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
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:

\[ C_f = \sum_{i=1}^{N} a_i + b_i P_i^r + c_i \left( P_i^r \right)^2 + d_i \sin \left( e_i \left( P_i^m - P_i^s \right) \right) \]  

(1)

where \( a_i, b_i, c_i, d_i \) and \( e_i \) are the cost coefficients of unit \( i \), \( P_i^r \) 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:

\[ E_r = \sum_{i=1}^{N} a_i + b_i P_i^r + c_i \left( P_i^r \right)^2 + \eta_i \exp \left( \delta_i P_i^r \right) \]  

(2)

where \( a_i, b_i, c_i, \eta_i \), and \( \delta_i \) are the emission coefficients.

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

\[ F_\gamma = \delta C_f + (1 - \delta) \lambda E_r \]  

(3)

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

\[ \lambda_i = \frac{C_f^{\text{max}}}{E_r^{\text{max}}} \]  

(4)

where \( C_f^{\text{max}} \) and \( E_r^{\text{max}} \) are the maximum fuel cost and the maximum emission of unit \( i \) respectively.

In order to find the optimal Pareto solutions, the objective function \( F_\gamma \) is minimized for various values of \( \delta \) 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 \( P_i^{\text{min}} \) and upper \( P_i^{\text{max}} \) limits. The RRLs of the thermal units are shown in (7) and (8) while POZs constraints are given in (9).

\[ \sum_{i=1}^{N} P_i^t - P_i^D - P_i^L = 0, \quad t = 1,...,T \]  

(5)

where, \( P_i^D \) is the load at time \( t \).

\[ P_i^{\text{min}} \leq P_i^t \leq P_i^{\text{max}}, \quad i = 1,...,N \]  

(6)

\[ P_i^{t-1} - P_i^t \leq P_i^{\text{down}} \]  

(7)

\[ P_i^t - P_i^{t-1} \leq P_i^{\text{up}} \]  

(8)

where \( P_i^{\text{down}} \) and \( P_i^{\text{up}} \) are the down-ramp and up-ramp limits of unit \( i \).

\[ P_i^t \in \begin{cases} P_i^{\text{min}} \leq P_i^t \leq P_i^{\text{down}}, & k = 1,...,z_i \\ P_i^{\text{up}} \leq P_i^t \leq P_i^{\text{max}} & \end{cases} \]  

(9)

where \( P_i^{\text{down}} \) and \( P_i^{\text{up}} \) are the down and up bounds of POZ number \( k \) and \( z_i \) is the number of POZ for unit \( i \).

\[ P_L^t = \sum_{j=1}^{N} \sum_{i=1}^{N} B_{ij} P_i^t + \sum_{i=1}^{N} B_{oi} P_i^t + B_{oo} \]  

(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 \( N_{\text{pop}} \) students. Therefore, variable \( 'n' \) is equivalent to the number of problem design variables and \( N_{\text{pop}} \) 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 \( \{k \in \{0,1,2,\ldots,\text{max}\}\} \). 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 \( X_j^k \) 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 \( i \)-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.

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

If \( X_{ij,\text{new}}^k \) gives better results compared to \( X_{ij,\text{old}}^k \), 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.

\[
X_{ij,\text{new}}^k = X_{ij}^k + r \left( X_{ij}^k - X_{ij}^k \right) \quad (13)
\]

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

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 \( P_{DF}=2000 \text{MW} \), 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).

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

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.

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$.

![Fig. 2. Convergence of objective functions for \( P_d = 2000 \)MW. (a) cost, (b) emission.](image)

![Fig. 3. Pareto solutions for \( P_d = 2000 \)MW.](image)

### TABLE I. DYNAMIC ECONOMIC DISPATCH

| Hour | \( P_d^t \) | \( P_1 \) | \( P_2 \) | \( P_3 \) | \( P_4 \) | \( P_5 \) | \( P_6 \) | \( P_7 \) | \( P_8 \) |
|------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1    | 1036        | 150.1259    | 135.5687    | 73.0000     | 117.0485    | 175.1410    | 126.8753    | 130.0000    | 115.5441    |
| 2    | 1110        | 150.0664    | 135.0000    | 73.0000     | 105.9781    | 225.4140    | 160.0000    | 130.0000    | 120.0000    |
| 3    | 1258        | 150.2382    | 135.0000    | 153.0000    | 125.7599    | 223.8123    | 159.6342    | 129.5876    | 119.8801    |
| 4    | 1406        | 150.5784    | 135.0000    | 206.7431    | 175.7599    | 243.0000    | 159.0079    | 129.5631    | 119.0141    |
| 5    | 1480        | 150.5888    | 135.0000    | 255.5104    | 225.7599    | 221.4589    | 156.7358    | 130.0000    | 119.9033    |
| 6    | 1628        | 150.2503    | 135.0000    | 335.5104    | 275.7599    | 243.0000    | 159.7944    | 129.6301    | 119.9085    |
| 7    | 1702        | 150.1468    | 198.5926    | 331.5975    | 300.0000    | 241.5421    | 160.0000    | 130.0000    | 119.9352    |
| 8    | 1776        | 210.1460    | 213.1343    | 340.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 9    | 1924        | 273.4194    | 293.1343    | 340.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 10   | 2022        | 300.5145    | 373.1343    | 340.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 11   | 2106        | 315.4490    | 453.1343    | 337.4498    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 12   | 2150        | 344.5307    | 470.0000    | 340.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 13   | 2072        | 331.2602    | 397.3814    | 340.0000    | 300.0000    | 242.9249    | 159.9539    | 130.0000    | 119.9397    |
| 14   | 1924        | 251.3135    | 317.3814    | 338.7426    | 300.0000    | 242.6072    | 159.6948    | 129.9303    | 120.0000    |
| 15   | 1776        | 171.7944    | 237.3814    | 339.7179    | 300.0000    | 242.9112    | 159.5908    | 129.9045    | 118.7763    |
| 16   | 1554        | 150.0967    | 157.3814    | 296.4912    | 250.7445    | 238.7315    | 159.4043    | 129.3618    | 119.9695    |
| 17   | 1480        | 150.9007    | 135.0000    | 240.7998    | 242.3687    | 242.1751    | 159.6100    | 129.7144    | 119.7307    |
| 18   | 1628        | 150.3632    | 174.5376    | 300.0000    | 292.3687    | 242.2373    | 159.9336    | 130.4308    | 119.2750    |
| 19   | 1776        | 217.4110    | 254.5376    | 300.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 20   | 1972        | 284.3186    | 334.5376    | 340.0000    | 300.0000    | 243.0000    | 160.0000    | 130.0000    | 120.0000    |
| 21   | 1924        | 259.9202    | 309.6601    | 340.0000    | 300.0000    | 243.0000    | 159.2709    | 129.8075    | 119.9798    |
| 22   | 1628        | 180.1857    | 229.9838    | 291.1958    | 250.6165    | 223.4006    | 159.0422    | 126.6683    | 120.0000    |
| 23   | 1332        | 150.2720    | 150.0578    | 211.4456    | 201.6378    | 174.2186    | 160.0000    | 130.0000    | 90.0000     |
| 24   | 1184        | 150.5086    | 135.0000    | 131.4456    | 167.0485    | 175.3310    | 110.0000    | 130.0000    | 120.0000    |

**Cost ($)**: 2472116.66

**Emission (ton)**: 330411.81
method [9] is employed to extract the optimal best compromise.

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 (2472116.665) and less than the cost obtained for the pure environmental dispatch (2594148.328). 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 (NGSII) in finding the optimum generation schedule for the DEEDP.

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

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 NSGII, and it was found that the proposed algorithm outperforms them.

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