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Modified Teaching Learning Based Optimisation for Economic Dispatch Considering Valve Point Effects

Sharmiladeve,V., Geetha.K, Geethanjali, S., Keerthivasan, K

Anna University, Kumaraguru College of Technology, Electrical and Electronics Engineering, Coimbatore, India

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ABSTRACT

In this paper, Modified Teaching Learning Based Optimisation is used to solve the Economic Dispatch problems of the generating units considering valve point loadings effects. A recently developed optimisation is the Teaching Learning Based Optimisation which operates on two different phases– teacher phase and learner phase. A modification is done in the Teaching Learning Based Optimisation and is used in this paper as Modified Teaching Learning Based Optimisation. Here, in addition to the two phases, an mutation phase is also introduced. In contrast to the other Optimisation methods this proposed method does not require any algorithm specific parameters, does not depend on any tuning parameters of algorithm and it enables global optimum solution and also avoids premature convergence to local optima of the objective function. The proposed method finds an optimum solution with extraordinary convergence rates and high consistency. The proposed method is tested on standard IEEE bus with 10 generating unit system, 13 generating unit system and 40 generating unit system with valve point effects. The effectiveness of this method is demonstrated by comparing the results with other optimization techniques. Also, the result confirms that this proposed method has a great potential in determining the optimum solution.

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INTRODUCTION

Over the past few years, the demand for electricity has increased abruptly. Since it has become important to generate power from the generation stations with regards to the economical operation of the generation units, the proper planning and effective operation of generating units is necessary (Vahid Hosseinnezhad and Ebrahim Babaei, 2013), (Vahid Hosseinnezhad *et al*, 2014). The selection of units to generate maximum power for economic operation is the most important task, as thermal units, consists of multi valve-steam turbines. Hence, the designing approach to Economic Dispatch (ED) must be done along with valve point effects. Though the ultimate objective involved in the economic dispatch problem is to minimize the operating cost satisfying the load demand, various types of equality and inequality constraints make ED a highly nonlinear constrained optimization problem, particularly for larger systems (T.A. Victoire and A.E.Jeyakumar, 2004). Hence a careful survey and study is quite necessary in determining the reduction of the operating cost by proper scheduling of the generating units.

While considering the traditional methods like lambda-iteration and gradient method needs the units input-output curves of generators. But due to the presence of prohibited operating zones their curves cannot increase monotically. So, in the optimisation of non-linear cost function this traditional method does not perform well. Similarly the classical calculus-based method and Newton-based algorithms does not hold good to solve this ED problem. Inspite of nonlinearity and the variability of cost curves, its dynamic programming remains unaffected, still "curse of dimensionality" and local optimality (N.Sinha *et al*, 2003) is a drawback.

Many other Optimisation techniques have been adopted to solve the Economic Dispatch problem like combination of hybrid particle swarm optimisation-sequential quadratic programming PSO-SQP (T.A. Victoire and A.E.Jeyakumar, 2004), Evolutionary Techniques (N.Sinha *et al*, 2003), Genetic Algorithm (GA) (D.C Walters and G.B Sheble, 1993), Improved Quantum-Inspired Evolutionary Algorithm (J.X.V Neto *et al*, 2011), Shuffled Differential Evolution (SDE) (A. Srinivasa Reddy and K. Vaisakh, 2013), Honey Bee Mating optimization (Ali Ghasemi, 2013), Incremental Artificial Bee Colony (Do gan Aydın and Serdar Ozyon, 2013), Particle Swarm

Corresponding Author: Sharmiladeve,V., Anna University, Kumaraguru College of Technology, Electrical and Electronics Engineering, Coimbatore, India

Optimisation (A. Mahor *et al* ,2009), Hybrid Differential Evolution (STHDE) (Wang, S.K *et al*, 2007), Chaotic Differential Bee Colony Optimisation (Peng Lu *et al*, 2014), Improved Genetic Algorithm (C.L. Chiang , 2005), Quantum Inspired Particle Swarm Optimisation [QSPO] (Ke Meng *et al*, 2010), Hybrid Quantum inspired PSO (HQPSO) Coelho LS Marino Particle Swarm approach based on quantum (S.K. Wang *et al*, 2007).

It can be noted that the above optimisation techniques suffered from drawbacks like the results were not accurate and certain algorithms required some specific controlling parameters during optimisation process. Though the evolutionary algorithm such as the genetic algorithm is better than simulated annealing because of the inherent parallel search technique and its advantages like global search capability, robust and effective constraints handling capacity, reliable performance and minimum information requirement, makes it a feasible choice for solving ED problems. Its converging capability of the parameters fall within a local optima (Z.L.Gaing, 2003). Though there are many other artificial intelligence approaches available, the neural networks have been best suited to work with the ED problems satisfying their constraints (K.Y.Lee, 1998), (J.H.Park *et al*, 1993). However, they require abundant number of iterations that leads to complex calculations. As an add-on to the above mentioned methods, a few other algorithms have been developed for solving the ED problem like Basu formulated artificial bee colony (M. Basu, 2013) optimization technique to figure out the multi-area economic dispatch problem involving the constraints and nonlinearities like multiple fuels, valve point loading and prohibited operating zones and its effectiveness was exemplified by testing it on different cases. Similarly, Cai *et al*, 2012 formulated fuzzy adaptive chaotic ant swarm optimization algorithm to solve the ED problems. Kumar *et al*, 2012 developed a multi-objective directed bee colony optimization algorithm and tested it by applying it for a multi-objective problem of ED with equality and with inequality constraints. Mohamed *et al*, 2012 developed a multi-objective mesh adaptive direct search algorithm for minimizing the cost and emissions .A recently developed algorithm is Krill herd algorithm done by Gandomi and Alavi, 2012 for solving non-convex optimization problem suffered from a disadvantage that it cannot generate global optimal solutions on some high-dimensional nonlinear optimization problems.

The Teaching Learning Based Optimisation (TLBO) Algorithm recently developed by Rao *et al*, 2011 differs from the other algorithms in such a ways that it does not require any specific control parameter, and so its implementation is simple. It requires only common controlling parameters like population size, number of generation. Hence, it was used for many cases of implementation like solving unconstrained optimisation problems (Rao *et al*, 2011), hydrothermal scheduling problem (Provas Kumar Roy, 2013) mechanical designed optimisation problem. But its performance is reduced in global search as it converges to a local optima.

The Modified Teaching Learning Based Optimisation (MTLBO) is a modification to the TLBO such that the performance is enhanced in global search also. The TLBO operates on classroom mode of teaching-learning process and consists of two phases Teacher phase and the Learner phase. But in the MTLBO, mutation operation is carried out in extra by including an additional phase called mutation phase. Here in this research work, the MTLBO algorithm is implemented so that the above drawbacks can be overcome to the maximum, and hence an optimal solution can be obtained introduced. Further, the MTLBO results are compared with the other Optimisation algorithms for different IEEE standard system like 10 bus system, 13 bus system and 40 bus system.

2. Problem Formulation:

The major part of production cost involved in the thermal generation is the fuel cost. Hence, the main objective of ED is to determine the optimal combination of power generations to obtain a minimum generation cost solution satisfying the equality and inequality constraints. The most widely represented form for expressing the energy related characteristics such as energy consumption characteristics is the quadratic form of function. The Economic Dispatch with the valve point effects can be formulated in terms of fuel consumption for a time interval t.

The total fuel cost function is calculated for N generation units with each having a load of P_i MW as follows

$$F\ (P_i)=\sum_{i=1}^{N}[a_i + b_i P_i + c_i P_i^2] \quad (1)$$

where $F\ (P_i)$ is the objective function describing the total generation cost

P_i is the real power generated by the i^{th} generating unit

N is the number of generating units

a_i, b_i and c_i are the cost coefficients of i^{th} generating unit.

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. Generally, the generating units with multi valve steam turbines produce ripples due to the valve point loading and so they are distinguished by complex nonlinear cost function. Hence a sinusoidal component is to be superimposed on quadratic curve for simulation. Thus the equation (1) must be altered using a sine function to overcome the ripples due to valve point effect and as a result the fuel cost function is given as

$$F(P_i)=\sum_{i=1}^{N}[a_i + b_i P_i + c_i P_i^2 + |g_i * sin(h_i(P_i - P_i^{min}))|] \quad (2)$$

where g_i ,h_i are the valve point parameters of the generating unit.

The constraints to be met while determining the economic dispatch of the generating units are

2.1. Power Balance constraints:

The total power generated must be same as the total demand and the transmission losses. Here the transmission losses is considered and the power balance is given by

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

where P_D is the total power demand in MW and P_L is the transmission losses and it is calculated in terms of B-loss matrix and is denoted by a quadratic equation as

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

2.2. Generator capacity constraints:

The power output of the generator must vary between the minimum and maximum limits.

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

where $P_{i,min}$, $P_{i,max}$ are the minimum and maximum power output of the i^{th} generating unit.

The rest of the paper is discussed as follows. In Section 2, the problem formulation is carried out. In Section 3, description of the MTLBO algorithm is given. In Section 4, the step by step implementation of MTLBO algorithm in ED problem is done. In Section 5, the obtained results and their analysis is shown and Section 6 gives the final conclusion.

3. Mtlbo algorithm:

Here, in this part the Modified Teaching Learning Based Optimization algorithm (MTLBO) is explicated. Like the other evolutionary optimization techniques, MTLBO is an algorithm stirred from the nature. Likewise, MTLBO also proceeds with a population of solutions to attain the global solution.

Generally, the basic method of teaching–learning process in which each individual improves by learning from teacher and also by learning from other individuals was followed. Such a method was proposed by Rao *et al* and they termed it as TLBO algorithm. The classroom mode of teaching–learning is enhanced in this optimisation. The students are considered as the learners and in this paper the population is chosen to be the group of learners and the various subjects they learn are termed here as design variables for the system. The result of the learners depicts the fitness value. The teacher is chosen from the solutions of population i.e., the best solution forms teacher. A teacher is the one who tries to broadcast the knowledge to the learners, aspires to increase the level of knowledge of learners to achieve a good result. In reality a teacher is the person who upgrades the learner's knowledge level. The basic operation of TLBO includes both the teacher phase and the learner phase. Description of the TLBO procedure can be found in Rao R.V., 2011.

A student gains knowledge from both the phases such as Brilliant students learns from the teacher phase while the others learn from the fellow students in the learner phase. Hence, the knowledge gained by the student depends not only both the phases but also they rely on interactions between the students. In the MTLBO, a modification is enabled in the TLBO by adding another phase termed mutation phase which eliminates the drawbacks of TLBO.

Teacher phase:

In the teacher phase, the best individual is chosen to be $X_{Teacher}$ and the other individuals are chosen to be X_i. So, we have to upgrade the individuals, knowledge X_i by moving their levels of positions towards $X_{Teacher}$. This is done by considering the current mean value M_{mean} of the individuals. These functions are carried out using the value obtained from teacher phase parameters. The equation formed for determining the improved solution is based on the difference between the knowledge levels is

$$X_{new,i} = X_i + r_i[X_{Teacher} - T_f M_{mean}] \quad (5)$$

Where r_i is a random number ranging between 0 and 1. T_f is the teaching factor which is chosen to be either 1 or 2, X_i is the individuals in the class, $X_{Teacher}$ is the best individual

Learners phase:

In the learner phase, an individual X_i tries to gain knowledge from another individual student X_j, i.e., peer learning.

If X_j is better than X_i , then

$$X_{new,i} = X_i + r_i(X_j - X_i) \quad (6)$$

else

$$X_{new,i} = X_i + r_i(X_i - X_j) \quad (7)$$

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

Mutation Phase:

Similar manner, Hosseinpour *et al*, 2011 confronted a MTLBO algorithm in which the mutation process was carried out like the Differential Evolution Algorithm. Mutation is nothing but a persuasive strategy implemented to broaden the population to achieve a higher performance and upgrade the global search effectively rather than to avoid local optima convergence. Hence, a new phase is introduced to the existing TLBO and the simulation is carried out. This new phase is called the Mutation phase which is explained below

This mutation phase provides a modification in the previous or the learners phase. An updation is done by repeating the Eqns. (8) and (9) for all the students. This phase can also be understood as a modification of the previous phase or Learner Phase. Hence during each iterative process anew mutant operator is created as:

$$X_{mut} = X_{rand1} + r(X_{rand2} - X_{rand3}) \quad (8)$$

where X_{rand1}, X_{rand2}, X_{rand3} are the three randomly selected students for the ith learner,

satisfying the *rand1 ≠ rand2 ≠rand3* and r is the mutation scaling factor which ranges in (0,1). The r value in this work cannot be altered as its randomly generated during the iterative process.

And next, the following implementation is carried out

$$X_{new} = \begin{cases} X_{mut} \text{ if r1} \geq \text{r2} \\ X_i \text{ otherwise} \end{cases} \quad (9)$$

The r1, r2 are the random values in the range (0, 1) and X_{mut} is the resulted mutated vector yielded for X_i. X_i is the student from population. Using the crossover rate from the algorithm, the Eqn. (9) can be made

$X_{new} = X_{mut}$ if r1≥r2 equal to 0.5 crossover rate which implies $X_{new} = X_{mut}$ if r1 ≥ 0.5.

At a conclusion, X_{new} is accepted if value is better than the value of X_i. Using the Eqns. (6-9), mathematical modeling can be made for optimizing the non-linear functions. However if individuals after each phase is discretized by rounding to the nearest integer value , in a way such that they form a positive integer value , then this optimization can be used for solving a discrete function.

4. Implementation of MTLBO in ED Problem:

In this section, the proposed MTLBO algorithm is implemented and the steps to be followed are described below. While encoding part is carried out, a careful study is quite necessary for the implementation.

Step1: Initialisation: Initializing the parameters involved in the optimization of the ED problem is the initial step i.e., the number of populations is chosen, number of generating units $P_1, P_2, \ldots, P_N$.

Step 2: The initial population is generated in a random number depending on the number of generating units and the population size by considering the limits. From this created population a best one is chosen as the teacher.

Step3: Teacher phase: In the teacher phase step, the population is modified using equation (5) which determines the new population solution. It can be found that this solution is better than the initial population and hence a good performance can be obtained in the generating units.

Step4: Learners phase: The tuning process is done in this step from the new best solution (population) from the teacher phase is taken and is implemented in equation (6, 3). Equation (6) is carried out if new solution is better than the existing else equation (3) goes on.

Step5: Mutation phase: This step is regarded as the deviation step since it forms the main difference between the TLBO and MTLBO. Here, the population is altered by using the equations [8, 9]. Each new generated solution is accepted if it is better than the existing individual.

Step6: Termination condition: The whole process comes to an end in the step i.e., when the specified iteration has been performed else it moves to step3.

5. Simulation Results:

The proposed MTLBO algorithm is implemented in ED problem with valve point effects using MATLAB 2009 running on i5 processor, 2.24Hz and 4GB RAM personal computer. In order to elucidate the performance of this method, it was tested on three different cases : i)10 bus system, ii) 13 bus system and iii) 40 bus system and the results were compared against well inspired and bio inspired optimization algorithms.

Ten bus system:

In this section the proposed MTLBO is implemented for a10- bus system considering the valve point effects. The load demand of 2000MW must be encountered by these 10 units. The necessary data can be obtained from (M. Basu, 2011). The minimum cost solution of 111434.3 $/hr was obtained during the simulation process. The results obtained are compared with the few other optimisation algorithms like Strength Pareto Evolutionary Algorithm (SPEA) (U. Güvenç *et al*, 2011), Gravitational Search Algorithm (GSA), Differential Evolution (DE), Pareto Differential Evolution (PDE), Multi-Objective Differential Evolution (MODE)] and Real Coded Chemical Reaction Algorithm (RCCRO) (Kuntal Bhattacharjee, 2014) and are summarized in Table (1). From the Table (1) it can be seen that the proposed MTLBO produced a satisfactory solution and a better convergence of global optima. The convergence profile of the ten bus system can be seen in Fig.1.

Thirteen unit test system:

A system of 13 generating units including the valve point loading effects was considered in this case. The task was carried out for a load demand of 1800MW and the system data can be determined from (4).The results obtained in Table 2 shows that the MTLBO produced the best dispatch solution and the minimum cost solution obtained is 17960.3928428$/hr. Fig.2 shows the variations of the minimum fuel cost in the thermal generating units obtained by MTLBO for 100 runs for a thirteen unit system. The results confirms that the MTLBO algorithm is effective and produces optimum solution compared to the other optimization algorithms like SDE, HQPSO (L.S. Coelho and V.C. Mariani, 2008), IGA_MU (C.L. Chiang, 2005), Q-PSO (Ke Meng *et al*, 2010),STHDE, DEC-SQP (L.S. Coelho and V.C. Mariani , 2006), ICA-PSO (29). Hence, it is clear that this proposed method enhances better solution and it outperforms by producing a global optimum solution satisfying the constraints involved in the ED problem.

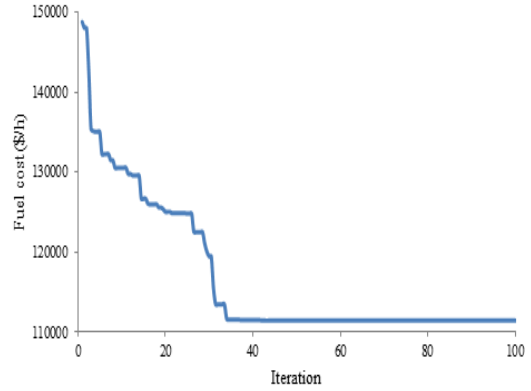

Fig. 1: Convergence profile of the total fuel cost for 10-generating units with 2000MW load.

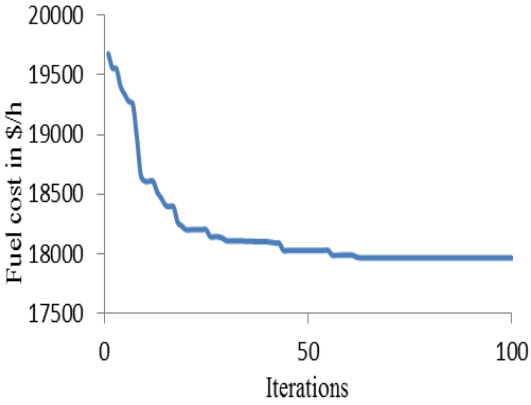

Fig. 2: Convergence profile of the total fuel cost for 13-generating units with 1800MW load.

Forty unit test system:

In this section TLBO is implemented for a 40 bus system considering the valve point loading effects. The load demand of 10,500MW must be met by these 40 units. The constraints are handled while determining the fuel cost and the system data can be discovered in (4). The minimum cost solution of 121411.5959346808$/hr was obtained. The result obtained is compared with the other well settled optimisation methods like the IABC-LS, QPSO, and SDE are summarized in Table (3). Fig.3 shows the convergence profile of the thermal generating units fuel cost incurred by MTLBO for 150 trials. From analysing the data in the Table (3) it can be inferred that MTLBO produced a satisfactory solution and it has a better performance compared to the other methods.

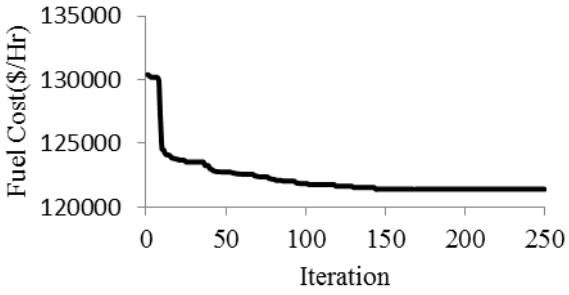

Fig. 3: Convergence profile of the total cost for 40-generating units.

Table 1: Comparisons of simulation results of different methods for 10-unit system with PD = 2000 MW.

UNITS	MTLBO	RCCRO	MODE	PDE	SPEA	GSA	DE
1	56.84091	55.0000	54.9487	54.9853	52.9761	54.9992	55.0000
2	68.038	79.9999	74.5821	79.3803	72.8130	79.9586	79.8063
3	93.21589	106.9220	79.4294	83.9842	78.1128	79.4341	106.8307
4	102.478	100.5426	80.6875	86.5942	83.6088	85.0000	102.8307
5	86.5541	81.5216	136.8551	144.4386	137.2432	142.1063	82.2418
6	71.25883	83.0528	172.6393	165.7756	172.9188	166.5670	80.4352
7	292.9427	299.9999	283.8233	283.2122	287.2023	292.8749	300.0000
8	340	339.9999	316.3407	312.7709	326.4023	313.2387	340.0000
9	478.3611	469.9999	448.5923	440.1135	448.8814	441.1775	470.0000
10	498.6053	469.9999	436.4287	432.6783	423.9025	458.6306	469.8975
Fuel cost	111434.3	111497.6319	113480	113510	113540	113490	111500

Table 2: Comparisons of simulation results of different methods for 13-unit system with PD = 1800 MW.

UNIT	DEC-SQP	STHDE	IGA_MU	ICA-PSO	QPSO	HQPSO	SDE	MTLBO
1	623.3173	628.3172	628.3151	628.32	538.56	628.318	628.3185	628.31992
2	149.2407	149.5986	148.1027	149.6	224.7	149.1094	149.5997	149.59856
3	223.1685	222.7987	224.2713	222.75	150.09	223.3226	222.7491	222.74902
4	109.854	109.8673	109.8617	109.86	109.87	109.865	109.8666	109.86650
5	109.8657	109.8418	109.8637	109.86	109.87	109.8618	109.8666	109.86650
6	109.8666	60.0000	109.8643	60.0000	109.87	109.8656	109.8666	109.86650
7	109.8211	109.8641	109.855	109.87	109.87	109.7913	60.0000	109.86650
8	109.8664	109.8547	109.8662	109.87	109.87	60.0000	109.8666	600.00000
9	60.0000	109.8576	60.0000	109.87	109.87	109.8664	109.8666	109.86650
10	40.0000	40.0000	40.0000	40.0000	77.41	40.0000	40.0000	40.00000
11	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.00000
12	55.0000	55.0000	55.0000	55.0000	55.01	55.0000	55.0000	55.00000
13	55.0000	55.0000	55.0000	55.0000	55.01	55.0000	55.0000	55.00000
TC*	17963.9401	17963.89	17963.9848	17963.88	17969.01	17963.9571	17963.8292	17960.39280

Table 3: Comparisons of simulation results of different methods for 40-unit system with PD = 10500 MW.

	IABC-LS	SDE	PSO	MTLBO		IABC-LS]	SDE	PSO	MTLBO
Bus No	Output power	Output power	Output power	Output power	Bus No	Output power	Output power	Output power	Output power
1	110.7998	110.7998	114.000	110.83677	21	523.2794	523.2797	550.000	523.27965
2	110.7998	110.7998	114.000	110.80015	22	523.2794	523.2794	523.655	523.27833
3	97.3998	97.3999	120.000	97.39717	23	523.2794	523.2794	534.661	523.27831
4	179.7331	179.7331	182.222	179.73032	24	523.2794	523.2794	550.000	523.28074
5	87.8011	87.7999	97.000	87.80874	25	523.2794	523.2794	525.057	523.28268
6	140.0000	140.0000	140.000	140.00000	26	523.2794	523.2794	549.155	523.27246
7	259.5996	259.5997	300.000	259.62747	27	10.0000	10.0000	10.000	10.00000
8	284.5994	284.5997	299.021	284.60912	28	10.0000	10.0000	10.000	10.00000
9	284.5997	284.5997	300.000	284.60716	29	10.0000	10.0000	10.000	10.00000
10	130.0000	130.0000	130.000	130.00000	30	87.8004	87.7999	97.000	87.75358
11	94.0000	94.0000	94.000	94.00000	31	189.9999	190.0000	190.000	190.00000
12	94.0000	94.0000	94.000	94.00000	32	189.9999	190.0000	190.000	190.00000
13	214.7592	214.7598	125.000	214.75545	33	190.0000	190.0000	190.000	190.00000
14	394.2793	394.2794	304.485	394.27584	34	164.1994	164.7999	200.000	164.80565
15	394.2794	394.2794	394.607	394.27826	35	199.9990	200.0000	200.000	194.36412
16	394.2794	394.2794	305.323	394.27539	36	194.3990	194.3978	200.000	200.00000
17	489.2794	489.2794	490.272	489.27699	37	109.9999	110.0000	110.000	110.00000
18	489.2794	489.2794	500.000	489.27996	38	109.9999	110.0000	110.000	110.00000
19	511.2794	511.2794	511.404	511.27542	39	109.9999	110.0000	110.000	110.00000
20	511.2793	511.2794	512.174	511.28061	40	511.2793	511.2794	512.964	511.27530
					P(MW)	10500.0000	10500.0000	10500.000	10500.00000
					F(TOTAL)	121412.7358	121412.5355	122252.265	121411.59593

Conclusion:

In this study, for the solution of Economic Dispatch considering valve point effects, the MTLBO method is being used. The performance and the effectiveness of the proposed method in solving the non-convex ED is determined by applying for three different cases of IEEE standard test systems with 10,13,and 40 generating units. And also the potential of this method was tested by operating it under both equality and inequality constraints. The simulation is carried out for different iterations as described earlier and the results obtained are compared with the other optimisation methods for 100 trials in 10 bus system and 100 trials in13 bus system and 100 trials in 40 bus system and the convergence characteristics were also studied. It was observed from the comparison result that the MTLBO method produced a better optimum solution with high convergence rates and the minimum cost was produced compared to other methods. Moreover, the MTLBO algorithm in future can be extended for determining the solution of complex power system optimisation problems.

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