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Biogeography Based Optimization For Dynamic Economic Load Dispatch

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Abstract
This paper attempts to develop a new methodology for dynamic economic load dispatch (DELD) using biogeography based optimization (BBO). The DELD is an extension of static economic load dispatch to determine the generation schedule of the committed units so as to meet the predicted load demand over a time horizon at minimum operating cost taking into account the ramp rate constraints. The BBO, inspired from the geographical distribution of biological species, searches for optimal solution through the migration and mutation operators. The proposed method divides the DELD problem into several sub-problems, each representing an ELD of an interval, and solves the each sub-problem using BBO. The simulation results on a 10 unit test problem clearly indicate that the developed method is robust and computationally efficient.
Keywords: Dynamic economic load dispatch, biogeography based optimization.

NOMENCLATURE

a_i b_i c_i	fuel cost coefficients of the i^{th} generator
BBO	biogeography based optimization
B B_o B_{oo}	loss coefficients
DELD	dynamic economic load dispatch
DR_i	down-ramp limit of i^{th} generator in MW/h
d_i e_i	coefficients of valve point effects of the i^{th} generator
ELD	economic load dispatch
$F_i(P_{Gi})$	fuel cost function of the i^{th} generator in $\$/h$
HSI	habitat suitability index
h_i	i^{th} habitat
$Iter^{\max}$	maximum number of iterations for convergence check
nt	number of intervals
ng	number of generators
nh	number of habitats
neh	number of elite habitats
PM	proposed method
P_{Git}	real power generation of i^{th} generator at interval-t
$P_{Gi}^{\min}$ & $P_{Gi}^{\max}$	minimum and maximum generation limits of i^{th} generator respectively
P_{Dt}	total power demand at interval-t
P_{Lt}	net transmission loss at interval-t
P^{mod}	habitat modification probability
P_m	mutation probability
SIV	suitability index variable
UR_i	up-ramp limit of i^{th} generator in MW/h
$\Phi(P_G)$	objective function to be minimized
Ψ	augmented objective function to be minimized
λ	immigration rate
μ	emigration rate

1. INTRODUCTION
Dynamic Economic Load Dispatch (DELD) is used to determine the optimal generation schedule of on-line generators, so as to meet the predicted load demand over certain problem period of time at minimum operating cost under various system and operational constraints. It is a dynamic optimization problem taking into account the constraints imposed on system operation by generator ramp-rate limits. Due to the ramp-rate constraints of a generator, the operational decision at an hour may affect the operational decision at a later hour. It has a look-ahead capability which is necessary to schedule the load beforehand so that the system can anticipate sudden load changes in near future. The DELD problem can be formulated as a large-scale, optimization problem, which is quite difficult due to its inherent high dimensional, non-convex and nonlinear nature. The dimension of the problem increases rapidly with the system size and the scheduling horizon [1].
Over the years, numerous methods with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics are suggested in the literature for solving the dynamic dispatch problems. These optimization techniques can be classified into three main categories. The first category is mathematical programming-based or

heuristically-based, such as the lambda iterative method [2], gradient projection method [3], Lagrange relaxation [4], linear programming [5], nonlinear programming [6], interior point methods [7], dynamic programming [8], etc. The advantages of these methods are: optimality is mathematically proven in some algorithms; they can be applied to large-scale problems; they have no problem-specific parameters to specify; moreover, some of these methods are computationally fast. However, these methods can converge to a local optimum and are sensitive to the initial starting points [9]. Many of these techniques are not applicable to a certain class of cost functions; for example lambda-iterative, Lagrange relaxation and gradient technique methods, etc when used to solve DELD with non-smooth or non-convex cost functions, can fail to get global optimal solutions. For non-monotonically increasing incremental cost functions, the lambda iterative method may not result in the optimal solution and Linear programming usually faces poor computation efficiency. Dynamic programming can solve DELD problems with non-smooth cost functions; however, it suffers from the “curse of dimensionality” and local optimality [8].

The second category is the methods based on artificial intelligence, such as artificial neural networks [10] and stochastic optimization methods such as genetic algorithm (GA) [11], simulated annealing (SA) [12], evolutionary programming (EP) [13], differential evolution (DE) [14], particle swarm optimization (PSO) [15] and Hopfield neural network (HNN) that have been successfully used for solving the DELD problems. Artificial neural networks such as HNN have been found to generate a high quality solution for the DELD problems with smooth cost functions [10]. Stochastic optimization methods can solve DELD without any or fewer restrictions on the shape of the cost function curves due to their ability to seek the global optimal solution. Moreover, these algorithms do not depend on the first and second differentials of the objective function.

The third category is the hybrid methods, which combine two or more techniques previously mentioned in order to get best features in each algorithm. These methods such as evolutionary programming with sequential quadratic programming [16], particle swarm optimization with sequential quadratic programming [17], Hopfield neural network with quadratic programming [18] have proven their effectiveness in solving the DELD problems.

Recently, a Biogeography-Based Optimization (BBO), a population based stochastic optimization technique sharing information between candidates solutions based on their fitness values, has been suggested for solving optimization problems by Simon [19]. It has been applied to a variety of power system optimization problems [20-23] and found to yield satisfactory results. This paper attempts to apply BBO in solving the DELD problem by splitting it into several sub-problems with a view of enhancing the computational efficiency and robustness.

2. PROBLEM FORMULATION

The goal of the DELD problem is to determine the combination of output of all generating units that minimize the total fuel cost over the dispatch period while satisfying all kinds of physical and operational constraints DELD can be expressed as an optimization problem with various complicated constraints.

The objective of DELD problem is to minimize the total fuel cost of all ng generators over the given dispatch period of nt intervals

$$\text{Minimize } \Phi(P_G) = \sum_{t=1}^{nt} \sum_{i=1}^{ng} F_i(P_{Git}) \tag{1}$$

Subject to

$$\sum_{i=1}^{ng} P_{Git} - P_{Dt} - P_{Lt} = 0 \qquad t \in nt \tag{2}$$

$$P_{Gi}^{\min} \le P_{Git} \le P_{Gi}^{\max} \qquad i \in ng, t \in nt \tag{3}$$

$$\begin{aligned} &P_{Git} - P_{Git-1} \le UR_i \quad i \in ng \quad t = 2, \cdots, nt \\ &P_{Git-1} - P_{Git} \le DR_i \quad i \in ng \quad t = 2, \cdots, nt \end{aligned} \tag{4}$$

Where

$$F_i(P_{Git}) = a_i P_{Git}^2 + b_i P_{Git} + c_i + \left| d_i \sin\{e_i (P_{Gi}^{\min} - P_{Git})\} \right| \tag{5}$$

$$P_{Lt} = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_{Git} B_{ij} P_{Gjt} + \sum_{k=1}^{ng} B_{0k} P_{Gkt} + B_{00} \tag{6}$$

3. BIOGEOGRAPHY BASED OPTIMIZATION

BBO, based on the concept of biogeography, is a stochastic optimization technique for solving multimodal optimization problems [19]. In BBO, a solution is represented by a habitat-i consisting of solution features named Suitability Index Variables (*SIV*), which are represented by real numbers. It is represented for a problem with nd decision variables as

$$h_i = [SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}] \tag{7}$$

The suitability of sustaining larger number of species of a habitat-i can be modeled as a fitness measure referred to Habitat Suitability Index (HSI) as

$$HSI_i = f(h_i) = f(SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}) \tag{8}$$

High *HSI* represents a better quality solution and low *HSI* denotes an inferior solution. The aim is to find optimal solution in terms of *SIV* that maximizes the *HSI*.

Each habitat is characterized by its own immigration rate λ and emigration rate μ . A good solution enjoys a higher μ and lower λ and vice-versa. The immigration and emigration rates are the functions of the number of species in the habitat and defined for a habitat containing k -species as

$$\mu_k = E^{\max}\left(\frac{k}{n}\right) \tag{9}$$

$$\lambda_k = I^{\max}\left(1 - \frac{k}{n}\right) \tag{10}$$

When $E^{\max} = I^{\max}$, the immigration and emigration rates can be related as

$$\lambda_k + \mu_k = E^{\max} \tag{11}$$

A population of candidate solutions is represented as a vector of habitats similar to any other evolutionary algorithm. The features between the habitats are shared through migration operation, which is probabilistically controlled through habitat modification probability, P^{mod}. If a habitat h_i in the population is selected for modification, then it λ is used to probabilistically decide whether or not to modify each *SIV* in that habitat. The μ of other solutions are thereafter used to select which of the habitats in the population shall migrate randomly chosen *SIVs* to the selected solution h_i.

The cataclysmic events that drastically change the *HSI* of a habitat is represented by mutation of *SIVs*. The mutation operation modifies a habitat's *SIV* randomly based on mutation rate P_m and tends to increase diversity among the population, avoids the dominance of highly probable solutions and provides a chance of improving the low *HSI* solutions. Mutation rate of each solution set can be calculated in terms of species count probability using the following equation:

$$P_m = m^{\max}\left(\frac{1-P^k}{P^{\max}}\right) \tag{12}$$

4. PROPOSED METHOD

In all the evolutionary based solution methods, each member in the population consists of real power generation of all the generating plants at all intervals of the scheduling horizon. These methods involve a large number of decision variables, which is the product of the number of generating plants and the number of intervals over the scheduling period. For example, a problem with 10 generating units over a scheduling horizon of 24 intervals involves 240 decision variables, representing a search space with dimension of 240, thereby making the search process very complex and time consuming [3, 7, 24]. In the proposed method (PM), the DELD problem is divided in to a number of sub-problems, each representing an ELD of interval-t. The real power generations of each sub-problem at interval-t, involving ng decision variables, are considered to denote the habitat as

$$h_i = \left[P_{G1t}, P_{G2t}, \cdots, P_{Gngt}\right] \tag{13}$$

The HSI function can be tailored through penalizing the fuel cost by the power balance constraint for the $t-th$ sub-problem as

$$\text{Maximize } HSI = \frac{1}{1+\Psi} \tag{14}$$

Where

$$\Psi = \sum_{i=1}^{ng} F_i(P_{Git}) + K_1 \sum_{i=1}^{ng} \left(P_{Git} - P_{Dt} - P_{Lt}\right)^2 \tag{15}$$

Initially the interval $t = t^o$, whose power demand approximately equals the average of the minimum and maximum power demands, is chosen; and the lower and upper bound of the habitat for the initial interval is set as

$$\begin{aligned} h^{\min} &= \left[P_{G1}^{\min}, P_{G2}^{\min}, \cdots, P_{Gng}^{\min}\right] \\ h^{\max} &= \left[P_{G1}^{\max}, P_{G2}^{\max}, \cdots, P_{Gng}^{\max}\right] \end{aligned} \tag{16}$$

The ELD problem is iteratively solved using the BBO for the chosen initial interval-t. Then the ELD problem is formulated for the subsequent intervals $t = t+1$, with the lower and upper limits for the habitat is set by considering the ramp rate limit constraint of Eq. (4) and solved for this interval using BBO.

$$\begin{aligned} h^{\min} &= \left[h_1^{\min}, h_2^{\min}, \cdots, h_{ng}^{\min}\right] \\ h^{\max} &= \left[h_1^{\max}, h_2^{\max}, \cdots, h_{ng}^{\max}\right] \end{aligned} \tag{17}$$

Where

$$\begin{aligned} h_j^{\min} &= \begin{cases} P_{Git-1} - DR_i & if\ \left(P_{Git-1} - DR_i\right) \geq P_{Gj}^{\min} \\ P_{Gj}^{\min} & else \end{cases} \\ h_j^{\max} &= \begin{cases} P_{Git-1} + UR_i & if\ \left(P_{Git-1} + UR_i\right) \leq P_{Gj}^{\max} \\ P_{Gj}^{\max} & else \end{cases} \end{aligned} \tag{18}$$

The above BBO based solution process is repeated by incrementing the interval-t till the last interval-nt of the scheduling horizon. Similarly the preceding sub-problems of the initial interval $t = t^o$ is obtained by decrementing the interval as $t = t-1$ and solved using the BBO till the solution for the first interval is obtained. The limits of the habitat during this phase can be set as

$$\begin{aligned} h_j^{\min} &= \begin{cases} P_{Git+1} - UR_i & if\ \left(P_{Git+1} - UR_i\right) \geq P_{Gj}^{\min} \\ P_{Gj}^{\min} & else \end{cases} \\ h_j^{\max} &= \begin{cases} P_{Git+1} + DR_i & if\ \left(P_{Git+1} + DR_i\right) \leq P_{Gj}^{\max} \\ P_{Gj}^{\max} & else \end{cases} \end{aligned} \tag{19}$$

The real power generations obtained for each interval over the scheduling horizon represent the optimal solution of the DELD problem. The solution process of the PM is explained through the flow chart of Fig.1.

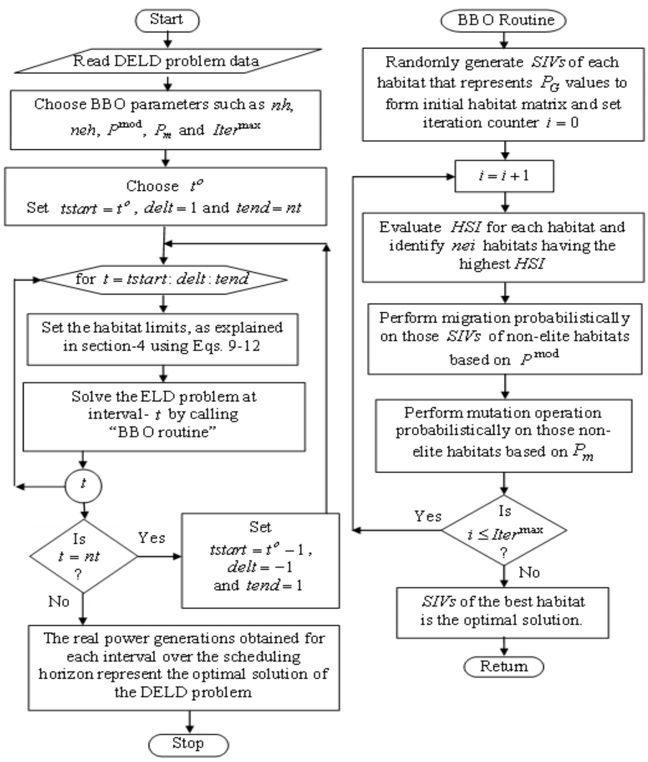

Fig.1 Flow Chart of the PM with BBO subroutine

5. NUMERICAL RESULTS

The PM is tested on a test system possessing 10 generating units. The fuel cost coefficients including valve-point effects, generation limits, and ramp rate limits are given in Table 1. The power demand data over a scheduling period of 24 hours are given in Fig.2. The network loss is neglected in the solution process. The software package for PM is developed in Matlab platform and executed in a 2.3 GHz Pentium-IV personal computer. There is no guarantee that different executions of the BBO converge to the same solution due to the stochastic nature of the algorithm, and hence the PM is applied to these test system for 20 independent trials (300 iterations per trial) with the selected parameters and the best ones are presented. The results obtained by the PM for the test system are compared with a few of the existing methods of SQP, EP, HQ-PSO, AIS and ICPSO, outlined in [16, 25-27] and discussed.

Table 1 Generator Data

	P_G^{min}	P_G^{max}	a	b	c	d	e	UR	DR
1	150	470	21.600	958.200	958.200	450	0.041	80	80
2	135	460	21.050	1313.600	1313.600	600	0.036	80	80
3	73	340	20.810	604.970	604.970	320	0.028	80	80
4	60	300	23.900	471.600	471.600	260	0.052	50	50
5	73	243	21.620	480.290	480.290	280	0.063	50	50
6	57	160	17.870	601.750	601.750	310	0.048	50	50
7	20	130	16.510	502.700	502.700	300	0.086	30	30
8	47	120	23.230	0.004800	639.400	340	0.082	30	30
9	20	80	19.580	0.109080	455.600	270	0.098	30	30
10	55	55	22.540	0.009510	692.400	380	0.094	30	30

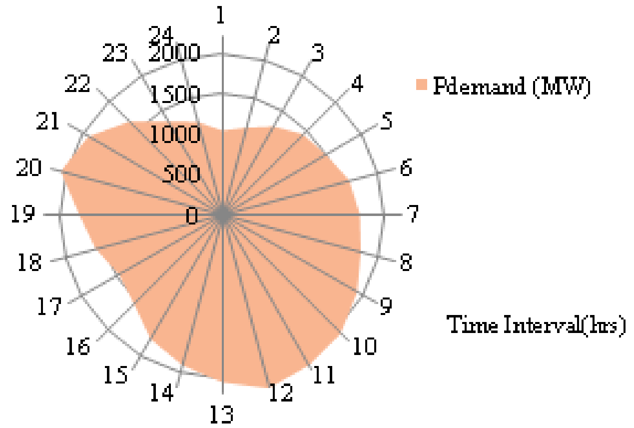

Fig.2 Power Demand over the scheduling horizon

The optimal generations obtained by the PM over the scheduling period is graphically presented in Fig 3. The corresponding fuel cost over the scheduling horizon is presented through Fig 4. The best fuel cost obtained by the PM for this test system is compared with those of the existing method in Fig.5. It is observed from these results that the PM offers the lowest fuel cost of 1016818 $\$/h$ compared to other methods. The computational efficiency of any optimization method is a crucial factor for its practical applicability. Therefore the normalized execution time (NET) in seconds is compared with those of the existing methods in Fig 6. It can be observed from the figure that the PM is computationally efficient in offering the optimal solution.

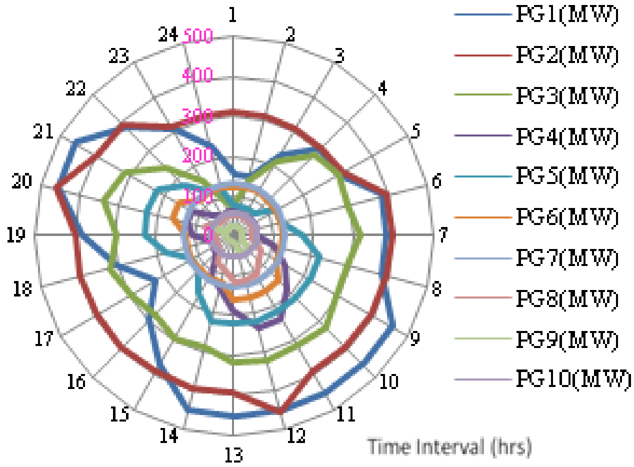

Fig.3 Optimal real power generations of the PM

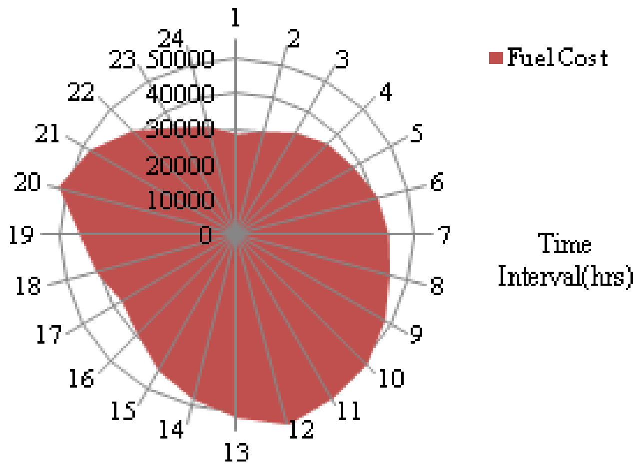

Fig.4 Fuel cost of the PM over the scheduling period

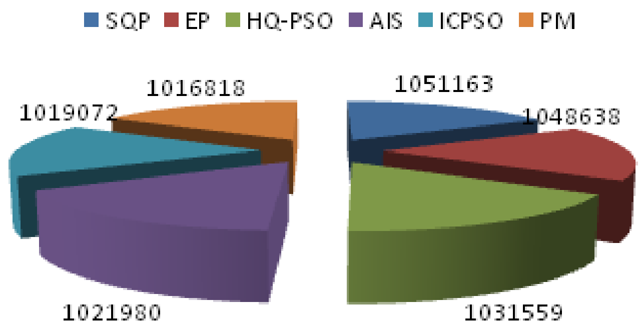

Fig 5 Comparison of Fuel Costs ($/h)

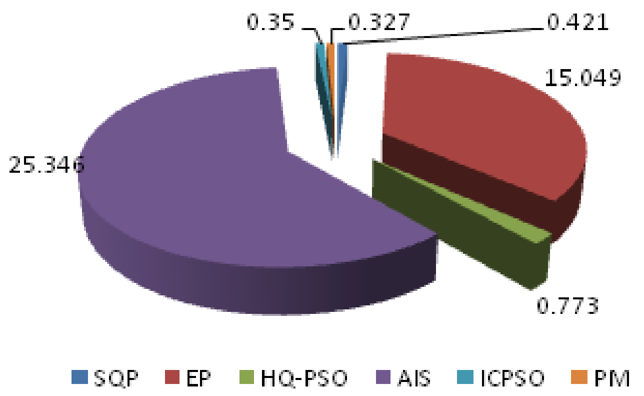

Fig 6 Comparison of NET

6.CONCLUSION

The BBO, inspired from the geographical distribution of biological species, searches for optimal solution for multimodal optimization problems through the migration and mutation operators. A new innovative methodology using BBO has been elucidated for solving DELD problem, which is a complex non-linear optimization problem involving large number of decision variables and the ramp rate constraints. The problem has been split into a number of sub-problems and each sub-problem has been solved using BBO. The simulation results on 10 unit test system clearly revealed that the dignifying method is robust and computationally efficient.

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