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TLBO Algorithm for Non-Convex Economic Load Dispatch Considering Losses

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Abstract:

Abstract— This work presents a new approach to solve the economic distribution (ED) problem with valve point load effects considering losses. In this paper, a new algorithm for teaching learning-based optimization (TLBO) is developed and applied to the Economic dispatch (ED) problem. The proposed TLBO lacks the disadvantages of classical heuristics, such as local optimal swing due to premature convergence, insufficient ability to find nearby extrema, and lack of an efficient mechanism to handle constraints. The algorithm describes two basic forms of learning: (i) through a teacher (known as the teacher phase) and (ii) through interaction with other students (known as the learner phase). In this optimization algorithm, a group of students is considered as a population, and the subjects offered to different learners are treated as different design variables of the optimization task, and the efficiency of the learner is analogous to the "fitness" value of the optimization task. A teacher is considered the best solution in the entire population. The effectiveness and feasibility of the proposed TLBO method was demonstrated on a 6-unit test system and then compared with other algorithms such as PSO, DE and HSA. The experiment showed that the proposed approach was able to determine a higher quality solution when solving complex ED problems.

Index Terms—ED, transmission line losses, TLBO

I. Introduction

Economic allocation is generally defined as the process of allocating production levels to production units so that the load is delivered as a whole and at the lowest cost. In the power system, economic transmission is one of the most important optimization problems and is a central task of economic activity. Good load transfer can reduce production costs, increase system reliability and maximize the energy output of thermal units. The main objective of this economic allocation problem is to determine the optimal capacity combination of all generating units that minimizes the total fuel consumption while satisfying the load and operation constraints, which are equal and unequal constraints [1-2].

Recently, many researchers have tried to apply several optimization methods to solve ED problems with different types of fuel consumption functions, such as Hopfield Neural Networks (HNN) [3,4], Simulated Annealing (SA) [5], Genetic Algorithms (GA)) [6–8], particle swarm optimization (PSO) [9–10], tabu search algorithms [11] and cloning algorithm [12].

Rao et al. proposed a new optimization method called "teaching-learning-based optimization (TLBO). [13] for constrained optimization problems. The method is based on the influence of the teacher on the students and the influence of the students on each other. Rao and others [14] presented five different constrained benchmark functions to demonstrate the reliability of TLBO. The results obtained from the design examples were compared with other metaheuristic optimization methods. The comparisons showed that TLBO showed better performance with less computing power compared to other metaheuristic optimization methods. Rao et al. [15] developed a TLBO method for large-scale nonlinear optimization problems to find global solutions. Rao et al. after pioneering research. [16], TLBO was used for the optimal design of planar steel frames [17]. The effectiveness of the method was verified on three pre-optimized steel frames with GA, HS and advanced ACO. Regarding the results related to the number of analyzes and the frameworks presented in the study, the TLBO method showed excellent results compared to the GA, ACO, HS and improved ACO methods [18].

This paper uses TLBO to solve a non-convex economic dispatch problem considering a cost function with valve point load effects and losses. To test the effectiveness of the proposed algorithm, it is implemented on a 6-unit system. The remainder of this study is organized as follows. The formulation of the optimal design problem is given in Section 2. The TLBO method is explained in Section 3. A comparison of TLBO with other algorithms is explained in Section. The results obtained by TLBO are presented and compared with other metaheuristic optimization methods in Section 5 Finally, conclusions are presented in Section 6.

II. FORMULATION OF ECONOMIC DISPATCH PROBLEM

The main goal of solving the ED problem is to minimize the total fuel consumption of each generator in the power system in operation, satisfying all the actual power demand, the actual power balance, and the limits of the generators. The ED problem formulation can be modeled as follows

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

(1) Where $FC(P_i)$ is the total fuel cost, N is the total number of thermal generating unit, P_i is the power generation of i_{th} thermal generating unit and $F_i(P_i)$ is the fuel cost function. Conventionally, the fuel cost curve for any thermal generating unit can be represented by segments of quadratic functions of the active power output of the generator. So $F_i(P_i)$ can be defined by (2)

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

Subjected to $$\sum_{i=1}^{n} P_i = P_D + P_L \quad (3)$$

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

where a_i, b_i, c_i are fuel cost coefficients of the i_{th} thermal generating unit, P_i is the real power of generating unit i, P_D is total load demand, P_L is total transmission line loss, $P_{i,\min}$ is the minimum generation limit of unit i and $P_{i,\max}$ is the maximum generation limit of unit i.

ED PROBLEM WITH VALVE-POINT LOADING EFFECT

A generator that takes into account the effect of valve point loading has a different input-output curve compared to a flat cost function. To account for the valve point load effects, sinusoidal functions are added to the quadratic cost functions as follows [1-5]:

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

Where e_i and f_i are coefficient of the generating units reflecting valve-point loading effects.

TRANSMISSION LINE LOSSES:

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

Where B_{ij},B_{0i} and B_{00} are transmission line loss coefficeients.

III. THE TEACHING-LEARNING BASED OPTIMIZATION ALGORITHM

TLBO is a coaching-mastering method stimulated set of rules proposed through Rao et al. (2011, 2012), Rao and Savsani (2012) and Rao and Patel (2012) primarily based totally at the impact of impact of a trainer at the output of freshmen in a class. The TLBO is a populace-primarily based totally meta-heuristic seek approach like HS, ACO, PSO and ABC. The TLBO approach affords a mathematical version for optimization troubles primarily based totally at the easy coaching method.

The set of rules describes simple modes of the mastering: (i) thru trainer (called trainer phase) and (ii) interacting with the alternative freshmen (called learner phase). In this optimization set of rules a collection of freshmen is taken into consideration as populace and one of a kind topics supplied to the freshmen are taken into consideration as one of a kind layout variables of the optimization hassle and a learner's end result has similarities to the 'fitness' fee of the optimization hassle. The great answer with inside the whole populace is taken into consideration because the trainer. The layout variables are genuinely the parameters concerned with inside the goal feature of the given optimization hassle and the great answer is the great fee of the goal feature. The running of TLBO is split into parts, 'Teacher phase' and 'Learner phase'.

Teacher Phase:

During this phase a teacher tries to increase the mean result of the class in the subject taught by him or her depending on his or her capability. A good teacher brings his or her learners up to his or her level in terms of knowledge. But in practice this is not possible and a teacher can only move the mean of a class up to some extent depending on the capability of the class. This follows a random process depending on many factors.

Let M_i be the mean and T_i be the teacher at any iteration i. T_i will try to move mean M_i towards its own level, so now the new mean will be T_i designated as M_{new}. However, as the teacher is usually considered as a highly learned person who trains learners so that they can have better results, the best learner identified is considered by the algorithm as the teacher.

The difference between the existing mean result of each subject and the corresponding result of the teacher for each subject is given by,

$$Difference = r * (M_{new} - T_F M_i) \quad (6)$$

Where T_F is the teaching factor that decides the value of mean to be changed, r is the random number in the range [0,1] . The value of T_f can be either 1 or 2, which is again a heuristic step and decided randomly with equal probability as

$$T_F = round[1 + rand * (0,1) * (2-1)] \quad (7)$$

This difference modifies the existing solution according to the following expression

$$X_{new,i} = X_{old,i} + difference \quad (8)$$

Where $X_{new,i}$ is the updated value of $X_{old,i}$. Accept $X_{new,i}$ if it gives a better function value. All function values accepted at the end of the teacher phase are saved and these values become inputs to the learner phase. The learning phase depends on the teacher's phase.

Learner phase:

Students increase their knowledge in two different ways: on the one hand, with the input of the teacher. And the second through students increase their knowledge by interacting with each other. The student communicates with other students from time to time to improve his knowledge.

Number of units	***Global generations in MW***			
	PSO	**HSA**	**DE**	**TLBO**
1	400.6115	399.4068	500	500
2	199.5996	200	149.9957	151.4009
3	232.1225	232.0630	230.3581	300
4	124.7998	125.2627	125.8899	87.7215
5	199.5996	200	149.9629	149.4573
6	120	120	120	88.4572
Min cost ($/h)	15616.7991	15624.4473	15615.6937	15611.6988
Power loss (MW)	13.7331	13.5483	13.2068	14.0371

A student learns something new when another student has more knowledge than him. Based on the population size 'Pn', the learning phenomenon at this stage is expressed below.

Randomly select two learners X_i and X_j where i≠j

$$X_{new,i} = X_{old,i} + r*(X_i - X_j) \text{ if } f(X_i) < f(X_j)$$

$$X_{new,i} = X_{old,i} + r*(X_j - X_i) \text{ if } f(X_i) > f(X_j) \quad (9)$$

Accept $X_{new,i}$ if it gives better function value.

IV. COMPARISON OF TLBO WITH OTHER ALGORITHM

Like GA, PSO, ABC, HS, etc., TLBO is a population-based technique that applies a set of solutions to find the optimal solution. Many optimization methods require algorithm parameters that affect algorithm performance. GA requires transition probability, mutation rate and selection method; PSO requires learning factors, weight variation and velocity maximum value; ABC requires the number of worker bees, onlooker bees and a threshold value; HS requires harmonic memory weight frequency, pitch adjustment frequency, and number of improvisations: SFLA requires number of memeplexes, iteration per memeplex: ACO requires exponent parameters, pheromone evaporation rate, and reward factor. Unlike other optimization techniques, TLBO does not require tuning of algorithm parameters, which makes TLBO easier to implement. As with PSO, TLBO uses the best solution in an iteration to modify the existing solution in the basis set, which increases the convergence rate. TLBO does not divide the population like ABC and SFLA. Similar to GA, which uses selection, crossover, and mutation phases, and ABC, which uses worker, bystander, and scout bee phases, TLBO uses two separate phases, a "teacher phase" and a "learner phase." TLBO uses the population to update the solution. TLBO applies greed to accept a good solution such as ABC.

V. SIMULATION RESULTS

To validate the proposed procedure, the TLBO algorithm was tested on a common load transfer problem consisting of valve point load effect and losses of two cases, and these two cases are 6 and 10 unit systems. The proposed algorithm was implemented using MATLAB.

Case-1:

In this case, a system of six thermo blocks with valve point loading effect and losses is investigated. The expected load demand of all generation units is 1263 MW. System information can be taken from [25]. To find out the effectiveness of the proposed method, 25 independent paths with 200 repetitions per path were made for 60 populations.

Table 6.1. Global generations for 6unit system

Global generations of global costs and comparisons of minimum costs for each path are presented in Tables 6.1 and 6.2. Convergence properties are also plotted for global generations and independent paths, which can be shown in figures 6.1 and 6.2.

Table 6.2. Minimum cost obtained for 25 runs

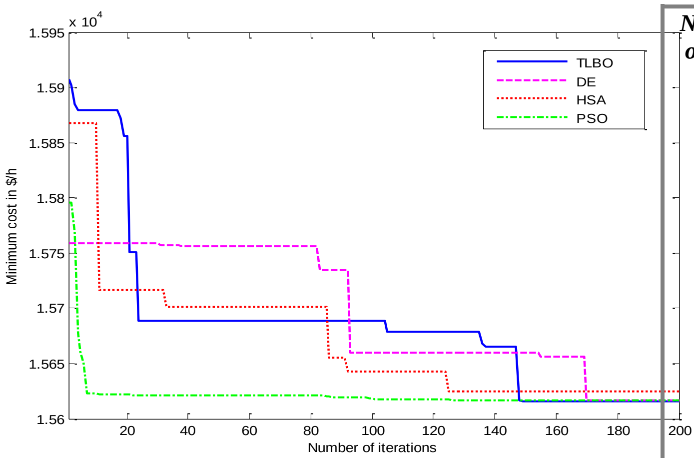

Fig 6.1convergence characteristics of 6unit system

From Table 6.1, the minimum cost of PSO was $15616.7991/h, the minimum cost of HSA was $1562.73/h, the minimum cost of DE was $15615.6937/h, and the minimum cost of TLBO was 15611.6988. So it can be seen from the above results that a better price is obtained for TLBO compared to other algorithms. A power loss of 1.0371 MW was obtained for TLBO.

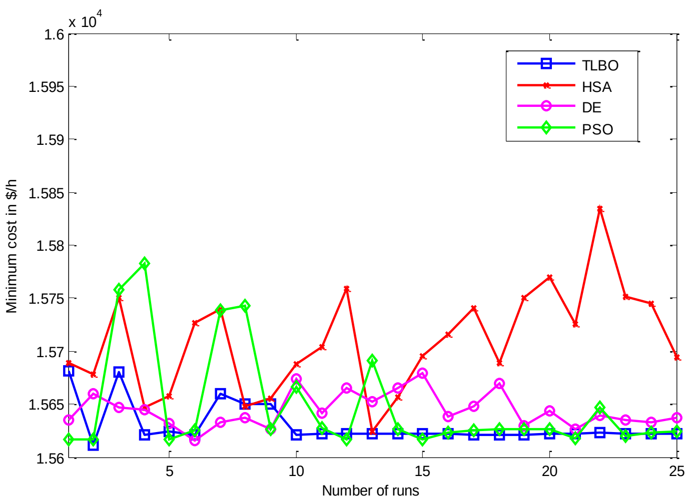

Fig.6.2. **Comparison characteristics of minimum cost Obtainedfor 25 runs**

Case-2:

In this case, a system of ten thermo blocks is studied with valve point loading and losses. The expected load demand of all production units is 2000 MW. System information can

Number of runs	*Minimum cost in $/h*			
	PSO	**HSA**	**DE**	**TLBO**
1	15616.8546	15688.4303	15635.2652	15681.9111
2	15616.8756	15677.7093	15660.2286	15611.6988
3	15758.1765	15750.0689	15646.7544	15680.6254
4	15782.4748	15647.0857	15645.1185	15621.5284
5	15616.8511	15657.9900	15631.8830	15624.2276
6	15625.1855	15726.5923	15615.6937	15621.4526
7	15738.7735	15739.6564	15632.6176	15659.3512
8	15743.2094	15647.9531	15636.6707	15650.3453
9	15626.6348	15655.4437	15626.5942	15650.3141
10	15665.8478	15688.3176	15673.4684	15621.5109
11	15627.0714	15703.6266	15641.7270	15622.5178
12	15616.7991	15759.3145	15665.2332	15621.6119
13	15691.2273	15624.4473	15652.6820	15622.4532
14	15626.6205	15656.2226	15665.7099	15622.1312
15	15616.9367	15695.9180	15679.2265	15621.6684
16	15623.5040	15715.6528	15638.6161	15621.6008
17	15625.1855	15740.7103	15648.2682	15621.5467
18	15626.5741	15688.7322	15670.0528	15621.3824
19	15626.7418	15750.1998	15629.4167	15620.9401
20	15626.7085	15769.2848	15643.9360	15621.6385
21	15618.0267	15725.9458	15626.4920	15622.2550
22	15647.0017	15834.2254	15639.1709	15622.9964
23	15619.6076	15751.9471	15635.1169	15621.7541
24	15623.5005	15744.5482	15633.0052	15622.5070
25	15624.3020	15694.8515	15637.5919	15621.6983
Min cost ($/h)	**15616.7991**	**15624.4473**	**15615.6937**	**15611.6988**
Max cost($/h)	**15782.4748**	**15834.2254**	**15679.2265**	**15681.9111**
Avg cost ($/h)	**15649.2276**	**15709.3950**	**15644.4216**	**15630.0667**

be taken from [26]. To find out the effectiveness of the proposed method, 25 independent paths with 200 repetitions per path were made for 100 residents. Tables 6.3 and 6.4 show global cost generations and minimum cost comparisons for each route. Convergence properties are also plotted for global generations and independent paths, which can be shown in figures 6.3 and 6.

Table 6.3.Global generations for 10unit system

Number of units	*Global generation in MW*			
	PSO	**HSA**	**DE**	**TLBO**
1	55	50.8495	55	55
2	80	75.8420	78.7733	80
3	107.3388	115.8420	99.3983	106.9392
4	100.3117	94.02348	107.1068	100.5765
5	81.4700	109.7019	89.0972	81.5012
6	82.9208	95.2030	81.4078	83.0217
7	300	295.8420	296.1400	300
8	340	335.8420	340	340
9	470	465.8420	470	470
10	470	446.8475	470	470
Min cost ($/h)	111497.6596	111907.4666	111537.6219	111497.6301
Power loss (MW)	87.0414	85.8360	86.9237	87.0387

From Table 6.3, the minimum cost of PSO was 11197.6596 $/h, the minimum cost of HSA was 111907.666 $/h, the minimum cost of DE was 111537.6219 $/h, and the minimum cost of TLBO was 1631197. Observe from the above results that TLBO can better price compared to algorithms. A power loss of 87.0387 MW was obtained for TLBO

Table 6.4minimum cost obtained for 25 runs

Number of runs	*Minimum cost in $/h*			
	PSO	**HSA**	**DE**	**TLBO**
1	111641.4441	111959.2697	111569.1983	111500.9854
2	111525.8322	112694.2246	111673.5325	111505.7236
3	111497.6763	111947.6861	111695.2852	111497.6765
4	111521.5108	112047.7053	111567.3306	111521.7364
5	111525.8275	112302.8949	111742.5223	111525.7565
6	111525.6877	112206.2944	111743.0718	111521.5768
7	111525.7571	112052.4801	111670.3818	111502.6754
8	111525.7976	112071.9085	111705.6591	111505.8768
9	111525.8834	111947.8623	111751.1809	111497.6301
10	111497.7631	111987.3196	111648.195	111497.6764
11	111497.6695	111919.8793	111645.2498	111497.6765
12	111497.7148	112337.6419	111601.2568	111497.6987
13	111497.6784	112250.1165	111689.5033	111497.6877
14	111525.7557	112185.1190	111663.6215	111500.6301
15	111497.8285	112235.6711	111679.4047	111504.6375
16	111497.7403	112094.2826	111654.574	111525.6384
17	111525.6996	112026.1773	111629.5029	111518.6311
18	111525.7043	112125.7557	111537.6219	111499.6343
19	111525.5897	112010.5037	111706.3123	111497.6301
20	111525.8344	112131.3220	111714.4087	111497.6301
21	111525.7345	112421.2877	111551.2658	111497.6301
22	111525.7724	112461.9869	111675.4585	111499.6383
23	111497.6596	112385.1277	111707.5187	111499.6376
24	111525.71	112111.6850	111608.6125	111497.6301
25	111497.7123	111907.4666	111652.1783	111497.6301
Min cost($/h)	**111497.6596**	**111907.4666**	**111537.6219**	**111497.6301**
Max cost($/h)	**111641.4441**	**112694.2246**	**111751.1809**	**111525.7565**
Avg cost($/h)	**111520.1193**	**112152.8667**	**111659.3138**	**111504.2789**

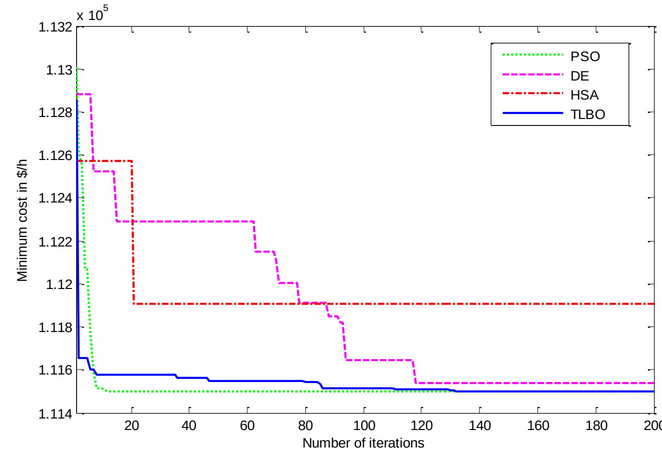

Fig 6.3minimum cost obtained for 25 runs

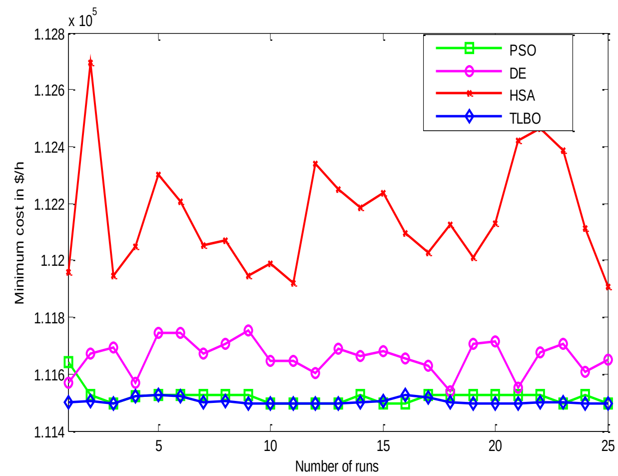

Fig 6.4convergence characteristics of 10-unit system

VI. CONCLUSION

All evolutionary and sub-swarming algorithms require proper tuning of algorithm-specific parameters in addition to tuning of general control parameters. A change in the setting of certain parameters affects the efficiency of the algorithm. The newly proposed TLBO algorithm does not require any algorithm-specific parameters. It only requires setting the general control parameters of the algorithm to work. In this paper, a state-of-the-art optimization algorithm such as TLBO was successfully used to solve the power system ED problem considering valve point load effects and losses. The feasibility and effectiveness of the proposed algorithm were studied for the economic transfer problem of 6- and 10-unit systems. A better price is obtained for TLBO compared to other algorithms. The results showed the satisfactory performance of the TLBO algorithm for constrained optimization problems. The proposed algorithm can be easily adapted to suit the optimization of any system containing a large number of variables and objectives.

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