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COMPARATIVE ANALYSIS OF A METAHEURISTIC OPTIMIZER APPROACH FOR THE SOLUTION OF OPTIMAL POWER FLOW PROBLEM

Shweta Singh, Rajnish Bhasker*

Electrical Engineering Department, Uma Nath Singh Institute of Engineering and Technology, VBSPU, Jaunpur, UP, India

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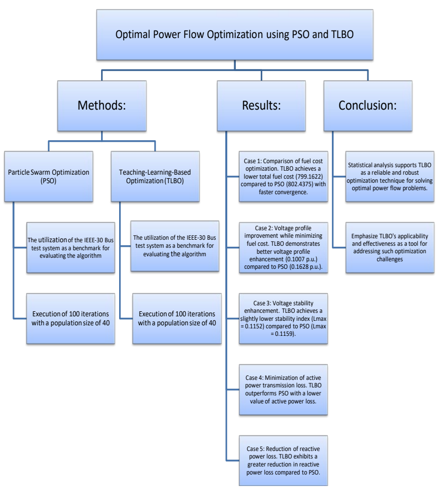
*Corresponding author
rbhasker@vbspu.ac.in

Graphical abstract



Abstract

This work uses population-based particle swarm optimization (PSO) and teaching-learning- based optimization (TLBO) methodologies to solve the optimal power flow problem, and the outcomes of both methods are contrasted. One issue that needs to be addressed in power systems is financial loss. Appropriate scheduling of energy produced by different generation sources in the power network is necessary to address the aforementioned issue. This paper formulates an optimal power flow (OPF) issue and solves it to find the optimal values for the control variables. In this case study, five objective functions are developed for five distinct scenarios to verify the effectiveness of the proposed methodology in MATLAB application. The five objectives are as follows: minimizing fuel costs, improving voltage profiles, reducing active and reactive power losses on transmission lines, and improving voltage stability. The fitness function is considered as a single-objective function based on the control parameters. In order to assess the applicability of the proposed method, it has been used to the IEEE 30 bus test system to investigate the performance of the power system for certain objective functions. According to results from PSO and TLBO optimization techniques as well as results from the techniques mentioned in the literature, the Teaching-Learning-Based Optimization technique offers an effective and dependable solution when tackling the optimal power flow problem with a variety of complexities. To demonstrate how rapidly the offered technique may converge to optimal and useful global solutions and how it can handle the problem's various complexities, the achieved optimal solutions are contrasted.

Keywords: Optimal Power Flow, Teaching-Learning Based Optimization, Particle Swarm Optimization, IEEE-30 bus test system.

1.0 INTRODUCTION

Nowadays, a number of electric firms are continuously working to schedule generation and achieve a suitable operating state in order to gain the best cost of generation possible while still maintaining security constraints.

The optimal power flow (OPF) problem subject to various limitations plays a significant role in optimization techniques [1] for obtaining optimal value, adjusting various control parameters, and changing various power system operations. Many traditional strategies were used in the past to tackle various optimal power flow issues that were bound by a variety of inequality and equality constraints [2]. The dependent and decision variables within the stated boundaries are analyzed under inequality constraints, while power flow equations or different balancing equations are taken into account under equality requirements [3].

To identify the best solutions on the basis of technological and economic concerns, numerous single-objective and multiple-objective optimum power flow techniques have been used. [1], [2]. To deal with the solutions of optimal power flow formulation, so many traditional and recent optimization techniques are developed[3]. In earlier days, many deterministic optimization techniques[4], [5] were in use, some of the most popular techniques are: simplex method, gradient-based method, quadratic-programming method, interior-point method. The most popular traditional optimization techniques[6], [7], [8] for solving optimal power flow problem are surveyed in paper. Although certain commonly used conventional optimization approaches have some drawbacks, they are still in use due to their successful convergence. The limitations of deterministic optimization techniques such as continuity, differentiability, and convexity include their inability to ensure global optimality and their propensity to become locked in local optimal solutions.[9], [10], [11], and they are not able to perform on integer and binary variables readily, as they are developed with. On the other hand, there are some recently developed metaheuristic optimization techniques which are in use now-a-days[12], [13], [14], [15]. Some of them are as follows: Ant Colony Optimization[16], [17], Artificial Bee Colony Optimization[18], [19], Differential Evolution, Genetic Algorithm, Particle Swarm Optimization, Teaching Learning Based Optimization, Black-hole optimization algorithm and so on. These methods are well-known for their capacity to identify global solutions as well as their ability to prevent the local optima from capturing ideal solutions. [20]. The metaheuristic optimization techniques are able to quickly search through enormous solution spaces and are also capable of taking into account uncertainty in various power system components.[21]

Now days, the concerned area of research in science and engineering is global optimization[22], [23]. By using global optimization problems various real-world optimization problems can be formulated[24], [25]. Various robust and efficient optimization algorithms are required to solve the global optimization problems efficiently[26], [27]. In the past two decades, a number of well-known metaheuristic optimization strategies have been developed to help solve global optimization problems and avoid the challenges that conventional approaches presented.[28] Particle swarm optimization and instructional learning-based optimization play essential roles in defining the answer of the global optimization issue, among other metaheuristic optimization strategies. The conventional particle swarm optimization approach, however, might become stuck in local optima while attempting to solve complex issues.[29], [30]. Lack of velocity control is a challenge in particle swarm optimization. Given that the PSO algorithm technique is widely used to solve optimization problems, its main disadvantage is the requirement for determining a large number of parameters, which frequently compromises the algorithm's effectiveness.[30], [31], [32] (i.e., more than two parameters) are required to learn about individual updates in process. For instance, three parameters (c1, c2, and w) must be determined in order to update the PSO equation. Since it is challenging to achieve the ideal algorithmic procedure settings. So, a recently proposed technique called TLBO is employed to lessen the impact of the programme's parameters. [33], [34]. The findings reported in the results obtained below shows that the TLBO algorithm has superior convergence properties to PSO. Based on the statistical analysis results, it can be said that the TLBO algorithm is a trustworthy and dependable optimization tool for resolving issues with optimal power flow.[35], [36] Therefore, it can be concluded that the TLBO approach is an excellent instrument for solving the optimal power flow problem based on its applicability and operation.

The portions of the paper are as follows: The mathematical formulation of the ideal power flow is described in the first section. The PSO (Particle Swarm Optimization) and TLBO (Teaching Learning Based Optimization) strategies are discussed in the following section. The OPF (Optimal Power Flow) problem is then solved using the proposed PSO and TLBO optimization approach. A comparison of the PSO and TLBO outcomes is then made using five cases and five objective functions. The paper is ended with a few comments and notes in the final portion.

2.0 METHODOLOGY

2.1 Optimal Power Flow Formulation

In this case study, five objectives are created for five cases in order to assess the efficacy of the suggested strategy. An electrical power network's fuel cost F can be described as follows:

$$F_a = \sum_{i=1}^{n_g} F$$

where ng is the number of units that produce power. As seen below, the i-th generating unit's fuel cost is:

$$F = a_i + b_i P_{g_i} + c_i P_{g_i}{}^2$$

where, fuel price coefficients are represented by a_i , b_i and. c_i . The active power generated by i_{th} generating unit is represented as P_{g_i}

In order to reduce objective functions like fuel cost, voltage deviation, and active power loss, among others, it is important to carry out optimal tuning of the demand and load management variables.

An illustration of how on-line constrained optimization is used to formulate the optimal power flow problem is shown below:

Objective function:

Minimize J(x,u)……………………..(1)

Equality constraints:

subjected to g (x,u)=0……………(2)

where, u is control or independent variables, x is state or dependent variables

Real power constraints:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{n_b} V_i \left[G_{ij} \cos(\theta_{ij}) + B_{ij} \sin \theta_{ij}) \right] = 0$$

………..(3)

Reactive power constraints:

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{n_b} V_i \left[G_{ij} \cos(\theta_{ij}) + B_{ij} \sin \theta_{ij}) \right] = 0$$

…………….(4)

where, active power generated is represented by P_g , reactive power generated is represented by Q_g , P_d represents demand of active load, Q_d represents demand reactive load, susceptance and conductance between bus i and j is represented by B_{ij} and G_{ij} respectively.

- **Inequality constraints:** These constraints are restricted by their specified upper and lower limits.

(a) Generator constraints:

$$V_{gi}^{\min} \le V_{gi} \le V_{gi}^{\max} \quad \text{i=1.......... } n_g \quad \text{..........(5)}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad \text{i=1........ } n_g \quad \text{.............(6)}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad \text{i=1........... } n_g \quad \text{............(7)}$$

(b) Transformer Constraints:

$$T^{\min} \le T \le T^{\max} \quad \text{i=1............nT} \quad \text{.........(8)}$$

(c) Security Constraints:

$$V_{li}^{\min} \le V \le V_{li}^{\max} \quad \text{i=1.........nl} \quad \text{.......(9)}$$

$$S_{li}^{\min} \le S \le S_{li}^{\max} \quad \text{i=1........nl} \quad \text{............(10)}$$

(d) Shunt reactive power compensator constraints:

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \quad \text{i=1......nc} \quad \text{............(11)}$$

- **Control variables:** These are the variables that can be altered without having an impact on the load flow equations that are satisfied. The following are the controlled parameters: Except for slack-bus, active power generated at PV buses (P_g), voltage generated at PV buses (V_g), tap settings for the transformer (T), and shunt reactive power compensation (Q_c). Therefore, u can be written as:

$$u^T = [P_{g2}, \ldots P_{gng}, V_{g1} \ldots V_{gng}, Q_{c1} \ldots Q_{cnc}, T_1 \ldots\ldots T_{NT}] \quad \text{.......(13)}$$

- **State variables:** These are the parameters that show the system's non-identical condition. All generator reactive power output (Q_g), Slackbus active power output (P_{g1}), voltage magnitude at the load or PQ bus (V_l), and transmission line loading (S_l).

  Thus, x can be illustrated as follows:

$$x^T = [P_{g1}, V_{l1} \ldots V_{\ln 1}, Q_{g1} \ldots Q_{gng}, S_{l1} \ldots S_{\ln l}] \quad \text{.......(14)}$$

2.2 Particle Swarm Optimization

PSO is an optimization approach used to obtain the best value and solve the mathematical formulation of the optimal power flow problem. The PSO equation is used to find the overall best solution for particle motion in the search space. The proposed (PSO) algorithm's flowchart and parameters are shown in Figure 1 below and Table 1, respectively.

The two equations p_{best} and g_{best} are represented by the particle swarm optimization technique. Position and velocity are updated after each iteration.

Table 1 Parameters of the Proposed (PSO) algorithm

1.Population Size	40
2.Inertia weight, w	0.1618
3. Social acceleration, c1	1.8903
4.Social acceleration, c2	2.1225
5.No of iterations	100

Implementation of PSO for Optimization

This section provides a step-by-step explanation on how to implement PSO:

- To discover the best solution, the technique starts with a population of random solutions or particles and updates generations. Each particle has three properties: a current velocity, a personal best position in search space, and a position in search space at the moment.
- The two best values from each iteration are applied to each particle. The first is the particle's "personal best position," or the spot in the search space where it has so far discovered the best solution. The second is the place that produces the best response out of all, which is known as the global best solution. Regular changes are made to the values of p_{best} and g_{best}..
- Each particle modifies its velocity and present position after determining the two optimal values. The particle's velocity is modified in accordance with both its own and its partners' prior-best positions. The particle's current position and its new velocity are combined to determine its subsequent position.

$$V_i(t+1) = wv_i(t) + c_1r_1(p_{best}(t) - x_i(t)) + c_2r_2(g_{best}(t) - x_i(t)) \quad \text{.........(15)}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad \text{.......(16)}$$

where, w = inertia weight and its value is -0.1618

c_1, c_2 = social acceleration and their values are 1.8903 and 2.1225 respectively.

r_1, r_2 = random numbers uniformly distributed in the range (0, 1).

• The acceleration coefficients regulate how far a particle travels throughout an iteration. The convergence behavior of PSO is controlled by the inertia weight. The inertia weight was once assumed to have a constant value. The inertia weight should be initially set to a higher amount and then gradually reduced to provide more refined solutions, according to testing results.

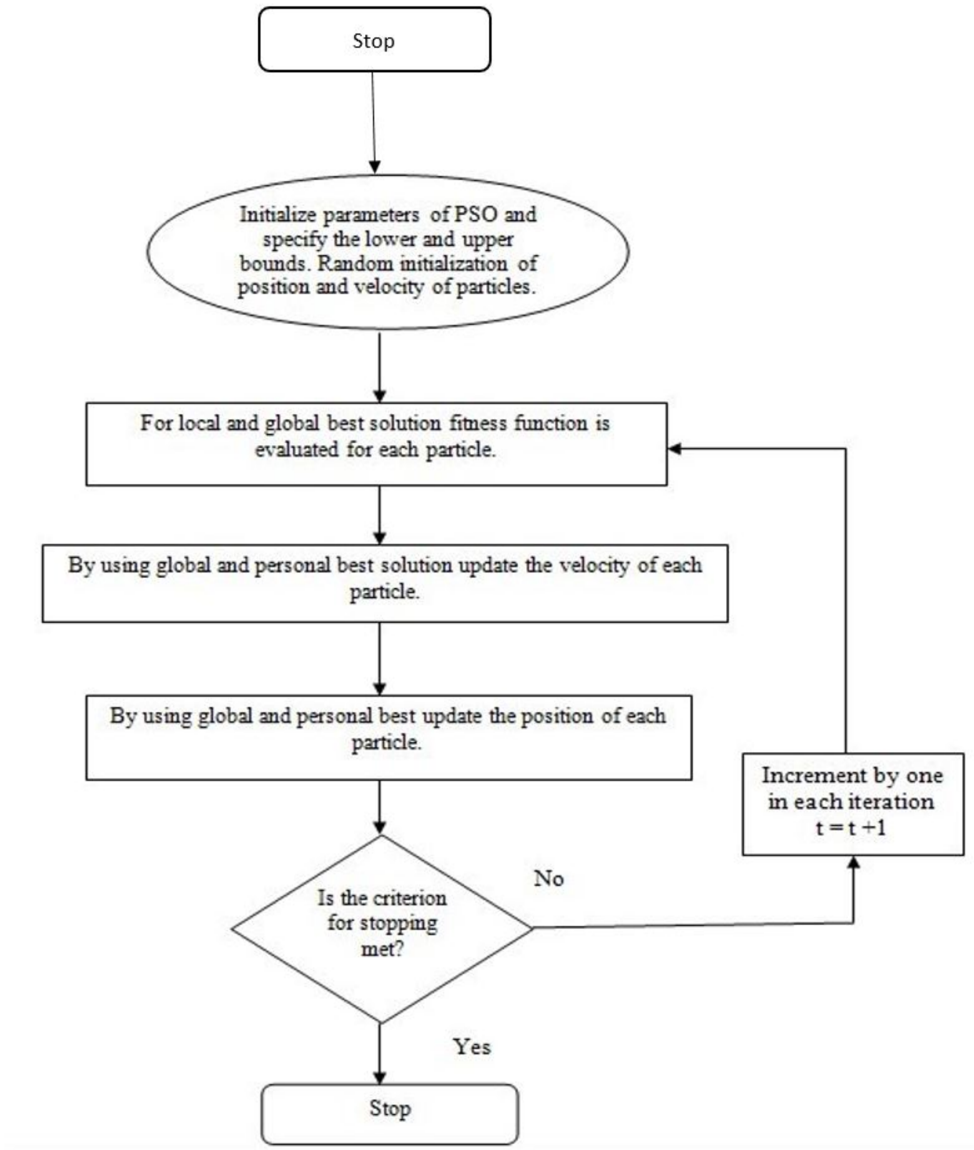


Figure 1 Flow chart of Proposed (PSO) algorithm

2.3 Teaching-Learning Based Optimization

Rao and colleagues created Teaching Learning Based, a metaheuristic optimization technique with fewer parameters that draws inspiration from nature. This methodology does not function with specified parameters, in contrast to other algorithm methods. Only a few control factors, such the number of generations and population size, are needed for it to operate. Similar to other population-based optimization techniques, it also makes use of a set of solutions to determine the ideal value of the answer.[33], [37]. This method uses the population as the learner's class, the designed parameters as the learner's subject, and the fitness function as the learner's output. In this case, the teacher is thought to be the best option. Therefore, it is clear that this method affects both how students and teachers interact with one another in the classroom. Unlike other optimization techniques, it also begins with initialization, where candidates' solutions are used to populate a randomly generated population. Each candidate's solution is kept in the problem's search space with a specific population size, and each size is constrained by specific lower and upper bounds. Additionally, the full TLBO approach is divided into two stages: The two stages are the teacher and student phases.[38]. The flow chart of proposed (TLBO) algorithm is shown in below Figure 2

For TLBO to operate, only the common control parameters—such as population size and generation number—must be present. These common control parameters are also necessary for all population-based optimization algorithms.[39], [40]. As a result, TLBO is referred to as an algorithm-specific parameter-less algorithm

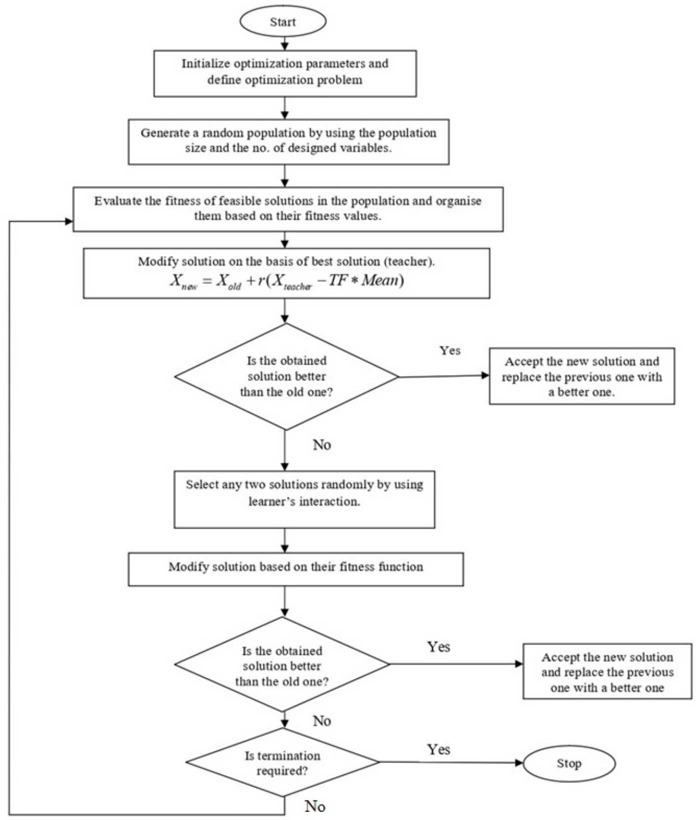


Figure 2 Flow chart of proposed (TLBO) algorithm

Implementation of TLBO for Optimization

This section explains how to implement TLBO in a step-by-step manner:
Step1: Initialization and define optimization problem
Set up the optimization parameters, including:

Limits on the following factors: population size (number of learners or students), iterations, parameters, and design variables.
Step 2: Population initiation
Create a random population using the size of the population and the number of design variables.

Step 3: Fitness function evaluation
Assess the population's fitness for workable solutions, then arrange the solutions according to the fitness levels.

Step 4: Teaching Phase
Modify the result by encouraging the idea of student learning through the teacher, i.e., change the result based on the best option (the teacher).

$$X_{new} = X_{old} + r(X_{teacher} - TF * Mean) \quad \text{………………(16)}$$

where r is a number selected at random between 0 and 1. Transfer function, or TF, is selected at random and might be either 1 or 2.
The term "mean" refers to the average of all class members.

Step 5: Phase of the Student
Change the result by encouraging the idea of kids learning through collaboration.

Step 6: Step 3 should be repeated up to a maximum number of iterations before the halting criteria are met.

Step 7: Termination criterion.

3.0 RESULTS AND DISCUSSION

The optimal power flow problem is benchmarked against the standard IEEE-30 Bus test system to assess the performance of the proposed PSO and TLBO algorithms. Both methods are used with a population size of 40 and for 100 iterations total.

3.1 IEEE-30 Bus Test System

To analyze the power system performance, this technique has been applied to IEEE 30 bus test system for various objective functions. Figure 3 represents single-line diagram of IEEE-30 bus network. The system has unit with 6 generators at the bus 1,2,5,8,11 and 13. System has four tap controllable transformers that are placed in between 6-9,6-10,4-12,27-28 transmission lines with voltage limits 0.9 to 1.1. Reactive Power Sources are installed at the load buses of 10,12,15,17,20,21,23,24 and 29 with limits of 0-5 and rating of MVAR. In addition to, the PV buses voltage magnitudes are in the range of 0.95-1.1 in per unit.

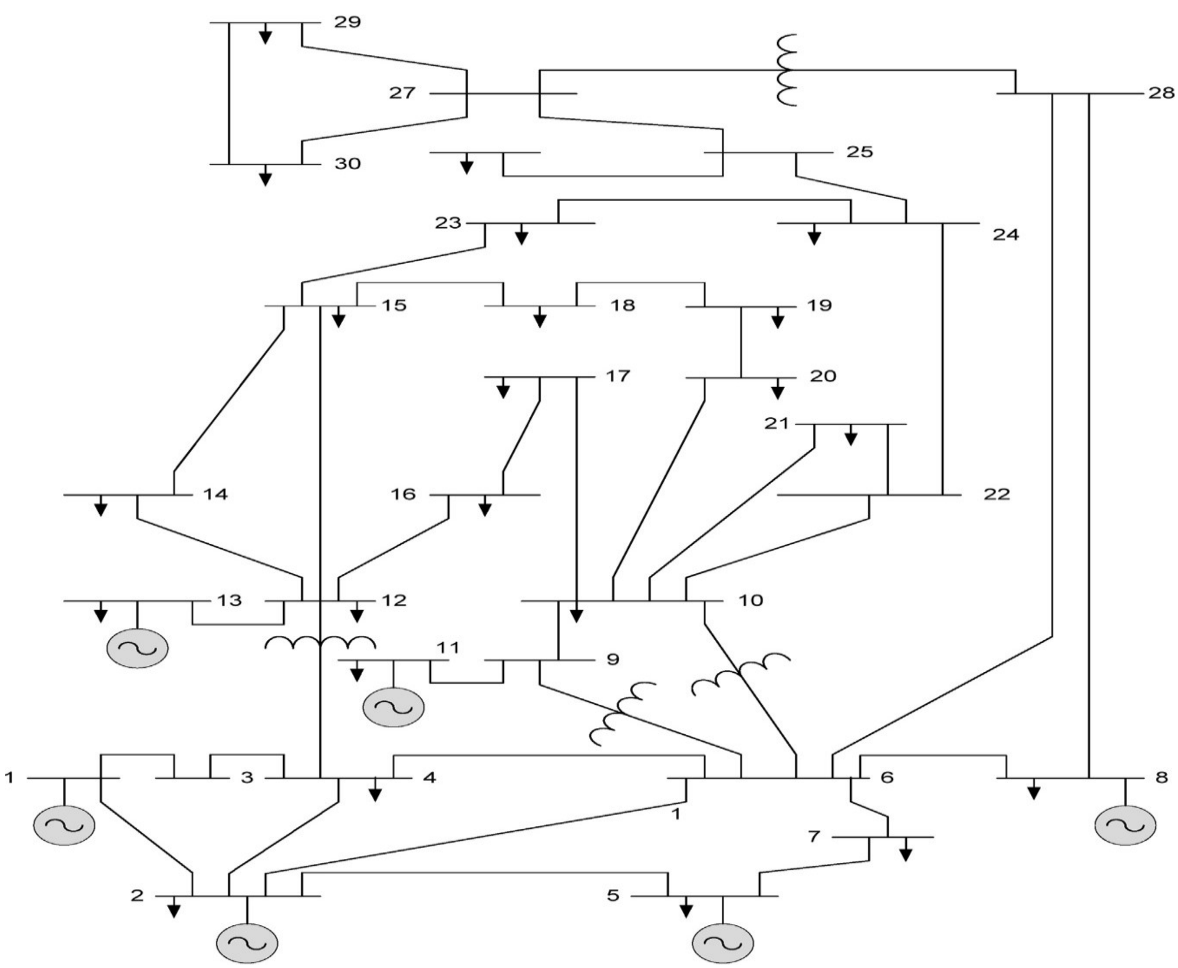


Figure 3 Single-Line Diagram of IEEE-30 Bus Test System

To verify the effectiveness and robustness of the above-mentioned techniques, various cases with several objective functions are simulated below.

Case1-Minimization of fuel cost

Cost of fuel F of an electrical power network can be characterized as follows:

$$F_a = \sum_{i=1}^{n_g} F$$

where n_g represents no. of units that generates power. The cost of fuel of i_{th} generating unit is represented as:

$$F = a_i + b_i P_{gi} + c_i P_{gi}^2$$

where, fuel price coefficients are represented by ai, bi and ci. Pgi stands for the active power produced by the i_{th} generating unit. As the primary purpose for using the suggested strategies is to minimize total fuel costs. The output waveform in Figure 4 shows that the suggested (TLBO) algorithm requires 25 iterations to reach the ideal value, while the proposed (PSO) algorithm requires 40 iterations. Compared to the proposed (PSO) algorithm, the proposed (TLBO) approach has a far better rate of convergence. Tables 2 and 3 display the values of the control parameters as well as the ideal values. Based on Table 2 and 3, The table 4 provides a comparison of the fuel cost as applied to the IEEE-30 bus test system, results are shown in Figure 4.

Table 2 Five examples of the proposed (PSO) approach using the IEEE-30 bus test system's best adjusted dependent variables.

	Min	Max	Case1	Case2	Case3	Case4	Case5
P1	50	200	176.39	168.76	168.4882	51.3480	51.9684
P2	20	80	49.446	47.13	25.0376	79.9982	79.9913
P5	15	50	21.877	22.85	22.3680	49.9998	49.9994
P8	10	35	21.64	22.999	20.2633	35.0000	34.9998
P11	10	30	11.298	17.685	15.2148	29.9993	29.9411
P13	12	40	12.27	13.235	39.9611	40.0000	39.9990
V1	0.95	1.1	1.0541	1.0243	1.1000	1.1000	1.1000
V2	0.95	1.1	1.0342	1.0108	1.0874	1.1000	1.1000
V5	0.95	1.1	1.0014	1.0022	1.0690	1.0864	1.1000
V8	0.95	1.1	1.0057	1.0095	1.0647	1.1000	1.1000
V11	0.95	1.1	1.0291	1.0523	1.0469	1.1000	1.0461
V13	0.95	1.1	1.0484	1.0528	1.0993	1.1000	1.1000
T11(6-9)	0.9	1.1	0.94293	0.97087	1.1000	1.1000	1.0420
T12(6-10)	0.9	1.1	1.0539	0.99167	0.9008	0.9001	1.1000
T15(4-12)	0.9	1.1	0.99587	1.0456	0.9500	0.9978	1.0062
T36(28-27)	0.9	1.1	0.96919	0.95547	0.9383	0.9984	1.0400
QC10	0	5	2.0825	3.3091	4.9904	4.6232	0.0002
QC12	0	5	1.7209	0.97009	4.7116	0.0000	4.9935
QC15	0	5	4.0925	1.9919	4.9999	4.9995	4.9998
QC17	0	5	1.2855	1.8193	3.1530	5.0000	4.9999
QC20	0	5	3.2046	4.0854	3.0122	0.0000	0.0001
QC21	0	5	4.1781	3.2477	4.9955	4.9995	0.0002
QC23	0	5	1.7577	3.3674	4.9572	0.0032	0.0001
QC24	0	5	1.6139	1.809	2.0283	5.0000	0.0005
QC29	0	5	3.9931	1.0399	3.6016	5.0000	4.7580
Cost($/h)	-	-	**802.4375**	805.2722	832.3746	967.2876	968.4664
Power loss(MW)	-	-	9.6317	9.3669	7.9337	**2.9473**	3.5010
Power loss (MVAR)	-	-	9.6317	10.3716	9.5863	3.0736	**3.5010**
Voltage deviations	-	-	0.2121	**0.1628**	1.6591	1.8220	1.0094
Lmax	-	-	0.1375	0.1396	**0.1159**	0.1179	0.1310

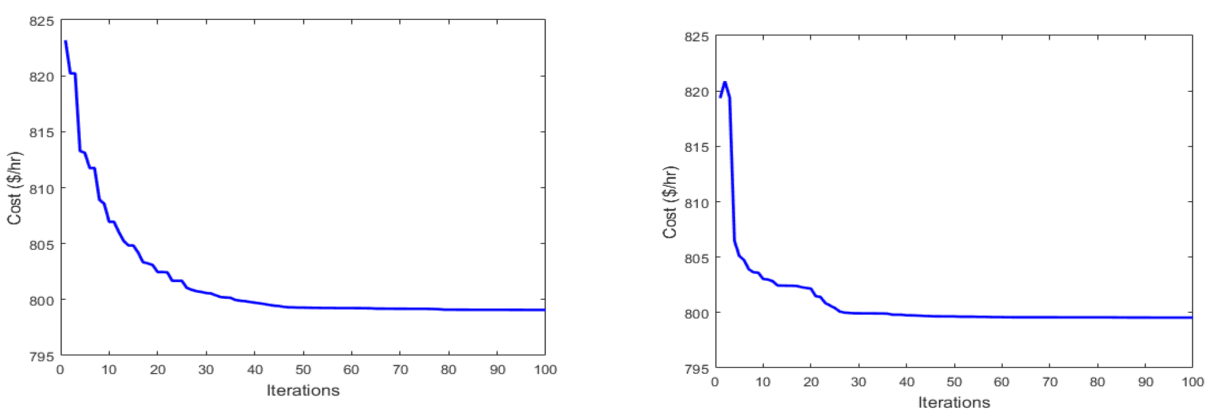


Figure 4 Converged curve of minimization of total fuel cost on the basis of (a) Proposed (TLBO) method, and (b) Proposed (PSO) method

Table 3 Five instances of the proposed (TLBO) approach using the IEEE-30 bus test system's optimally tuned dependent values
.

	Min	Max	Case1	Case2	Case3	Case4	Case5
P1	50.0000	200.0000	177.0100	175.4400	171.5100	51.2780	51.4490
P2	20.0000	80.0000	48.7700	48.1140	46.0670	79.9890	80.0000
P5	15.0000	50.0000	21.2710	21.1180	21.2200	50.0000	50.0000
P8	10.0000	35.0000	21.1920	22.7270	28.7030	35.0000	35.0000
P11	10.0000	30.0000	11.8070	13.2990	11.6880	29.9980	30.0000
P13	12.0000	40.0000	12.0000	12.3740	12.7920	39.9930	40.0000
V1	0.9500	1.1000	1.1000	1.0347	1.0849	1.1000	1.1000
V2	0.9500	1.1000	1.0876	1.0187	1.0706	1.0977	1.1000
V5	0.9500	1.1000	1.0614	1.0037	1.0332	1.0796	1.0928
V8	0.9500	1.1000	1.0689	1.0038	1.0359	1.0871	1.1000
V11	0.9500	1.1000	1.1000	1.0537	1.0928	1.1000	1.0372
V13	0.9500	1.1000	1.1000	0.9930	1.0869	1.1000	1.0645
T11(6-9)	0.9000	1.1000	1.0372	1.0729	1.0232	1.0389	1.0789
T12(6-10)	0.9000	1.1000	0.9100	0.9055	0.9001	0.9018	1.0240
T15(4-12)	0.9000	1.1000	0.9910	0.9580	0.9003	0.9837	1.0265
T36(28-27)	0.9000	1.1000	0.9708	0.9679	0.9307	0.9736	1.0491
QC10	0.0000	5.0000	5.0000	4.8649	4.9700	0.1993	4.9998
QC12	0.0000	5.0000	0.0423	4.9920	0.0153	4.9992	5.0000
QC15	0.0000	5.0000	4.9960	4.9619	4.9286	4.8284	4.9995
QC17	0.0000	5.0000	0.0017	1.1570	4.8735	4.9955	4.9999
QC20	0.0000	5.0000	4.9924	4.9939	4.9247	4.9924	5.0000
QC21	0.0000	5.0000	5.0000	4.8476	4.9156	4.9797	4.9999
QC23	0.0000	5.0000	3.8684	4.9979	4.9979	4.0442	5.0000
QC24	0.0000	5.0000	4.9994	4.9843	5.0000	4.9982	4.9999
QC29	0.0000	5.0000	2.9287	2.5821	4.9525	2.6656	3.1148
Cost($/h)	-	-	**799.1622**	803.4406	801.5363	967.0309	967.5414
Power loss (MW)	-	-	8.6503	9.7658	8.5765	**2.8575**	3.0512
Power loss (MVAR)	-	-	8.6640	9.9179	8.9977	2.8718	**3.0512**
Voltage deviations	-	-	1.7196	**0.1007**	1.7571	2.0338	1.0681
L_{max}	-	-	0.1188	0.1362	**0.1152**	0.1159	0.1274

Table 4 Comparison of the fuel cost reduction strategies found (as applied to the IEEE-30bus test system).
Bold face values signify optimal values.

Method Description	Fuel Cost	References
Proposed Algorithm (TLBO)	**799.1622**	
Proposed Algorithm (PSO)	**802.4375**	
Multi-verse Optimizer (MVO)	799.242	[41]
Jaya Algorithm	800.479	[42], [43]
Differential Evolution (DE)	799.289	[44]
Black-Hole-Based Optimization (BHO)	799.921	[45]

Case2: Voltage Profile Improvement

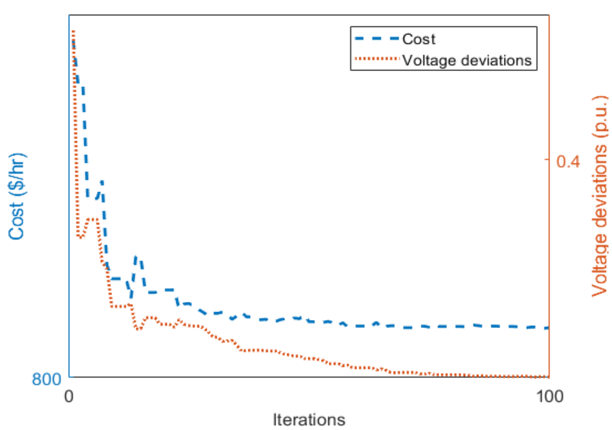
Voltage of the bus is a key factor in securing and providing service for quality indices. The second scenario aims to reduce fuel costs while also enhancing the voltage profile.

Reduce the voltage variation of the PQ buses to enhance the voltage profile. The objective function for the second case is given as:

$$F_b = \sum_{i=1}^{n_g} F + k\sum_{i=1}^{n_g} |V_i - 1.0| \quad \text{...(18)}$$

where, k represents weight factor, used to maintain stability between two objectives, so as to avoid dominant effect between each other. The graph in Figure 5 below depicts the variation in fuel cost and voltage deviation. Based on the Figure 5, Table 5 displays the ideal settings for the control variables. It is clear that the voltage profile in TLBO is far better than that in PSO, having decreased from 0.1628 p.u. in PSO to 0.1007 p.u. in TLBO. It claims that the proposed (TLBO) algorithm results in a decrease in voltage deviation. In contrast to instance 1, there is a modest increase in power loss in case 2.

To find the value of k, we need to balance the objectives of reducing fuel costs and enhancing the voltage profile. The value of k determines the trade-off between these objectives. The optimal value of k should be chosen such that it minimizes the combined objective function while considering the relative importance of both the objectives. So, we can set k to 0.5. if one objective is more important than the other, then the value of k would need to be adjusted accordingly to reflect that importance.



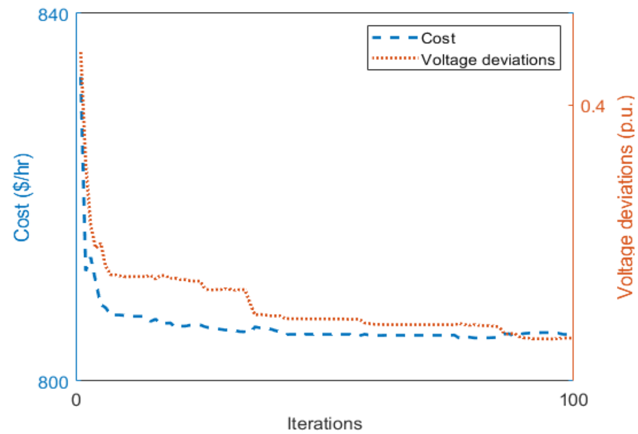


Figure 5 Voltage Profile Improvement curve on the basis of (a) Proposed (TLBO) method, and (b) Proposed (PSO) method.

Table 5 Comparing the outcomes of the voltage profile improvement.
Bold face values signify optimal values.

Method description	Voltage-Deviation	References
Proposed Algorithm (TLBO)	**0.1007**	
Proposed Algorithm (PSO)	**0.1628**	
Multi-verse Optimizer (MVO)	0.1056	[41]
Firefly Algorithm(FA)	0.1474	[46]
Differential Evolution (DE)	0.1357	[44]
Black Hole Based Optimization (BHBO)	0.1262	[47]

Case 3: Voltage Stability Enhancement

The performance of the transmission line systems must be extremely close to the secured limits in order to improve voltage stability. As an objective function's unpredictable and suboptimal solution might result in voltage collapse, voltage stability may become a significant problem. Voltage stability must therefore be taken into account as an objective function in order for this element to receive more attention. Table displays the ideal settings for the control variables. Since k represents a weight factor used to balance the objectives, a higher value of k will give more weight to voltage stability in the objective function. We can start with a value of k=2 to emphasize the importance of voltage stability while still considering other objectives. However, the exact value of k may need to be fine-tuned based on specific requirements, constraints, and system characteristics.

The graph in Figure 6 illustrates how the voltage stability index varies for the two proposed strategies. Kessel and Glavitch introduced the voltage stability index, or Lindex, based on the viability of the power flow at each bus, Table 6 indicate the comparison of the voltage stability enhancement findings based Figure 6 and their optimal values.

By Lindex the proximity condition of voltage collapse can be determined at the buses. Lindex or Lmax factor changes as 0 for no-l

$$L_{\max} = \max(L_k) \qquad (19)$$

k=1,2,3,4,……… n_l

where, L_k denotes the $L_{\max}$ of k_{th} demand-bus (PQ-bus) and n_l is the integer of PQ-bus. The objective function for case 3 is represented as:

$$F_c = \sum_{i=1}^{n_g} F + k\left|L_{\max}\right| \text{……………………………………(20)}$$

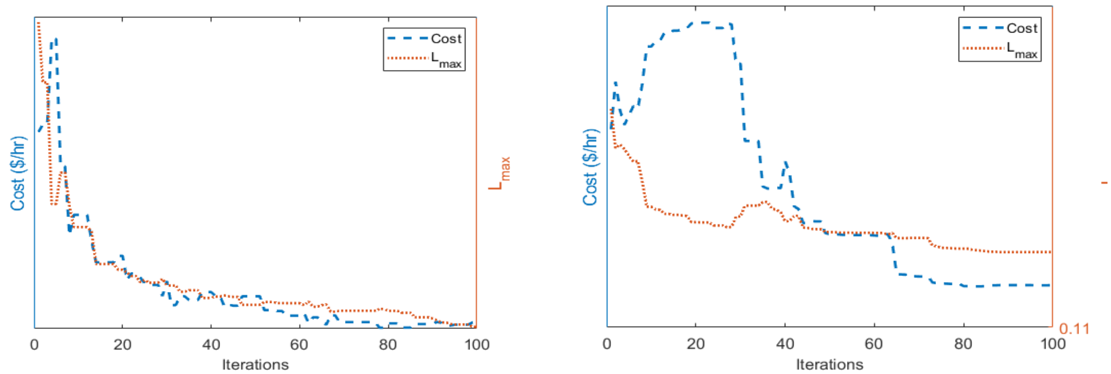


Figure 6 Voltage Stability Index curve on the basis of (a) Proposed (TLBO) method, and (b)Proposed (PSO) method.

Table 6 Comparison of the voltage stability enhancement findings
Bold face values signify optimal values.

Method Description	Lmax	References
Proposed Algorithm (TLBO)	**0.1152**	
Proposed Algorithm (PSO)	**0.1159**	
Multi-verse Optimizer (MVO)	0.1146	[41]
Jaya Algorithm	0.1243	[42]
Differential Evolution (DE)	0.1219	[44]
Black Hole Based Optimization (BHBO)	0.1167	[47]

Case 4: Active Power Transmission Loss Reduction

Table 7 demonstrates that the TLBO optimization technique yields the least amount of active power loss when compared to PSO optimization and other techniques addressed in the literature. Therefore, table 7 represent the, active power loss is used as an objective function to lower active power loss.

$$F_a = \sum_{i=1}^{n_1} P = \sum_{i=1}^{n_1} P_{gi} - \sum_{i=1}^{n_1} P_{di} \text{………………………(21)}$$

where, P_i is active power of transmission loss, P_{gi} generated active power and P_{di} is demand active power of the i_{th} load.

Table 7 Comparison of the active power loss reduction test results (using the standard IEEE 30-bus test system).
Bold face values signify optimal values.

Method Description	Active Power Losses (in MW)	References
Proposed Algorithm (TLBO)	**2.8575**	
Proposed Algorithm (PSO)	**2.9473**	
Black Hole Based Optimization (BHBO)	3.503	[47]
Multi-verse Optimizer (MVO)	2.881	[41]
Jaya Algorithm	3.101	[42]

Case 5: Reactive Power Transmission Loss Reduction

Reducing the reactive power loss of transmission lines is the case's objective. The results of these techniques are compared to those of other techniques stated in the literature in Table 8 below. Reactive power is regarded as a crucial component in keeping the voltage balance in the power system. The objective function for minimization of reactive power loss is represented as follows:

$$F_r = \sum_{i=1}^{n_1} Q = \sum_{i=1}^{n_1} Q_{gi} - \sum_{i=1}^{n_1} Q_{di} \quad \text{..........................(22)}$$

where, Q_i is reactive power loss of transmission loss, Q_{gi} generated reactive power and Q_{di} is demand reactive power of the i_{th} load. The graph to represent variation in reactive power loss is shown in Figure 7. Based on Figure 7, Table 8 indicate the comparison methods found for minimizing the reactive power loss. Comparative analysis of figures obtained from the above results is shown in Figure 8

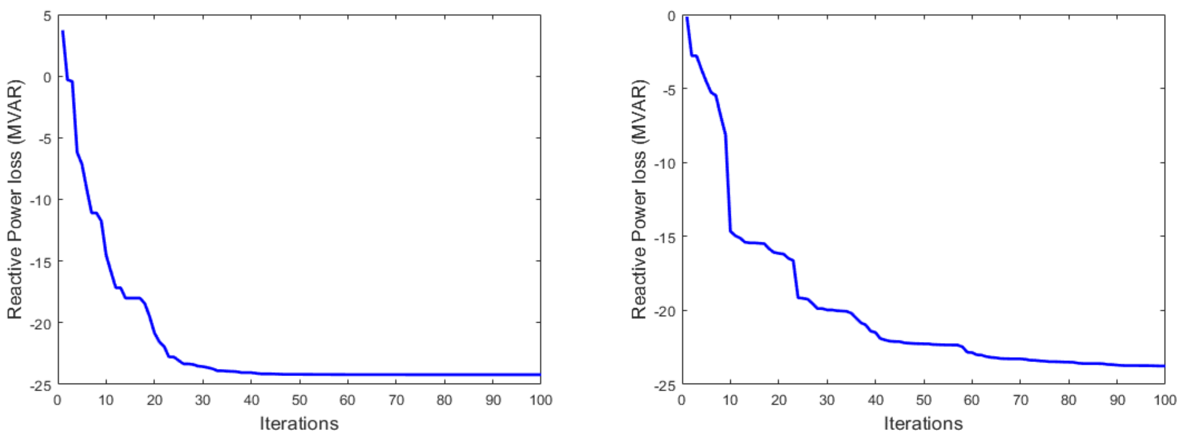


Figure 7 Curve of minimization of reactive power loss on the basis of (a) Proposed (TLBO) method, and (b) Proposed (PSO) method

Table 8 Comparison of the methods found for minimizing reactive power losses

Bold face values signify optimal values.

Method	Reactive Power Losses	Reference
Proposed Algorithm (TLBO)	**-24.2129**	
Proposed Algorithm (PSO)	**-22.6265**	
Firefly Algorithm(FA)	-20.464	[48], [49]
Multi-verse Optimizer (MVO)	-25.038	[50]
Black Hole Based Optimization (BHBO)	-20.152	[47]

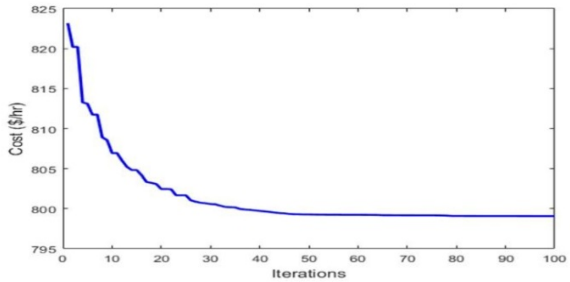


Fig. 4 (a)

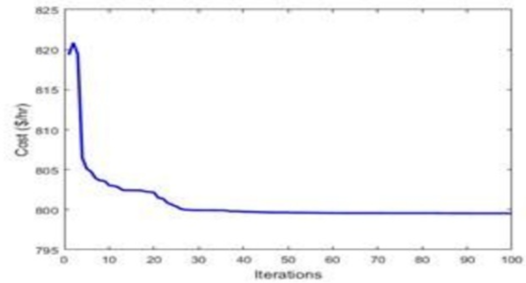


Fig. 4 (b)

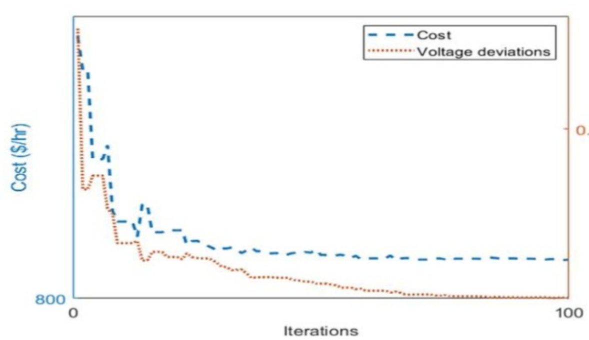


Fig. 5 (a)

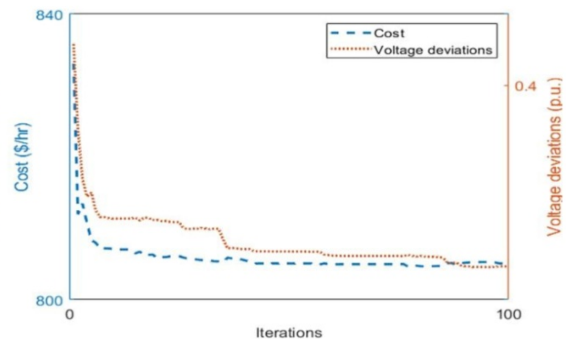


Fig. 5 (b)

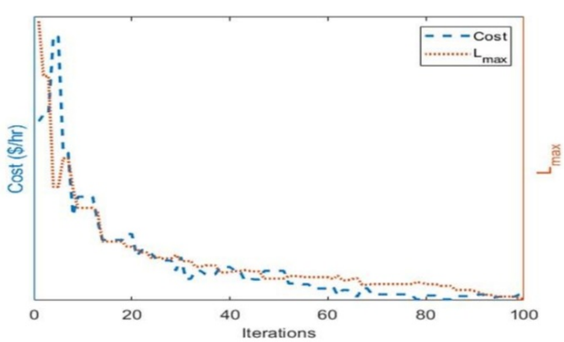


Fig. 6 (a)

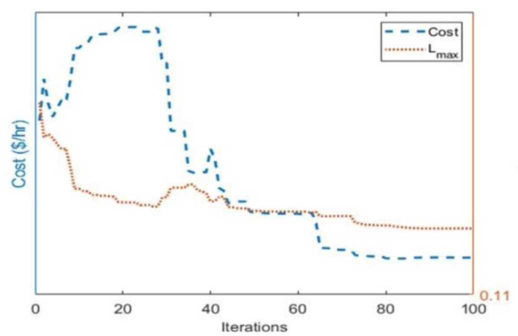


Fig. 6 (b)

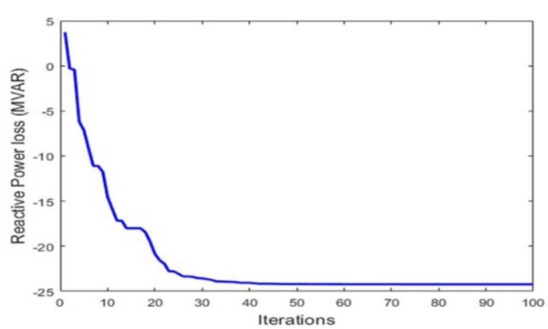


Fig. 7 (a)

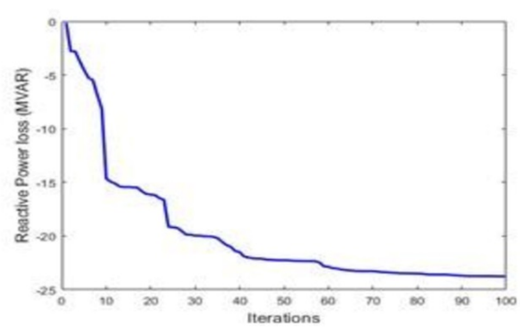


Fig. 7 (a)

Figure 8 Comparative analysis of figures obtained from the above results

Statistical Results

The efficiency of the given method is assessed by a number of trials that involve 100 iterations. The table below shows that all statistical calculations are extremely close to one another and have minimal standard deviation values

Table 9 Statistical calculation of Proposed (PSO)

Cases	MIN	MAX	MEAN	MEDIAN	SD
Case 1	799.5430	802.4380	800.6310	800.3860	1.0756
Case 2	0.0000	824.8660	658.2340	821.5490	367.9680
Case 3	1510.1100	1541.8000	1523.2100	1522.5400	12.5065
Case 4	0.0000	3.0736	1.2041	0.0000	1.6495
Case 5	-22.6265	0.0000	-4.5253	0.0000	10.1189

Table 10 Statistical calculation for Proposed (TLBO)

Cases	MIN	MAX	MEAN	MEDIAN	SD
Case1	799.0740	799.1830	799.1260	799.1210	0.04589
Case2	0.0000	814.4150	651.1340	813.6420	363.9950
Case 3	1504.2200	1532.2200	1510.1000	1514.1400	10.2343
Case4	0.0000	2.8718	1.1458	0.0000	1.5690
Case5	-24.2129	0.0000	-4.84258	0.0000	10.8283

4.0 CONCLUSION

Two meta-heuristic optimization strategies have been presented in this paper, and the outcomes of each are compared. The research's findings are helpful in identifying four other scenarios, including minimizing voltage deviation, improving voltage stability, and minimizing active and reactive power loss of transmission lines, in addition to helping to determine the generator's ideal cost value. An IEEE-30 Bus test network is utilized to confirm the validity of the two proposed approaches, TLBO and PSO. The outcomes of the execution of both algorithms show that the TLBO Algorithm can reflect the optimal value obtained in each scenario. Although the PSO algorithm methodology has a substantial impact on the world's ability to solve optimization problems, this method has a number of limitations. because it is challenging to find the best algorithmic settings. The TLBO algorithm is therefore proposed with a few parameter adjustments in order to lessen the impact of the parameters on the algorithm. Real-world applications also use the teaching learning-based optimization technique. The findings reported above show that the TLBO algorithm has superior convergence properties to PSO. Based on the statistical analysis results, it can be said that the TLBO algorithm is a trustworthy and dependable optimization tool for resolving issues with optimal power flow. Therefore, it can be concluded that the TLBO approach is an excellent instrument for solving the optimal power flow problem based on its applicability and operation.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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