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Optimized Reactive Power Distribution for Enhancing Power System Efficiency Using a Generalized Teaching-Learning-Based Optimization Algorithm

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ABSTRACT

Electrical energy generation in power systems aims to minimize the total production cost of active units within the power network, making it one of the most critical aspects of modern power systems. Optimal reactive power distribution is a key approach to ensuring the reliable and economical operation of power systems. The primary objective of reactive power distribution in power networks is to determine the control variables that minimize the objective function while adhering to system constraints. In this paper, a hybrid optimization algorithm is introduced, combining the Multi-Objective Teaching-Learning-Based Optimization (MTLBO) method with a fuzzy decision-making algorithm to solve the Reactive Power Dispatch (RPD) problem. The proposed method addresses multiple objectives, including reducing active power losses, improving voltage profiles, and enhancing network security. To assess the effectiveness of the proposed approach, simulations were performed on IEEE 57-bus and 118-bus test systems. The simulation results confirm the efficiency and superiority of the proposed method compared to conventional optimization techniques.

1. INTRODUCTION

With advancements in technology and economic conditions in power networks worldwide, as well as the transition of power systems toward competition and restructuring, the importance of ancillary services such as reactive power support, voltage control, and spinning reserves has received increasing attention. One of the critical factors influencing the security and economic operation of power systems is the optimal distribution of reactive power. While reactive power generation does not directly incur costs during operation, it significantly impacts overall system losses, thereby affecting total expenses. Reactive power management has become one of the most widely used strategies for ensuring the safe and efficient operation of power systems.

The primary objective of solving the Optimal Reactive Power Dispatch (ORPD) problem is to determine the optimal operating conditions of the power system and adjust control variables such as generator voltage set points,

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reactive power injections from shunt capacitors and reactors, and transformer tap settings. These adjustments aim to minimize total system losses while satisfying a set of physical and operational constraints. However, the continuous growth of electricity demand, which does not always align with generation expansion, may lead to voltage deviations beyond acceptable limits under heavy loading conditions, potentially resulting in voltage collapse. Therefore, in addition to minimizing transmission losses, improving voltage profiles and ensuring voltage stability should also be considered as objective functions in ORPD.

Since the ORPD problem is a nonlinear and nonconvex optimization challenge, there has been growing interest in applying stochastic search methods to solve such optimization problems. One of the widely used techniques is the Genetic Algorithm (GA), which begins with a randomly generated population of solutions and employs genetic operators based on the theory of evolutionary optimization to find an optimal solution. However, the primary drawbacks of GA include premature convergence and high computational complexity, which may cause the algorithm to converge to a local optimum rather than the global optimum, leading to prolonged execution times [1, 2]. Other metaheuristic approaches include Evolutionary Programming, Evolution Strategies [3], Ant Colony Optimization [4], and Particle Swarm Optimization (PSO) [5]. Among these, PSO is a population-based stochastic optimization algorithm that demonstrates faster convergence and robustness compared to many other techniques. Moreover, PSO is relatively simple to implement and requires fewer parameter adjustments. The application of PSO and its enhanced versions has been successfully demonstrated in solving power system problems, including economic load dispatch [6], power plant expansion planning [7], and optimal capacitor placement [8]. Additionally, a PSO variant with time-varying acceleration coefficients (TVAPSO) has been used for solving economic dispatch problems in combined heat and power systems [9].

In [10], the Seeker Optimization Algorithm (SOA) was applied to ORPD, a key aspect of secure and economic power system operation, where three objective functions active power loss reduction, voltage deviation improvement, and voltage stability enhancement were investigated separately and in a multi-objective framework. Furthermore, the Biogeography-Based Optimization (BBO) algorithm has been applied to ORPD [11], as well as the Gravitational Search Algorithm (GSA) [12, 13]. These approaches typically consider the ORPD problem as a single-objective optimization, simplifying implementation but failing to incorporate all operational constraints. Additionally, such methods lack robustness and may lead to system instability under abnormal operating conditions due to their simplified linear modeling. By contrast, modeling the system in a nonlinear framework can yield solutions closer to the global optimum.

To enhance results and better evaluate the ORPD problem, this study formulates ORPD as a multi-objective optimization problem, considering both transmission loss minimization and voltage deviation reduction (i.e., voltage profile improvement). The problem is optimized using a multi-objective Teaching-Learning-Based Optimization (MTLBO) algorithm, a recently developed metaheuristic method with efficient computational capabilities. The TLBO algorithm is inspired by the influence of a teacher on students' learning progress in a classroom. The standard TLBO consists of two phases: (1) the teacher phase and (2) the learner phase. However, in the modified MTLBO, a third phase is introduced. In this proposed framework, all objective functions and constraints are considered, and a fuzzy-based decision-making mechanism is used to determine an optimal trade-off solution among the generated Pareto-optimal solutions.

The remainder of this paper is structured as follows: Section 2 presents the theoretical background of the problem, Section 3 and Section 4 discuss the proposed solution methodology, and Section 5 presents simulation results and their evaluation.

2. PROPOSED PROBLEM MODELING

With the continuous rise in electricity consumption over the past several decades, power supply systems have expanded significantly. Consequently, optimal reactive power distribution has become one of the most complex and widely studied challenges in power system operation and planning. Ensuring the optimal allocation of reactive power among generating units at minimal cost is essential for enhancing power system efficiency and reliability. The mathematical formulation of the reactive power dispatch problem, considering both linear and nonlinear constraints, is defined as follows.

One of the primary objectives of optimal reactive power distribution is to minimize active power losses in the transmission network. In this study, active power loss minimization is considered as the primary objective function for the optimization problem. The total active power loss in the transmission network can be calculated as follows [7]:

$$f_1 = min(P_{Loss}) = min\left[\sum_{k=1}^{N_{TL}} G_k (V_i^2 + V_j^2 - 2V_i V_j \cos \alpha_{ij})\right] \quad (1)$$

Where P_{Loss} represents the total active power loss of the system, G_k is the conductance of the *k*-th branch between buses *i* and j, α_{ij} is the admittance angle of the transmission line connected between buses *i* and *j*, N_{TL} is the number of transmission lines, and V_i and V_j are the voltages at buses iii and *j*, respectively.

2.1. Voltage Profile Improvement

Bus voltage is a critical indicator of service quality and system security. Minimizing voltage deviation from the desired value is widely applied in power system operation. The objective of enhancing the voltage profile or minimizing voltage deviation at load buses can be mathematically expressed as follows:

$$TVD = \sum_{i \in N_L} \left| V_i - V_i^{ref} \right| \quad (2)$$

Where V_i represents the voltage at the i-th load bus, and V_i^{ref} is the desired voltage at the i-th load bus, which is typically 1 p.u.

2.2. Problem Constraints

The optimal reactive power dispatch (ORPD) problem is subject to a set of constraints to ensure system feasibility and operational limits. These constraints can be categorized as equality and inequality constraints.

2.2.1. Equality Constraints

The equality constraints in this problem correspond to power flow equations, ensuring that the system adheres to power balance conditions. These equations are expressed as follows:

$$P_{G_i} - P_{D_i} - V_i \sum_{j-1}^{N_B} V_j \left[G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)\right] = 0; i = 1, \ldots\ldots, N_B \quad (3)$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j-1}^{N_B} V_j \left[G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)\right] = 0; i = 1, \ldots\ldots, N_B \quad (4)$$

Here, N_B represents the number of buses; G_{ij} is the real part of the admittance matrix, and B_{ij} is the imaginary part of the admittance matrix. P_{G_i} and Q_{G_i} denote the active and reactive power generated at the *i*-th bus, respectively, while P_{D_i} and Q_{D_i} represent the active and reactive power demand at the *i*-th bus.

2.2.2. Inequality Constraints

The inequality constraints are expressed as follows:

Generator Constraints:

$$\begin{aligned} &Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \quad ; \; i = 1, \ldots, N_G \\ &V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \quad ; \; i = 1, \ldots, N_G \end{aligned} \quad (5)$$

Transformer Constraints:
The tap settings of the transformer are defined by upper and lower limits, expressed as inequality constraints in the following form:

$$T_i^{\min} \le T_i \le T_i^{\max} \quad ; \; i = 1, \ldots, N_T \quad (6)$$

Constraints Related to Shunt Compensators:
For reactive power compensation, the constraints associated with shunt compensators are expressed through the following limitations as a relationship:

$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max} \qquad ; \ i = 1,\ldots,N_C \tag{7}$$

Security Constraints:
These include voltage limits at load buses and constraints related to transmission lines, which are expressed as follows:

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max} \qquad ; \ i = 1,\ldots,N_L \tag{8}$$

The constraints related to the power appearing in the i_{th} bus are expressed as follows:

$$|S_{L_i}| \le S_{L_i}^{max_{TL}} \tag{9}$$

Here, $V_{G_i}^{min}$ and $V_{G_i}^{max}$ represent the minimum and maximum generator voltage limits at the *i*-th bus, respectively. $Q_{C_i}^{min}$ and $Q_{C_i}^{max}$ denote the minimum and maximum reactive power injection limits of the *i*-th capacitor, respectively. $T_i^{min}$and T_i^{max} are the minimum and maximum tap settings of the *i*-th transmission line, respectively. Additionally, V_{Li}^{min} and V_{Li}^{max} represent the minimum and maximum voltage limits at the *i*-th load bus, respectively. $Q_{G_i}^{min}$ and $Q_{G_i}^{max}$ are the minimum and maximum reactive power generation limits of the generator at the *i*-th bus, respectively. Finally, S_{Li}^{max} represents the maximum apparent power flow limit at the *i*-th bus.

3. REVIEW OF THE TEACHING-LEARNING-BASED OPTIMIZATION (TLBO) ALGORITHM

The Teaching-Learning-Based Optimization (TLBO) method is a novel optimization algorithm with an efficient computational capability for handling demands. This method is based on the influence of a teacher on students in a classroom. The standard TLBO algorithm consists of two phases: (1) the teacher phase and (2) the learner phase. However, a third phase has been added to the modified TLBO (MTLBO) algorithm.

3.1. Teacher Phase

A teacher, as an intellectual individual, shares their knowledge and information with students in a classroom to help enhance and improve their productivity (i.e., their grades or ranks). The teacher has the ability to elevate the class average to their own academic level.

Let Mi and Ti represent the mean performance and the teacher in the i-th iteration, respectively. As mentioned, Ti attempts to elevate Mi to their own academic level. Thus, the teacher phase of the algorithm can be formulated as follows:

$$DM_i = rand_i \times (T_i \text{-} T_F M_i) \tag{10}$$

$$T_F = round(1 + rand(0,1)) \tag{11}$$

$$X_i^{new} = X_i^{old} + DM_i \tag{12}$$

In these equations, $rand_i$ is a random number between [0, 1], and T_F is the teaching factor that determines whether the average value should be modified. The new value x_i is acceptable only if its fitness function value is better than its previous value.

3.2. Learner Phase

Each learner interacts randomly with other learners to enhance their knowledge through group discussions, presentations, formal communication, and other methods. The process of this phase is described as follows:

1. Randomly select two values x_i and x_j such that $i \neq j$.
2. Based on their fitness function values, if $F(X_i) < F(X_j)$, then the new value for the learner is calculated as:
$X_i^{new} = rand_i \times (X_i - X_j)$ Otherwise, the new value is:
$X_i^{new} = rand_i \times (X_i - X_j)$3. If the fitness function value of the new variable X_i is better than its previous value, the replacement method can be applied.

3.3. Modified Phase

The interactions in the learner phase may lead to improper information exchange among students, potentially causing the method to get stuck at a local optimum. Therefore, a modified learning phase has been introduced to overcome this shortcoming. This approach employs a Self-Adaptive Wavelet Mutation (SAWM) strategy to enhance the performance of the original TLBO algorithm. SAWM accelerates convergence and prevents the algorithm from being trapped in a local minimum. By utilizing wavelet theory, the SAWM method dynamically adjusts the mutation space in alignment with the convergence process.

This technique is based on the principle that students always strive for progress and improvement (aiming to reach their teacher's level) while avoiding the worst choices. A mutation probability (PX) is assigned to each student, with values ranging between [0,1]. A random number is then generated between 0 and 1 and compared with PX. The mutation is executed if the generated random number is equal to or less than PX. The new position of the student can be computed as follows:

$$X_i^{New} = \begin{cases} X_i^{Old} + \omega \times (T_i - X_i^{Old}) \ if \omega > 0 \\ X_i^{Old} + \omega \times (W_i - X_i^{Old}) \ if \omega \leq 0 \end{cases} \tag{13}$$

Here, W_i represents the worst learner in each iteration. Again, if the fitness function value of the new variable X_i has improved, this new variable will be acceptable and will be used for subsequent iterations. The value of ω is calculated using the Morlet wavelet function as follows:

$$\omega = \frac{1}{\sqrt{h}} exp\left[-\left(\frac{1}{2}\right)\left(\frac{\varphi}{h}\right)^2 cos\left(\omega_c(\frac{\varphi}{h})\right)\right] \tag{14}$$

The central frequency of the wavelet is denoted by ω_c. Here, ω_c= 5 is chosen. Larger values of |ω| lead to greater changes in the oscillation. Moreover, a positive ω causes the student's oscillation towards the teacher to increase. In contrast, if ω is negative, the student's status becomes even worse than that of the worst student. Since 99% of the total energy of the wavelet function is located within the interval [2.5, -2.5], the parameter φ can be randomly selected within the interval [2.5h+, 2.5h-]. Initially, this algorithm uses a larger search space to find the best global answers. Subsequently, to improve the accuracy of the final answers, this search space will be narrowed around these answers. In this regard, the parameter (h) changes iteratively to reach an optimal value that is well-adjusted. At the beginning, a small value is chosen for it, which makes the value of $|\omega|$ sufficiently large to achieve a larger search space. Then, to create a smaller value for $|\omega|$ in each iteration, it is increased, leading to a smaller search space. As a result, h can be computed as follows:

$$h = exp[-ln(\eta) \times (1 - k/k\,max)^{\sigma} + ln(\eta)] \tag{15}$$

Here, k and k_{max} represent the current iteration and the total number of iterations, respectively. The upper limit and the shape of the ascending function h can be defined by $\eta$and σ, respectively. The value of σ significantly impacts the performance of the algorithm. To achieve the exploratory capabilities of the algorithm and enhance the accuracy of the final results, σ must be properly defined. To accomplish this, we initially select small values for σ and increment it iteratively as follows:

$$\sigma = \sigma_{min} + \left(\frac{\sigma min_{max}}{k_{max}} k\right) \tag{16}$$

In this equation, the upper and lower bounds of σ are defined as σ_{max} and σ_{min}, respectively. Figure 1 illustrates the flowchart of the satisfied equality constraints.

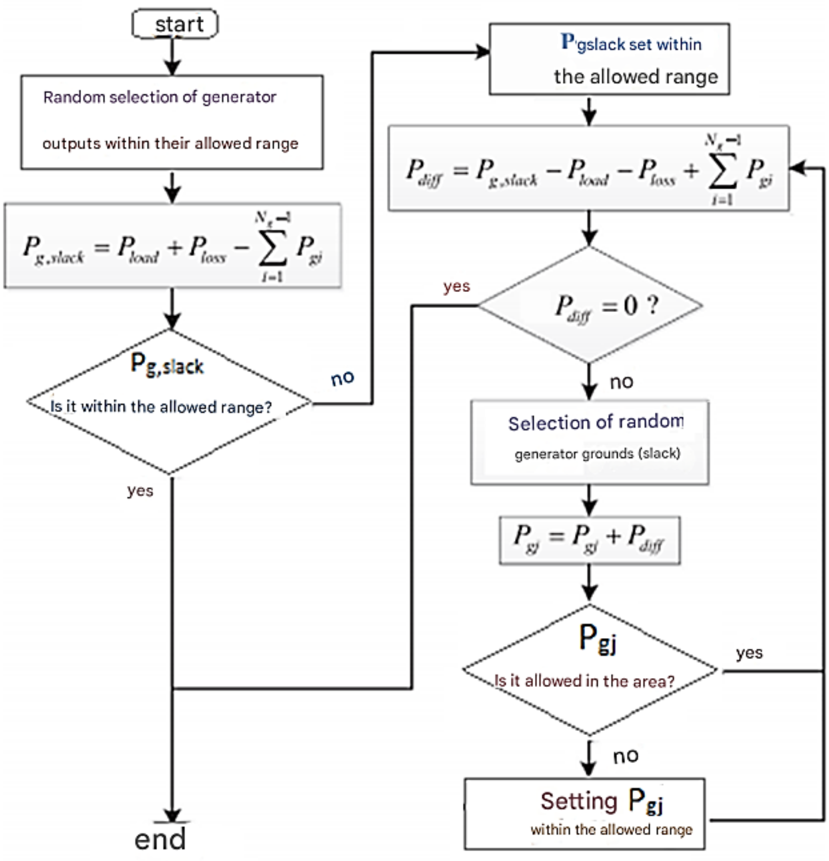

Fig. 1. Flowchart of Equality Constraints Satisfied

4. PRINCIPLES OF MULTI-OBJECTIVE PROBLEMS

The goal of solving a multi-objective optimization problem is to simultaneously optimize several different objectives that are not directly comparable. The algorithm presented for solving the Multi-Objective Problem (MOP) provides a set of dominant solutions known as the Pareto Optimal Front (POF), where, in general, no solution has priority over others. Let X_1 and X_2 represent two distinct solutions of the system. If the following conditions are met, X_1 will dominate X_2, and X_1 will be considered non-dominant.

$$\begin{cases} \forall i \in \{1,2,\dots,n\}, F_i(X_1) \le F_i(X_2) \\ \exists j \in \{1,2,\dots,n\}, F_j(X_1) < F_j(X_2) \end{cases} \tag{17}$$

where n represents the number of objective functions. Thus, the Pareto Optimal Front (POF) is obtained by mapping these non-dominated solutions into the objective space:

$$POF = \{F_1(X), F_2(X), \dots, F_n(X) | X \in S\} \tag{18}$$

where S is the set of non-dominant solutions obtained by the presented algorithm. Here, the capability of the MTLBO algorithm is used in searching the feasible space and solving the multi-objective optimization problem.

4.1. External Information Reservoir

The proposed MTLBO method uses an external information reservoir to store the non-dominant solutions obtained so far. In each iteration of the MTLBO algorithm, in addition to the optimization process, the solutions computed at each stage of the algorithm are compared with the values stored in the information reservoir. New non-dominant solutions are stored in the reservoir. Furthermore, the algorithm removes dominant solutions from the reservoir. The size of the reservoir for most optimization problems can be increased to a large value during the optimization process. It is clear that a large number of members in the information reservoir increases the computational load and can even cause memory limitations. Therefore, limiting the size of the reservoir without losing the properties and quality of the Pareto Optimal Front (POF) is essential and important. Here, a reservoir of fixed size is used, and new solutions are added to the reservoir if they meet the following conditions:

- The reservoir is empty.
- The new solution dominates one of the solutions in the information reservoir.
- The reservoir is not full, but the new solution does not dominate any of the solutions in the reservoir.
- The reservoir is full, the new solution does not dominate any of the solutions in the reservoir, and the position of this solution relative to at least one of the existing members in the reservoir lies in the low-density region of the POF.

4.2. Fuzzy Decision-Making Method

4.2.1. Fuzzy Clustering

Whenever the capacity of the reservoir is full, a fuzzy decision-making strategy is used to determine when a new non-dominant solution should replace one of the existing members in the reservoir. Since, from the expert's perspective, the objective functions exhibit conflicting behaviors, a decision-making mechanism can define its settings for the respective objectives in a fuzzy set to obtain a Pareto optimal solution. In a multi-objective problem, a fuzzy membership function will be assigned to each objective. For solutions with better fitness values, a higher degree of membership in the fuzzy membership function will be assigned, and vice versa. Suppose that the *i*-th objective function, $F_i(X)$, has upper and lower bounds denoted by F_i^{min} and F_i^{min}, respectively. These boundary values are determined considering only this particular objective function. In other words, the other objective functions of the MO-OPF problem will not be taken into account when determining these bounds. The fuzzy membership function, $F_i(X)$, can then be expressed as follows:

$$\mu_i(X)=\begin{cases} 1 & ,F_i(X)\le F_i^{\min} \\ \dfrac{F_i^{\max}-F_i(X)}{F_i^{\max}-F_i^{\min}} & ,F_i^{\min}\le F_i(X)\le F_i^{\max} \\ 0 & ,F_i(X)\ge F_i^{\max} \end{cases} \tag{19}$$

In the proposed MO-OPF problem, the resulting Pareto Optimal Front (POF) is quite large. Therefore, each member of the reservoir generates a cluster with a certain radius. Adjacent clusters are merged until the required reservoir size is determined. During the merging process, the member with the higher membership degree is selected for storage in the reservoir. The entire clustering process based on fuzzy logic is shown in Figure 3. Note that in this flowchart, S represents the number of non-dominant solutions, N_{max} is the maximum reservoir size, and N_i and N_j are the number of solutions in clusters C_i and C_j, respectively. The function that calculates the distance between solutions X and Y is denoted as d(x, y).

4.2.2. 4-2-2. Best Compromise Solution

To find the best solution among the final members of the information reservoir, the fuzzy membership functions for all objectives are extracted separately, and the fuzzy solutions are computed as follows:

$$F(X) = min[\mu_1(X), \ldots, \mu_n(X)] \tag{20}$$

where n is the number of objective functions. The best compromise solution is the one that provides the maximum value of F(X) among all other values.

4.3. Teacher Selection in the MTLBO Method

As mentioned earlier, the teacher in the TLBO algorithm is the individual whose fitness function is better than all other students. Therefore, a fuzzy decision-making process must be applied to find the best solution, and thus, in each iteration, a teacher corresponding to the obtained solutions will be determined. To accomplish this, a decision-making function is considered as follows:

$$\mu^k = \frac{\sum_{i=1}^{n} \sigma_i \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{n} \sigma_i \mu_i^k} \tag{21}$$

Here, M represents the number of non-dominant solutions (the number of Pareto optimal solutions), and μ^k is the membership function value of the k-th non-dominant solution. The Pareto optimal solution that results in the maximum membership function value μ^k is then selected as the teacher for the next iteration. Note that σ_i is the weighting factor for the i-th objective function, which can be determined based on the expert's experience or using trial and error. It is evident that the relationship $\sum_{i=1}^{n} \sigma_i = 1$ holds.

4.4. Intelligent Population

As mentioned earlier, MO-OPF is a nonlinear, non-convex, non-smooth, and high-dimensional optimization problem. Therefore, finding a Pareto Optimal Front (POF) with a uniform distribution to solve this problem is very challenging. Here, based on the solutions obtained in previous iterations, a heuristic method for selecting the population is proposed. This approach consists of two phases.

Phase 1: When the reservoir is not full, MTLBO finds new non-dominant solutions. These non-dominant elements in subsequent iterations can stimulate the students to search for Pareto optimal solutions by adopting the MTLBO method. Therefore, the population is stored and defined as follows:

S0: the current members of the information reservoir;
S1: solutions that have been dominated once;
S2: solutions that have been dominated twice;
S3: solutions that have been dominated three times.

Thus, the population for the next iteration will be determined based on these prioritized sets, such that the members of the reservoir S0 are followed by sets S1, S2, and S3 until the maximum population size for the next iteration is reached.

Phase 2: Whenever the reservoir is full, the algorithm seeks to find solutions close to the optimal. To do this, R percent of the members of the reservoir are selected, and the remaining population will be randomly selected from the current population in the next iteration. This process enables the evolutionary algorithm to find global and near-optimal solutions in a non-convex, high-dimensional problem. The percentage R can be defined as follows:

$$\%R = \left(sin \frac{\pi(k_{amx} - k)}{p(k_{amx} - k_{rep.filled})} \right) \times 100 \tag{22}$$

where K, kmax, and krep represent the current iteration, the maximum number of iterations, and the iteration in which the reservoir is full, respectively. The constant value P determines the performance of R (from an almost linear function to an oscillatory function).

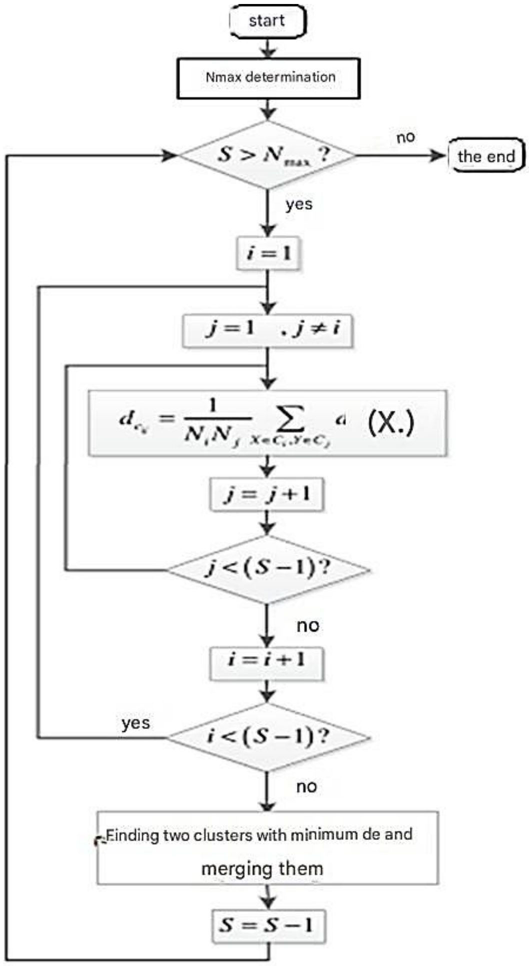

Fig. 3. Flowchart of Clustering Based on the Fuzzy Approach

5. SIMULATION RESULTS

The objective of this section is to evaluate the performance of the proposed MOTLBO approach on the IEEE 57-bus and 118-bus standard systems. For simulation purposes, MATLAB software version 2015 was used on a computer with a 2.2 GHz processor. Simulations were conducted under various scenarios with the systems under study. The results obtained are analyzed in the following section.

5.1. Results for the 57-Bus Standard Network

In this section, the ORPD problem is solved using the MOMTLBO algorithm, considering all the constraints of the problem on the IEEE 57-bus network, and the results are compared with other algorithms. This system consists of 7 generators, 80 transmission lines, 3 capacitor banks, and 15 power transformers. Table 1 shows the constraints of the decision variables in the ORPD problem.

Table 1. Range of Decision Variables Changes

Decision Variables	Lower Bound	Upper Bound
Generator Voltage (P.U)	0.94	1.06
Transformer Tap Setting (P.U)	0.9	1.1
Capacitor Banks (MVar)	0	20

Considering both objectives of the reactive power distribution problem, the solution results in a Pareto Front. This Pareto Front is shown in Figure 4. In multi-objective problems, since the decision variables for both objective functions are the same, any change in one variable affects both objective functions. As a result, each objective function moves toward the direction of its minimum value. In fact, in multi-objective problems, the players are different, and reducing one objective results in an increase in the other. Therefore, we can have a set of points for the two objective functions, and by plotting these points, we arrive at the Pareto Front. This Pareto Front is shown in Figure 4. According to this figure, the closer we move toward optimizing the loss function, the worse the voltage profile becomes, and the closer we move toward optimizing the voltage profile, the higher the losses. This demonstrates the true concept of multi-objective optimization. The key question now is: which solution on the Pareto Front is the best? At which point do both objective functions have the lowest values? To answer these questions, we focus on the point where the best solution is the one where both objective functions are satisfied. To obtain this solution, fuzzy logic is used. The best solution is presented in Table 2, and the results of this table are compared with other works. An important point in this comparison is that the reported works in Table 2 have adhered to the range of decision variable changes as shown in Table 1. Table 2 shows the results for loss reduction and voltage profile improvement for the 57-bus system. In this table, the results of other algorithms are compared with the best response of the proposed algorithm.

Table 2. Comparison of Results for Loss Reduction and Voltage Profile Improvement for the 57-Bus System

Methods	**MOMTLBO**		**PSO –ICA[14]**		**ICA**		**PSO**	
Objective Functions	**P_{Loss}**	**TVD**	**P_{Loss}**	**TVD**	**P_{Loss}**	**TVD**	**P_{Loss}**	**TVD**
V_{g1}	1.0600		1.0395	1.0099	1.06	1.06	1.0284	1.0290
V_{g2}	1.0442		1.0259	1.00301	1.0388	1.0414	1.0044	1.0129
V_{g3}	1.0189		1.0077	1.0073	1.0078	1.0169	0.9844	1.0123
V_{g6}	1.0009		0.9982	1.0044	0.9688	0.9956	0.9872	1.0079
V_{g8}	1.0214		1.0158	1.047	0.9715	0.9915	1.0262	1.0366
V_{g9}	0.9984		0.985	1.0145	0.9556	0.9670	0.9834	1.0059
V_{g12}	1.0182		0.9966	1.0336	0.9891	0.9935	0.9844	1.0286
Q_{C-18}	4.0359		9.9846	0	0	0	9	6.9827
Q_{C-25}	16.0795		10	10	10	10	7.0185	8.6683
Q_{C-53}	17.6210		10	0	9.5956	10	5.0387	4.8687
T_{4-18}	1.0745		0.9265	1.0438	0.9584	0.9100	0.9743	0.9743
T_{4-18}	0.9067		0.9532	0.9338	0.9309	1.0291	0.9716	0.9610
T_{21-20}	0.9873		1.0165	0.9732	1.0269	0.9801	1.0286	0.9963
T_{24-26}	1.0017		1.0071	1.1	1.0085	1.0134	1.0183	1.0251
T_{7-29}	0.9856		0.9414	0.9490	0.9	0.9622	0.9401	0.9602
T_{34-32}	0.9403		0.9555	0.9344	0.9872	0.9170	0.94	0.9149
T_{11-41}	0.9017		0.9032	0.9	0.9097	0.9	0.9761	0.9155
T_{15-45}	0.9488		0.9356	0.9510	0.9377	0.9668	0.9211	0.9633
T_{14-46}	0.9679		0.9172	0.9910	0.9166	0.9	0.9165	0.9482
T_{10-51}	0.9783		0.9337	1.0164	0.9057	0.9748	0.9044	0.9566
T_{13-49}	0.9201		0.9	0.9	0.9	0.9	0.9118	0.9568
T_{11-43}	0.9506		0.9206	0.9606	0.9	0.9	0.92	0.9534
T_{40-56}	1.0121		1.0042	1.0211	0.9575	1.0262	0.9891	0.9653
T_{39-57}	0.9062		1.0297	0.9	1.0476	0.9	0.9430	1.0053
T_{9-55}	0.9786		0.9294	0.9808	0.9	0.9266	0.9998	0.9808
P_{Loss}	**25.3189**		**25.5856**	29.3169	**26.99968**	26.9373	**27.5543**	26.8937
TVD	**0.6681**		1.1548	**0.7130**	1.2846	**0.7952**	1.1379	**0.8007**

Based on Table 2, it is observed that the results obtained for both losses and voltage profile are better than those of other works. Since this algorithm is implemented as a multi-objective approach, it is natural that it may perform worse in at least one of its objective functions compared to other works, which are single-objective. However, this algorithm demonstrates its strength here, as the values obtained for both objectives are better than all previous single-objective works.

On the other hand, considering that the base losses of the 57-bus network are 27.864 MW, the proposed multi-objective algorithm reduces losses by 9.134%, whereas the ICA, PSO, and PSO-ICA hybrid algorithms reduce losses by 3.1%, 1.11%, and 8.18%, respectively.

Similar analyses can be performed for the voltage profile. Since the base TVD of the 57-bus network is 1.2334, the proposed multi-objective algorithm improves the voltage profile by 45.83%, which is the highest among the other algorithms, based on the results reported in Table 2.

Figure 4 shows the performance graph of the objective function indices, i.e., loss reduction and voltage profile improvement, using the proposed algorithm. One key takeaway from this figure is that the proposed algorithm has a high convergence speed and has been able to achieve the optimal solution. It should be noted that adhering to constraints is a fundamental principle in optimization problems. In this paper, an effort has been made to implement the constraints correctly using a penalty coefficient method. Figure 5 shows the voltage profile. As shown in this figure, it is clear that the voltage at all buses is within the permissible range.

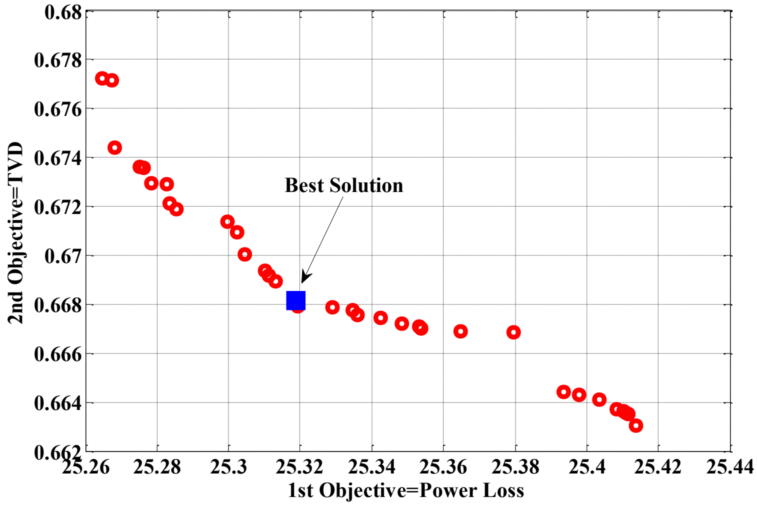

Fig. 4. Performance of the Proposed Algorithm for the Objective Functions of Loss Reduction and Voltage Profile Improvement in the 57-Bus Network

The results presented in Table 2 indicate that the algorithms have achieved near-optimal results in improving the voltage profile. This implies that they are close to the global optimal point. Despite the algorithms being close to the global optimal point, the proposed MOMTLBO algorithm has reached a better solution compared to other algorithms. As discussed in the previous section, after performing the optimization and reducing the objective function related to voltage profile improvement, Figure 5 is obtained. Considering that the best voltage profile corresponds to a flat voltage profile (ideal state), meaning the closer the network voltage profile is to a flat profile, the better it is. Therefore, Figure 5 completely shows the improvement in the voltage profile, i.e., after optimization, the voltage profile has approached the flat state.

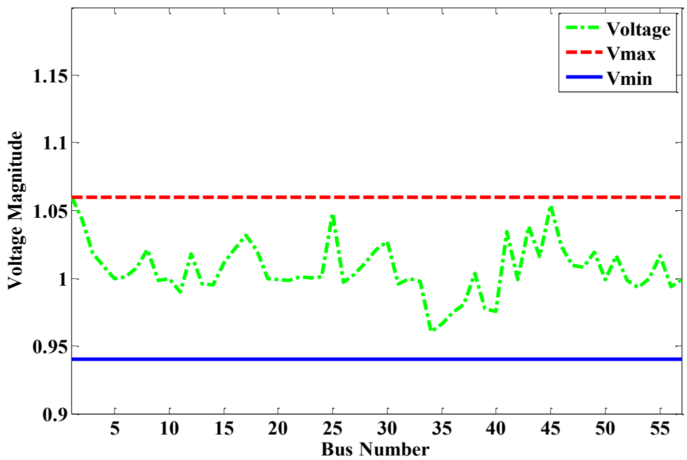

Fig. 5. Improved Voltage Profile of the IEEE 57-Bus Network

5.2. Results for the 118-Bus Standard Network

In this section, the ORPD problem with the MOMTLBO algorithm, considering all the constraints of the problem, is applied to the IEEE 118-bus network, and the results are compared with other algorithms. Given that the physical dimensions of the system increase in this section, it serves as a suitable test system for evaluating the performance of the proposed algorithm. Table 3 presents the constraints of the ORPD problem, which include generator voltages, transformer taps, and the capacity of capacitor banks and parallel reactors.

Table 2. Decision Variables Range of Variation

Upper Limit	Lower Limit	Decision Variables
1.06	0.94	**Generator Voltage (P.U)**
1.1	0.9	**Transformer Tap Setting (P.U)**
	Capacitor Banks (MVar)	
0	-40	Q_{C5}
14	0	Q_{C34}
0	-15	Q_{C37}
10	0	Q_{C44}
10	0	Q_{C45}
10	0	Q_{C46}
10	0	Q_{C48}
12	0	Q_{C74}
20	0	Q_{C79}
20	0	Q_{C82}
10	0	Q_{C83}
20	0	Q_{C105}
6	0	Q_{C107}
6	0	Q_{C110}

Similar to the IEEE 57-Bus Network, by considering both objectives of the optimal reactive power distribution problem and solving it as a multi-objective Pareto front for the IEEE 118-Bus Network, the result shown in Figure 6 is obtained. According to this figure, as we move towards optimizing the loss function, the voltage profile function deteriorates, and as we move towards optimizing the voltage profile function, the losses increase. This, in fact, illustrates the true concept of multi-objective optimization. Similar to the IEEE 57-Bus Network, to obtain the optimal solution point for both objectives—i.e., a point where both objectives are satisfied—we use fuzzy logic. The best solution is presented in Table 4. Unfortunately, previous studies did not use the correct range of variation for the capacitor banks, as presented in Table 3, so comparisons with those methods are not feasible. For example, in reference [15], the range of variation for the capacitor banks, according to the reported results, does not match the variation range in Table 3, and therefore, the results are not comparable.

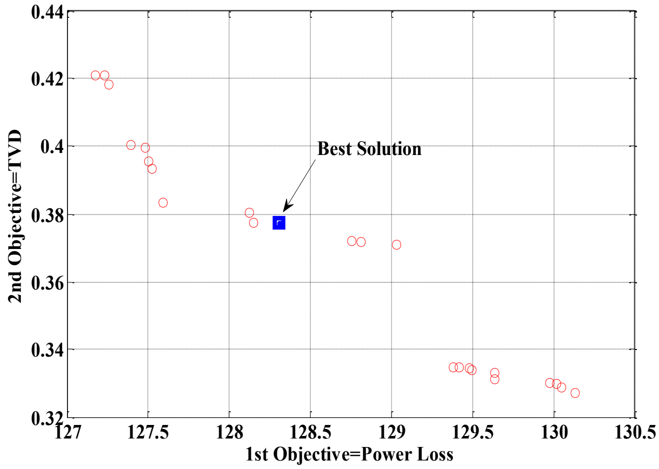

Fig. 6. Pareto Front of the 118-Bus Network with Loss and Voltage Profile Objectives

As shown in Figure 7, it is clear that the voltage at all buses remains within the allowable range. According to the principles studied in power systems analysis, a flat voltage profile is considered the ideal voltage profile. In this figure, the bus voltages have been optimized to approach the flat profile more closely.

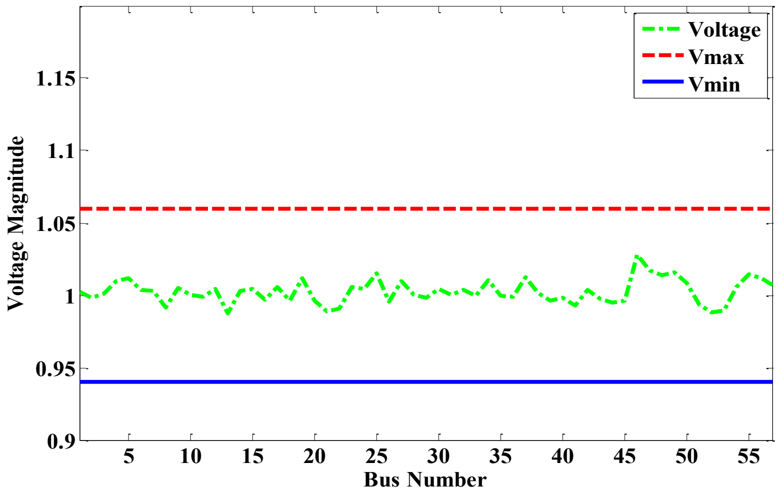

Fig. 7. Improved Voltage Profile of the 118-Bus Network

Table 4 presents the results for the reduction in losses for the 118-bus network. Given that the base loss for the 118-bus network is 132.863 MW, the proposed multi-objective algorithm reduces the losses by 3.4308%. Similar analysis can be performed for the voltage profile. With the base TVD of the 118-bus network being 1.43934, the proposed multi-objective algorithm improves the voltage profile by 73.79%.

Table 4. Results for Loss Reduction and Voltage Profile Improvement for the 118-Bus System

Variables	MOMTLBO	Variables	MOMTLBO
Voltage Generators (in pu)		V_{91} , pu	0.9960
V_{1} , pu	1.0023	V_{92} , pu	1.0147
V_{4} , pu	1.0095	V_{99} , pu	1.0015
V_{6} , pu	1.0034	V_{100} , pu	1.0148
V_{8} , pu	0.9917	V_{103} , pu	1.0075
V_{10} , pu	1.0001	V_{104} , pu	0.9950
V_{12} , pu	1.0043	V_{105} , pu	0.9978
V_{15} , pu	1.0046	V_{107} , pu	0.9985
V_{18} , pu	0.9966	V_{110} , pu	1.0046
V_{19} , pu	1.0120	V_{111} , pu	1.0060
V_{24} , pu	1.0044	V_{112} , pu	0.9970
V_{25} , pu	1.0151	V_{113} , pu	1.0006
V_{26} , pu	0.9955	V_{116} , pu	0.9937
V_{27} , pu	1.0098	**Capacitor Banks (in MVar)**	
V_{31} , pu	1.0002	**Q_{C-5}**	-40.0000
V_{32} , pu	1.0038	**Q_{C-34}**	6.1010
V_{34} , pu	1.0107	**Q_{C-37}**	-8.3955
V_{36} , pu	0.9989	**Q_{C-44}**	6.0928
V_{40} , pu	0.9982	**Q_{C-45}**	9.3327
V_{42} , pu	1.0034	**Q_{C-46}**	4.6875
V_{46} , pu	1.0281	**Q_{C-48}**	3.7796
V_{49} , pu	1.0161	**Q_{C-74}**	3.6439
V_{54} , pu	1.0060	**Q_{C-79}**	8.9015
V_{55} , pu	1.0144	**Q_{C-82}**	10.4861
V_{56} , pu	1.0115	**Q_{C-83}**	6.8716
V_{59} , pu	1.0073	**Q_{C-105}**	9.4702
V_{61} , pu	1.0068	**Q_{C-107}**	1.9253
V_{62} , pu	1.0003	**Q_{C-110}**	3.3230
V_{65} , pu	1.0004	**Transformer Tap Settings**	
V_{66} , pu	1.0136	**T_{8}**	0.9665
V_{69} , pu	1.0279	**T_{32}**	1.0012
V_{70} , pu	1.0077	**T_{36}**	0.9990
V_{72} , pu	0.9999	**T_{51}**	0.9809
V_{73} , pu	1.0007	**T_{93}**	1.0090
V_{74} , pu	0.9942	**T_{95}**	0.9795
V_{76} , pu	0.9954	**T_{102}**	0.9963
V_{77} , pu	1.0007	**T_{107}**	0.9855
V_{80} , pu	1.0151	**T_{127}**	0.9950
V_{85} , pu	1.0047	**$P_{Loos\ MW}$**	**128.3047**
V_{87} , pu	1.0164	**TVD, pu**	**0.3773**
V_{89} , pu	1.0302		
V_{90} , pu	1.0027		

6. CONCLUSION

This paper addresses the problem of optimal reactive power distribution in the studied 57-bus and 118-bus IEEE networks. The goal is to identify control variables in order to minimize objective functions such as active power losses, improve voltage profiles, and enhance network security, while considering the system's equality and inequality constraints. The problem is evaluated and analyzed using a multi-objective optimization algorithm based on generalized teaching-learning-based optimization (MTLBO) and a fuzzy decision-making algorithm. For a better comparison of the proposed method with other optimization methods, the algorithm has been executed multiple times, and the results were examined. In terms of optimization quality, this approach has outperformed the PSO and

ICA algorithms. Furthermore, by analyzing the responses of the algorithms across several execution iterations with different initial populations, it was found that the proposed method is more efficient in solving the problem.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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