $I$ : maximum immigration rate, $E$ : maximum emigration rate, $S$ : number of species, $S_{\text{max}}$ : maximum number of species.

Each population member has an associated probability, which indicates the likelihood that it exists as a solution for a given problem. If the probability of a given solution is very low then that solution is likely to mutate to some other solution. Similarly if the probability of some other solution is high then that solution has very little chance to mutate. Therefore, very high HSI solutions and very low HSI solutions are equally improbable for mutation i.e. they have less chances to produce more improved SIVs in the later stage. But medium HSI solutions have better chances to create much better solutions after mutation operation. Mutation rate of each set of solution can be calculated in terms of species count probability using the equation (12) [11]:

$$m(s) = m_{\text{max}} \left( 1 - \frac{P_s}{P_{\text{max}}} \right) \quad (12)$$

where, $m_{\text{max}}$: Maximum mutation rate, $m(s)$: The mutation rate for habitat contains $S$ species, $P_{\text{max}}$: Maximum probability.

This mutation scheme tends to increase diversity among the populations. Without this modification, the highly probable solutions will tend to be more dominant in the population. This mutation approach makes both low and high HSI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier values. Few elite solutions are kept in mutation process to save the features of a solution, so if a solution becomes inferior after mutation process then previous solution (solution of that set before mutation) can revert back to that place again if needed. So, mutation operation is a high-risk process. It is normally applied to both poor and better solutions. Since medium quality solutions are in improving stage so it is better not to apply mutation on medium quality solutions.

Here, mutation of a selected solution is performed simply by replacing it with randomly generated new solution set. Other than this any other mutation scheme, like mutation of GA can also be implemented for BBO.

IV. BBO ALGORITHM APPLIED TO ELD

The algorithm of the proposed method is as enumerated below.

Step1: Initialization of the BBO parameters.

Step2: The initial position of SIV of each habitat should be selected randomly while satisfying different equality and inequality constraints of ELD problems. Several numbers of habitats depending upon the population size are being generated. Each habitat represents a potential solution to the given problem.

Step3: Calculate the HSI i.e. value of objective function for each habitat of the population set for given emigration rate, $\mu$, immigration rate, $\lambda$, and species, $S$.

Here, in ELD problem HSI$_i$ represents the cost function of $i$-th generation set (i.e. $i$-th habitat) in $$/hr.

$\text{SIV}_{iq}$ represents the value of power output of $q$-th generator of $i$-th habitat set $H^i$. In this paper, each habitat is a vector with $m$ generating units. Each individual habitat within the total of $H$ habitat represents a candidate solution for solving the ELD problem. The $i$-th individual $H_i$ can be defined as follows:

$$H^i = [SIV_{i1}^q, SIV_{i2}^q, ..., SIV_{im}^q] \quad (13)$$

where $i = 1, 2, ..., S; q = 1, 2, ..., m$

where $SIV_{iq}$ is the power output of the $q$-th unit of the $i$-th individual.

Step4: Based on the HSI value elite habitats are identified.

Step5: Each non-elite habitat is modified by performing probabilistically migration operation as described below:

Select $H_i$ with probability $\propto \lambda_i$.

If $H_i$ is selected

For $j = 1$ to (no of habitats)

Select $H_j$ with probability $\propto \mu_j$

If $H_j$ is selected

Randomly select an SIV $\beta$ from $H_j$

Replace a random SIV in $H_i$ with $\beta$

end

end

Step6: HSI of each modified set is recomputed. Feasibility of a problem solution is verified i.e. each SIV should satisfy equality and inequality constraints of generator as mentioned in the specific problem.

Step7: Species count probability of each habitat is updated using (9). Mutation operation is performed on the
worst half of the non-elite habitat and HSI value of each new habitat is computed.
Step 8: Sort the population from best to worst.
Step 9: Replace worst with best Habitat.
Step 10: Feasibility of a problem solution is verified.
Step 11: Go to step (3) for the next iteration.
Step 12: Stop iteration after a predefined number of iterations.

V. INPUT PARAMETERS

After several runs, the following input control parameters are found to be best for optimal performance of the proposed algorithm. Habitat Modification Probability, \( P^{\text{mod}} = 1 \); Mutation Probability = 0.005, maximum immigration rate, \( I = 1 \), maximum emigration rate, \( E = 1 \), step size for numerical integration, \( dt = 1 \), maximum iteration cycles = 50, elitism parameter = 4, number of SIVs = number of generator units and number of Habitats = population size = 50.

VI. SIMULATION RESULTS AND DISCUSSION

A. Test System I

In this example 10 generating units are considered and both valve point loading & multiple fuels are incorporated in the cost function. The system data of [1] is employed on BBO and its performance is compared to that of IGA_MU [1], & CGA_MU [1] and the comparative results together with fuel type (FT) & convergence characteristics are shown in Table I and Figure 1 respectively for total load of 2700MW.

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![Figure 1 Convergence characteristic of BBO (10-units system )](image)

B. Test System II

In this example, 6 generating units with the constraints of ramping rate limit and prohibited zones of units are considered. System data of [7] is used. Simulation results & convergence curve of BBO for 1263 MW load with 50 iterations are shown in Table II and Figure 2 respectively. Results show that generation cost obtained from BBO is the lowest and thus establish that BBO has better quality of solution.

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<td>Loss (MW)</td>
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CONCLUSIONS

In this paper, the authors have successfully employed the BBO algorithm to solve ELD problems for units having valve point effect, ramping rate, prohibited operating zones and multiple fuels. The comparison of the results with other methods reported in the literature show the superiority of the proposed method and its potential for solving non-smooth ELD problems in a power system. This method shows excellence in dealing with multi-constrained nonlinear power system problems.

REFERENCES


