

An Effective Biogeography Based Optimization Algorithm to Solve Economic Load Dispatch Problem

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Abstract: Problem statement: Implementation of an Effective Biogeography Based Algorithm (EBBO) for Economic Load Dispatch (ELD) problems in power system in order to obtain optimal economic dispatch with minimum generation cost. **Approach:** A viable methodology has been implemented for a 20 unit generator system to minimize the fuel cost function considering the transmission loss and system operating limit constraints and is compared with other approaches such as BBO, Lambda Iteration and Hopfield Model. **Results:** Proposed algorithm has been applied to ELD problems for verifying its feasibility and the comparison of results are tabulated and pictorial visualization for convergence of EBBO is represented. **Conclusion:** Comparing with the other existing techniques, the EBBO gives better result by considering the quality of the solution obtained. This method could be an alternative approach for solving the ELD problems in practical power system.

Key words: Economic Load Dispatch (ELD), Effective Biogeography Based Algorithm (EBBO), low generation cost, quadratic cost function, lambda iteration, hopfield model

INTRODUCTION

The most significant crisis in the planning and operation of electric power generation system is the effective scheduling of all generators in a system to meet the required demand. The Economic Load Dispatch (ELD) is the important optimization problem to schedule the generation among generating units in power system. The main aim of ELD problem is to minimize the operation cost by satisfying the various operational constraints in order to meet the load demand. Many traditional algorithms (Wood and Wollenberg, 1996) like lambda iteration, Gradient search, Newton method are applied to optimize ELD problems however in these methods it is assumed that the incremental cost curves of the units are monotonically increasing piecewise linear functions, but the practical systems are nonlinear.

In the past years many optimization algorithms are being developed to solve the ELD problems such as Genetic Algorithms (GA) (Chen and Chang, 1995; Orero and Irving, 1996) Particle Swarm Optimization (PSO) (Gaing, 2003; Selvakumar and Thanushkodi, 2007; Kuo, 2008; Khamsawang *et al.*, 2009), Simulated Annealing (SA) (Wong and Fung, 1993; Wong, 1995), Differential Evolution (DE) (Das *et al.*, 2008; Khamsawang and Jiriwibhakorn, 2009) and

Biogeography Based Optimization (BBO) (Bhattacharya and Chattopadhyay, 2010a). GA is inspired by the study of genetics and conceptually based on natural evolution mechanisms. PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. SA is a stochastic optimization technique which is based on the principles of statistical engineering. DE is technically population based Evolutionary Algorithm. Biogeography is the nature's way of distributing species. The migration of species from one island to another, evolution of new species and extinction of species are expressed by the mathematical models of biogeography. This study describes a new optimization algorithm, an Effective Biogeography Based Optimization Algorithm. This algorithm is validated by applying it to 20 units system with generator constraints, power balance constraints and transmission loss. The total generation cost and the computational time obtained by this method is better or comparable when compared to other methods.

MATERIALS AND METHODS

The ELD problem having an objective function minimizes the total generation cost, F_T , while fulfilling

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various constraints when supplying the required load demand of a power system. The objective function is given by Eq. 1:

$$\min F_T = \min \left(\sum_{i=1}^n F_i(P_{Gi}) \right) = \min \left(\sum_{i=1}^n A_i P_{Gi}^2 + B_i P_{Gi} + C_i \right) \quad (1)$$

where, P_{Gi} is the output power generated by the i th generator, $F_i(P_{Gi})$ is the Generation cost function of i th generator and A_i , B_i , C_i are the Cost coefficients of i th generator, n is the number of generators.

Two constraints are considered in this problem, i.e., the generation capacity of each generator and the power balance of the entire power system.

Constraint 1: This constraint is an inequality constraint for each generator. For normal system operations, real power output of each generator is within its lower and upper bounds and is known as generation capacity constraint given by Eq. 2:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (2)$$

where, P_{Gi}^{\min} and P_{Gi}^{\max} are the lower and upper limit of the power generated by i th generator.

Constraint 2: This constraint is an equality constraint. In which the equilibrium is met when the total power generation must equals the total demand P_D and the real power loss in transmission lines P_L . This is known as power balance constraint can be expressed as given in Eq. 3:

$$\sum_{i=1}^n P_{Gi} = P_D + P_L \quad (3)$$

The transmission losses are considered as a function of the generators output, can be expressed as given in Eq. 4:

$$P_L = \sum_{i=1}^n \sum_{j=1}^n P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^n B_{oi} P_{Gi} + B_{oo} \quad (4)$$

where, B_{ij} , B_{oi} , B_{oo} are the transmission power loss B-coefficients, which are assumed to be constant. In the summary, the objective of economic power dispatch optimization is to minimize F_T subject to the constraints given by the Eq. 2-4.

Particle Swarm Optimization: PSO is a population based optimization technique, motivated by biological concepts like swarming and flocking. PSO is initialized

with the population, which is randomly generated and it always conducts a search in the population of particles. Every particle in the population represents a possible candidate solution (i.e. fitness) to the given problem. In a PSO system, the search towards optima is carried out in a multidimensional search space. Every particle memorizes its best solution in addition to its position achieved so far is known as Pbest, the Personal best. It also knows the best value along with its position found in the group among Pbest, known as Gbest, the Global best. The basic theory of PSO insists on accelerating each particle towards its Pbest and the Gbest locations as shown in Fig. 1.

Differential evolution: DE is also a population based optimization algorithm. The optimization process in DE is carried with four basic operations namely, Initialization, Mutation, Crossover and Selection. Through initialization operation new population is created and the individuals are known as target vectors. New parameters are introduced by the mutation operation into the population and generate a mutant vector. The crossover operation generates trial vectors by combining the parameter of the mutant vectors with the target vectors. Selection is the process through which the next generation population vector is created by comparing the fitness of target vector and trial vector.

Biogeography: BBO is based on the concept of Biogeography, two different processes identified as Migration and Mutation are carried out. The population of individuals or candidate solutions can be represented as a solution vector having integers. Every integer in the solution vector is equal to one SIV. The quality of the solutions is evaluated by SIVs. The good solutions are considered as high HSI habitats where as others are known as low HSI habitats. The habitats HSI is the fitness function to a given problem. By using the migration operation the information is shared between habitats probabilistically. A sudden change can occur in the HSI of a natural habitat due to some natural calamities or other events known as mutation. The diversity of the populations is increased by the mutation

Proposed EBBO approach: A popular research trend is to merge or combine the PSO with the other techniques, especially the other evolutionary computation techniques. Evolutionary operators like selection, crossover and mutation have been applied into the PSO. In EBBO approach, first the PSO concept is used to initialize the population of particle with its velocity and position.

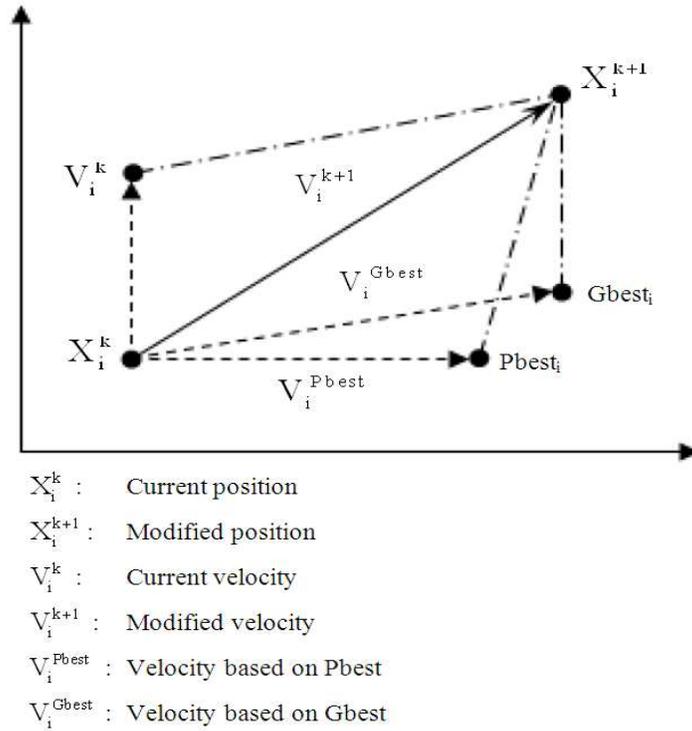


Fig. 1: Concept of modification of a searching point by PSO

The velocity of the particle is updated if the calculated velocity is out of boundary or closely to zero ($\text{rand}(0, 1)$), a mutation operator of the DE is activated; recalculate the velocity of this particle by using DE mutation operator. If the calculated velocity using DE is less than crossover rate (CR), calculate the immigration rate λ and the emigration rate for each individual X_i and Modify the population with migration operator and update the position according to the new velocity. Using this, again calculate the Gbest value.

EBBO Algorithm:

- Step 1: The individuals of the population are randomly initialized. The velocities of the different particles are also randomly generated keeping the velocity within the maximum and minimum value [0.5 to -0.5]. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints (both the linear and non-linear constraints) of the given problem. Choose CR, F values.
- Step 2: The cost function of each individual is calculated in the population using the evaluation function F_T . The present value is set as the pbest value.

Step 3: Each pbest values are compared with the other pbest values in the population. The best evaluation value among the pbest is denoted as *gbest*.

Step 4: The member velocity V of each individual in the population is updated according to the velocity update Equation

$$V_i^{(t+1)} = w \times V_i^{(t)} + c_1 \times r_1 \times (pbest_i - x_i^{(t)}) + c_2 \times r_2 \times (gbest - x_i^{(t)})$$

Step 5: The member velocity, V of each individual in the population is checked. If the calculated velocity is out of boundary or closely to zero ($\text{rand}(0, 1)$), a mutation operator of the DE is activated, recalculate the velocity of this particle by using mutation operator

$$V_i^{(t+1)} = F \times ((x_k^{(t)} - x_i^{(t)}) - (x_q^{(t)} - x_i^{(t)}))$$

Else go to step 8, without activating DE mutation operator.

Step 6: If the calculated velocity using DE is less than CR value, Calculate the immigration rate λ and the emigration rate for each individual X_i
Else go to step 8

- Step 7: Modify the population with migration operator and go to step 2
- Step 8: The position of each individual is modified according to the position update equation
New position=old position + updated velocity
Go to step 2
- Step 9: Continue the process, until a maximum iteration is obtained.

RESULTS

The performance of the proposed algorithm was tested on a 20-unit system with a demand of 2500 MW. The software was written in matlab-7 and executed.

The results of fuel cost and cpu time obtained by the proposed EBBO algorithm are compared with other methods such as BBO (Bhattacharya and Chattopadhyay, 2010b), Lambda Iteration and Hopfield Model (Su and Lin, 2000) to evaluate the performance of the proposed method.

The input data and transmission loss coefficients for 20 units system is taken from (Su and Lin, 2000). Table 1 provides the statistic results that involved the generation cost, evaluation value and CPU time. Table 2 provides the parameter setting for the proposed method. Figure 2 provides the characteristics graph between iteration and the total generation cost.

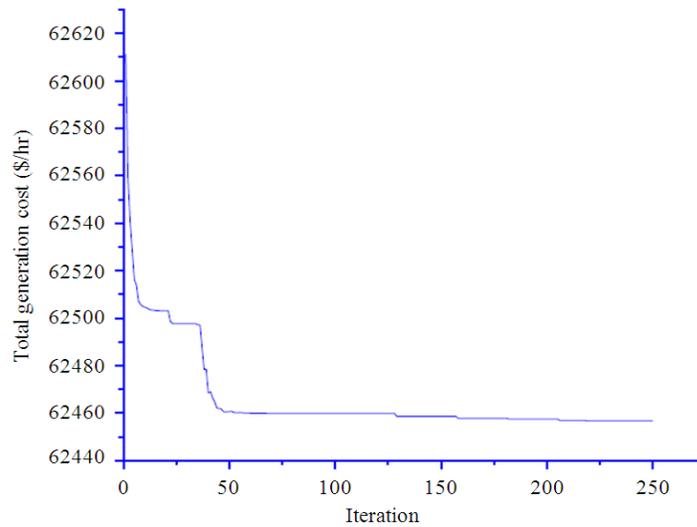


Fig. 2: Convergence characteristic of 20-generator system

Table 1: Best Power Output for 20-Generator System

Unit output	EBBO	BBO	Lambda iteratio	Hopfield model
P1 (MW)	513.4359	513.08920	512.780500	512.780400
P2 (MW)	169.6626	173.35330	169.103300	169.103500
P3 (MW)	127.4739	126.92310	126.889800	126.889700
P4 (MW)	103.1807	103.32920	102.865700	102.865600
P5 (MW)	113.9900	113.77410	113.683600	113.683600
P6 (MW)	73.5092	73.06694	73.571000	73.570900
P7 (MW)	115.3057	114.98430	115.287800	115.287600
P8 (MW)	116.6982	116.42380	116.399400	116.399400
P9 (MW)	100.7520	100.69480	100.406200	100.406300
P10 (MW)	106.2595	99.99979	106.026700	106.026700
P11 (MW)	150.3157	148.97700	150.239400	150.239500
P12 (MW)	291.6540	294.02070	292.764800	292.764700
P13 (MW)	119.3330	119.57540	119.115400	119.115500
P14 (MW)	30.9885	30.54786	30.834000	30.834200
P15 (MW)	115.9033	116.45460	115.805700	115.805600
P16 (MW)	36.2575	36.22787	36.254500	36.254500
P17 (MW)	67.1866	66.85943	66.859000	66.859000
P18 (MW)	88.0014	88.54701	87.972000	87.972000
P19 (MW)	101.0420	100.98020	100.803300	100.803300
P20 (MW)	51.0917	54.27250	54.305000	54.305000
Total Power Output (MW)	2592.0410	2592.10100	2591.967000	2591.967000
Total Generation Cost (\$/h)	62456.6300	62456.79000	62456.640000	62456.630000
Power Loss (MW)	91.5352	92.10110	91.967000	91.966900
CPU time/ iteration(sec)	0.0650	0.29282	0.033757	0.006355

Table 2: Parameter Settings

C1	C2	Iteration	ω_{\min}	ω_{\max}	CR	F	μ	λ
2	2	250	0.9	0.9	0.89	0.8	0.9	1

DISCUSSION

The previous method results taken from the literature is compared with the proposed method. The comparison proves that all the four algorithms have the potential to find the global solution, but the minimum generation costs achieved by EBBO is less than those reported in recent literature. It is also clear that the EBBO algorithm is efficient and require less computational time. As a whole it can be said that the EBBO algorithm is computationally efficient than earlier mentioned methods. Thus, the EBBO algorithm is more reliable to find out the minimum fuel cost in this example.

CONCLUSION

This study presents a novel coding scheme for EBBO algorithm to solve practical ELD issues and confirmed by a simulation process. The proposed combined method uses the mutation property of DE and migration property of BBO in PSO, which can provide a good optimal solution even when the problem begins with optimal solution. The performance of proposed coding scheme used in the case study of 20-units system with transmission loss, proved to have salient features including better quality solution, stable convergence characteristics and good computational efficiency when compared with the results obtained from other heuristic methods.

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