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Multi-Objective Economic Emission Load Dispatch using Teacher-Learning-Based Optimization Technique

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Abstract: In this paper, a new parameter-less diversity preservation approach to solve the non-linear multi-objective economic emission load dispatch (EED) problem is envisaged using Teacher-Learning Based Optimization (TLBO) method. The TLBO technique is totally parameter less and takes less computation time as compared to other optimization techniques for the determination of solutions in the Pareto-optimal front. The TLBO method is tested for EED problem on 6-generator test system (IEEE 30-bus) and the results obtained are compared with those obtained from Non-dominated Sorting Genetic Algorithm (NSGA). The simulation results confirm the computational advantage of the TLBO method .

Keywords: Multi-objective optimization, Teacher-Learning-Based Optimization, Parameter less algorithm, cost minimization, Emission Dispatch .

1. INTRODUCTION

The main objective of economic load dispatch (ELD) of electric power generation is to schedule the generator outputs so that the required load demand is met at minimum operating cost, subject to system equality and inequality constraints. Hence ELD problem is a highly constrained nonlinear optimization problem. The environmental pollutants such as NO_X and SO_2 which are released to the atmosphere through the emission produced by the combustion of fossil fuel are big issues in ELD problem. Thus, to maintain the Clean Air Act Amendments ,November 1990, the objective of total emissions should also be included in the ELD problem. The new model now includes both operating fuel costs of the generators and the emissions produced by them so as to meet the load demand , while satisfying all equality and inequality constraints. This makes Economic Emission Dispatch (EED) problem a multi-objective optimization problem where both the objective functions are to be minimized.

Different techniques have been reported in the literature to solve the EED problem .However practical EED problem is a highly non-linear optimization problem and conventional techniques that make use of derivates are not able to produce global optimum solution .Hence the operators don't have much flexibility in scheduling the loads. Many meta-heuristic optimization techniques are being introduced by many researchers to overcome the disadvantages of conventional techniques. These techniques include evolutionary programming (EP), genetic algorithm (GA), Particle swarm optimization (PSO) and so on. Such algorithms work best for single objective optimization problems. These algorithms are mostly nature-inspired optimization algorithms .GA uses the theory of Darwin based on the survival of the fittest, PSO implements the foraging behaviour of a bird for searching food, ABC uses the foraging behaviour of the honey bee, ACO uses the behaviour of the ant in searching for a destination from the source. These algorithms have been applied to many engineering problems and proved effective in solving many problems.

Apart from the above mentioned algorithms there are also population based multi-objective optimization Pareto-based algorithms Vector Evaluated Genetic Algorithm(VEGA, 1984), Multi-Objective Genetic Algorithm (MOGA, 1993), Niched Pareto Genetic Algorithm (NPGA,June,1993), Non-Dominated Sorting Genetic Algorithm (NSGA,1994), Strength Pareto Evolutionary Algorithm (SPEA,Sept.,1998), Pareto Archived Evolutionary Strategy (PAES, 1999), Micro-Genetic Algorithm (u-GA, 2001), Strength Pareto Evolutionary Algorithm-II (SPEA-II, 2002), Non-dominated Sorting Genetic Algorithm-II (NSGA-II, 2002), and Multi-Objective Particle Swarm Optimization (MOPSO). Teacher-Learning-Based Optimization (TLBO) (Rao, R.V., 2012) is one of the recently proposed population based algorithm which simulates the *teaching-learning process* of the classroom. This algorithm does not require any algorithm specific control parameters and also the algorithm is computationally faster than other optimization algorithms.

TLBO method has been attempted for many single objective optimization problems. This technique was earlier implemented to solve EED problem by Roy, P.K., and Bhui, S. (2013). The paper focused on Quasi-oppositional

Learning based TLBO and compared those results with that obtained from TLBO, NSGA-II ,SPEA-II and Differential Evolution (DE). In this paper, the EED problem is first solved using NSGA and then, the problem is attempted with TLBO. Both the results are compared with each other and it has been found that since there are not many mathematical operations in TLBO , the time required for determining the solution becomes less in TLBO. The results obtained confirm that the number of solutions in the Pareto-optimal front of TLBO is better than that obtained from NSGA, where dynamic sizing of the sharing parameter makes the algorithm more complex. Hence, TLBO gives a good computational advantage as compared to other optimization algorithms.

2. PROBLEM FORMULATION AND SOLUTION METHODOLOGY

The main objective of EED problem is to determine the optimal operation strategy for allocation of generation of committed generating units so as to meet the load demand that minimizes the fuel cost and pollutant emission simultaneously and subjected to various equality and inequality constraints. In essence, it is a multi-objective optimization problem with a mixture of linear and non-linear constraints which attempts to minimize both generation cost as well as emission.

The objectives considered in the formulation of EED problem (Abido, 2006)are given below.

2.1 Minimization of Fuel cost

The generator cost curves are represented by quadratic functions and the total fuel cost $F(P_G)$ in ($/h) can be expressed as

$$F(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^{\ 2} \tag{1}$$

Where N is the number of generators; a_i, b_i, and c_i are the cost coefficients of the *i*th generator; and P_{Gi} is the real power output of the *i*th generator . P_G is the vector of real outputs of generators and defined as

$$P_G = [P_{G1}, P_{G2}, ...\ ...., P_{GN}]^T. \tag{2}$$

2.2 Minimization of Emission

The total emission $E(P_G)$ in (ton/h) of atmospheric pollutants such as sulphur oxides SO_X and nitrogen oxides NO_X due to the usage of fossil fuel for electricity generation can be expressed as

$$E(P_{Gi}) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^{\ 2}) + \xi_i \exp(\lambda_i P_{Gi}) \tag{3}$$

where α_i, β_i, γ_i, ξ_i, and λ_i are the emission coefficients of the *i*th generator emission characteristics.

2.3 Constraints

1) Generator Capacity Constraint: The maximum real power output of each generator should be restricted .There is a lower limit pertaining to the flame instability of the boiler and a upper limit due to thermal consideration of the generator. This constraint is formulated follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \qquad i = 1, ...N \tag{4}$$

2) Power Balance Constraint: The total power output should be equal to the sum of total power demand (P_D) and the real power loss in transmission lines (P_{loss}) .Therefore ,in mathematical form :

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{loss} = 0 \tag{5}$$

P_{loss} can be calculated using Newton-Raphson Load flow method. In this paper IEEE 30 bus system is used for illustration . The slack bus (Bus 1 is considered as the slack bus while simulating) covers the P_{loss} in the system so as to satisfy the constraint in (5).

2.4 Formulation

The two objective functions (1) and (3), subjected to constraints (4) and (5) are now clubbed together to form a multi-objective optimization problem as follows:

$$\begin{aligned} &Minimize \quad [F(P_G), E(P_G)] && (6)\\ &Subject\ \ to \quad g(P_G) = 0 && (7)\\ &\qquad\qquad\quad h(P_G) \le 0 && (8) \end{aligned}$$

where *g* is the equality constraint representing the power balance, while *h* is the inequality constraint representing the generation capacity.

3. MULTI-OBJECTIVE OPTIMIZATION (MOO) AND PARETO-OPTIMAL CONCEPT

Most of the real world problems employ the simultaneous optimization of several functions without violating the constraint(s), which are often conflicting in nature and equally important. In general, a multi-objective optimization problem is mathematically represented (Davalos, Goytia, Alacaraz, and Hernamdez ,2007) as :

$$Min \backslash Max \ f_m(\mathrm{x}) \quad (9)$$

Subject to

$$x_l \le x \le x_u$$
$$g(x) = 0$$
$$h(x) \le 0$$

Where

$f_m(\mathrm{x})$ is a vector of objective functions

x is a vector of independent variables

x_l is a vector of lower limits

x_u is a vector of upper limits

g(x) is a vector of equality constraints

h(x) is a vector of inequality constraints

The objective functions defined in the vector $f_m(\mathrm{x})$ can be either be minimized or maximized. Since the objective functions are mutually competing, there is no single solution but a set of solutions in the given search space of the problem.

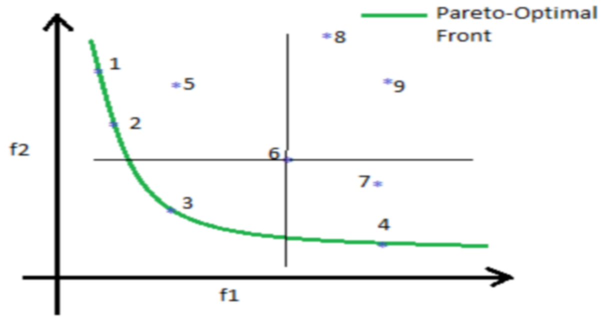

Fig.1. Pareto Optimality concept

To illustrate the concept of Pareto optimality consider Fig. 1 which shows solutions to a given optimization problem of two objective functions, f_1 and f_2, being minimized. While choosing the solutions let solution number 6 be the reference. Comparing other solutions with solution 6, it is observed that solutions 2 and 3 are better than 6 since they have smaller objective function values. Solutions 8 and 9 are totally rejected as their objective function values are compared with those of solution 6 are worse. Similarly solutions 1, 2, 3, and 4 are neither better nor worse because each can satisfy either of the objective functions. The observation from this is that a single solution satisfying all the objective functions is extremely rare.

To resolve this issue, a different view of optimality is required. The optimization can also be done through a set of trade-off solutions often referred to as Pareto-optimal solutions. For such solutions, no improvement is possible in any objective function without previously sacrificing at least one objective function. According to this concept the solutions which dominate solution 6 can be considered as better solutions for the given optimization problem. Hence, solutions 2 and 3 dominate solutions 8 and 9. Therefore, solutions 2 and 3 form a part of the non-dominated set. From the Figure 1, it can be seen that out of 9 solutions in the search space, solutions 1, 2, 3, and 4 shapes the non-dominated set and hence these solutions are the part of Pareto-optimal front that is obtained by the curve (green in colour) in which these solutions are joined together.

3.1 Challenges in Multi-objective optimization

It is very difficult to choose a solution over another if no additional piece of information about the problem is available Therefore the solutions must have large diversity and as close as possible to the Pareto-optimal front. Thus, the goals to be achieved while developing such MOO algorithms are

1.) To find a set of solutions as close as possible to the Pareto-optimal front, and

2.) To find a set of solutions as diverse as possible.

4. NSGA DESCRIPTION

This is the non-dominated sorting Genetic Algorithm (GA) of Srinivas and Deb (1994). This method identifies non-dominated solutions in the population, at each generation, to form non-dominated fronts. A fitness assignment scheme is used on the non-dominated solutions also a sharing strategy which preserves the diversity among the solutions obtained from each non-dominated front. After this as usual GA operators such as selection, reproduction, crossover, mutation and elitism are performed on the population.

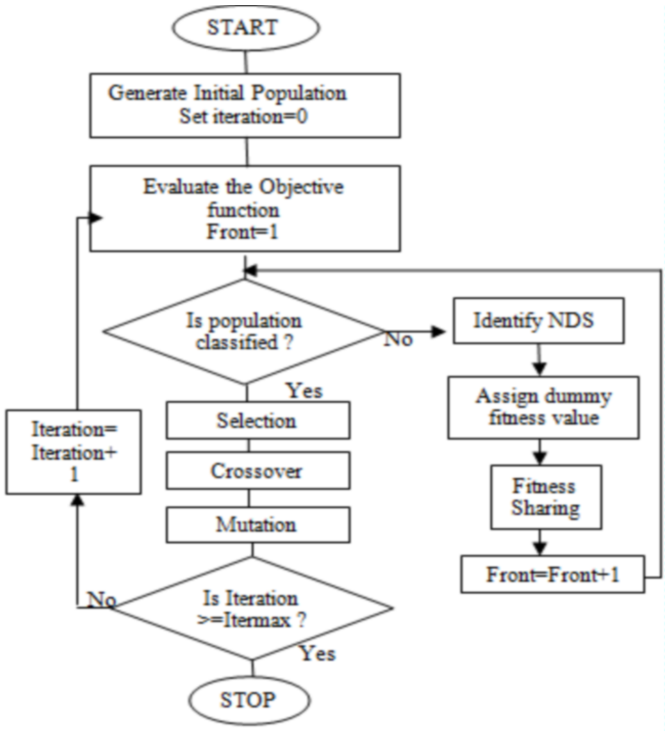

Fig. 2. NSGA Flowchart

The non-dominated individuals in the current population is first identified and assigned a large dummy fitness value. This constitutes the first non-dominated front (Dias and Vasconcelos, 2002). Since same fitness value is assigned to all the individuals, a sharing method is then applied to maintain the diversity. Then the rest of the population other than those in the non-dominated front, are processed in the same way to constitute the second non-dominated front. The new front thus created is assigned with a smaller dummy fitness value and this process continues until whole population is classified into non-dominated fronts. Then the population is reproduced according to the dummy fitness value.

4.1 NSGA Fitness Assignment

To maintain diversity, all the non-dominated solutions are shared with dummy fitness .Here sharing function is achieved by degrading the fitness value of points belonging to the same niche in search space. The fitness value degradation of near individuals can be executed using (10) and (11), where the parameter d_{ij} is the Euclidean distance between individuals i and j and σ_{share} is the maximum distance allowed between any two individuals to become members of the same niche.

$$\mathrm{Sh}(\mathrm{d}_{ij}) = \begin{cases} 1-\left(\dfrac{d_{ij}}{\sigma_{share}}\right)^2 & \text{if } d_{ij} < \sigma_{share} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$\mathrm{df}_i{}' = \mathrm{df}_i \left[\sum_{i=1}^{N} Sh(d_{ij})\right]^{-1} \tag{11}$$

where df_i is the dummy fitness value assigned to the individual in the current front and $\mathrm{df}_i{}'$ is corresponding shared value.

5. TEACHER LEARNING BASED OPTIMIZATION

This method has been evolved from the learning phenomena of the students from the teachers. The population resembles the students and the non-dominated solutions are the teachers or the students with high learning ability . This method has been applied for many Mechanical Engineering problems and a very few papers implemented for Power Systems problems.

The method is well described in the paper by Rao, Savsani and Vakharia, (2011) where a constrained mechanical design problem is solved.

The method simulates the *teaching-learning process* in a classroom. To illustrate this concept let us assume two different teachers, T1 and T2 are teaching a subject with the same content to the some students with equal learning power in two different classes. Hereafter, the students will be called as *Learners*.

After a subject has been taught by the teacher, all the Learners may not have gained equal knowledge. So, there will be unequal knowledge levels of the learners. To improve the knowledge levels, the learners will interact in themselves comparing each-others knowledge in a particular subject. The learners will continue this process until their knowledge levels are improved. Thus the learners will repeatedly continue the process of gaining knowledge until the termination criteria, i.e., the examination approaches. When the termination takes place, the learners will have different knowledge level of each subject taught by the teacher. These learners represent our solutions in the Pareto-Optimal front, which goes better and better as the mean knowledge level of the learners improve. The flowchart of TLBO technique is given in Fig. 3.

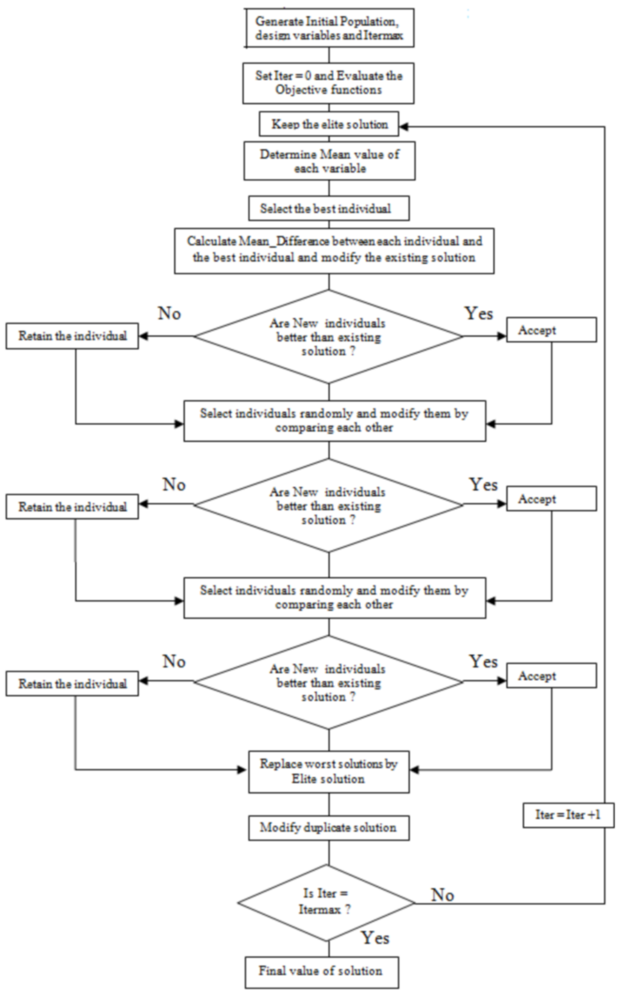

Fig. 3. Flowchart of TLBO algorithm

5.1 Teacher phase

In this phase the teacher tries to impart most of knowledge to all the learners. Based on the learning capability of the individuals, their objective function values are decided. The teacher tries to boost up the mean knowledge level of the class and brings all the learners up to his knowledge level.

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}. The solution is updated according to the difference between the existing and the new mean given by :

$$\text{Mean \_Difference}_i = r_i (M_{new} - M_i) \qquad (13)$$

where r_i is a random number between 0 to 1.

The existing solutions are then modified as follows :

$$X_{new,i} = X_{old,i} + \text{Difference\_Mean}_i \qquad (14)$$

5.2 Learner phase

Learners increase their knowledge by two different means: one through input from the teacher and the other through interaction between themselves. A learner interacts randomly with other learners with the help of group discussions, presentations, formal communications, etc. A learner learns something new if the other learner has more knowledge than him or her. Learner modification is expressed as :

For i=1:N
Randomly select two learners X_i and X_j ,where $i \neq j$
If $f(X_i) < f(X_j)$
$X_{new,i} = X_{old,i} + r_i (X_i - X_j)$
Else
$X_{new,i} = X_{old,i} + r_i (X_j - X_i)$
End if

End for

where $f(X_i)$ and $f(X_j)$ are the objective function values of individuals X_i and X_j.

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

6. EED PROBLEM IMPLEMENTATION

The techniques and all simulations developed in this study were implemented using MATLAB R2011b package on Intel core i3 2.2 GHz PC. The algorithms developed in the previous sections has been implemented to the standard 6-generator test system (IEEE 30-bus). The values of fuel cost and emission coefficients of the generators (Wahed and Elsisy) are given in Appendix A.

To demonstrate the potential advantage of the TLBO approach for obtaining more number of Pareto-optimal solutions for a Multi-objective optimization problem in the given search space , same population size is used in both NSGA and TLBO methods.

6.1 Non dominated sorting Genetic Algorithm(NSGA)

The parameters used in this algorithm for the Pareto-optimal solution of the EED problem are as follows

Population size, N = 50

String length = 60

$\sigma_{share} = 0.158$

Probability of elitism = 0.5

Probability of crossover = 0.9

Probability of mutation = 0.05

Iterations = 75

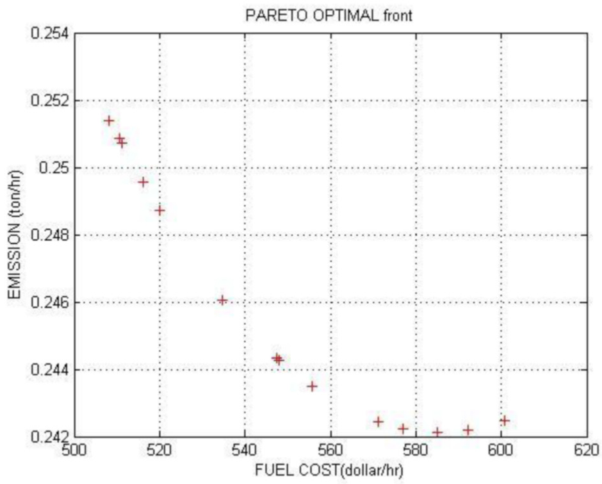

Fig. 4. Pareto-optimal front obtained by using NSGA algorithm for EED problem .

It is clear from the Fig. 4 that out of 50 solutions there are only 14 different solutions available for the operator .These solutions forms the trade off between minimum fuel cost and minimum emission.

The solutions highlighted in Table 1, and 2 are all same and do not contribute to the Pareto front more than once, hence these solutions reduces the flexibility of the operator to explore more operating conditions. In this case, best trade off solution is found to be solution 6 in Table 1 with optimal fuel cost 555.62 ($/h) and optimum emission 0.2435 (ton/h). The main objective of this paper is show many important solutions are obtained in the Pareto-optimal front, which in this case is 13.The computation time taken for obtaining the solutions is 1.910927 sec.

6.2 Teacher-learning-Based Optimization (TLBO)

This algorithm is a parameter less algorithm. So keeping the population size same as those used in section 6.1 the EED problem is solved using TLBO. It takes only 10 iterations for the convergence of solutions in the Pareto-Optimal front and hence provides a computational advantage over other algorithms using same number of population size.

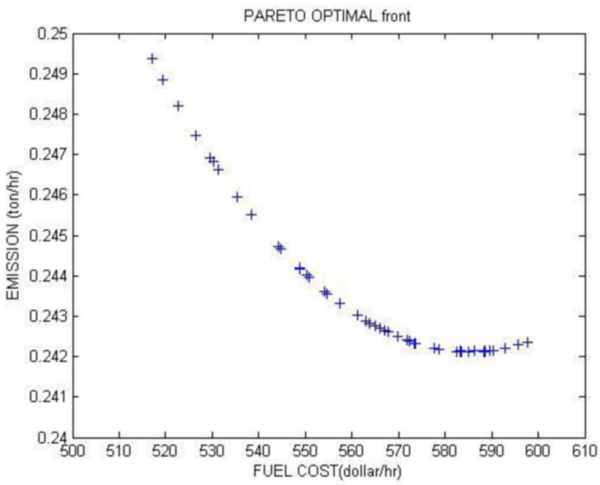

Fig. 5. Pareto-optimal front obtained by using TLBO algorithm for EED problem

It is clear from the Fig. 5 and Table 1, and 2 that all 50 solutions are different and available for the operator .These solutions forms the trade off between minimum fuel cost and minimum emission. The operator has the flexibility to explore more operating conditions, provided acceptable range of operating conditions are available.

In this case, best trade off solution is found to be solution 49 in Table 3 with optimal fuel cost 554.18 ($/h) and optimum emission 0.2436 (ton/h). The main objective of this paper is show how many important solutions are obtained in the Pareto-optimal front, which in this case is 50. The computation time taken for obtaining the solutions is 0.824812 sec, which is quite less than that obtained in section 6.1.

Less computational time can be of a great advantage because of the time complexity that is often faced with real-time systems. TLBO can also be used for other power system MOO problems.

7. COMPARATIVE STUDY

A combined figure showing the solutions from both NSGA and TLBO is given in Fig. 6.

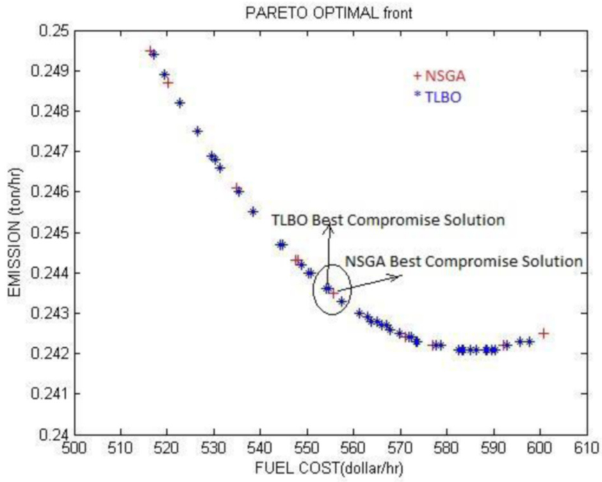

Fig. 6. Pareto-optimal fronts obtained by using NSGA and TLBO algorithm for EED problem.

The following table 1, and 2 shows the various solutions in the Pareto-Optimal front obtained by using both NSGA and TLBO.

Table 1. Solution obtained from NSGA and TLBO for EED problem (Solution No. 1 to 25)

Solution No.	TLBO		NSGA	
	Total Fuel Cost ($/h)	Total Emission (ton/h)	Total Fuel Cost ($/h)	Total Emission (ton/h)
1	568.3563	0.2947	516.2245	0.2495
2	589.4872	0.2421	592.0785	0.2422
3	565.9543	0.2427	511.1072	0.2507
4	517.0071	0.2494	600.675	0.2425
5	588.6886	0.2421	600.675	0.2425
6	592.8962	0.2422	520.1696	0.2487
7	510.4291	0.2509	555.6177	0.2435
8	588.2231	0.2421	600.675	0.2425
9	597.655	0.2423	600.675	0.2425
10	548.7701	0.2442	600.675	0.2425
11	566.9792	0.2427	600.675	0.2425
12	511.245	0.2507	508.2	0.2514
13	530.2545	0.2468	571.1392	0.2424
14	550.2608	0.244	600.675	0.2425
15	583.1995	0.2421	577.0143	0.2422
16	544.2614	0.2447	600.675	0.2425

17	571.979	0.2424	547.3991	0.2443
18	585.0212	0.2421	510.5175	0.2508
19	554.7053	0.2436	600.675	0.2425
20	573.6788	0.2423	600.675	0.2425
21	572.4057	0.2424	600.675	0.2425
22	522.6616	0.2482	534.8331	0.2461
23	510.96	0.2507	585.1441	0.2421
24	573.5002	0.2423	547.9994	0.2443
25	535.4779	0.246	600.675	0.2425
26	595.6052	0.2423	516.2245	0.2495
27	582.6239	0.2421	516.2245	0.2495
28	577.7016	0.2422	516.2245	0.2495
29	564.9025	0.2428	516.2245	0.2495
30	519.4738	0.2489	516.2245	0.2495
31	588.4677	0.2421	516.2245	0.2495
32	563.6938	0.2428	516.2245	0.2495
33	557.5201	0.2433	516.2245	0.2495
34	583.3144	0.2421	516.2245	0.2495
35	569.9232	0.2425	516.2245	0.2495
36	531.3198	0.2466	516.2245	0.2495
37	548.702	0.2442	516.2245	0.2495
38	554.1823	0.2436	516.2245	0.2495
39	563.043	0.2429	516.2245	0.2495
40	586.3277	0.2421	516.2245	0.2495
41	567.8088	0.2426	516.2245	0.2495
41	538.3962	0.2455	516.2245	0.2495
42	526.6108	0.2475	516.2245	0.2495
43	578.681	0.2422	516.2245	0.2495
44	529.6153	0.2469	516.2245	0.2495
45	583.5273	0.2421	516.2245	0.2495
46	550.8255	0.244	516.2245	0.2495
47	544.7286	0.2447	516.2245	0.2495
48	561.1723	0.243	516.2245	0.2495
49	590.253	0.2421	516.2245	0.2495
50	568.3563	0.2947	516.2245	0.2495

Table 2. Best Compromised Solution obtained from NSGA and TLBO for EED problem as decided by the Decision Maker

Method	Best solution Total Fuel Cost ($/h)	Best solution Total Emission (ton/h)	No. Of solutions in the Pareto-Optimal front	CPU time (sec)
NSGA	555.62	0.2435	14	1.910
TLBO	554.18	0.2436	50	0.824

Table 3. Generator schedules for best compromised solution obtained from NSGA and TLBO for EED problem as decided by the Decision Maker

Generator Output (in MW)	TLBO	NSGA
P1	0.4381	0.4392
P2	0.4542	0.4513
P3	0.5006	0.5104
P4	0.4210	0.3872
P5	0.5010	0.5553
P6	0.5191	0.4905

The best compromise solution from NSGA method was found to be 555.62 ($/h) of total fuel cost and corresponding optimum emission of 0.2435 (ton/h). Using TLBO we get 554.18 ($/h) of total fuel cost and corresponding optimum emission of 0.2436 (ton/h).There is no much difference in the outputs but when computation time is compared TLBO gives much better result than NSGA ,which is somewhat superior to other optimization algorithms like MOGA, VEGA, etc. The EED problem is a constrained non-linear problem and using TLBO method the CPU computation time has been drastically reduced, which may also vary from processor to processor.

8. CONCLUSIONS

In this paper we presented a different approach to solve a multi-objective optimization problem using Teacher-Learning-Based Optimization method. This method is a *parameter less* approach and also provides a great computational advantage over NSGA.

The lesser computation time in case of TLBO is because it includes only few mathematical operations like addition and subtraction as compared to those tedious operations in NSGA where ranking of solutions and assigning a dummy fitness value to each individual includes too many mathematical operations. Thus, TLBO technique can be used for solving many other MOO problems which have conflicting objective functions in nature. This also helps the decision maker to choose the best compromise solution in lesser time. Thus , the burden of time constraint is the least thing to be considered by the decision maker . The settings for all the generators as decided by the decision maker obtained from the pareto-optimal front of TLBO based approach can be implemented very easily .

This technique is a parameter less algorithm so, selecting appropriate parameters for the convergence of the MOO problem is not required and can be very helpful in studying various optimization problems in power systems.

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Appendix A.

Table 1. IEEE 30-bus generator real power output limits, cost coefficients, and emission coefficients

		G1	G2	G3	G4	G5	G6
Cost Coefficients	a	100	120	40	60	40	100
	b	200	150	180	100	180	150
	c	10	10	20	10	20	10
Emission Coefficients	α	4.091	2.543	4.258	5.236	4.258	6.131
	β	-5.554	-6.047	-5.094	-3.55	-5.094	-5.555
	γ	6.49	5.638	4.586	3.38	4.586	5.151
	ξ	2.00E-04	5.00E-04	1.00E-06	2.00E-03	1.00E-06	1.00E-05
	λ	2.857	3.33	8	2	8	6.667
Real Power Limits	P_{Gmin}	0.05	0.05	0.05	0.05	0.05	0.05
	P_{Gmax}	0.5	0.6	1	1.2	1	0.6