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Non-linear BBO for valve-point Economic Load Dispatch Problem

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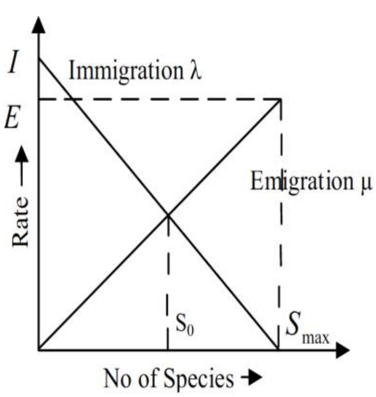
***Abstract*—This paper is an extension made in biogeography based optimization (BBO) by modifying its migration model to make it more realistic. The migration model used is non-linear sinusoidal migration model. This BBO technique is then applied on IEEE 40 generator system with valve point effect to analyze the behavior of non-linear model. Our analysis concludes that the sinusoidal models provide the best result for the ELD valve point effect problem than linear migration model.**

***Index Terms*- Biogeography based optimization; economic load dispatch; emigration; immigration; quadratic migration model.**

I. Introduction

Economic load dispatch problem (ELD) is one of the oldest problems encountered in the power system. Generation of power in an optimal manner is a major challenge for system utility operators. ELD schedules the generators to supply the demand while satisfying various equality and inequality constraints of the system. Through proper scheduling of the units the overall generation cost of the system can be significantly reduced. A lot of researches have been done in this area but due to the non smooth cost function with different equality and inequality constraints and the large search space, a global optimal solution for the problem is yet to be attained. In the past decade, conventional optimization techniques such as lambda iterative method, linear programming and dynamic programming [1] have been used to obtain the optimal solution. But, as the number of constraints, generating units and non-linearity increase in the system, these methods face difficulties to locate the global optimal solution. Now-a- days more focus is given to the Artificial Intelligence techniques such as Genetic Algorithm (GA) [2], Artificial Neural Network (ANN) [3], Particle Swarm Optimization (PSO) [4], Evolutionary Strategy (ES) , Differential Evolution (DE) [5], Biogeography Based Optimization (BBO) [6] etc. These techniques replaced the conventional techniques to provide better results in less time. These were also callable of handling high non-linearity in the problem without any restriction on the shape of the cost curve. GA was invented by John Holland in 1960s and was further developed by his students and colleagues at the University of Michigan in the 1970s. This technique is based on the behavior and evolution of genes in the living organism. Mutation and Cross-over are the two main operators of the GA. Mutation operator shows the change occurred in the gene due to radiation or any other such cause and Cross-over operator shows the reproduction of two genes to produce offspring's. ANN [3] is a simple model based on the structure and function of the nervous system. The learning process in the ANN is done by various learning algorithms such as back- propagation algorithm, etc. The learning in the ANN is now being provided through other AI techniques, such as PSO and GA. In 1995, Kennedy and Eberhart invented PSO [4]. In this technique, the system is initialized with a population of random solutions and searches for the optimal solution by updating generations. This technique is based on the behavior of birds in search of food. In this the effective solution is to follow the bird which is nearest to the food. This principle is applied in the algorithm. Once, the solution reaches the optimal region the algorithm proceeds slowly due to inability to adjust the velocity step size to continue the search at a finer grain. Differential evolution was invented by Ken Price's in 1996 [5]. DE uses three main operators to modify the initial population to obtain the results. They are mutation, crossover and selection operator. During the initial stage the DE algorithm moves rapidly towards the optimal point but in the later stages fine tuning operator is required. The latest in the series is Biogeography Based optimization (BBO), based on the phenomena of Biogeography proposed by D. Simon in 2008 [6].

Biogeography is the study of the geographical distribution of the biological organisms. Mathematical equations that govern the distribution of these species were first developed in 1960s [7,8]. These mathematical models elucidate how the species migrate from one island to another, how the species become extinct, and how new species arise. An island refers to any habitat that is isolated from other habitat. In BBO the suitability of a solution is expressed in terms of Habitat Suitability Index (HSI). BBO algorithm views the value of the HSI as the objective function and has to determine the solution to maximize the HSI. More is the HSI better is the solution on optimization problem and less is the HSI and poorer is the solution. Solution having more HSI resists change more than the solution with less HSI. BBO has two operators to find the optimal solution. These are Migration and Mutation. The Migration operator borrows features from good solution to bad solution whereas the Mutation operator modifies the features of the poor solution to obtain a better solution.



Many modifications have been successfully added on the original BBO to improve the operation and performance of the algorithm and hence to obtain optimal result. Hybrid of BBO with DE has been developed in [9] and has been applied to ELD in [10]. It introduces a new hybrid migration operator which combines the migration of BBO and mutation of DE. Oppositional based learning has also been applied to classical BBO algorithm in [11]. Oppositional based learning is a very classical approach to enhance results in ANN and many other techniques and is also being applied with BBO. BBO has also been combined with ES in [12]. Different Migration models have been introduced in BBO in [13]. The process of migration is more complicated than a linear curve because the ecosystem is inherently nonlinear, where simple changes in one part of the system produce complex effects throughout the entire system. Hence the need for new migration models arises. The sinusoidal model is more close to the models obtained in the real world hence the output obtained for this are better compared with that obtained from different techniques.

II. Economic Load Dispatch Problem

ELD

is a non-linear constrained optimization problem, with both convex and non-convex curves. The different types of ELD problems formulated and applied in the paper on the Blended BBO approach have been explained below. A. ELDOCTL The objective function Ct of the ELD problem may be written as, Where, Ci is the cost of ith generator to produce Pi power, usually a quadratic function. ai, bi, ci are the cost coefficients of the ith generator. m is the total number of committed generators. The following constraints are applied to the ELD problem. Real Power Balance Constraint: The total power generated should be able to supply the load and the losses of the system.

A. *Mathematical problem formulation*

Objective Function

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

The objective function of ELD is:

Minimize: $C(P_g) = \sum_1^{ng} C_i(Pg_i)$ (1)

Where:

$C(P_g)$: total fuel cost,

$C_i(Pg_i)$:fuel cost of i-th generating unit,

$P(g_i)$: generating power of i-th unit,

NG : number of generators.

Subject to the following constraints:

B. *Cost Function*

The cost function of ELD problem is defined as follows:

1) Total cost of generating units without valve point effect is given by:

$$C(P_g) = \sum_{i=1}^{NG} a_i {P_{G_i}}^2 + b_i P_{G_i} + c_i \quad (2)$$

where

a_i, b_i, c_i: cost coefficients of i-th generator.

2) For more practical and accurate model of the cost function, multiple valve steam turbines are incorporated for flexible operational facilities. Total cost of generating units with valve point loading is given by equation 2.

C. ECONOMIC LOAD DISPATCH PROBLEMS [1]

The ELD may be formulated as a nonlinear constrained problem. Both convex and non-convex ELD problems have been modeled in this paper. 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.

The objective function F_t of ELD problem may be written as:

$$F_t = Min(\sum_{i=1}^{m} F_i(P_i)).$$

$$= Min(\sum_{i=1}^{m} a_i + b_i P_i + c_i P_i^2 \qquad (3)$$

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

a. Real Power Balance Constraint

$$\sum_{i=1}^{m} P_i - P_d - P_l = 0 \qquad (4)$$

The transmission loss P_l may be expressed using B-coefficients as:

$$P_l = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \qquad (5)$$

b. 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

$$P_i^{min} \leq P_i \leq P_i^{max} \qquad (6)$$

The objective function F_t of this type of ELD problem is same as mentioned in. Here the objective function is to be minimized subject to the following constraints.

c. Real Power Balance Constraint

The real power balance constraint remains the same as in equation 5.

d. Generator Capacity Constraints

This constraint remains unchanged as given in equation 6.

e. Ramp Rate Limit Constraints

The power generated, P_i, by the i^{th} generator in certain interval may not exceed that of previous interval P_{i0} by more than a certain amount UR_i, the up-ramp limit and neither may it be less than that of the previous interval by more than some amount DR_i the down-ramp limit of the generator. These give rise to the following constraints.

As generation increases

$$P_i - P_{i0} \leq UR_i \qquad (7)$$

As generation decreases

$$P_{i0} - P_i \leq DR_i \qquad (8)$$

and

$$\max(P_i^{min}, P_{i0} - DR_i), \leq P_i \leq \min(P_i^{max}, P_{i0} + UR_i) \qquad (9)$$

The transmission loss PL may be expressed using B- coefficients as,

Generator Capacity Constraints: The power generated by any generator should be within the generating limit, i.e. the upper and the lower limit.

B. ELDVPL The objective function of ELD problem with ―Valve point loadings‖ is given as in (5). This objective function has to be minimized using the constraints in (2) and (4). PL is taken zero here.

III. EQUILIBRIUM MIGRATION MODELS

Biogeography theory proposes that immigration and emigration rates determine the number of species in an undisturbed habitat. Immigration is the arrival of new species into a habitat, while emigration is the act of leaving one's native region. Habitats with a lot of species have high emigration rates because of the accumulation of random effects on large populations which causes them to leave, while they have low immigration rates because they are already nearly saturated with species. By the same token, habitats with a small number of species have high immigration rates because there is a lot of room for additional species, and low emigration rates because of their sparse populations. In addition, there are other important factors which influence migration rates between habitats, including the distance to the nearest neighboring habitat, the size of the habitat, climate, plant and animal diversity, and human activity [6]. According to the various mathematical models of biogeography, six migration curves have been obtained in [13]. These six models have been divided into two categories as linear and non-linear models. The first three models are the linear models which do not exist in natural biogeography. The next three models are the non-linear models. Suppose that the largest number of species in a habitat is n, whenever there are k species in the habitat, the immigration rate for the habitat is λk and the emigration rate for the habitat is μk. k0 is the equilibrium species count, where the immigration rate and the emigration rate is equal.

In Sinusoidal migration model, the immigration and emigration rates are sinusoidal function of the number of species. The curve hence results in a bell like shape as shown in Fig 1. The immigration and emigration rates are defined as.

IV. NUMERICAL EXAMPLE AND RESULT

The proposed BBO with different migration models has been applied on different ELD problems. Two basic cases have been chosen, which are described below. The programming has been done on MATLAB-7.10.0.499 language and executed on a 2.3-GHz Intel Core i3-380M processor personal computer with 2GB RAM. The test Case is a 40 generator system with valve point loading. The total load demand is 10500 MW. The data is taken from [14]. The value of BBO parameters have been settled as, upper and lower bounds of immigration probability per gene = [0,1], Maximum rate of immigration and emigration (I and E) = 1, Blending operator, Number of Elites = 4, Mutation probability = 0.005, Habitat size = 50. The results obtained are shown in Table I. The result contains the minimum cost, maximum cost and average cost obtained for 50 runs. It also contains the time per iteration, A comparison has been done between the results obtained through BBO with sinusoidal migration model and other existing techniques. They are shown in Table II. The comparison of generator value for the proposed BBO and other existing techniques has been shown below.

No. of runs 50

Minimum Cost 121418.73

Maximum Cost Average Cost 121831.4

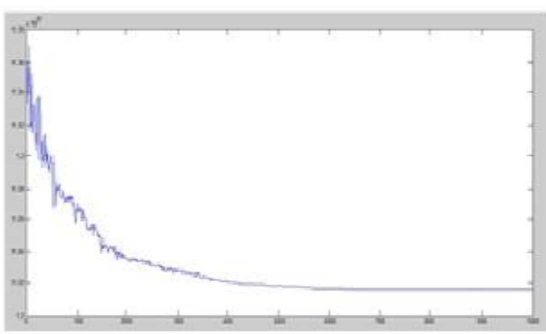
Time per iteration (sec) 0.018286

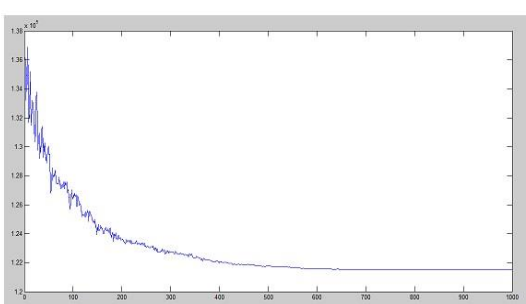
Average cost 121624.6

N	C_{min}	C_{max}	C_{avg}	Standard Deviation	Time per iteration
20	121692.4	122847.9	122104.98	0.002408	0.011484
30	121502.2	122123.5	121693.3	0.00101	0.017379
50	121416.9	121765.3	121551.4	0.000489	0.025324
70	121576.6	121767.7	121660.9	0.000388	0.043167
100	122569.9	123044	122838.3	0.000945	0.076851
120	123590.2	124419.6	123966.7	0.001613	0.079869

p	dt	C_{min}	C_{max}	C_{avg}	Standard Deviation	Time per iteration (Sec)
0.5	0.1	133363.6	143896.7	138560.9	2340.509	1493.28908
0.5	0.2	132074.9	144815.5	138301.9	2474.813	1634.113982
0.5	0.3	133294.9	142605.6	138363.8	2064.495	1596.30576
0.5	0.4	133199.2	143311.7	137719.5	2650.043	1263.432135
0.5	0.5	133667.9	144327.1	137136.5	2261.709	1668.334139
0.5	0.6	130428.5	140070	135411.3	2323.449	1825.23552
0.5	0.7	131710.8	137819.1	134013	1487.433	1580.369883
0.5	0.8	129533.8	135066.7	131582.4	1110.076	1613.326889

0.5	0.9	126429.8	128382.1	127438.8	481.5856	1672.963247
0.5	1	121940.3	122412.6	122171	117.3862	1536.344048
0.5	1.2	121552.9	122158.2	121687.1	114.2973	1649.571098
0.5	1.4	121543.2	121928.5	121692.9	87.98741	1679.907131
0.5	1.6	121535.5	121925.5	121694.7	97.71304	1596.187476
0.5	1.8	121504.2	121924.7	121689.7	99.66739	1702.187007
0.5	2	121518.3	122162.1	121716.2	140.678	1655.020956
0.05	0.1	132341.8	140652.9	136628.7	2261.683	1702.267843
0.05	0.2	130190	137193.4	133379.4	1455.196	1565.732992
0.05	0.3	129026	133397.8	131117.3	916.7545	1645.636863
0.05	0.4	126845.8	130190.8	128816.1	624.4977	1614.399822
0.05	0.5	125604.4	127842.8	126985.5	504.1213	1503.341526
0.05	0.6	124456.5	126168.4	125293.1	339.5576	1540.123416
0.05	0.7	123399.2	124531.2	123988.1	254.8462	1464.368389
0.05	0.8	122474.5	123033	122765.5	119.1888	1783.437517
0.05	0.9	121767.2	122117.4	121898.7	65.78172	1722.268431
0.05	1	121426.9	121780.1	121590.3	67.13391	1774.844561
0.05	1.2	121484.5	121787.4	121586	78.61808	1444.09379
0.05	1.4	121423.9	121756.1	121575.5	71.41644	1567.313478
0.05	1.6	121437.2	121728.9	121579	51.80865	1616.254787
0.05	1.8	121475.2	121753.5	121593.9	71.06279	1611.712414
0.05	2	121417.4	121776.8	121609	88.48217	1466.968193
0.005	0.2	123081.5	123854.1	123446.8	207.4056	1819.957835
0.005	0.3	122107.5	122787.5	122468.5	119.7509	1849.224432
0.005	0.4	121794.5	122063.8	121935.1	60.35948	1792.399608
0.005	0.5	121597.7	121844.6	121694.8	50.99752	1743.937491
0.005	0.6	121484.5	121758	121597.1	55.51912	1750.684807
0.005	0.7	121431.7	121771.7	121563.1	62.03867	1736.173443
0.005	0.8	121476.1	121654.6	121538.9	48.44689	1621.535064
0.005	0.9	121417.2	121646.5	121533	44.2025	1471.632046
0.005	1	121416.4	121672.9	121537.6	52.38457	1600.16704
0.005	1.2	121417.5	121771.5	121576.2	66.18264	1675.020192
0.005	1.4	121417.2	121762.2	121584.2	75.7901	1646.850202
0.005	1.6	121463.6	121764.4	121563.8	60.88568	1649.054948
0.005	1.8	121471.4	121736.3	121565.5	60.90509	1660.179587
0.005	2	121479.6	121769.8	121577.4	61.83601	1601.754893





V. CONCLUSION

We have presented non-linear sinusoidal migration model for BBO has been applied on the valve point ELD problem. Sinusoidal model provides better solution from the linear BBO. Hence we can see that BBO with sinusoidal migration model provides a superior result with the change in the modelling of migration model. Further the result obtained is better than the existing techniques. Therefore, the sinusoidal model is more realistic and hence provides better results than the linear migration model for given valve point ELD problem.

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