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A New Methodology for Solving Different Economic Dispatch Problems

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Abstract- This paper presents a Biogeography-Based Optimization (BBO) algorithm to solve various types of Economic Load Dispatch (ELD) problems of the thermal power plants in a power system. The proposed methodology can handle economic load dispatch problems having constraints like transmission losses, prohibited operating zones, etc. Biogeography basically is the science of geographically distribution of the biological species. The mathematical model of the biogeography describes the process how species arise, migrate from one place to another and gets vanish. This methodology has some common features with other biogeography based optimization methods like Genetic algorithm (GA), Particles swarm optimization (PSO). This algorithm search the global optimum value through two steps: Migration and Mutation. The effectiveness of the proposed methodology has been verified with some test systems. Considering the quality of the solution of the different problems obtained, this method seems to be better than other optimization methods.

Index Terms- **Biogeography-Based Optimization, Economic Load Dispatch, Genetic Algorithm, Particle Swarm Optimization, Prohibited Operating Zones.**

I. INTRODUCTION

Economic load dispatch (ELD) seeks “the best” generation schedule for the generating plants to supply the required demand plus transmission losses at minimum production cost. The ELD may be formulated as a nonlinear constrained problem. The convex ELD problem assumes quadratic cost function along with system power demand and operational limit constraints. The practical non-convex ELD (NCELD) problem, in addition, considers generator nonlinearities such as valve point loading effects, prohibited operating zones, ramp rate limits, and multi-fuel options. For these types of problems a new methodology using Biogeography is being introduced in the optimization process. The science of biogeography can be traced to the work of nineteenth century naturalists such as Alfred Wallace and Charles Darwin. The application of biogeography to engineering is similar to what has occurred in the past few decades with genetic algorithms (GAs), neural networks, fuzzy logic, particle swarm optimization (PSO), and other areas of computer intelligence. Various investigations on Economic Load Dispatch have been undertaken until date, as better solutions would result in significant economical benefits. Previously a number of derivative-based approaches including Lagrangian multiplier method [1] have been applied to solve ELD problems. But these methods require that incremental cost curves are monotonically increasing in nature. The calculus-based methods fail in solving these types of problems. Wood and Wollenberg proposed dynamic programming [2], which does not impose any restriction on the nature of the cost curves and solves both convex and non-convex ELD problems. But this method suffers from the curse of dimensionality and simulation time increases rapidly with the increase of system size. The application of artificial intelligence technology for solution of ELD problems such as genetic algorithm (GA) [3]; artificial neural networks [4]; simulated annealing (SA), Tabu search; evolutionary programming [5]; particle swarm optimization (PSO) [6]; ant colony optimization; differential evolution [7]; etc. have been developed. The SA method is usually slower than the GA method because the GA has parallel search capabilities. However, research has identified some deficiencies in application to highly epistatic objective functions where the parameters being optimized are strongly correlated. In PSO there are only a few parameters to be adjusted, which make PSO more attractive. But once inside the optimum region, the algorithm progresses slowly due to its inability to adjust the velocity step size to continue the search at a finer grain.

Very recently, a new optimization concept, based on biogeography, has been proposed by Simon [8]. Biogeography is the nature’s way of distributing species. Mathematical models of biogeography describe how species migrate from one island to another, how new species arise, and how species become extinct. An island is any habitat that is geographically isolated from other habitats. Geographical areas that are well suited as residences for biological species are said to have a high habitat suitability index (HSI). Features that correlate with HSI include such factors as rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature. The variables that characterize habitability are called suitability index variables (SIVs). SIVs can be considered the independent variables of the habitat, and HSI can be considered the dependent variable.

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Let us consider an optimization problem with some trial solutions of it. In BBO, a good solution is analogous to an island with a high Habitat Suitability Index (*HSI*), and a poor solution represents an island with a low *HSI*. High *HSI* solutions resist change more than low *HSI* solutions. Low *HSI* solutions tend to copy good features from high HSI solutions. The shared features remain in the high *HSI* solutions, while at the same time appearing as new features in the low *HSI* solutions. BBO works based on the two mechanisms: migration and mutation. BBO, as in other biology-based algorithms like GA and PSO, has the property of sharing information between solutions.

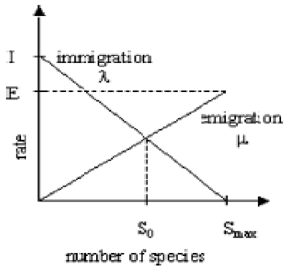

Fig.1. Species Model of a Single Habitat

Fig. 1 illustrates a model of species abundance in a single habitat. The immigration rate λ and the emigration rate μ are functions of the number of species in the habitat. Consider the immigration curve. The maximum possible immigration rate to the habitat is *I*, which occurs when there are zero species in the habitat. As the number of species increases, the habitat becomes more crowded, fewer species are able to successfully survive immigration to the habitat, and the immigration rate decreases. The largest possible number of species that the habitat can support is S_{max}, at which point the immigration rate becomes zero. If there are no species in the habitat then the emigration rate must be zero. As the number of species increases, the habitat becomes more crowded, more species are able to leave the habitat to explore other possible residences, and the emigration rate increases. The maximum emigration rate is *E*, which occurs when the habitat contains the largest number of species that it can support. The equilibrium number of species is S_o, at which point the immigration and emigration rates are equal. Now, consider the probability P_S that the habitat contains exactly *S* species. P_S changes from time *t* to time $(t+\Delta t)$ as follows:

$$P_s(t+\Delta t) = P_s(t)(1-\lambda_s\Delta t-\mu_s\Delta t)+P_{s-1}\lambda_{s-1}\Delta t+P_{s+1}\mu_{s+1}\Delta t$$

(1)

Where λ_s = immigration rates

μ_s = emigration rates

To have species at time *t*, one of the following conditions must hold:

1) There were *S* species at time *t*, and no immigration or emigration occurred between *t* and $(t+\Delta t)$;

2) There were *(S-1)* species at time *t*, and one species immigrated;

3) There were *(S+1)* species at time *t*, and one species emigrated.

We assume that Δt is small enough so that the probability of more than one immigration or emigration can be ignored. Taking the limit Δt→0 of (1) as gives equation (2)

$$\dot{P_s} = \begin{cases} -(\lambda_s+\mu_s)P_s+\mu_{s+1}P_{s+1}, & S=0 \\ -(\lambda_s+\mu_s)P_s+\lambda_{s-1}P_{s-1}+\mu_{s+1}P_{s+1}, & 1\le S\le S_{max}-1 \\ -(\lambda_s+\mu_s)P_s+\lambda_{s-1}P_{s-1} & S=S_{max} \end{cases}$$

(2)

II. BIOGEOGRAPHY BASED OPTIMIZATION (BBO)

In this section, we discuss how the biogeography theory can be applied to optimization problems with a discrete domain. BBO concept is based on the two major steps, e.g., migration and mutation as discussed below.

A. Migration

The emigration and immigration rates of each solution are used to probabilistically share information between habitats. With probability P_{mod}, known as habitat modification probability, each solution can be modified based on other solutions. According to BBO if a given solution S_i is selected for modification, then its immigration rate λ is used to probabilistically decide whether or not to modify each suitability index variable (*SIV*) in that solution. After selecting the *SIV* for modification, emigration rates μ of other solutions are used to select which solutions among the habitat set will migrate randomly chosen *SIVs* to the selected solution S_i. In order to prevent the best solutions from being corrupted by immigration process, some kind of elitism is kept in BBO algorithm.

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Here, best habitat sets, i.e., those habitats whose *HSI* are best, are kept as it is without migration operation after each iteration. This operation is known as elitism operation.

B. Mutation

It is well known that due to some natural calamities or other events *HSI* of natural habitat might get changed suddenly. In BBO such an event is represented by mutation of *SIV* and species count probabilities are used to determine mutation rates. The probabilities of each species count can be calculated using the differential equation of (2). Mutation rate of each set of solution can be calculated in terms of species count probability using the following equation:

$$m(S) = m_{max}\left(\frac{1-P_s}{P_{max}}\right) \qquad (3)$$

Where m_{max} is a user-defined parameter. This mutation scheme tends to increase diversity among the habitats. Without this modification, the highly probable solutions will tend to be more dominant in the total habitat. 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 value. To apply BBO on ELD problems first we have to design the problem using related parameters. The objective function F_t of ELD problem may be written as

$$F_t = min\left(\sum_{i=1}^{m} F_i(P_i)\right)$$

$$= min(\textstyle\sum_{i=1}^{m} a_i + b_iP_i + c_iP_i^2)$$

(4)

Where $F_i(P_i)$ is the *i*th generator's cost function, and is usually expressed as a quadratic polynomial; a_i, b_i, c_i and are the cost coefficients of the *i*th generator; *m* is the number of committed generators to the power system; P_i is the power output of the *i*th generator. The ELD problem consists in minimizing F_t subject to the following constraints

1) Real Power Balance Constraint:

$$\textstyle\sum_{i=1}^{m} P_i - P_D - P_L = 0 \qquad (5)$$

The transmission loss P_L may be expressed using B-coefficients
As

$$P_L = \textstyle\sum_{i=1}^{m}\sum_{j=1}^{m} P_iB_{ij}P_j + \sum_{i=1}^{m} B_{0i}P_i + B_{00} \quad (6)$$

2) *Generator Capacity Constraints:* The power generated by each generator shall be within their lower limit P_i^{min} and upper limit P_i^{max}. So that

$$P_i^{min} \le P_i \le P_i^{max} \qquad (7)$$

BBO Algorithm for ELD Problem

In this section, a new approach to implement the BBO algorithm will be described for solving the ELD problems. The process of the BBO algorithm can be summarized as follows.

1) *Representation of the SIV:* Since the decision variables for the ELD problems are real power generations, they are used to represent individual habitat. The real power output of all generators is represented as the *SIV* in a habitat. For initialization, choose number of *SIV* of BBO algorithm *m*, number of habitat *N*.

The complete habitat set is represented in the form of the following matrix:

$$.H = [H^1 \quad H^2 \quad H^3. \quad . \quad . \quad . \quad . \quad . \quad H^i. \quad . \quad . \quad . \quad . \quad . \quad H^N \quad]$$

2) *Initialization of the SIV:* Each element of the Habitat matrix, i.e., each *SIV* of a given habitat set , is initialized randomly within the effective real power operating limits.

3) Calculate the HSI for each habitat set of the total habitat set for given emigration rate λ, immigration rate μ. HSI represent the fuel cost of the generators in the power system for a particular power demand. Here, HSI^i indicates the fuel cost due to the *i*th set of generation value (i.e., *i*th set of habitat matrix *H*) in $/h.

4) Based on the *HSI* (fuel cost in case of ELD problem), value elite habitats are identified. Here elite term is used to indicate those habitat sets of generator power output, which give best fuel cost.

5) Probabilistically perform migration operation on those *SIVs* of each non-elite habitats, selected for migration.

6) Species count probability of each habitat is updated using (2). Mutation operation is performed on the non-elite habitat. If mutation rate as calculated using (3) of any habitat is greater than a randomly generated number, then that habitat is selected for mutation.

7) Go to step 3) for the next iteration. This loop can be terminated after a predefined number of iterations.

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III. NUMERICAL EXAMPLE & SIMULATION RESULT

A simple system with ten thermal units is considered here. The input data are taken from [9]. The load demand is 2700 MW. Transmission loss has not been considered here. The result obtained from the proposed BBO, different PSO techniques [10], and different GA [9] methods are shown in Table I at the next page.

IV. CONCLUSION

The BBO method has been successfully implemented to solve different ELD problems with the generator constraints. The BBO algorithm has the ability to find the better quality solution and has better convergence characteristics, computational efficiency, and robustness. It is clear from the results obtained by different trials that the proposed BBO method has good convergence property and can avoid the shortcoming of premature convergence of other optimization techniques to obtain better quality solution. Due to these properties, the BBO method in the future can be tried for solution of complex unit commitment, dynamic ELD problems in the search of better quality results.

Table I. Best Power Outputs For Ten- Generator System (P_l=2700mw)

Unit Power Output	BBO	NPSO-LRS [10]	NPSO[10]	PSO-LRS [10]	IGA_MU [9]	CGA_MU [9]
P_1 (MW)	214.56	223.33	220.657	219.015	219.126	222.010
P_2 (MW)	210.48	212.19	211.785	213.890	211.164	211.635
P_3 (MW)	333.78	276.21	280.402	283.761	280.657	283.945
P_4 (MW)	271.32	239.41	238.601	237.268	238.477	237.805
P_5 (MW)	238.89	274.64	277.562	286.016	276.417	280.448
P_6 (MW)	270.51	239.79	239.120	239.398	240.467	236.033
P_7 (MW)	281.12	285.53	292.139	291.176	287.739	292.049
P_8 (MW)	239.12	240.63	239.153	241.439	240.761	241.970
P_9 (MW)	415.97	429.26	426.114	416.972	429.337	424.201
P_{10} (MW)	268.65	278.65	274.463	271.062	275.851	269.900
Total Cost ($/h)	607.98	624.1273	624.1624	624.229	624.5178	624.719
Mean CPU Time (sec.)	0.90	0.52	0.35	0.88	7.25	26.17

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