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Oppositional Teaching and Learning Based Optimization of Economical Load Dispatch Problem with Valve Point Loading Effect

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ABSTRACT

Economic load dispatch (ELD) problems are traditionally solved by convex optimization techniques. However, these techniques are no longer effective if the ELD problem has a non-convex cost function. This paper aims to find a suitable meta-heuristic method to solve the ELD problem with non-convex cost function. The ELD of generators in a power system with valve point loading effect was taken as the research problem. Then, several meta-heuristic optimization techniques were compared in their abilities to find the global optimal solution, namely, the lambda iteration method, the teaching and learning based optimization (TLBO) and the oppositional teaching and learning based optimization (OTLBO). The optimization techniques were thoroughly compared through demonstrations on 6, 10, and 14 units test systems. The results show that the OTLBO outperformed the other algorithms in terms of the global optimal solution. Thus, our research confirms the feasibility and effectiveness of the OTLBO for ELD problems with valve point loading effect.

1. INTRODUCTION

Nowadays, the electric energy market became more and more competitive so that to survive this current situation, optimal power generation is required to minimize the total power generation cost. ELD determines minimum cost operation of network with dispatching the generation sources to meet the load demand. ELD main objective is to minimize the total generation cost and satisfying the several constraints. Nowadays, generator scheduling is a big problem for power engineers. Since from the past few decades, number of techniques are practiced for economic load dispatch problems. The ELD tells that optimal generator scheduling of loads so that supplying power must be equal to power demanding and power losses as a decreasing fuel cost [1]. Actually the power generation cost is very high. In India the major power is generated from thermal power plants where the running cost is too high. So it is necessary to minimize the power generation cost as well as transmission losses for ELD problems [2-3]. Many researchers implemented to number of algorithms to solution of economic load dispatch problems.

Simulated & evolutionary programming algorithms which are integrated based and developed for solving the problems of ELD [4]. Barisal et al. has presented a novel optimization method which contains bacterial foraging technique used to solve the ELD Problems [5]. Issarachai et al. implemented an effective novel technique which is based on ant colony method for optimizing ELD problems based on non-smooth cost functions [6]. Lin et al. [7] developed novel quantum genetic algorithm which is used to solving the ELD problems that having wind power. Seeker optimization technique is used for solving ELD problems which attains human capabilities like understanding and searching [8]. Artificial immune technique which is clonal selection based is applicable to solve the ELD Problems with valve loading effects [9]. Devendra Sharma et al. implemented a hybrid PSO which is based on multi-agent technique to solve ELD problems [10] ELD problems include transmission loses, cubic fuel and quadratic fuel cost functions are solved by equal embedded algorithm [11]. Mohammadi-Ivatloo et al. [12] have been implemented to solve the dynamic economic load dispatch problems by using optimality condition decomposition technique.

A novel technique and coding is implemented for power system economical load dispatch problems using effortless hybrid method (EHM) [13]. Subrahmanyam et al. [11] implemented a novel technique which is used to power system economical load dispatch problems with cubic fuel cost function and transmission loses through hybrid partcile swarm optimization technique which is multo agent based. This technique resolves the PSO problems which are randomness, variables tuning and unique solution [14]. Both convex and nonconvex economic dispatch problems of thermal plants are solved by aBBOmDE techinc [15]. A novel technic is proposed to solve the economic dispatch problems using reinforcement learning method [16].

Ongsakul et al. [17] proposed a novel technique to solve the nonconvex economic problems using on Hopfield neural networks technique which hybrid-based method. Further, augmented Lagrange Hopfield network was introduced to solve ELD problems with prohibited zones. Basically this method is based on quadratic programming and piecewise quadratic cost function [18]. However these methods are suffering from the excessive iterations and resulting in large competitions. Singh et al. have been formulated and modelled both stochastic and deterministic technique which is improved particle swarm optimization have been developed to solve the economical dispatch problems with environmental effect [19]. This paper explores the new meta-heuristic algorithm i.e. oppositional teaching and learning based optimization technique to solve the ELD problems with valve point loading effect. Previously many mathematical programming methods are developed for solving ELD problems in order to get convergence solution. Linear programming techniques are effective but it will applicable only for piecewise linear cost functions. So nonlinear programming approaches have to be implement for solution of non-linear cost functions. NR based methods cannot solve the equality constraints problems [20].

This paper tells the solution of ELD problem with valve point loading effect by OTLBO algorithm with consideration of transmission losses. In this paper, OTLBO algorithm is implemented for different test systems i.e. 6, 10 and 14 unit test system and also compared with TLBO algorithm. Finally, OTLBO algorithm gives high quality solution for global minimization.

Section 2 describing about problem formulation related ELD Problem

Section 3 discusses the simulation results about proposed optimization technique and also compared with existing techniques and Section 4 explains conclusions from the present work gestions for future investigations.

2. PROBLEM FORMULATION

Load dispatch solutions defines reducing the fuel cost, real power balancing and satisfying the demand of active power. The ELD problem is represented by Savsani et al. [21].

$$FC(P_i) = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

Here $FC(P_i)$ = overall fuel cost,

P_i= Power generation of i^{th} thermal generating unit

The fuel cost is quadratic function so it is,

$$F_i(P_i) = a_i P_{gi}^2 + b_i P_{gi} + c_i \tag{2}$$

Subjected to

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{3}$$

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{4}$$

2.1 Economic dispatch problem with valve-point loading effect

Here valve point effect means sum of quadratic function function plus sinusoidal cost function which is represented by Pal et al. [22].

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i * \sin(f_i * (P_i^{\min} - P_i)) \right| \tag{5}$$

Here e_i and f_i are generating units reflecting coefficients. The line losses are represented by

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} P_i B_{0i} + B_{00} \tag{6}$$

Here B_{ij}, B_{0i} and B_{00} are coefficients of line loss.

3. SIMULATION RESULTS & DISCUSSION

The OTLBO algorithm effectiveness and feasibility is tested on standard test systems like 6, 10, 14 and results are also compared with TLBO algorithm as well as Lambda iteration method.

3.1 The proposed algorithm is implemented as per the flow chart

Step 1: Define the system data includes generators fuel cost coefficients, generation limit and demand power.

Step 2: now teacher phase starts and generators mean value will be determined. Obtain the all population size cost value.

Step 3: select the fittest population size and teacher is assigned based on minimum cost.

Step 4: now learner phase starts and improvement of generation due to interaction with different learners.

Step 5: Stop the iteration process if termination criteria satisfies. The number of iterations are represented in this paper is termination criteria. Finally, the global best fitness and corresponding generation is obtained.

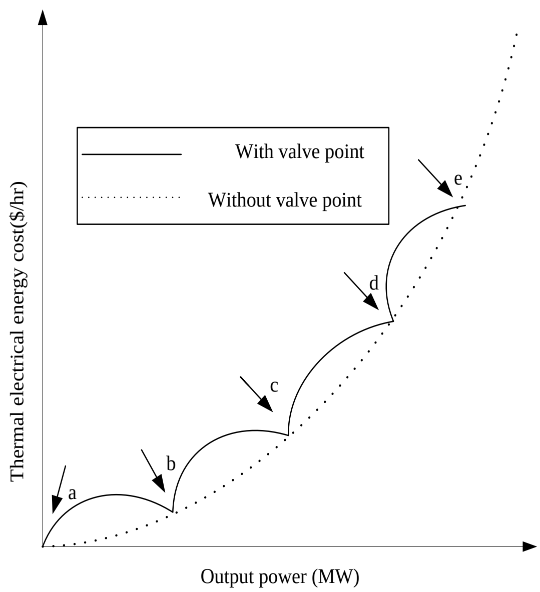

Figure 1. Input and output curve with and without valve-point loading effect- a, b, c, d and e are valve points

Figure 1 shows the operating cost characteristics of thermal station generators with and without valve-points loading Effect.

Figure 2 illustrates the step by step procedure of TLBO algorithm to optimize the ELD problem in the power system network.

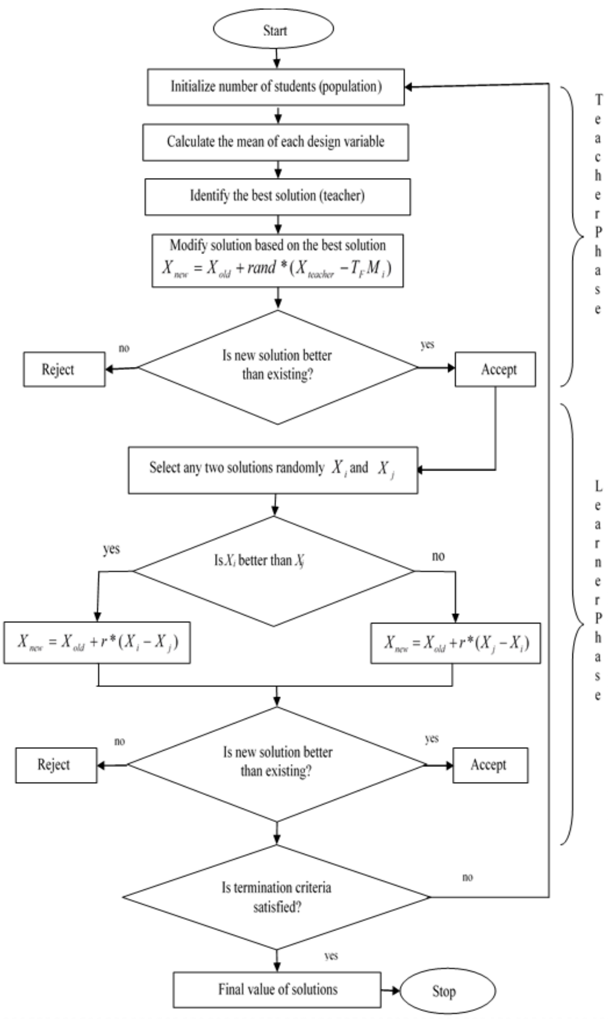

Figure 2. TLBO algorithm flow chart

3.2 Test system1: Six unit test system

This case, a non-convex cost function based 6 thermal units are considered. The proposed method effectiveness is tested on two different load demands 800 and 1263 MW that can be meet by 6 thermal units. The test system data taken from Ref. [23]. In this case population size is assumed as 60. The TLBO & OTLBO load dispatch results are formulated in Table 1. In this case, 25 independent trails have been made with 200 iterations per trail. Based on the performance, three different methods results are compared shown in below Table 1 & 2.

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

From Table 2, now the power demand of 1263MW, the obtained minimum cost by Lambda iteration method and OTLBO is 15449.8995$/h with the power loss of 12.9582MW. The minimum cost obtained by TLBO is 15450.6753$/h with the power loss of 12.8536MW. The cost obtained by Lambda iteration method and OTLBO is same as the global solution.

Figure 3 shows the comparison of convergence characteristics at different populations for different methods. As shown fig x axis represents iterations and y axis represents minimum cost in $/hr.

3.3 Test system 2: 10-unit system

This case, a non-convex cost function based 10 thermal units are considered. The performance of the proposed methods was demonstrated at two different load demands and that load demands meet by ten thermal units are 1500 and 2000MW. The test data taken from [24]. Here 100 population size is taken. The dispatch results of 10-unit system using the proposed methods are given in Table 2. For this test system, trails of 25 independent are made with 300 iterations/trail. Based on data obtained, the comparisons of six thermal units test by different methods are presented in Table 3 & 4.

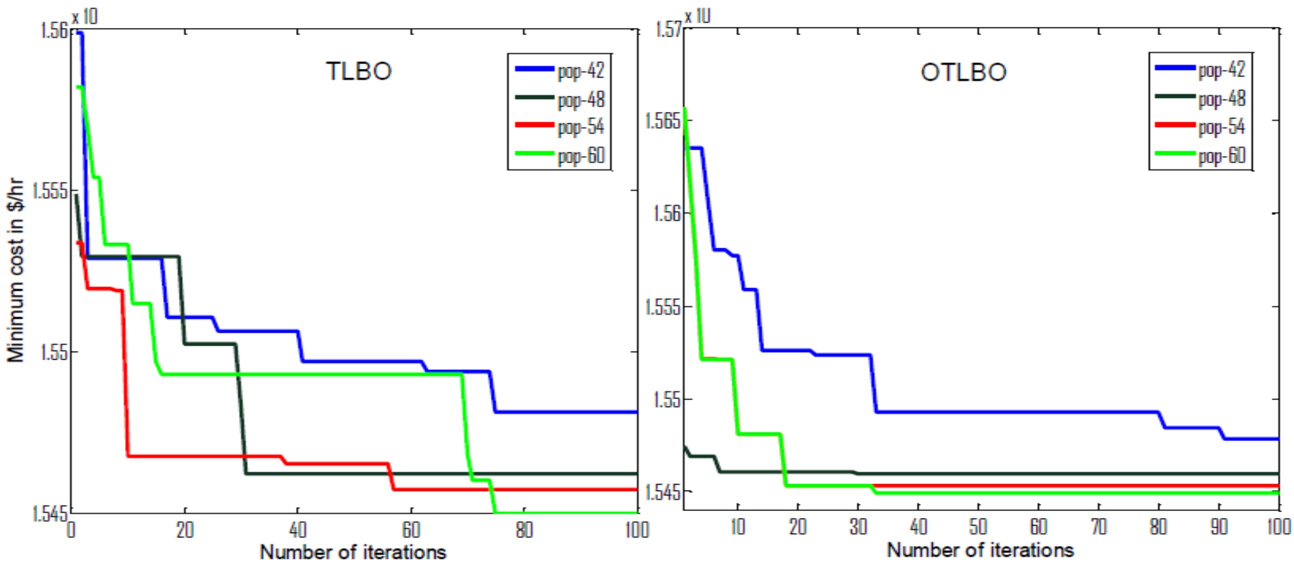

Figure 3. Comparison of convergence characteristics for different populations

From the Table 3, at load demand of 1500MW the obtained minimum cost by Lambda iteration technique and TLBO is 81130.0325$/h with the power loss of 49.0223MW. The obtained minimum cost by OTLBO technique is 81129.7603$/h with the power loss of 49.007MW. From the above records it says clearly that the obtained minimum cost by the OTLBO is the global solution at the load demand of 1500MW.

Table 1. Comparisonal results for 6-unit system with load demand of 800 MW

Unit	P_D=800 MW		
	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

Table 2. Comparisonal results for 6-unit system with load demand of 1263 MW

Unit	P_D=1263 MW		
	Lambda	**TLBO**	**OTLBO**
1	447.5038	444.4068	447.5038
2	173.3182	170.8177	173.3182
3	263.4628	263.9355	263.4628
4	139.0653	146.5230	139.0652
5	165.4734	166.4267	165.4733
6	87.1347	83.7436	87.1347
Generation cost in $/hr	15449.8995	15450.6753	15449.8995
Power loss in MW	12.9582	12.8536	12.9582

Table 3. Comparisonal results for 10-unit system with demand of 1500 MW

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

From Table 4, now power demand of 2000MW the obtained minimum cost by Lambda iteration method is 111261.5057$/h with the power loss of 87.0403MW. The obtained minimum cost by OTLBO method is 11261.5051$/h with the power loss of 87.0403MW. The TLBO obtained cost is 111289.9482$/h with power loss of 87.1252. Therefore, the cost obtained by Lambda iteration method and OTLBO is almost same but the cost obtained by OTLBO method is global minimum.

Figure 4 shows the graphical representation of comparison convergence characteristics of obtained minimum cost for 20runs at load demand 2000 MW. As shown in fig the cost obtained by Lambda iteration method is constant for all runs while the other methods are varying.

Table 4. Comparisonal results for 10-unit system with demand of 1500 MW

Unit	P_D=2000 MW		
	Lambda	**TLBO**	**OTLBO**
1	55.0000	55.0000	55.0000
2	80.0000	80.0000	80.0000
3	107.0165	120.0000	107.0151
4	99.9004	95.5547	99.9007
5	81.9005	77.8408	81.9024
6	83.2229	78.7297	83.2221
7	300.0000	300.0000	300.0000
8	340.0000	340.0000	340.0000
9	470.0000	470.0000	470.0000
10	470.0000	470.0000	470.0000
Generation cost in $/hr	111261.5057	111289.9482	111261.5051
Power loss in MW	87.0403	87.1252	87.0403

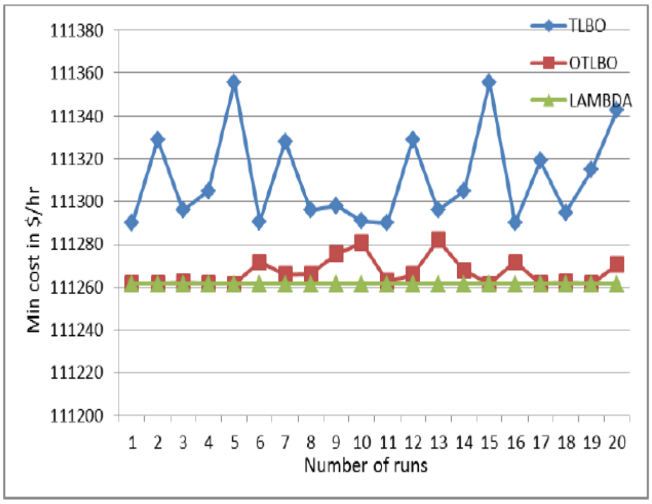

Figure 4. Comparison of convergence characteristics of obtained minimum cost for 20runs

3.4 Test system 3: 14-unit system

This case, a non-convex cost function based 14 thermal units are considered. The performance of the proposed methods is demonstrated at two different load demands and that load demands meet by 14 thermal units are 1500 and 2000MW. The data taken from Ref. [25]. Here population is 140. The dispatch results of 14-unit system using the proposed methods are given in Tables 5 & 6. For this test system, 500 iterations per trail are made with 25 independent trails. From the data, six thermal units' comparisons shown by different methods are presented in Tables 5 & 6.

From the Table 5, power demand of 1500MW, obtained minimum cost by Lambda iteration method is 6612.5868 $/h with the power loss of 17.9213MW. The obtained minimum cost by OTLBO technique is 6612.5089 $/h with the power loss of 18.1087 MW. TLBO produced the cost of 6612.5120 $/h with power loss of 18.1655 MW. It has been showed that the minimum cost obtained by all the methods is almost same but the cost obtained by OTLBO is the global solution at the load demand of 1500MW.

From Table 6, now at the power demand of 2000MW, the obtained cost from all the methods is almost same but the cost obtained by OTLBO method is global minimum and it is 8895.4566$/h with power loss of 30.7713 MW.

Table 5. Comparisonal results for 14-unit system with demand of 1500 MW

Unit	P_D=1500 MW		
	Lambda	**TLBO**	**OTLBO**
1	221.3101	220.1858	218.5729
2	189.0354	192.2743	190.7673
3	50.5688	49.1485	53.1257
4	88.2294	86.0241	88.1582
5	150.0000	150.0258	150.0026
6	135.0000	135.0258	135.0026
7	135.0000	135.0258	135.0026
8	60.0000	60.0258	60.0026
9	139.6414	139.3569	136.2976
10	127.1018	130.8644	132.3087
11	79.9875	80.0000	80.0000
12	79.9875	80.0000	80.0000
13	47.0593	45.1827	43.8651
14	15.0000	15.0258	15.0026
Generation cost in $/hr	6612.5868	6612.5120	6612.5089
Power loss in MW	17.9213	18.1655	18.1087

Table 6. Comparisonal results for 14-unit system with demand of 2000 MW

Unit	P_D=2000 MW		
	Lambda	**TLBO**	**OTLBO**
1	310.6826	308.1352	312.1435
2	269.8385	276.6890	271.6552
3	120.5517	117.5742	116.8470
4	129.9988	130.0000	130.0000
5	192.9272	192.3146	193.8548
6	163.3757	162.2258	165.2621
7	136.9125	136.0410	136.1677
8	84.6855	86.0736	82.8410
9	162.0000	162.0000	162.0000
10	159.9811	160.0000	160.0000
11	80.0000	80.0000	80.0000
12	80.0000	80.0000	80.0000
13	85.0000	85.0000	85.0000
14	55.0000	55.0000	55.0000
Generation cost in $/hr	8895.6328	8895.5806	8895.4566
Power loss in MW	30.9535	31.0534	30.7713

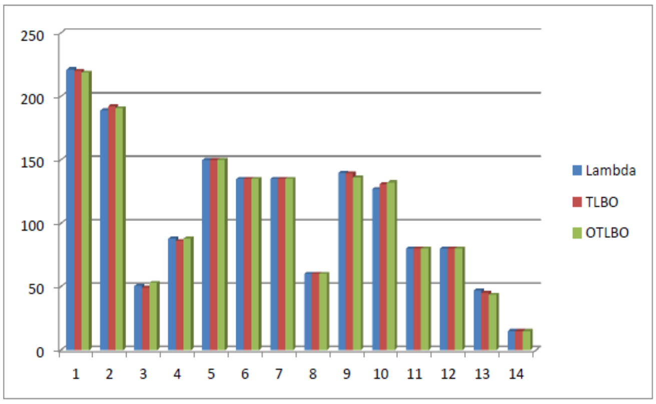

Figure 5. Distribution of generation conceded by ten generators at P_D=1500 MW

Figure 4 shows how the generation shared by fourteen generators with respect to their minimum and maximum limits which means it satisfies the inequality constraint. From the equality constraint, the fourteen generators generation should meet to given load demand.

4. CONCLUSION

In this paper, standard ELD problem can be solved in different cases with different methods. In first case ELD problem is represented with non-convex cost-function, already present there in network. The algorithms TLBO & OTLBO are successfully used to minimize the ELD problem considering 6, 10 and 14-unit test systems and also distinguished with lambda technique to test the performance of the proposed algorithm. The proposed algorithm OTLBO found better solution for all test systems than TLBO. This investigation results certainly says that the proposed method can be utilized as effective optimization providing better satisfactory solutions for ELD problems. The paper established algorithms for the ELD problem to have the optimal solution for valve point loading effect only. However i strongly recommend that, in few cases there is still a need to investigate more avenues such as prohibited operating zones, ramp rate limits and multiple fuel selections for each unit. Here only thermal generating units have been considered. The ELD of hydro units can be applied by engaging these novel techniques. I also recommend that the new techniques have been used for combined hydrothermal economic load dispatch for future scope.

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