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Opposition based Teaching Learning Based Optimization for Economic Dispatch Problem with Valve Point Loading Effect

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Abstract:

Cost minimization of power generation is one of the most important power system problems. In this paper, an attempt is made to minimize the cost for generation in a power system. The aim of this paper is to find the optimum set of power to be generated for a given loading conditions. In this paper, a new algorithm opposition based teaching learning based optimization is developed and applied to ED problem. The proposed OTLBO do not have the drawbacks of the classical heuristics such as local optimal trapping due to premature convergence, insufficient capability to find nearby extreme points, and lack of efficient mechanism to treat the constraints. The algorithm describes two basic modes of the learning: (i) through teacher (known as teacher phase) and (ii) interacting with the other learners (known as learner phase). The effectiveness and feasibility of the proposed OTLBO method were demonstrated on 6 and 10-unit test systems and then compared with other algorithms like PSO and HSA. The experiments showed that the proposed approach was capable of determining higher quality solution while addressing the complex ED problems.

Keywords-**Economic Dispatch; Valve Point Loading Effects; opposition based Teaching Learning Based Optimization; application of OTLBO on Economic Dispatch; Comparison of OTLBO with Other Algorithms.**

I. Introduction

The Engineers have been very successful in increasing the efficiency of boilers, turbines and generators so continuously that each new added to the generating unit plants of a system operates more efficiently than any older unit on the system. In operating the system for any load condition the contribution from each plant and from each unit within a plant must be determined so that the cost of the delivered power is a minimum. Any plant may contain different units such as hydro, thermal, gas etc. These plants have different characteristic which gives different generating cost at any load. So there should be a proper scheduling of plants for the minimization of cost of operation. The cost characteristic of the each generating unit is also non-linear. So the problem of achieving the minimum cost becomes a non-linear problem and also difficult. Many numerical methods such as lambda iteration method, gradient method and quadratic programming method [1] applied for solving ED problem by assuming that the incremental cost curve as piecewise-linear monotonically increasing function. Lin et al. [2] presented integrated evolutionary programming, tabu search (TS) and quadratic programming (QP) methods to solve non-convex ED problems. This integrated artificial intelligence method also requires two-phase computations. Various mathematical programming such as linear and non-linear programming have been applied for solving convex ED problems. The traditional algorithms, dynamic programming imposes no restrictions on the nature of the cost curve and therefore it can solve ED problems. However, this method cannot be applied to solve large dimensional problems due to requirement of enormous computational efforts. Hence stochastic search algorithm such as genetic algorithm [3] may prove to be very effective in solving nonlinear ED problems without any restrictions on the shape of the cost curves. A very fast and effective non-iterative lambda logic based method is applied to solve economic dispatch of thermal units in [4]. Some of the well-known meta-heuristics developed during the last three decades are: Genetic Algorithm (GA) [5] which works on the principle of the Darwinian theory of the survival of the fittest and the theory of evolution of the living beings; Particle Swarm Optimization (PSO) [6] which works on the foraging behaviour of the swarm of birds; differential Evolution (DE) [7] which is similar to GA with specialized crossover and selection method; Harmony Search (HS) [8] which works on the principle of music improvisation in a music player; Shuffled Frog Leaping (SFL) [9] which works on the principle of communication among the frogs; Shuffled Differential Evolution (SDE) [10-12] which works similar to DE with specified crossover and selection method; Modified Shuffled Frog Leaping Algorithm (MSFLA) [13-14] which works on the principle of communication among rogs; A novel optimization method called opposition based teaching-learning-based optimization (OTLBO) has been proposed by Rao et al. [15] for constrained optimization problems. The method bases on the effect of influence of a teacher on learners and the effect of learners each other. Rao et al. [15] presented five different constrained benchmark test functions in order to demonstrate the robustness of OTLBO. The results obtained from the design examples were compared with the other meta-heuristic optimization methods. The comparisons showed that the OTLBO showed better performance with less computational effort over other meta-heuristic optimization methods. Rao et al. [16] developed the OTLBO method for large scale non-linear optimization problems for finding global solutions. The results proved that the OTLBO method is effective in terms of the computational effort, consistency and obtaining the near optimum solutions. After the pioneering studies of Rao et al. [15, 16, 17], the OTLBO was employed for optimum design of planar steel frames [18]. The efficiency of the method was verified by using three steel frames previously optimized by the GA, HS, and improved ACO. With regard to the number of analyses and the results for the frames presented in the study, the OTLBO method demonstrated outstanding performance over the GA, ACO, HS, and improved ACO [18].

II. Formulation of Economic Dispatch Problem

Generally economic dispatch is defined as the process of allocating generation levels to the generating units, so that load is supplied entirely and most economically. In an electrical power system, economic dispatch is the one of the most important optimization problem and it is a crucial task in the economic operation. The main objective of this economic dispatch problem is to determine the optimal combination of power outputs for all generating units that minimizes the total fuel cost while satisfying load demand and operating constraints that are equality and inequality constraints.

A. ED Problem with Smooth Cost Function

The ED problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. The most simplified cost function of each generator can be represented as a quadratic function as given in whose solution can be obtained by the conventional mathematical methods.

$$F_T = \sum_{i=1}^{N} F_i(P_i) \quad (1)$$

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (2)$$

Where F_T is the total fuel cost, $F_i(P_i)$ is Fuel cost function of generator i. a_i, b_i, c_i are fuel cost coefficients of generator i, P_i is electrical output of generator i, N is total no of generators. While minimizing the total generation cost, the generation should satisfy the following constraints.

B. Equality Constraint

While minimizing the total generation cost, the total generation should be equal to the total demand plus the network transmission losses.

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0 \quad (3)$$

Where P_D is the total system demand and P_L is the transmission line loss. In this paper transmission line losses are not considered.

C. Inequality Constraint

The generation output of each unit should be between its minimum and maximum limits. That is, the following inequality constraint for each generator should be satisfied.

$$P_{min,i} \le P_i \le P_{max,i} \quad (4)$$

Where P_{imin} and P_{imax} is the minimum and maximum output of generator i.

D. ED Problem with Valve Point Loading Effect

The generator with multi valve steam turbines has very difficult input-output curve compared with the smooth cost function. Typically, the valve-point results in, as each steam valve starts to open the ripples like in the fig. 1 shown below.

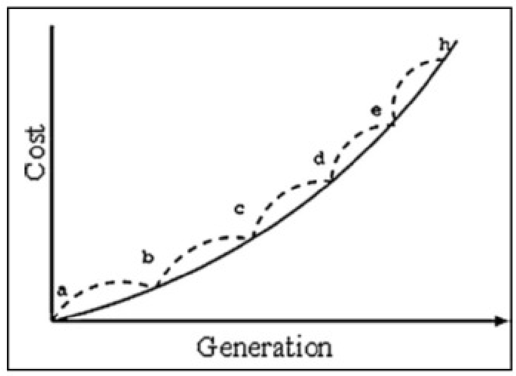

Fig. 1: Cost Function With and Without Valve Point Loading

To take these effects into the consideration, sinusoidal functions are added to the quadratic cost functions as follows.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i * \sin(f_i * (P_{i,min} - P_i)| \quad (5)$$

where e_i and f_i are the coefficients of generator i with respect to valve point effect

III. Opposition based TLBO algorithm (OTLBO)

The concept of opposition-based learning (OBL) was introduced by Tizhoosh [15] and has thus far been applied to accelerate reinforcement learning and back propagation learning in neural networks. The main idea behind OBL is the simultaneous consideration of an estimate and its corresponding opposite estimate (i.e., guess and opposite guess) in order to achieve a better approximation for the current learner solution. In this paper, OBL has been utilized to accelerate the convergence rate of TLBO. Hence, our proposed approach has been called opposition-based teaching learning based optimization (OTLBO). OTLBO uses opposite numbers during population initialization and also for generating new populations during the evolutionary process. To the best of our knowledge, this is the first time that opposite numbers have been utilized to speed up the convergence rate of this optimization algorithm.

III.I Opposition based learning

Generally speaking, evolutionary optimizations methods start with some initial solutions (initial population) and try to improve them toward some optimal solution(s). The process of searching terminates when some predefined criteria are satisfied. In the absence of a priori information about the solution, we usually start with random guesses. The computation time, among others, is related to the distance of these initial guesses from the optimal solution. We can improve our chance of starting with a closer (fitter) solution by simultaneously checking the opposite solution. By doing this, the fitter one (guess or opposite guess) can be chosen as an initial solution. In fact, according to probability theory, 50% of the time a guess is further from the solution than its opposite guess. Therefore, starting with the closer of the two guesses (as judged by its fitness) has the potential to accelerate convergence. The same approach can be applied not only to initial solutions but also continuously to each solution in the current population. However, before concentrating on OBL, we need to define the concept of opposite numbers [15].

III.II Definition (Opposite Number)

Let $x \in [a, b]$be a real number. The opposite number $\breve{x}$is defined by $\breve{x} = a + b - x$

Similarly, this definition can be extended to higher dimensions as follows [15].

III.III Definition (Opposite Point)

Let $P = (x_1, x_{12}, \dots, x_D)$ be a point in D-subjects, where $(x_1, x_{12}, \dots, x_D) \in R$ and $x_i \in [a_i, b_i] \forall i \in \{1,2, \dots, D\}$. The opposite point $\breve{P} = (\breve{x_1}, \breve{x_2}, \dots \breve{x_D})$ is completely defined by its components

$$\breve{x}_i = a_i + b_i - x_i$$

Now, by employing the opposite point definition, the opposition- based optimization can be defined as follows.

III.IV Opposition Based Optimization

Let $P = (x_1, x_{12}, \dots, x_D)$ be a point in D-subjects, Assume f(p) is a fitness function which is used to measure the learners' fitness. According to the definition of the opposition $\breve{P} = (\breve{x_1}, \breve{x_2}, \dots \breve{x_D})$ is the opposite of $P = (x_1, x_{12}, \dots, x_D)$. Now if $f(\breve{P}) \geq f(\breve{P})$, then point P can be replaced with$\breve{P}$; otherwise, we continue with P. Hence, the point and its opposite point are evaluated simultaneously in order to continue with the fitter one.

IV. Comparison of OTLBO with Other Algorithms

Like GA, PSO, ABC, HS, etc., OTLBO is also a population based technique which implements a group of solutions to proceed for the optimum solution. Many optimization methods require algorithm parameters that affect the performance of the algorithm. GA requires crossover probability, mutation rate, and selection method; PSO requires learning factors, variation of weight, and maximum value of velocity; ABC requires number of employed bees, onlooker bees and value of limit; HS requires harmony memory consideration rate, pitch adjusting rate, and number of improvisations: SFLA requires number of memeplexes, iteration per memeplexes: ACO requires exponent parameters, pheromone evaporation rate and reward factor. Unlike other optimization techniques OTLBO does not require any algorithm parameters to be tuned, thus making the implementation of OTLBO simpler. As in PSO, OTLBO uses the best solution of the iteration to change the existing solution in the population thereby increasing the convergence rate. OTLBO does not divide the population like ABC and SFLA. Like GA which uses selection, crossover and mutation phase and ABC which uses employed, onlooker and scout bees phase, OTLBO uses two different phases, 'Teacher Phase' and 'Learner Phase'. OTLBO uses the mean value of the population to update the solution. OTLBO implements greediness to accept the good solution like ABC.

V. Simulation Results

In order to validate the proposed procedure, the OTLBO algorithm was tested on standard load dispatch problem with valve-point loading effect consisting of two cases and the 2 cases are 6 and 14-unit systems respectively. The proposed algorithm was implemented using MATLAB 7.10.0(R2010a) running on i3 processor, 2.27GHz, 4GB RAM, PC.

Test system1: ***six unit system***

In this case a system of six thermal units with the quadratic cost function is studied. The performance of the proposed methods were demonstrated at 800 load demand and that load demand to be met by all the generating units are 800MW. The system data can be found from [19]. Here the population size is taken as 60.The dispatch results using the proposed methods, TLBO & OTLBO are given in Table 1. For this test system, 25 independent trails have been made with 200 iterations per trail. Based on the data obtained, the comparisons of the six thermal units test by different methods are presented in Table 1.Table 1: Comparison of Simulation Results for 6 Unit System

Unit	P_D=800MW		
	Lambda	**TLBO**	**OTLBO**
1	342.2421	343.4325	339.6431
2	95.4819	96.5919	96.5813
3	181.9937	183.1756	183.2407
4	53.6758	50	53.9589
5	82.5707	82.8179	82.5354
6	50.0000	50	50
Generation cost in $/hr	9528.7222	9528.8844	9528.7969
Power loss in MW	5.9642	6.0179	5.9597

From the Table 1, at load demand of 800MW the minimum cost obtained by Lambda iteration method is 9528.7222$/hr with the power loss of 5.9642MW. The minimum cost obtained by OTLBO methods 9528.7969$/hr with the power loss of 5.9597MW. The cost obtained by TLBO is 9528.8844$/hr with power loss of 6.0179MW. From the above records it is clear that the minimum cost obtained by all the methods is almost same as the global solution at the load demand of 800MW. The cost obtained by Lambda iteration method and OTLBO is same as the global solution.

Fig 2 shows the comparison of convergence characteristics at different populations for different methods. As shown fig x-axis shows number of iterations and y-axis shows minimum cost in $/hr.

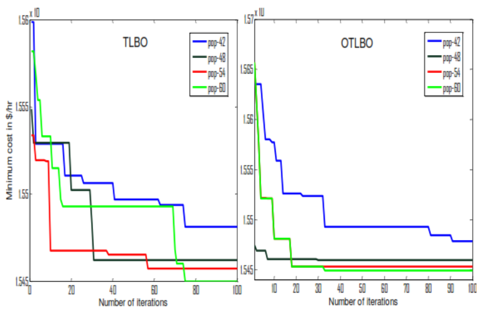

Fig. 2: Comparison of Convergence Characteristics for 6unit System

Test system2: *10-unit system*

In this case a system of ten thermal units with the quadratic cost function is studied. The performance of the proposed methods was demonstrated at 100MW load demand and that load demand to be met by all the generating units are 1500 MW. The system data can be found from [20]. Here the population size is taken as 100. The dispatch results of 10-unit system using the proposed methods are given in Table2. For this test system, 25 independent trails have been made with 300 iterations per trail. Based on the data obtained, the comparisons of the ten thermal units test by different methods are presented in Table 2. From the Table 2, at load demand of 1500MW the minimum cost obtained by Lambda iteration method and TLBO is 81130.0325$/hr with the power loss of 49.0223MW.

Table 2: Comparison of Simulation Results for 10 Unit System

Unit	P_D=1500MW		
	Lambda	**TLBO**	**OTLBO**
1	43.5706	43.5706	45.6086
2	60.8157	60.8157	61.7683
3	72.1301	72.1301	67.6629
4	60.3987	60.3987	55.5074
5	51.3367	51.3367	51.4848
6	71.3367	71.3367	71.4848
7	207.1676	207.1676	209.5246
8	222.2243	222.2243	232.5880
9	372.1789	372.1789	375.2049
10	387.8631	387.8631	378.1727
Generation cost in $/hr	81130.0325	81130.0325	81129.7603
Power loss in MW	49.0223	49.0223	49.0070

The minimum cost obtained by OTLBO method is 81129.76032$/hr with the power loss of 49.0070MW. From the above records it is clear that the minimum cost obtained by the OTLBO is the global solution at the load demand of 1500MW. Therefore the cost obtained by Lambda iteration method and OTLBO is almost same but the cost obtained by OTLBO method is global minimum.

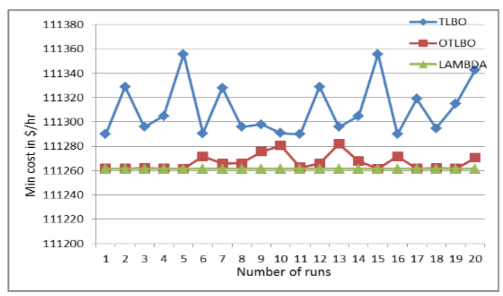

Fig. 3: Comparison Characteristics of Minimum Cost Obtained for 20 Runs

Fig.3 shows the graphical representation of comparison characteristics of minimum cost obtained for 20 runs at load demand 1500MW. As shown in fig the cost obtained by Lambda iteration method is constant for all runs while the other methods are varying.

VI. Conclusion

All the evolutionary and swarm intelligence algorithms require proper tuning of algorithm specific parameters in addition to the tuning of common controlling parameters. A change in the tuning of the specific parameters influences the effectiveness of the algorithm. The recently proposed OTLBO algorithm does not require any kind of algorithm-specific parameters. It only requires the tuning of the common controlling parameters of the algorithm for its working. In this paper, a latest optimization algorithm such as OTLBO has been successfully applied to solve power system ED problem considering valve point loading effect. The feasibility, effectiveness of the proposed algorithm has been investigated on economic dispatch problem having 6 unit and 10-unit system. The better cost is obtained by OTLBO as compared with other algorithms. Results have shown the satisfactory performance of OTLBO algorithm for the constrained optimization problems. The proposed algorithm may be easily customized to suit the optimization of any system involving large number of variables and objectives.

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