TEACHING LEARNING BASED OPTIMIZATION FOR ECONOMIC LOAD DISPATCH WITH VALVE-POINT LOADING EFFECTS

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Abstract: The Economic Dispatch ED problem is highly nonlinear due to presence of real power balance equation (RPB) and non-convex due nature of cost curves particularly when cost curve is modeled by practical considerations such as valve-point loading effects of thermal units and prohibitive operating zones on heat rate curve to prevent vibrations in thermal power unit. Besides these mathematical and technical issues, reducing the total cost of electrical power production is a societal need as fuel cost is ever increasing. These issues motivate researchers to test the efficacy of state ofart Optimization methods to reduce the fuel cost from global minimization point of view at the same time satisfying the practical issues which are constraints of ED problem. The Teaching learning based optimization is a relatively new evolutionary optimization where in optimization is performed in two stages such as teaches phase (imparting knowledge-exploration) and student phase(share of knowledge –exploitation) .This paper applies TLBO to solve ED with Valve Point Loading Effects (VPLE).TLBO's robustness in arriving at global cost of megawatt power generation is rigorously tested on typical test cases of varying degree of multimodal nature and dimensionality such as 3 unit, 13 unit and 40 unit power units .The ED results outperform few other evolutionary algorithms.

***Index Terms*: Teachers learning based optimization (TLBO),Valve-point loading effects, non-convex optimization.**

I.INTRODUCTION

The growing cost of electrical power generation demands the need to explore strategies to minimize the cost of electrical power generation [1] while satisfying the load demand within the resource and practical constraints of power generating units. This problem is known in the economic operation of power systems as Economic Dispatch (ED) which is an important function in operation and control of power systems [2]. For mathematical simplicity, the traditional ED problem assumes quadratic cost curves that enables ED solution using deterministic approaches including gradient method, lambda iteration method, linear programming, and non-linear programming [3,1]. The practical cost curves are highly non-linear due to valve point loading effects of fossil fired thermal units. These nonlinearitiesdue to valve point effects are modeled by superposing sinusoidal ripples to the quadratic cost curves[1,3].This leads to non-convex cost curves of fossil burning power plants.Furthermore, the operation of power units can have prohibitive operating zones to prevent amplification of unit vibrations in shaft bearings and associated auxiliaries of thermal power units. Also, ramp rate restrictions prevent unit adjustment quickly.This restriction is considered as constraints that alters the scale (actual limits of power units) of the power units. All these practical considerations make ED a challenging problem to arrive at minimum cost of total power production satisfying the load demand [4,5].The deterministic methods listed above, assumes quadratic cost curves hence ED solution leads sub-optimal solutions [5] and cause revenue loss to power utilities.The non-convex ED can be solved using Dynamic programming(DP) approach at the cost of more objective function computations [6].

A number of powerful[5] stochastic search algorithms which do not have restriction on shape of objective function such as genetic optimization GA, Evolutionary programming (EP), Particle Swarm optimization PSO, Harmony search HS, Firefly Algorithm FA, Bacteria Foraging BF,Ant colony optimization, Accelerated Particle Swarm optimization APSO etc. are applied to demonstrate near global solution to non-convex ED problem. These search algorithms are highly powerful and reaches sub optimal near-global solutions fast with suitable tuning parameters.

In recent times in an effort to obtain fast global optimality the authors [6] has developed an evolutionary optimization approach mimicking the concept of Teaching and learning process. In brief the update equation of teachers phase explores the new knowledge to approximate the objective function phase and students phase uses the knowledge imported by the best teacher.This two phase approach of EA in principle has attribute of prime requirement of success of any EA[7] i.e. crude exploration followed by intensification a strategy known as eagles strategy .

The TLBO in this paper is applied to solve ED with valve-point loading effects by exactly satisfying the equality constraint (real power balance (RPB)) while respecting the thermal power unit operating limits.The developed code in MATLAB environment is successfully applied to various test case of varying non-convex nature. The results are compared with Evolutionary programming (EP)[4] based and recent outstanding ED results by Fire Fly optimization [5].

II ED PROBLEM FORMULATION:

The aim of ED is to find optimal combination of thermal power generating units that minimizes the total cost of power generation (f)within unit minimum (P^{min}) and maximum (P^{max}),real power generation limits of n number of units to meet the real power demand P_d. Mathematically the problem is stated as follows.

$$\min f = \sum_{i=1}^{ng} F_i\,(P_i) \tag{1}$$

$$\text{subjected to} \sum_{i=1}^{ng} P_i = P_d + P_L \tag{2}$$

$$P_i^{min} \leq P_i \leq P_i^{max} \text{ , } i = 1,2,.,.,ng \tag{3}$$

The equation (2) is real power balance equation (RPB including real power losses P_L and equation (3) is power generation minimum P_i^{min} and maximum P_i^{max} limits of generating unit i . In equation (1), Real power losses are calculated using B-coefficient [] method using equation (4).

$$P_L = \sum_{i=1}^{ng}\sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i}\, P_i + B_{00} \tag{4}$$

In equation 1 F_i is generation cost of unit i, which is defined in equation (5) neglecting valve point effects.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{5}$$

In equation (5) ,a_i,$b_i$and c_i are coefficients of unit i.

The generating units with multi valve steam turbines exhibits variation of fuel cost compared with equation (5) due to introduction of ripples in heat rate curve. These ripples can be mathematically modeled as superposition of sinusoidal functions to the cost curves of equation (4). Thus, fuel cost function is defined as in equation (6).

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |d_i sin(\, e_i\big(P_i^{min} - P_i\big))| \tag{6}$$

where d_i and e_i are constants with valve- point effects. This sort of modeling cost curve is highly non-convex objective function with multiple local optimal solutions [2.1,2.2].

2.1Constraint handling:

The two types of constraints are considered in this paper which are stated in problem formulation they are inequality constraints of real power generation and equality constraints of real power balance (RPB). Any violation of inequality constraints during optimization process leads to infeasible solutions. The new solutions generated during the search process must be checked for feasibility. In case of infeasible solution out of many approaches like repair ,bounce back[1] etc the method followed in this paper is indicated below.

In equality constraint:

Any infeasible solution violating lower or upper bound is maintained at its violated limit as indicated below.

$$\text{If} \quad P_i > P_i^{max}, then P_i = P_i^{max} \quad \text{else if} \;\; P_i < P_i^{min}, then P_i = P_i^{min} \tag{7}$$

RPB:

In ED the power balance equality constraint can be satisfied either by exact power balance [4] or quadratic penalty approach [5]. In this paper for the test cases without considering P_L,the exact power balance is adopted. Any one generation unit can be chosen as dependent generator (P_s) the real power of that unit is as follows.

$$P_s = P_d - \sum_{i=1,\neq P_s}^{ng} P_i \tag{8}$$

If any violation in P_s computed by above is added as quadratic penalty and fitness function FIT is calculated as follows

$$FIT = f + R * \Omega \tag{9}$$

where R is static penalty,Ω is zero if P_s is within limit otherwise it is calculated as follows

$$\Omega = (P_s - P_s^{min})^2 if P_s < P_s^{min} or \Omega = (P_s^{max} - P_s)^2 if P_s > P_s^{max} \tag{10}$$

Having presented problem statement and approach to constraint handling in next section a brief over view of TLBO is presented.

2.2Teaching learning Based optimization(TLBO) Algorithm:

This algorithm was proposed by [6] targeting the difficulties in selection of tuning factors to successfully steer the search towards global optimality by few EA like PSO. In other words,this method is completely free from tuning parameters and the user can only vary population size to obtain global optimality reliably even when optimization is initialized from different random picks of search space. The working of TLBO is divided into two parts, 'Teachers phase' and 'Students phase'. The working of each part is explained below:

2.2.1Teachers phase:

It is the first phase of the optimization method where learners learn through 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 capability. At any iteration *t*, assume that there are *'ng'* number of subjects i.e. design variables, *'np'* number of learners i.e. population size and $Xmean_{ij}$be the mean result of the learners in a particular subject *'j'* (*j*=1,2,3….,d). The best overall value result *'gbest'* considering all the subjects together obtained in the entire population of learners can be considered as the result of best learner. 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 below in vector notation.

$$DIFFMEAN = rand(1,d).* tf.* (gbest - xmean) \quad (11)$$

Where *gbest* is the result of the best learner in the subject *ii*. $t_f$is the teaching factor which decides the value of mean to be changed and *rand* is the random number in the range [0, 1]. d is design variable number or number of subjectsfor each learner in a pool of np.

The value of tf for each subject is decided randomly with equal probability as below

$$tf = round\big(1 + rand * (2-1)\big) \quad (12)$$

Here, t_f is not a parameter of the TLBO algorithm. The value of t_f is not given as input to the algorithm and its value is randomly decided by the algorithm using the equation (2). Based on the '*diffmean*'the existing solution is updated in the teacher phase according to the following expression.

$$x_i^n = x_{i+}DIFFMEAN \;\; , i = 1\, tonp \quad (13)$$

Where x_i^n is the updated value of x_i and its acceptance is subjected to elitism. The learners phase depends upon the teachers phase acquired knowledge.

2.2.2Student phase:

It is the second phase of the algorithm where the learners increase their knowledge by interacting among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. A learner improves if the other learner has more knowledge that him. Considering a population size of *'np'*, randomly select two learners S_1 and S_2 such that the updated function values are not equal. In minimization context the following is the learners phase update equation

$$x_i^n = x_i^{s1} + rand.* (x_i^{s2} - x_i^{s1}), iffit(x_i^{s2}) < fit(x_i^{s1}) \quad (14)$$

$$elseiffit(x_i^{s1}) < fit(x_i^{s2})$$

$$x_i^n = x_i^{s2} + rand.* (x_i^{s1} - x_i^{s2}) \quad (15)$$

The x_i^n acceptance is subjected to elitism.

In brief first in the teachers phase, the difference mean is calculated to update old knowledge and then in the students phase, two solutions are randomly selected and modified by comparing with each other. The worst solutions are replaced, elite solutions are retained, duplicate solutions are modified and the process is continued until the termination criteria.

Steps involved in solving ELD using TLBO:

In the following explanation wherever the evaluate Fitness appears it is to be understood that such fitness evaluation is done after following theconstraint handlingprocedure explained in constraint handling part of this paper.

1) Read cost coefficients, P_d,P_i^{min},P_i^{max}
2) Randomly generate np search space variable
3) $x_i =,P_i^{min} + rand(1,ng).* \left(P_i^{max} - P_i^{min}\right), i = 1tonp$
4) $set\ itr = 0$ (TLBO-Iteration count is initialized)
5) Find Fit_i for $i = 1tonp$
6) Obtain $gbest, xmean$.

$$gbestasteachercorrespondsto \min(Fit_i)$$

$$xmean = \frac{1}{np}\sum_{i=1}^{np} x_i$$

7) Find diffemean using equation 11
8) Generate x_i^nusing after bounding the components of search strings if any component exceeds operating limits using equation 7
9) Find $Fitn_i$, for $i = 1tonp$
10) $Applyelitismif\ (Fitn_i) \leq Fit_i$,$x_i = x_i^n$&$Fit_i = Fitn_i$

$$ThiscompletesTeachersphase$$

Student –Phase follows: Repeat the step-11 np number of times.

11) randomly select two different learners x_1 and x_2

modify x_i as per learners'phase after applying elitism

12) check stopping criteria. If met print ELD. else$itr = itr + 1$,go to 5.

The stopping criteria of the algorithm is number of iteration which is set as 100 for all test cases of ED to establish global optimality.

Test results and discussion: The above algorithm to solve ED problems of 3,13 and south Indian utility are implemented using MATLAB 7.10.0 on a PC, Core i3, Intel(R) Core(TM)i3-4030U CPU, 1.9GHz, 6 GB RAM.The cost curve data is taken from[4]. Owing to the random nature of the EA's (and in fact all Met heuristic algorithms), their performance cannot be judged by the result of a single run. Many trails with independent population initializations should be made to obtain a useful conclusion of the performance of the approach. Therefore, the results should be analyzed using statistic measures such as mean and standard deviation. The best, worst and mean obtained in 100 trials are used to compare the performances of different EAs.

The variants of (EVOLUTIONARY PROGRAMMING) EP methods [4] with which the proposed TLBO is compared are 1) CEP (classical EP) 2) FEP(Fast EP) 3) MFEP(Mean of Gaussian and Cauchy EP) 4)IFEP(Improved Fast EP).And also with Firefly algorithm(FA)[5]

Test Case 1: This is three generating unit with PD of 850 MW.The np is set to 20 for maximum iterations of 100.The convergence chrematistics by TLBO is shown in figure 1,figure 2 and figure 3 respectively below.

The convergence characteristics of test case 1 clearly indicates TLBO's capability arriving at the best minima within 20 iterations within 1.2s.The comparative table 1 below indicates performance of TLBO with other state of art approaches from EA category.

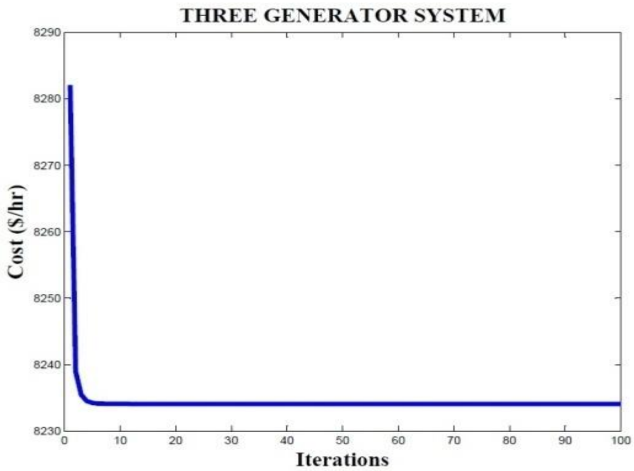

Figure 1: Convergence characteristics of 3 generating test case.

Table 1: Comparision of statistical performance of TLBO with other approaches

Evolution Method	**Mean cost($/hr)**	**Max cost($/hr)**	**Best cost($/hr)**
CEP	8235.97	8241.83	8234.07
FEP	8234.24	8241.78	8234.07
MFEP	8234.71	8241.8	8234.08
IFEP	8234.16	8234.54	8234.07
FA	8234.08	8241.23	8234.07
TLBO	8234.0717	8234.0719	8234.0717

From table 1it can be observed that though the best cost by all approaches are almost same i.e nearly 8234.0717 $/H, the mean cost and worst cost differ compared to best cost by other approaches however every time TLBO has arrived at best cost irrespective of initial starting of real power generations. Hence in this case global optimality of ED problem can be achieved with consistency.

Test Case 2: 13 Generating Units

This test case consists of 13 Generating units; the complexity to the solution process has significantly increased. In ED literature this test case is considered as highly multi modal and difficult to solve. The total search dimensionality of the problem is 13. The load demand of this test system is 1800 MW. Table 2 shows the best, average and worst results of different ED solution methods among 100 trials. The average execution time to find optimum minima by the TLBO for this test system is 5.2359s which occurs at 30 to 36 iterations with np=100.The best cost by TLBO is 17987.4295 **($/hr) .**

Table 2: comparison of statistical performance of TLBO test case 2 with other approaches.

Evolution Method	**Mean cost ($/hr)**	**Max cost($/hr)**	**Best cost($/hr)**
CEP	18190.32	18404.04	18048.21
FEP	18200.79	18453.82	18018

MFEP	18192	18416.89	18028.09
IFEP	18127.06	18267.42	17994.07
FA	18029.16	18168.8	17963.83
TLBO	18093.9254	18245.0254	17987.4295

Note that among comparative algorithms the first rank goes to FFA while next best rank to TLBO.This conclusion can be made upon by comparing the mean and worst costs by the EA approaches.

Test Case 3: 40 Generating Units:

The test system has forty generating units with non-convex fuel cost function incorporating valve loading effects. The required load demand to be met by all the 40 generating units is 10,500 MW. This case study has a larger and more complex solution space then all the previous case studies, and so any difference between different ED solution techniques can be better revealed in this test case[5].With np=50, the typical convergence characteristics is shownin figure 3.

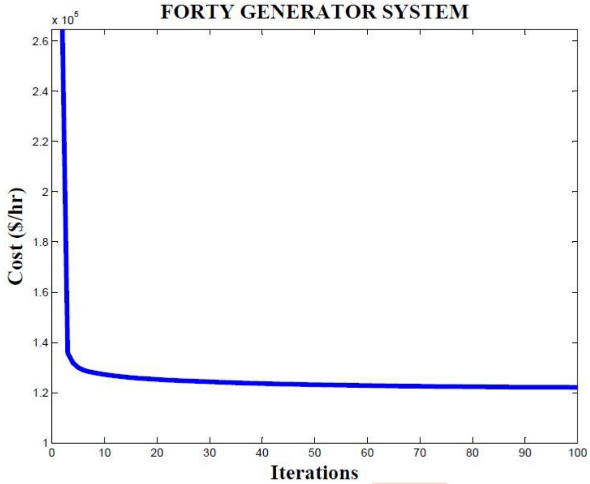

Figure 3: convergence characteristics of 40 thermal power units by TLBO.

For this highly non-convex multimodal problem the proposed TLBO for ED arrived at best cost within 30 to 40 iterations. The average execution time of the TLBO for this test system is 11.2287s and such a computation time to solve the ED problem is reasonable and practical. More over 30 to 40 iterations takes only about 3.73s to2.8s.

The TLBO algorithm has been executed for 100 times with various starting points. The obtained results of the proposed TLBO to resolve the ED problem for this test system are shown in table 3. In this table, the detailed comparisons of the best, average and worst solutions of the proposed TLBO and most recently published ED solution methods are shown. As seen from table 3, the best solution of the proposed method is better than those of all other methods, indicating TLBO's higher efficiency to solve the ED problem comparing with other methods. Hence, for power system ED problems of greater size with higher non-linearity, the proposed method is proved to be the best approach among all the methods. The average execution time of the TLBO for this test system is 11.2287s and such a computation time to solve the ED problem is reasonable and practical.

Table 3: Test case 3 statistical comparison of performance.

Evolution Method	Mean cost ($/hr)	Max cost($/hr)	Best cost($/hr)
CEP	125066.11	126702.6	123983.53
FEP	125504.08	127026.64	124518.59
MFEP	125021.73	126321.64	123743.73
IFEP	124862.42	126180.47	123292.23
FA	121416.57	121424.56	121412.05
TLBO	118663.0102	118670.3414	118660.3178

Table 3 clearly gives better advantage for TLBO in all aspects of statistical comparison.The best cost by Proposed TLBO is 118660.3178 ($/h) which is less than 4.3% compared with CEP approach while FFA could reduce cost compared to CEP is only 2.07%.Therefor one can conclude a promising nature of TLBO a two phase algorithm for high dimension multimodal ED problems. The following table 4 indicates the power outputs of generating units to achieve best cost by TLBO.

Table 4:The real power outputs of generating units by TLBO for the best cost

Pg(MW)	Test case1	Test case 2	Test case 3
pg1	300.2669	626.8591	113.4588
pg2	149.7331	223.552	113.8581
pg3	400	299.2689	97.4638
pg4	-	60.0015	180.1952
pg5	-	60	96.9602
pg6	-	60	139.959
pg7	-	110.0688	299.9852
pg8	-	60.0028	285.7481
pg9	-	110.2404	286.0914
pg10	-	40.0023	130.0493
pg11	-	40.0011	168.8682
pg12	-	55.0007	94.1742
pg13	-	55.0024	125.0622
pg14	-	-	304.5312
pg15	-	-	394.2285
pg16	-	-	394.3814
pg17	-	-	489.3443
pg18	-	-	489.5479
pg19	-	-	511.3436
pg20	-	-	511.6659
pg21	-	-	523.3067
pg22	-	-	523.7952
pg23	-	-	523.5061
pg24	-	-	523.5875
pg25	-	-	523.4236
pg26	-	-	523.5067
pg27	-	-	10.8039
pg28	-	-	10.0282
pg29	-	-	10.1139
pg30	-	-	90.1246
pg31	-	-	189.8046
pg32	-	-	189.9991
pg33	-	-	189.9757
pg34	-	-	199.9822
pg35	-	-	199.9845
pg36	-	-	199.9945
pg37	-	-	109.9971
pg38	-	-	109.9923

pg39	-	-	109.8556
pg40	-	-	511.3012
Total	850MW	1800MW	10500MW

The above table indicates the real power output of units for the three test cases considered to obtain best cost by TLBO. Note that total power demand is exactly met by the proposed approach which reflects the best cost by TLBO is not at the cost of violation of RPB. The new improved version of TLBO [8] need also to be applied to test possibility of reducing the population size to power system multi objective optimization methods [9,10].

CONCLUSION

This paper has successfully developed TLBO EA approach to effectively solve Economic dispatch of units with valve point loading effects.For power units with varying dimensionality from 3 units to 4-unit test cases the efficacy of TLBO is established upon comparing with Evolutionary based approaches and recent state of art Firefly optimization.

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