Teaching-Learning-Based Optimization Algorithm for the Combined Dynamic Economic Environmental Dispatch Problem

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Abstract-**The Dynamic Economic Environmental Dispatch Problem (DEEDP) is a major issue in power system control. It aims to find the optimum schedule of the power output of thermal units in order to meet the required load at the lowest cost and emission of harmful gases. Several constraints, such as generation limits, valve point loading effects, prohibited operating zones, and ramp rate limits, can be considered. In this paper, a method based on Teaching-Learning-Based Optimization (TLBO) is proposed for dealing with the DEEDP problem where all aforementioned constraints are considered. To investigate the effectiveness of the proposed method for solving this discontinuous and nonlinear problem, the ten-unit system under four cases is used. The obtained results are compared with those obtained by other metaheuristic techniques. The comparison of the simulation results shows that the proposed technique has good performance.**

Keywords-dynamic economic environmental dispatch; teaching-learning-based optimization; prohibited operating zones; ramp rate limits

I. INTRODUCTION

With the growing demand for electricity and rising fuel prices, electricity companies are constantly working to ensure continuous and reliable electrical power supply to their customers. In order to achieve this, system operators need to constantly adjust the control variables of power networks. This extremely difficult task is performed by the resolution of the Economic Dispatch Problem (EDP), which aims to determine the production levels of all thermal units which guarantee a balance between production and consumption at the lowest cost. Unfortunately, today network loads are dynamic, which means that it is required to plan the generation of units in real time to guarantee continuous power balance. The resolution of such Dynamic EDP problems (DEDP), considers the constraints imposed by generator Ramp-Rate Limits (RRL). Along with DEDP, the emission dispatch problem, which aims to minimize the emissions of fossil fuels, has emerged. The combination of the two problems in one single problem called Dynamic Economic Environmental Dispatch Problem (DEEDP) has become attractive. DEEDP aims to minimize simultaneously the total production cost and the emission of harmful gases. Thus, it can be considered as a multi-objective problem with conflicting objective functions [1]. In the past, several operating constraints have been taken into account in the DEEDP mathematical formulation, such as power balance constraint, Valve-Point Loading Effects (VPLE), Prohibited Operating Zones (POZ), and RRLs. During the past decades, several techniques have been proposed to solve this kind of problems, including linear programming [2], dynamic programming [3], and gradient algorithms [4]. Unfortunately, in these techniques, the cost function has been approximated by quadratic functions and VPLEs have been ignored in the problem formulation. This frequently leads to inexactitude of the optimal solutions. Moreover, those techniques may be trapped in local optima due to the non-convex and nonlinear characteristics of the cost function. In recent years, various meta-heuristic techniques have been suggested in the literature to overcome the limitations of the traditional methods.

In [1], a differential evolution-based technique has been used to solve the DEEDP where a fuzzy-based method has been employed to extract the optimal solution. Authors in [5] utilized the artificial bee colony algorithm to solve the EDP with VPLEs. Unfortunately, the environmental impact of thermal units has not been considered. Particle swarm optimization (PSO) has also been used to solve power dispatch problems [6-8]. Basu [9] has solved the DEEDP by applying the second version of the Non-dominated Sorting Genetic Algorithm (NSGAII) proving that such technique may provide promising results. Another technique based on NGSAII has been developed in [10] to handle the DEEDP incorporating POZ constraints. An optimization method based on Simulated Annealing (SA) algorithm has been implemented in [11] in this regard, the cost function has been approximated by a cubic function and the problem has been converted into mono-objective problem by using price penalty factors. Within this context, other metaheuristic techniques, such as Gravitational Search Algorithm (GSA) [12], Biogeography-Based Optimization (BBO) [13], Bacterial Foraging Algorithm (BFA) [14], and Harmony Search (HS) algorithm [15] have been developed and implemented for various complex dispatch problems. The main advantage of the aforementioned techniques is that they expand the entire search space for the optimal solution to avoid getting trapped in a local optimal. In addition, these techniques are not concerned with the nature and the shape of the objective functions. However, the

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convergence of most of these techniques depends on their parameters and their computational time is quite large.

The Teaching-Learning-Based Optimization (TLBO) algorithm [16] is a powerful algorithm which can provide promising results in single objective and multi-objective optimization. It is a population algorithm inspired from the teacher/learner relationship. The TLBO algorithm is based on two basic methods of learning: (i) through the teacher, known as the teacher phase, and (ii) through interaction with other students, called student phase. In this optimization algorithm, a group of students is considered as a population and the different subjects offered to the students are considered to be the feasible solutions and a student's result is considered to be the value of the fitness function [16]. The best solution in the whole population, which corresponds to the best value of the objective function, is assigned to the teacher. It has been shown that TLBO has the advantage of only requiring a few control parameters, such as the number of students in the class and the number of subjects presented for students, for its operation [17, 18].

In this regard, a TLBO-based method is proposed for dealing with the problem of DEEDP. In the DEEDP formulation all operating constraints, such as generation limits, energy balance, VPLEs, RRLs, and POZ constraints are considered. To render the problem more practical, total real power losses are taken into account. To assess the effectiveness of the proposed optimization method, a ten-unit system is employed. The simulation results obtained by the proposed method are compared with other metaheuristic techniques.

II. MATHEMATICAL FORMULATION OF THE DEEDP

The DEEDP is a principal problem in power network operation. It aims to determine the optimum allocation of power outputs of all thermal units to minimize simultaneously the total fuel cost and total emission according to the predicted load demands, over entire dispatch periods generally of one hour. Taking VPLEs into account, the total fuel cost can be expressed by:

$$C_T = \sum_{t=1}^{T}\sum_{i=1}^{N} a_i + b_i P_i^t + c_i\left(P_i^t\right)^2 + \left|d_i \sin\left\{e_i\left(P_i^{\min} - P_i^t\right)\right\}\right| \quad (1)$$

where a_i, b_i, c_i, d_i and e_i are the cost coefficients of unit *i*, P_i^t is the output power in MW of unit *i* at time *t*, *T* is the number of hours, and *N* is the number of units.

The second objective function considered in this study, which is the total emission of harmful gases, is described as:

$$E_T = \sum_{t=1}^{T}\sum_{i=1}^{N} \alpha_i + \beta_i P_i^t + \gamma_i\left(P_i^t\right)^2 + \eta_i \exp\left(\lambda_i P_i^t\right) \quad (2)$$

where α_i, β_i, γ_i, η_i and λ_i are the emission coefficients.

In this work, the two objective functions are combined in a single objective function by integrating the price penalty factor. The combined function is:

$$F_T = \delta C_T + (1-\delta)\lambda E_T \quad (3)$$

where $\delta = rand(0,1)$ and λ is the average of the price penalty factors of all units. The price penalty factor for unit *i* can be determined as:

$$\lambda_i = \frac{C_i^{\max}}{E_i^{\max}} \quad (4)$$

where $C_i^{\max}$ and $E_i^{\max}$ are the maximum fuel cost and the maximum emission of unit *i* respectively.

In order to find the optimal Pareto solutions, the objective function F_T is minimized for various values of δ subject to the constraints (5)-(9). Equation (5) describes the power balance constraint where the real power losses P_L^t at time *t* are calculated by (10) [19]. As given in (6), the output power of each generator *i* should be within its lower $P_i^{\min}$ and upper $P_i^{\max}$ limits. The RRLs of the thermal units are shown in (7) and (8) while POZs constraints are given in (9).

$$\sum_{i=1}^{N} P_i^t - P_D^t - P_L^t = 0,\ t = 1,...,T \quad (5)$$

where, P_D^t is the load at time *t*.

$$P_i^{\min} \le P_i^t \le P_i^{\max},\ i = 1,...,N \quad (6)$$

$$P_i^{t-1} - P_i^t \le R_i^{down} \quad (7)$$

$$P_i^t - P_i^{t-1} \le R_i^{up} \quad (8)$$

where R_i^{down} and R_i^{up} are the down-ramp and up-ramp limits of unit *i*.

$$P_i^t \in \begin{cases} P_i^{\min} \le P_i^t \le P_{i,1}^{down} \\ P_{i,k-1}^{up} \le P_i^t \le P_{i,k}^{down} & ,k = 2,...,z_i \\ P_{i,z_i}^{up} \le P_i^t \le P_i^{\max} \end{cases} \quad (9)$$

where $P_{i,k}^{down}$ and $P_{i,k}^{up}$ are the down and up bounds of POZ number *k* and z_i is the number of POZ for unit *i*.

$$P_L^t = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i^t B_{ij} P_j^t + \sum_{i=1}^{N} B_{oi} P_i^t + B_{oo} \quad (10)$$

where, B_{ij}, B_{oi}, B_{oo} are the loss coefficients of *B*-loss matrix.

III. THE TLBO ALGORITHM

TLBO algorithm, developed in [16], is a population-based optimization algorithm that mimics the teaching and learning phenomenon in a class. It is inspired by the transmission of knowledge from teacher to students and the mutual interaction between classmates. In TLBO algorithm, students in a class constitute the population and a student is considered as a feasible solution for the optimization problem. Subjects offered to students constitute the decision variables and student's result is the fitness function evaluated at the feasible solution. TLBO method is divided into two phases which are teacher phase and student phase.

A. Teacher Phase

In this phase, the teacher is the main interfering where his job is to improve the knowledge level of learners (students) and helps them to get high grades. However, grades or marks of students depend on teaching quality and student's quality. For simulation, consider there are 'n' subjects offered to N_{pop} students. Therefore, variable 'n' is equivalent to the number of problem design variables and N_{pop} is the population, in TLBO algorithm. Let M_j^k be the mean result of learners in a particular subject j where $j \in \{1,2,\ldots,m\}$, at the k-th teaching-learning cycle ($k \in \{0,1,2,\ldots,I^{\max}\}$). Since the teacher is the most highly learned and experienced person in the class, thus, he is considered the best learner in the entire population or class. Let X^{k*} be the best solution in the entire population at the k-th iteration. The difference between the teacher's results and the mean result of students in the j-th subject is calculated as [18]:

$$D_j^k = r\left(X_j^{k*} - T_F M_j^k\right) \quad (11)$$

where $r \in [0,1]$ is a random number. T_F is the teaching factor that is selected randomly from $\{1,2\}$. It is used to choose which value of mean should be changed.

At the k-th teaching-learning cycle, the i-th feasible solution is updated according to the following expression.

$$X_{ij,new}^k = X_{ij,old}^k + D_j^k \quad (12)$$

If $X_{ij,new}^k$ gives better results compared to $X_{ij,old}^k$, it is accepted, otherwise, it is rejected. All accepted solutions will be used as input for the student phase.

B. Student Phase

In this phase, students acquire knowledge through mutual interaction. The learning phenomenon is simulated as follows. Two feasible solutions, X_u^k and X_v^k with $u \neq v$, are randomly selected from the population. If X_u^k is better than X_v^k, then update X_v^k as given in (14) otherwise update X_u^k as given in (13). If the new solution is better than the old solution, then, the new solution will be accepted in the population and the old solution will be rejected, otherwise the new solution will be rejected and old solution will be kept in the population.

$$X_{uj,new}^k = X_{uj}^k + r\left(X_{uj}^k - X_{vj}^k\right) \quad (13)$$

$$X_{vj,new}^k = X_{vj}^k + r\left(X_{vj}^k - X_{uj}^k\right) \quad (14)$$

The TLBO algorithm's steps are shown in Figure 1.

```
Initialize the TLBO parameters:
    Generate randomly initial N_pop students
    Maximum number of cycles , I^max
    Number of subjects (design variables), m
    Set k = 0
While k ≤ I^max do
  Evaluation of fitness function
  Teacher phase
    Extract the best solution (teacher)
    Update feasible solutions according to (12)
    If new_solution is better than old_solution
      Replace old_solution by new_solution
    Else
      Reject new_solution
    End if
  Student phase
    Select randomly two students X_u^k and X_v^k
    If X_u^k is better than X_v^k
      Update X_v^k
    Else
        Update X_u^k
    End If
    If new_solution is better than old_solution
      Replace old_solution by new_solution
    Else
      Reject new_solution
    End if
    k = k + 1
End While
```

Fig. 1. Steps of the TLBO algorithm.

IV. TLBO ALGORITHM IMPLEMENTATION FOR THE DEEDP

To verify the effectiveness of the proposed method in solving the DEEDP, numerical experiments are carried out employing the ten unit system. The TLBO algorithm was firstly applied for static economic emission dispatch for total demand power of P_D=2000MW, and then for the dynamic case. All system data are taken from [20]. In this paper, TLBO and PSO algorithms are implemented in Matlab R2018B on a PC intel(R) Core i7, 1.5GHz, 64 bits. Population size and maximum number of iterations are both 200. The B-loss matrix of the studied system is shown in (15).

$$B = 10^{-4}\begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix} \quad (15)$$

A. Static Dispatch

The convergence of the objective functions for the proposed algorithm and PSO is shown in Figure 2. It can be seen that TLBO provides cheaper electricity production and lowest emission compared to PSO. In fact, the minimum cost and emissions are 132968.93\$/h and 18832.63ton/h respectively for the TLBO algorithm and 133088.62\$/h and 19054.12ton/h respectively for the PSO algorithm. The Pareto front generated by the proposed algorithm is shown in Figure 3. It is clear that that the Pareto solutions are uniformly distributed in the objective space. Moreover, Figure 3 shows that cost and emissions are conflicting functions.

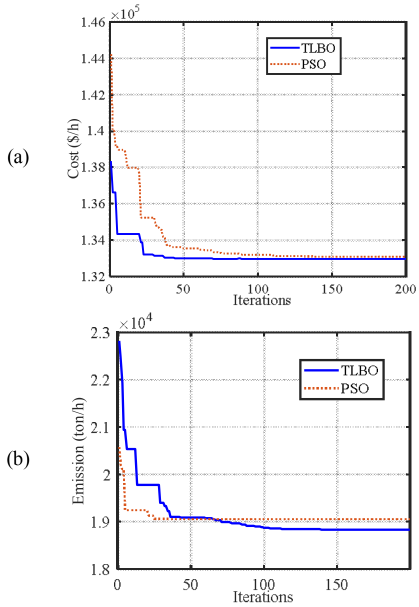

Fig. 2. Convergence of objective functions for P_D=2000MW: (a) cost, (b) emission.

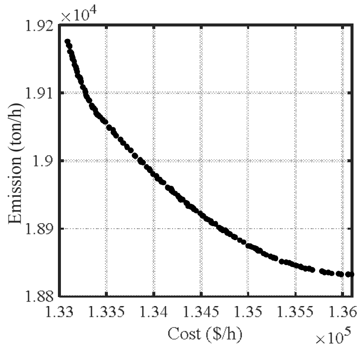

Fig. 3. Pareto solutions for P_D=2000MW.

B. Dynamic Dispatch

Pure dynamic economic dispatch and pure dynamic environmental dispatch are solved separately. Then, they are dynamically combined for economic environmental dispatch. Table I shows the optimal variation of the generation for dynamic economic dispatch, according to the daily variation of the load (P_D^t). It is clear that the optimal output powers of all units are within their limits. The minimum production cost is 2472116.66\$ while the corresponding emission is at its maximum value which is 330411.81ton. The optimum schedule of all system units for the dynamic emission dispatch is depicted in Table II. It can also be seen that output powers of all units are within their limits. The minimum emission is 294153.04ton while the total cost is at its maximum value which is 2594148.32\$.

TABLE I. DYNAMIC ECONOMIC DISPATCH

Hour	P_D^t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
1	1036	150.1259	135.5687	73.0000	117.0485	175.4140	126.8733	130.0000	117.5441	20.0000	10.0000
2	1110	150.0664	135.0000	73.0000	108.9781	225.4140	160.0000	130.0000	120.0000	20.0000	10.0000
3	1258	150.2382	135.0000	153.0000	125.7599	223.8123	159.6342	129.5876	119.8081	49.7545	39.8977
4	1406	150.5704	135.0000	206.7431	175.7599	243.0000	159.0079	129.5631	119.0141	79.6457	43.2159
5	1480	150.5888	135.0000	255.5104	225.7599	221.4589	156.7358	130.0000	119.9033	78.9610	45.4764
6	1628	150.2503	135.0000	335.5104	275.7599	243.0000	159.7044	129.6031	119.9085	79.8822	47.4658
7	1702	150.1468	198.5926	331.5975	300.0000	241.5421	160.0000	130.0000	119.9352	79.8647	43.3868
8	1776	210.1460	213.1343	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	38.2598
9	1924	273.4194	293.1343	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
10	2022	300.4154	373.1343	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
11	2106	315.4490	453.1343	337.4498	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
12	2150	344.5307	470.0000	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
13	2072	331.2602	397.3814	340.0000	300.0000	242.9249	159.9539	130.0000	119.9397	79.9670	55.0000
14	1924	251.3135	317.3814	338.7426	300.0000	242.6070	159.6948	129.9303	120.0000	79.9776	54.9429
15	1776	171.7944	237.3814	339.7179	300.0000	242.9101	159.5908	129.9045	118.7763	79.9693	54.4079
16	1554	150.0967	157.3814	296.4912	250.7445	238.3715	159.4043	129.3618	119.6965	53.0343	43.1300
17	1480	150.9007	135.0000	240.7998	242.3687	242.1751	159.6100	129.7144	119.7307	55.0000	44.0521
18	1628	150.3632	174.5376	300.0000	292.3687	242.2373	159.9336	129.4308	119.2750	54.7366	53.3392
19	1776	217.4110	254.5376	300.0000	300.0000	243.0000	160.0000	130.0000	120.0000	55.0000	55.0000
20	1972	284.3186	334.5376	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
21	1924	259.9202	309.6601	340.0000	300.0000	243.0000	159.2709	129.8075	119.9798	79.9277	53.0288
22	1628	180.1857	229.9838	291.1958	250.6165	223.4006	159.4022	126.6683	120.0000	51.6945	43.7541
23	1332	150.2720	150.0578	211.4456	201.6378	174.2186	160.0000	130.0000	90.0000	52.0055	44.2729
24	1184	150.5086	135.0000	131.4456	167.0485	175.3310	110.0000	130.0000	120.0000	50.0000	40.0000
Cost (\$)	2472116.66										
Emission (ton)	330411.81										

TABLE II. DYNAMIC EMISSION DISPATCH

Hour	P_D^t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
1	1036	150.3364	135.2479	88.8628	91.5246	133.1490	133.2677	96.0287	92.6589	79.7478	54.8723
2	1110	150.4649	138.1099	101.9172	99.8572	143.6597	143.8590	105.5614	114.0802	79.9698	55.0000
3	1258	164.2919	166.1639	117.3305	121.6243	172.9143	159.9093	129.7196	120.0000	80.0000	54.9823
4	1406	199.0112	203.9786	147.0126	144.0633	204.0232	159.7183	129.9286	119.9410	79.9646	55.0000
5	1480	216.9388	219.6330	157.4592	163.6519	218.2469	160.0000	129.9633	120.0000	79.9462	55.0000
6	1628	253.4935	255.9774	190.1283	190.7046	242.9276	159.9049	129.9803	119.9825	80.0000	55.0000
7	1702	275.2332	273.7700	209.7002	210.7657	242.8287	160.0000	129.9338	120.0000	79.9196	54.9987
8	1776	291.1351	295.7189	229.4559	232.4257	242.9839	159.8865	130.0000	120.0000	80.0000	54.8400
9	1924	324.3152	326.1564	277.5305	279.7439	243.0000	160.0000	129.9974	119.9869	79.9975	54.9994
10	2022	348.6556	349.0595	321.7455	294.5092	243.0000	160.0000	130.0000	119.9751	80.0000	55.0000
11	2106	383.1823	382.7515	339.9697	299.9955	243.0000	160.0000	130.0000	120.0000	80.0000	54.9992
12	2150	397.8457	425.6329	340.0000	300.0000	241.7596	152.4816	130.0000	120.0000	80.0000	55.0000
13	2072	364.1944	364.2761	339.9983	299.9967	243.0000	159.9968	130.0000	120.0000	79.9960	55.0000
14	1924	327.2057	322.9324	278.8479	278.7852	243.0000	159.9789	130.0000	120.0000	79.9829	55.0000
15	1776	292.5619	292.8412	230.3221	233.2478	242.7153	159.8868	129.8985	119.9561	80.0000	55.0000
16	1554	234.6654	237.5412	181.0347	183.2478	243.0000	160.0000	129.7930	120.0000	55.0000	55.0000
17	1480	224.4285	225.2253	162.6887	164.5307	224.1457	160.0000	129.9327	120.0000	54.9989	55.0000
18	1628	262.2682	260.2198	197.1840	196.3723	242.4237	159.9493	129.8766	119.9320	55.0000	55.0000
19	1776	298.9110	296.1538	240.5298	238.0002	243.0000	159.9865	129.9697	120.0000	54.9945	55.0000
20	1972	337.0679	337.4869	297.2509	287.9121	242.9982	159.9977	129.9953	119.9968	79.9966	54.9965
21	1924	328.1016	326.5158	278.6325	274.7016	243.0000	159.9165	130.0000	119.9709	79.9725	54.9936
22	1628	248.1062	246.5158	198.6325	224.7016	215.3974	159.6594	130.0000	119.9354	79.8864	55.0000
23	1332	176.4330	166.5158	127.4188	174.7016	174.6863	160.0000	129.7901	119.8400	80.0000	54.9865
24	1184	154.0152	155.7069	100.8685	124.7016	168.9035	152.3155	107.1434	110.9206	80.0000	55.0000
Cost ($)	2594148.32										
Emission (ton)	294153.04										

TABLE III. COMBINED ECONOMIC EMISSION DISPATCH

Hour	P_D^t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
1	1036	150.4594	135.3072	80.0281	120.0864	126.2070	124.4066	129.6379	86.1200	59.2616	44.0814
2	1110	150.0709	135.0000	81.2516	102.8341	167.8358	125.3782	129.3292	116.1200	79.9973	44.7038
3	1258	150.4932	135.0161	138.7766	129.6167	188.9086	160.0000	129.2388	120.0000	79.7994	54.6856
4	1406	154.9053	161.9512	177.1730	179.6167	223.7618	159.9893	129.7067	119.9437	79.9075	54.7681
5	1480	152.9466	217.8705	186.4596	185.1000	236.2579	159.5941	130.0000	119.8567	79.8784	52.1092
6	1628	213.1264	236.4829	260.3624	203.1865	243.0000	136.3359	130.0000	120.0000	80.0000	55.0000
7	1702	227.8217	221.6160	271.7060	246.9217	243.0000	160.0000	129.8277	120.0000	79.9719	55.0000
8	1776	228.2304	242.9587	290.8592	286.3618	242.9531	159.9532	130.0000	119.4716	79.8240	54.3041
9	1924	293.0721	293.5529	340.0000	280.7385	243.0000	160.0000	130.0000	120.0000	80.0000	54.5004
10	2022	306.2281	368.3049	340.0000	300.0000	243.0000	160.0000	129.8569	120.0000	80.0000	54.1663
11	2106	376.6213	389.3073	339.9899	299.9805	242.9987	159.9980	129.9979	119.9977	79.9869	54.9993
12	2150	385.6214	428.8158	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
13	2072	361.8808	397.2726	340.0000	300.0000	243.0000	160.0000	130.0000	90.0000	80.0000	55.0000
14	1924	289.4585	317.2726	300.7884	300.0000	243.0000	159.9907	129.6966	119.8300	80.0000	55.0000
15	1776	232.8384	281.4039	276.1673	257.2175	242.9575	159.8950	129.9781	120.0000	79.9478	55.0000
16	1554	153.0008	218.8426	222.2456	241.2300	243.0000	159.9386	130.0000	119.8715	55.0000	55.0000
17	1480	150.1175	217.9193	195.6985	194.4730	243.0000	159.8241	129.9954	119.9426	55.0000	54.0499
18	1628	229.1932	233.6730	207.0696	244.4730	243.0000	160.0000	130.0000	120.0000	55.0000	55.0000
19	1776	257.6630	290.2181	268.7446	256.2676	242.9809	159.9782	130.0000	120.0000	54.9739	54.9997
20	1972	271.6633	347.2125	340.0000	300.0000	243.0000	160.0000	130.0000	120.0000	80.0000	55.0000
21	1924	301.8759	308.5015	297.6986	299.7156	242.8737	159.9440	129.6663	119.8831	79.9622	54.9860
22	1628	222.0018	228.5015	217.6986	249.7616	222.5752	159.8970	129.6350	119.9210	79.9730	47.2841
23	1332	150.2022	148.5746	138.5624	200.3815	223.2994	159.5506	130.0000	89.9210	80.0000	43.5042
24	1184	150.4527	135.1441	73.0000	170.0864	173.2994	127.6795	130.0000	114.8581	80.0000	55.0000
Cost ($)	2519909.93										
Emission (ton)	303338.20										

Table III depicts the best compromise solution obtained from the resolution of the combined DEEDP. Fuzzy-based method [9] is employed to extract the optimal best compromise solutions. The total cost is 2519909.93$ which is more than the cost obtained for the pure economic dispatch (2472116.66$) and less than the cost obtained for the pure environmental dispatch (2594148.32$). Similarly, the emission is 303338.20ton which is less than the emission obtained for the pure economic dispatch (330411.81ton) and more than the emission obtained for the pure environmental dispatch. The comparison results shown in Table IV show that the proposed TLBO outperforms PSO, Improved Bacterial Foraging Algorithm (IBFA), and the second version of the Non-dominated Sorting Genetic Algorithm (NSGAII) in finding the optimum generation schedule for the DEEDP.

TABLE IV. COMPARISON WITH OTHER META-HEURISTIC TECHNIQUES

Method	Minimum cost ($)	Minimum emission (ton)
TLBO	2472116.66	294153.04
PSO	2497562.38	301539.82
IBFA [21]	2481733.3	295833.0
NSGAII [10]	$2.5168x10^6$	$3.1740x10^5$

V. CONCLUSION

In this study, a new metaheuristic called Teaching-Learning-Based Optimization (TLBO) algorithm was used for solving the DEEDP. The problem is described as an optimization problem. The decision variables of the problem are the output powers of units at the hours of a single day. Energy balance equation, generation limits, valve point loading effects, prohibited operating zones and ramp rate limits are considered as problem constraints. To assess the effectiveness of the proposed method, the ten-unit system is used. The TLBO is applied for the pure dynamic economic dispatch, the pure dynamic environmental dispatch and the combined dynamic economic environmental dispatch. The obtained results were compared with other techniques proposed recently in the literature, such as PSO, IBFA and NSGAII, and it was found that the proposed algorithm outperforms them.

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