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Large Scale Economic Dispatch of Power Systems using Teaching Learning Based Optimization

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Abstract

In this paper, a novel optimization technique is planned to solve large scale non smooth Economic Dispatch (ED) problem involving Cubic Cost Functions (ED-CCF). The proposed approach is based on a Teaching Learning Based Optimization (TLBO) algorithm which mimics teaching–learning process in a class between the teacher and the learners. The TLBO method works on the philosophy of teaching and learning. In order to validate the proposed methodology, comprehensive simulation results acquired on 156 unit test system are presented and examined. A comparative analysis with other settled nature inspired solution algorithm demonstrates the superior performance of the proposed methodology in terms of both solution accuracy and convergence performance.

Keywords: Economic dispatch, teaching learning based optimization, non smooth, cubic cost functions, and large scale system.

Introduction

Economic Dispatch is one of the main functions of the modern energy management system which determines the optimal real power settings of generating units with an objective to minimize the total fuel cost of dispatch solutions in cases where the classical methods ceases to be applicable. Classical search techniques employed to solve economic dispatch problem produce inaccurate results because the operating units have non-linear incremental cost curves and the conventional procedure either ignores or flattens out the portions of non-linear regions of the curves. But such approximations are not desirable as they may lead to sub-optimal operation and hence huge revenue loss results over time. Hence, there is a demand for techniques that do not impose restrictions on the shape of the fuel cost curves.

In order to get the qualitative solution for the ED-CCF problem, optimization techniques have been successfully applied for thermal generators. A literature survey is carried out for the solution techniques to ED-CCF problem are elaborated as follows. Limited reports are available in the literature for the chosen problem. Initially in the 20th century, different mathematical [1] and heuristic solution techniques such as iterative method [2], sorted table method [3], dedicated projection method [4], Newton's Method (NM) [5], Evolutionary Programming (EP) [6], and Quadratic Programming (QP) [7] have been developed and applied successfully to ED problems. Recently in 21th century, meta-heuristic and hybrid techniques such as Dynamic Hopfield Neural Network (HNN) [8], Partition Approach Algorithm (PAA) [9], Pattern Search (PS) algorithm [10], Bacterial Foraging-Nelder Mead (BF-NM) Method [11] and TLBO [12] have been effectively applied to ED problems with cubic cost functions.Still extensive research is being conducted in the area of ED with the support of nature inspired algorithms. As a result, meta-heuristic optimization algorithms were developed by inspiring natural phenomena or biological behavior and were applied to solve various engineering optimization problems. Some of the most well known algorithms are genetic algorithm, simulated annealing, EP, particle swarm optimization, Bacterial Foraging Algorithm (BFA) and artificial bee colony algorithm. These optimization techniques require algorithm parameters that decide their performance. Improper selection of parameters leads to trap the solution on local optima.

In this paper, a recent heuristic algorithm introduced by Rao et al. [13] named Teaching Learning Based Optimization (TLBO) algorithm [14], based on the effect of the influence of a teacher on the output of learners in a class, is utilized for the solution of ED-CCF problem.

ED with Cubic Cost Functions

The objective of the large scale ED-CCF problem is to minimize the total system fuel cost over some appropriate period while satisfying various constraints, and thus the problem can be defined as the following constrained optimization problem:

$$\sum_{i=1}^{N} F_i(P_i) = a_i + b_i P_i + c_i p_i^2 + d_i p_i^3 \quad (\$/h) \qquad (1)$$

Where a_i, b_i, c_i and d_i are the fuel cost coefficients and N is the number of generating units.

Power balance constraints: The generated power of all thermal generating units must fulfil the load demand, which is defined as

$$\sum_{i=1}^{N} P_i = P_d \ (MW) \qquad (2)$$

Power generation limits: The generating unit power output must falls within its minimum ($P_{i,\min}$) and maximum limits ($P_{i,\max}$), which can be formulated as:

$$P_{i,\min} \le P_i \le P_{i,\max} \qquad (3)$$

Teaching Learning Based Optimization

TLBO is an innovative optimization algorithm inspiring the natural phenomena, which mimics teaching–learning process in a class between the teacher and the students (learners). The TLBO method works on the philosophy of teaching and learning. Teacher generally wishes to attain best level on the output of learners in a class. Output is evaluated by means of exam conducted by the teacher. Generally the teacher is considered as highly intellectual person whose quality affects the outcome of the learners.Teacher and learners are the two vital components of the algorithm. In this optimization algorithm, a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and the learners' result is analogous to the 'fitness' value of the optimization problem. In the entire population, the best solution is considered as the teacher. The working of TLBO is divided into two parts, 'teacher phase' and 'learner phase'. Functioning of both the phases is explained below.

Teacher Phase

It is the first part of the algorithm where initially learners learn through the teacher. 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 ability. The teacher is generally considered the most learned person in the society. This aspect is considered in the TLBO algorithm. This algorithm is a population-based method which starts with a set of solutions known as the population. As the teacher is considered the most learned person, the best solution from the population is considered as the teacher. The purpose of a teacher is to increase the knowledge of the students. In practice, however, it is not possible for a teacher to increase the level of the students equally as different students possess different knowledge levels.

A survey of the knowledge possessed by the students will give some mean knowledge value. A teacher, after teaching, will improve this mean level of the students to a better mean knowledge value. This aspect is represented in mathematical form and is implemented for the optimization. During the teacher phase, a teacher tries to increase the mean result of the classroom from any value M_1 to his or her level (i.e. T_A). But practically it is not possible and a teacher can move the mean of the classroom M_1 to any other value M_2 which is better than M_1 depending on his or her capability. Consider M_j be the mean and T_i be the teacher at any iteration i. Now T_i will try to improve existing mean M_j towards him or her so the new mean is designated as M_{new} and the difference between the existing mean and new mean is given by Equation (4).

$$\text{Difference mean}_i = \text{rand}_i\,(M_{new} - T_F M_j) \qquad (4)$$

where T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. T_F is not a parameter of the TLBO algorithm and it is decided randomly with equal probability. The value of T_F can be determined heuristically which is either 1 or 2, using Equation (5). The existing solution is updated using Equation (6).

$$T_F = \text{round}\,[1+\text{rand}\,(0, 1)\,\{2-1\}] \qquad (5)$$

$$X_{new,\,i} = X_{old,\,i} + \text{Difference mean}_{i.} \qquad (6)$$

Learner Phase

It is the second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. A learner learns new things if the other learner has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed below.

At any iteration i, considering two different learners X_i and X_j where $i \neq j$ the new solution is updated as

$$X_{new,\,i} = X_{old,\,i} + \text{rand}_i\,(X_i - X_j) \text{ if } f(X_i) < f(X_j) \qquad (7)$$

$$X_{new,\,i} = X_{old,\,i} + \text{rand}_i\,(X_j - X_i) \text{ if } f(X_j) < f(X_i) \qquad (8)$$

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

The candidate solution composes of design variables and is qualified according to its fitness. The solution having best fitness in the population is determined as the teacher. The entire process is continued until reaching the termination criteria.

Results and Discussion

The chosen test system is a 156 unit large scale system involving cubic cost functions make the test system non-smooth in nature. The operating range, cost coefficients of the 156 thermal generators are obtained from [12]. The proposed algorithm has been implemented in Matlab 7.9 and executed on HP personal computer with Intel core i3 processor with 4GB ram. The TLBO based ED-CCF is carried out for demands of 9000MW, 10000MW and 11000 MW and the obtained results are compared with other rival BBO algorithm in Table 2. Table 1 lists the detailed dispatch results of 156 unit system for a demand of 10000MW. The minimum cost obtained by the proposed method for demand of 9000MW, 10000MW and 11000 MW are respectively 154406.25 $/h, 162712.80 $/h and 176931.46 $/h without violation of power balance constraint and other operational constraints.

Table 1: Dispatch results of 156 unit large scale system for a demand of 10000 MW

Units	P_i (MW)	Units	P_i (MW)	Units	P_i (MW)	Units	P_i (MW)	Units	P_i (MW)	Units	P_i (MW)
1	3.346974	27	6.466011	53	2.4	79	8	105	8.344719	131	8
2	8.738011	28	8	54	3.220959	80	2.4	106	7.440288	132	9
3	8.539432	29	6.13665	55	5	81	2.4	107	2.4	133	2.4
4	4.93002	30	8	56	6.096689	82	3.125669	108	3	134	3.203074
5	2.4	31	4	57	5.305705	83	2.54402	109	7	135	7.00018
6	8	32	5.109299	58	18.52641	84	4	110	8.809672	136	14.5239
7	12.84227	33	11.68227	59	4.307442	85	5	111	15.82333	137	4
8	14	34	4	60	4	86	5.77802	112	4	138	4
9	4	35	14.82766	61	9	87	6.159178	113	7.870075	139	4.886435
10	15.2	36	69.19729	62	15.2	88	15.2	114	49.71649	140	27
11	64.17912	37	15.2	63	44.37123	89	39.26075	115	56.95882	141	15.2
12	20.61357	38	67.24467	64	26	90	29.43445	116	29.68728	142	15.2
13	29	39	27.7368	65	62.13097	91	41.65048	117	15.2	143	17
14	25	40	43.54648	66	25	92	27.71934	118	76.77837	144	37
15	70.84116	41	45.38855	67	35	93	55	119	69.85147	145	48.23208
16	35.92165	42	44.14257	68	49.31468	94	58.87839	120	36.35189	146	68
17	54.25	43	60	69	61.93787	95	91.07402	121	54.25	147	143.879
18	111	44	96	70	74	96	54.25	122	99.2129	148	84.77316
19	101.9174	45	108	71	108.069	97	54.25	123	87.32719	149	74
20	54.25	46	68.97791	72	54.25	98	54.25	124	91.49022	150	54.25
21	123	47	72	73	148.6117	99	68.95	125	189.5878	151	103
22	107.8098	48	80.88483	74	119.8775	100	177.4776	126	85	152	147
23	68.95	49	85	75	68.95	101	98.29502	127	68.95	153	68.95
24	254.7451	50	258	76	140	102	267	128	270.3687	154	166.5441
25	398.051	51	337.9693	77	154	103	194.5416	129	177	155	221
26	179.825	52	368.4132	78	175	104	250.0793	130	295.9771	156	100
Fuel Cost ($/h)										162712.8	

Table 2: Comparative results of 156 unit system

Demand	TLBO	BBO
9000 MW	154406.25	155068.96
10000 MW	162712.80	163322.56
11000 MW	176931.46	177069.07

It can be seen from the Table 2 that, the solution quality of TLBO algorithm is better than those obtained by BBO method. The proposed algorithm settings are selected after conducting many experiments so as to obtain the best fuel cost value and to accelerate the convergence rate. The variations of the fuel cost against iterations are illustrated as convergence characteristics in Fig. 1, which clearly shows the higher convergence rate of the proposed algorithm.

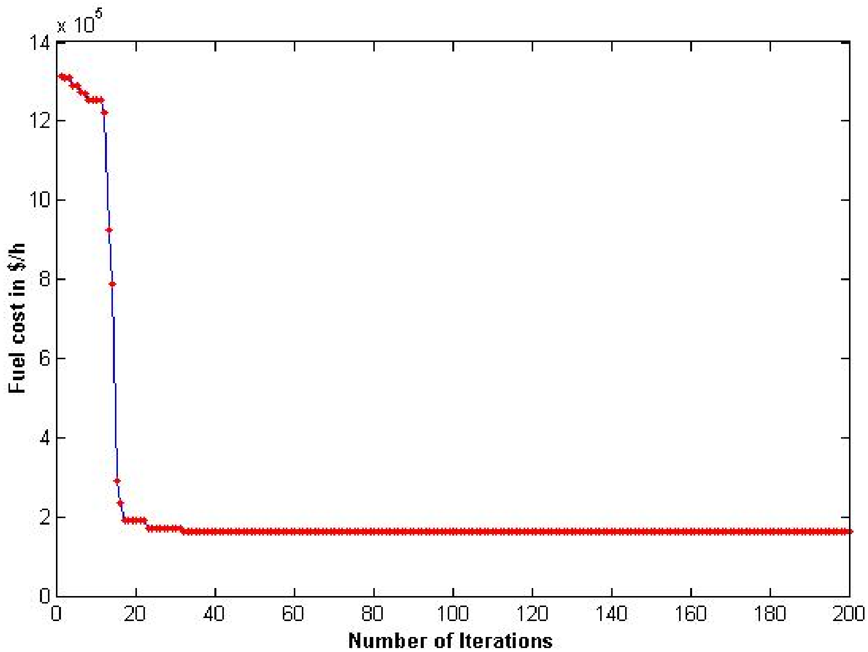

Figure 1: Convergence Characteristics of TLBO for 156 unit system for P_d = 10,000 MW.

Conclusion

In this paper, TLBO algorithm is proposed to solve the large scale ED-CCF problem. Performance of the proposed algorithm is compared with BBO technique. The comparison validates the ability of proposed TLBO to solve such a complex large scale system. In addition, the proposed approach has been successfully implemented to the non-smooth ED-CCF problem. This test system is large enough to validate the performance of the TLBO algorithm. Based on the comparable differences between TLBO and BBO, it can be concluded that the TLBO appears to be a robust and reliable optimization technique for solving ED-CCF in large scale power system.

References

1. Wood AJ, Wollenberg BF. Power generation, operation and control. Wiley: New York, 1996.
2. Navarro SO, Baker AD. The use of cubic cost curves in the economic loading of electric power systems. IEEE Transactions on Power Apparatus and Systems 1965; 84(6): 439-445.

3. Shoults RR, Mead MM. Optimal estimation of piece-wise linear incremental cost curves for EDC. IEEE Transactions on Power Apparatus and Systems 1984; PAS-103(6): 1432-1438.
4. van den Bosch PPJ. Optimal static dispatch with linear, quadratic and non-linear functions of the fuel costs. IEEE Transactions on Power Apparatus and Systems 1985; PAS-104(12): 3402-3408.
5. Jiang A, Ertem S. Economic dispatch with non-monotonically increasing incremental cost units and transmission system losses. IEEE Transactions on Power Systems 1995; 10(2): 891–897.
6. Hong-Tzer Yang, Pai-Chuan Yang, Ching-Lien Huang. Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions. IEEE Transactions on Power Systems 1996; 11(1): 112-118.
7. Yoshikawa M, Toshida N, Nakajima H, Harada Y, Tsurugai M, Nakata Y. On- line economic load dispatch based on fuel cost dynamics. IEEE Transactions on Power Systems 1997; 12(1): 315–320.
8. Deepak Mishra, Amit Shukla, Prem K. Kalra. OR-neural based hopfield neural network for solving economic load dispatch problem. Neural Information Processing- Letters and Reviews 2006; 10(11): 249-259.
9. Whei-Min Lin, Hong-Jey Gow, Ming-Tong Tsay. A partition approach algorithm for non-convex economic dispatch. International Journal of Electrical Power and Energy Systems 2007; 29: 432-438.
10. Al-sumait JS, Sykulski JK, Al-Othman AK. Solution of different types of economic load dispatch problems using a pattern search method. Electric Power Components and Systems 2008; 36: 250-265.
11. Rahmat-Allah Hooshmand, Moein Parastegari, Mohammed Javad Morshed. Emission, reserve and economic load dispatch problem with non-smooth and non-convex cost functions using the hybrid bacterial foraging-Nelder-Mead algorithm. Applied Energy 2012; 89: 443-453.
12. Elanchezhian, E. B., Subramanian, S. and Ganesan, S. Economic power dispatch with cubic cost models using teaching learning algorithm. IET Generation, Transmission & Distribution 2014; 8: 1187-1202.
13. Rao RV, Savsani VJ, Vakharia, DP. Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems. Computer – Aided Design 2011; 43: 303–315.
14. Vedat Togan. Design of planar steel frames using teaching-learning based optimization. Engineering Structures 2012; 34: 225-232.