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Optimal Reactive Power Dispatch Using a Chaotic Turbulent Flow of Water-Based Optimization Algorithm

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Abstract: In this study, an optimization algorithm called chaotic turbulent flow of water-based optimization (CTFWO) algorithm is proposed to find the optimal solution for the optimal reactive power dispatch (ORPD) problem. The ORPD is formulated as a complicated, mixed-integer nonlinear optimization problem, comprising control variables which are discrete and continuous. The CTFWO algorithm is used to minimize voltage deviation (VD) and real power loss (P_loss) for IEEE 30-bus and IEEE 57-bus power systems. These goals can be achieved by obtaining the optimized voltage values of the generator, the transformer tap changing positions, and the reactive compensation. In order to evaluate the ability of the proposed algorithm to obtain ORPD problem solutions, the results of the proposed CTFWO algorithm are compared with different algorithms, including artificial ecosystem-based optimization (AEO), the equilibrium optimizer (EO), the gradient-based optimizer (GBO), and the original turbulent flow of water-based optimization (TFWO) algorithm. These are also compared with the results of the evaluated performance of various methods that are used in many recent papers. The experimental results show that the proposed CTFWO algorithm has superior performance, and is competitive with many state-of-the-art algorithms outlined in some of the recent studies in terms of solution accuracy, convergence rate, and stability.

Keywords: optimal reactive power dispatch; chaotic maps; turbulent flow of water-based optimization; real power loss; voltage deviation

1. Introduction

The optimal reactive power dispatch (ORPD) problem plays a very important role in the optimal operation of electric power systems. It is a subclass of the optimal power flow (OPF) problem [1]. The power system must be operating with high reliability, and finding a safe way to achieve this should obtain the optimal operating state and the control variable values (such as the generator voltage ratings, the tap ratios for the tap setting transformers, and the reactive power of the shunt capacitors/reactors) [2]. There are three main objectives of ORPD, which include reducing and minimizing the active power losses, the voltage deviation values, and the stability index. Researchers have studied several problems related to the power systems, including the security assessment of online power systems [3], a two-stage active and reactive power coordinated optimal dispatch for an active distribution network, considering load flexibility [4], the early detection and prevention of blackouts in power interconnections [5], OPF [6], and economic emissions dispatch [7].

Recently, different optimization methods have been studied to solve the ORPD problem; various optimization methodologies are recommended, such as deterministic and metaheuristic algorithms [8]. These algorithms include original, modified deterministic,
original, modified metaheuristic, and crossbreed heuristic algorithms [9]. Deterministic algorithms are the earliest methods, and these involve minimizing real power losses using the interior point method, Newton method, quadratic programming method, and an ANN-based memory model [10–13].

Metaheuristic algorithms, such as the genetic algorithm (GA) [14–19], which mimics the rule of natural selection or heredities, relate to the terms of genetics and mutation selection. Another algorithm, SARCGA, considers the updating of RCGA to be self-adaptive [14]. Another technique is linear programming with the genetic algorithm [15]. For handling the ORPD problem when considering power loss minimization, the SGA algorithm was introduced in [16]. The hybrid loop-genetic-based algorithm [17] and the adaptive genetic algorithm (AGA) [18] are also used to solve the ORPD problem. Additionally, the enhancement of a new evolutionary GA through the addition of a specific mechanism is achieved in [19]. The particle swarm optimizer (PSO) is a different technique for optimization that is no less famous than the GA. Additionally, it has been used with other algorithms to create new hybrid techniques, such as the imperialist competitive algorithm (HPSO-ICA) [20], aging leader and challengers (ALC-PSO) [21], the original PSO for OPF [22], PSO for ORPD [23], HPSO-TS [24], PSO-GT [25], improved pseudo-gradient (PSO-IPG) [26], and a lot of variant methods, including CLPSO [27] and hybrid particle swarm optimization and differential evolution (HPSO) [28]. Moreover, the differential evolution (DE) algorithm is used to solve the ORPD problem [29], which is also achieved in combination with other algorithms, such as DE-AS [30], quasi-oppositional DE (QODE) [31], CABC-DE [32], and MTLA-DDE [33].

Not only are there the above methods, but there are a lot of other methods that are used to solve the ORPD problem through various systems and techniques, with a single objective or multiple objectives. These methods are improved, such as the gravitational search algorithm (GSA) [34–36], the exchange market optimization algorithm (EMOA) [37], the artificial bee colony (ABC) with firefly algorithm (ABC-FF) [38], the ant lion optimizer (ALO) [39], moth flame optimization (MFO) [40], the cuckoo search optimization algorithm (CSOA) [41], the differential search algorithm (DSA) [42], the multi-objective grey wolf algorithm (MOGWA) [43], improved colliding bodies optimization (ICBO) [44], the Jaya algorithm (JA) [45], the whale optimization algorithm (WOA) [46], ant colony optimization (ACO) [47], the harmony search algorithm (HAS) [48], Gaussian bare-bones teaching–learning-based optimization (GBTLBO) [49], the hybrid Nelder–Mead simplex-based firefly algorithm (HFA-NMS) [50], the Gaussian bare-bones water cycle algorithm (GGBWCA) [51], the gray wolf optimizer (GWO) [52], the cuckoo search algorithm (CSA) [53], the chaotic krill herd algorithm (CKHA) [54], ABC [55], quasi-oppositional teaching–learning-based optimization (QOTLBO) and TLBO [2], the Rao-3 algorithm [56], and the improved Cuckoo search algorithm (ICSA) [57]. Among these methods, there are methods that have improved upon the original methods to find more promising solutions than those of the original methods for the ORPD problem.

This paper suggests a new modification of the TFWO algorithm based on the chaotic maps, which is named the chaotic turbulent flow of water-based optimization (CTFWO) algorithm, to solve the optimum reactive power dispatch problem. The conventional TFWO algorithm was developed by Ghasemi, Mojtaba, et al. in 2020 [58]. The original TFWO algorithm was used to solve many problems, such as the estimation of the parameters of photovoltaic (PV) models [59,60], the maximum power point tracking (MPPT) of photovoltaic systems in partial shading conditions [61], economic load dispatch [62], the optimal settings of back-to-back voltage source converters (BTB-VSC) in an interconnected power system [63], and the optimal allocation of shunt compensators in distribution systems [64]; therefore, we selected it for modification to improve the global search ability and to increase the local search capability and the convergence precision. Meanwhile, we tested it to try and achieve the best results for different single-objective functions, including the minimization of power losses and voltage deviation in two tested power systems. The main contributions of this article are summarized as:
1. Applying four different algorithms as search algorithms, including artificial ecosystem-based optimization (AEO), the equilibrium optimizer (EO), the gradient-based optimizer (GBO), and turbulent flow of water-based optimization (TFWO), on IEEE 30-bus and IEEE 57-bus power systems to solve ORPD problem.

2. The TFWO algorithm gives the best results for different single-objective functions, namely, the minimization of power losses and voltage deviation in both tested power systems.

3. Proposing a new chaotic TFWO algorithm (CTFWO), which based on applying the chaotic approach to improve the performance of the original TFWO

4. The proposed CTFWO algorithm solves the ORPD problem and gives better results than all other compared algorithms on the tested power systems, the 30-bus and the 57-bus systems, for all studied cases.

The rest of the paper is organized as follows:
The ORPD problem is formulated in Section 2. In Section 3.1 the conventional TFWO algorithm is described and in Section 3.2 the proposed CTFWO algorithm is explained. In Section 4, the main achieved results and discussion are given. In Section 5, the conclusion drawn from this research is illustrated.

2. Materials and Methods

The ORPD has three main objectives: first, minimize and reduce the active power losses ($P_{\text{loss}}$); second, reduce the voltage deviation (VD), which is the difference between load voltage (which changes continually) and the reference voltage (with a value of 1.0 pu); finally, minimize the stability index (L-index), which takes values from 0 to 1, with 0 meaning that the system is stable and 1 meaning that there is a system disturbance.

2.1. Objective Functions

The two key objectives of this paper are as follows:

2.1.1. Minimization of the Active Power Loss

When operating any power systems, we can consider that the total active power loss is the main objective of the ORPD:

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

where:

- $P_{\text{loss}}$ is the active power loss.
- $G_k$ is the conductance of the kth branch connected between the $i$th and the $j$th bus.
- $\alpha_{ij}$ is the admittance angle of the transmission line connected between the $i$th and the $j$th bus.
- $N_{\text{TL}}$ is the number of transmission lines (branches).
- $V_i$ and $V_j$ are the voltage magnitudes of the $i$th and the $j$th bus, respectively.

2.1.2. Improvement of the Voltage Profile

The difference between the voltage magnitude at each load bus and what the specified reference value of the voltage ought to be is outlined in the following equation:

$$f_2 = \min\left( \sum_{i=1}^{N_L} |V_{li} - V_{li}^{sp}| \right)$$

where:

- $V_{li}$ is the voltage at the $i$th load bus.
- $V_{li}^{sp}$ is the desired voltage at the $i$th load bus, which is usually set to (1.0 p.u.).
2.2. System Constraints

2.2.1. Equality Constraint

This constraint ensures that there is load balance (i.e., the generation of real and reactive power is balanced against consuming):

\[
P_i - V_i \sum_{j=1}^{N_B} V_j \left[ G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right] = 0
\]

For \( i = 1, \ldots, N_B \) \( (3) \)

\[
Q_i - V_i \sum_{j=1}^{N_B} V_j \left[ G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j) \right] = 0
\]

For \( i = 1, \ldots, N_B \) \( (4) \)

where:

\( P_i = (P_{Gi} - P_{Di}) \) and \( Q_i = (Q_{Gi} - Q_{Di}) \) represent the real and reactive power injection at bus \( i \).

\( P_{Gi} \) and \( Q_{Gi} \) are the active and reactive power generation of the \( i^{th} \) bus.

\( P_{Di} \) and \( Q_{Di} \) are the active and reactive load demand of the \( i^{th} \) bus.

\( G_{ij} \) is the real part of the bus admittance matrix of the \((i, j)^{th}\) entry.

\( B_{ij} \) is the imaginary part of the bus admittance matrix of the \((i, j)^{th}\) entry.

\( N_B \) is numbers of buses.

2.2.2. Inequality Constraints

The inequality constraints should be within limited values, as follow:

\[
V_{Gi}^{\text{min}} \leq V_{Gi} \leq V_{Gi}^{\text{max}}
\]

For \( i = 1, \ldots, N_G \) \( (5) \)

\[
Q_{Gi}^{\text{min}} \leq Q_{Gi} \leq Q_{Gi}^{\text{max}}
\]

For \( i = 1, \ldots, N_C \) \( (6) \)

\[
T_i^{\text{min}} \leq T_i \leq T_i^{\text{max}}
\]

For \( i = 1, \ldots, N_T \) \( (7) \)

where:

\( V_{Gi}^{\text{min}} \) and \( V_{Gi}^{\text{max}} \) are the minimum and maximum generator voltage values of the \( i^{th} \) bus, respectively.

\( Q_{Gi}^{\text{min}} \) and \( Q_{Gi}^{\text{max}} \) are the minimum and maximum values of the reactive power injection of the \( i^{th} \) shunt compensator, respectively.

\( T_i^{\text{min}} \) and \( T_i^{\text{max}} \) are the minimum and maximum tap setting values of the \( i^{th} \) transmission line, respectively.

\( N_C, N_G, \) and \( N_T \) are the numbers of shunt compensators, generators, and tap changing transformers, respectively.

The inequality constraints on the dependent variable are given by:

\[
V_{Li}^{\text{min}} \leq V_{Li} \leq V_{Li}^{\text{max}}
\]

For \( i = 1, \ldots, N_L \) \( (8) \)

\[
Q_{Gi}^{\text{min}} \leq Q_{Gi} \leq Q_{Gi}^{\text{max}}
\]

For \( i = 1, \ldots, N_G \) \( (9) \)

\[
S_{Li} \leq S_{Li}^{\text{max}}
\]

For \( i = 1, \ldots, N_L \).
For \( i = 1, \ldots, N_L \)

where:

- \( V_{min}^{Li} \) and \( V_{max}^{Li} \) are the minimum and maximum voltages of the \( i \)th load bus, respectively.
- \( Q_{min}^{Gi} \) and \( Q_{max}^{Gi} \) are the minimum and maximum reactive power generation values of the \( i \)th generator bus, respectively.
- \( S_{max}^{Li} \) is the maximum apparent power flow through the \( i \)th line [2,65,66].

3. Methodology

3.1. The Conventional TFWO

In this subsection, we briefly explain the concept of the original turbulent flow of water-based optimization (TFWO) algorithm. It is inspired by the whirlpools created in the turbulent flow of water. The whirlpool \((Whj)\) is a random behavior of nature that happens in seas, rivers, and oceans. Its rotation and flow are affected by the force of gravity. The center of the whirlpool \((Whj)\) functions as a sucking hole that attracts the objects and particles nearby towards its middle via internal forces. Though the centripetal force attracts the moving objects towards the whirlpool, the centrifugal force takes the object away from the corresponding center. The effects of the Whj on the object’s particles are displayed in Figure 1. As can be seen from Figure 2, the objects \((X)\) move with their special angle \((\delta)\) around the Whj’s center. Therefore, this angle at each moment is changing as follows:

\[
\delta_{i}^{new} = \delta_{i} + \text{rand}_1 \times \text{rand}_2 \times \pi
\]  

(11)

3.2. The Proposed CTFWO

The proposed CTFWO technique is the combination of the conventional TFWO algorithm with chaotic maps. Chaotic systems are deterministic systems that present unpredictable conduct, whose action is complex and similar to randomness [67]. In [67], a chaos-based exploration rate was proposed to enhance the performance of three well-known optimization algorithms. Based on this proposed, the real random numbers \((\text{rand}_1, \text{rand}_2)\) in Equation (11) are replaced by a chaotic number. Figure 2 displays the flow chart of the proposed CTFWO algorithm.
Figure 1. The proposed model of a whirlpool for the TFWO algorithm.

Figure 2. The proposed CTFWO algorithm flow chart.

4. Simulation Results and Discussion

The algorithms proposed in our study are applied to two different standard power systems (IEEE 30-bus and IEEE 57-bus test systems). Figure 3 displays the IEEE 30-bus system, while Table 1 presents the description of the two test power systems. The proposed technique uses MATLAB 2018a programming, and all sections of the simulations have been executed on a PC with a 2.40 GHZ frequency CPU, and the installed memory (RAM) is 4.0 GB.
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![Figure 3. The IEEE 30-bus system.](image)

| Description | IEEE 30 Bus | IEEE 57 Bus |
|-------------|-------------|-------------|
| Buses, NB   | 30          | 57          |
| Generators, NG | 6      | 7           |
| Transformers, NT | 4 | 15         |
| Shunts, NQ  | 9           | 3           |
| Branches, NE | 41          | 80          |
| Equality constraints | 60 | 114        |
| Inequality constraints | 125 | 245        |
| Control variables | 19 | 27         |
| Discrete variables | 6  | 20         |
| Base case for \(P_{\text{loss}}\), MW | 5.660 | 27.8637 |
| Base case for TVD, p.u. | 0.58217 | 1.23358 |

The software used is MATLAB 2018, and our computer has a 2.67 GHz Intel Core i5 processor and 4 GB RAM. The results relating to the performance for all our algorithms are taken after many trials. In our study, we have taken the population size of 30, while the number of iterations is 500 in both tested systems. In Table 1, we show that the values produced by the CTFWO algorithm, in the case of power losses, are better and more optimal values compared with the other four algorithms for the IEEE 30-bus system. In Table 2, we show the generator voltage, transformer tap ratio, capacitor bank, and generator reactive power values for case one, which simulates power losses in the 30-bus system.
Table 2. Results of case 1 for the 30-bus system.

| Parameters               | Min   | Max   | AEO | EO  | GBO  | TFWO | CTFWO |
|--------------------------|-------|-------|-----|-----|------|------|-------|
| Generator voltage       |       |       |     |     |      |      |       |
| V1 (p.u.)                | 0.95  | 1.1   | 1.071383 | 1.071472 | 1.071032 | 1.071288 | 1.071342 |
| V2 (p.u.)                | 0.95  | 1.1   | 1.062422 | 1.062185 | 1.061796 | 1.062056 | 1.06216 |
| V5 (p.u.)                | 0.95  | 1.1   | 1.039959 | 1.039844 | 1.039846 | 1.039836 | 1.039794 |
| V8 (p.u.)                | 0.95  | 1.1   | 1.040165 | 1.039817 | 1.039876 | 1.040013 | 1.031899 |
| V11 (p.u.)               | 0.95  | 1.1   | 1.029138 | 1.036577 | 1.032475 | 1.040013 | 1.031899 |
| V13 (p.u.)               | 0.95  | 1.1   | 1.060438 | 1.06159  | 1.062488 | 1.061949 | 1.062353 |
| Transformer tap ratio   |       |       |     |     |      |      |       |
| T11 (p.u.)               | 0.9   | 1.1   | 1.0131    | 0.996542 | 1.01535  | 0.992784 | 1.013433 |
| T12 (p.u.)               | 0.9   | 1.1   | 0.908055  | 0.926149 | 0.900161 | 0.93027  | 0.903073 |
| T15 (p.u.)               | 0.9   | 1.1   | 0.981065  | 0.982578 | 0.984448 | 0.983187 | 0.983546 |
| T36 (p.u.)               | 0.9   | 1.1   | 0.986214  | 0.986534 | 0.986786 | 0.986749 | 0.987144 |
| Capacitor bank           |       |       |     |     |      |      |       |
| QC10 (MVar)              | 0     | 5     | 2.578379  | 0.8186  | 0.521123 | 0     | 0.005125 |
| QC12 (MVar)              | 0     | 5     | 0.109959  | 0       | 0.260124 | 0     | 0       |
| QC15 (MVar)              | 0     | 5     | 4.465515  | 4.99961 | 4.99989  | 1.870626 | 1.870944 |
| QC17 (MVar)              | 0     | 5     | 1.942079  | 0.000254 | 0.080239 | 0.582313 | 0.792172 |
| QC20 (MVar)              | 0     | 5     | 0.672355  | 0.327968 | 1.739245 | 1.047382 | 4.978545 |
| QC21 (MVar)              | 0     | 5     | 2.894689  | 4.687609 | 0.309966 | 4.261626 | 2.360041 |
| QC23 (MVar)              | 0     | 5     | 3.222698  | 2.5062   | 4.03902  | 0     | 0.002876 |
| QC24 (MVar)              | 0     | 5     | 1.608914  | 4.962173 | 1.747189 | 4.089292 | 3.716173 |
| QC29 (MVar)              | 0     | 5     | 1.663508  | 3.687004 | 4.823309 | 0.000215 | 0     |
| Objective function       |       |       |     |     |      |      |       |
| Ploss (MW)               | NA    | NA    | 4.9449    | 4.944875 | 4.945    | 4.9449 | 4.9448 |
| Generator reactive power|       |       |     |     |      |      |       |
| QG1 (MVar)               | −29.8 | 59.6  | −3.37149  | −2.7178  | −3.06733 | −2.92771 | −2.98714 |
| QG2 (MVar)               | −24   | 48    | 12.04035  | 11.25537 | 10.63866 | 11.10803 | 11.47796 |
| QG5 (MVar)               | −30   | 60    | 1.583144  | 1.733564 | 1.953514 | 1.785632 | 1.750684 |
| QG8 (MVar)               | −26.5 | 53    | 26.77981  | 26.53406 | 26.73682 | 26.56385 | 27.28592 |
| QG11 (MVar)              | −7.5  | 15    | −5.89765  | −5.28439 | −4.32984 | −4.53925 | −4.66229 |
| QG13 (MVar)              | −7.8  | 15.5  | 8.15796   | 9.03965  | 9.728283 | 9.315351 | 9.62484 |

The best values obtained are in bold.

In Table 3, we show that the values for the CTFWO algorithm are better and more optimal compared with the other algorithms in the case of power losses in the IEEE 30-bus system. In Figure 4, the CTFWO algorithm gives the minimal values in the case of power losses compared to the other algorithms.

Table 3. Results of the first objective function for the IEEE 30-bus system.

|         | AEO | EO  | GBO  | TFWO | CTFWO |
|---------|-----|-----|------|------|-------|
| Worst   | 4.9473 | 4.94658 | 4.9755 | 4.9459 | 4.9453 |
| Best    | 4.9449 | 4.944875 | 4.945 | 4.9449 | 4.9449 |
| Median  | 4.94555 | 4.9453745 | 4.94635 | 4.94515 | 4.9449 |
| Mean    | 4.945715 | 4.9455445 | 4.94695 | 4.945205 | 4.944915 |
| Std. Deviation | 0.000640 | 0.00051849 | 0.00797776 | 0.00024381 | 0.00010399 |

The best values obtained are in bold.

The voltage profiles of all the algorithms for the 30 buses in this system are illustrated in Figure 5. The figure shows that the voltages magnitudes for all buses are within the specified limits. However, the voltage profile in the case of using the proposed CTFWO technique has the better profile for most buses in the system than the other algorithms. Figure 6 shows the reactive power values of the six generators for the 30-bus power system in case one, which simulates power losses, for all algorithms.
The best values obtained are in bold.

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Table 3. Results of the first objective function for the IEEE 30-bus system.

| Algorithm | Worst | Best | Median | Mean | Std. Dev |
|-----------|-------|------|--------|------|----------|
| AEO       | 4.9473| 4.94658 | 4.94555 | 4.945715 | 0.000640 |
| EO        | 4.9473| 4.94375 | 4.9453745 | 4.9455445 | 0.00051849 |
| GBO       | 4.9755| 4.945 | 4.94635 | 4.949695 | 0.00797776 |
| TFWO      | 4.9459| 4.9449 | 4.94515 | 4.945205 | 0.00024381 |
| CTFWO     | 4.9453| 4.94480 | 4.9449 | 4.944915 | 0.00010399 |

The best values obtained are in bold.

In Table 4, the generator voltage, transformer tap ratio, capacitor bank, and generator reactive power values are shown for the voltage deviation simulation with the 30-bus system. Table 5 shows that the values obtained by the CTFWO algorithm are better and more optimal than those obtained by the others in the case of voltage deviation for the IEEE 30-bus system.

Figure 4. Boxplots for all algorithms for the 30-bus system in case 1.

Figure 5. Voltage profiles of load bus for the 30-bus system in case 1.

In Table 4, the generator voltage, transformer tap ratio, capacitor bank, and generator reactive power values are shown for the voltage deviation simulation with the 30-bus system. Table 5 shows that the values obtained by the CTFWO algorithm are better and more optimal than those obtained by the others in the case of voltage deviation for the IEEE 30-bus system.
Figure 5. Voltage profiles of load bus for the 30-bus system in case 1.

Figure 6. Representation of reactive power values of the generators for the 30-bus system in case 1.

Table 4. Results of case 2 for the 30-bus system.

| Parameters                        | Min    | Max    | Case 2 (Min VD) |
|-----------------------------------|--------|--------|-----------------|
| Generator voltage                 |        |        | AEO  | EO  | GBO  | TFWO | CTFWO |
| V1 (p.u.)                         | 0.95   | 1.1    | 1.007321 | 1.004997 | 1.004141 | 1.006213 | 1.002472 |
| V2 (p.u.)                         | 0.95   | 1.1    | 1.008668 | 1.00445  | 1.004527 | 1.007222 | 1.002336 |
| V5 (p.u.)                         | 0.95   | 1.1    | 1.016353 | 1.017078 | 1.016646 | 1.017246 | 1.017129 |
| V8 (p.u.)                         | 0.95   | 1.1    | 1.004699 | 1.004935 | 1.005271 | 1.006619 | 1.006552 |
| V11 (p.u.)                        | 0.95   | 1.1    | 1.007415 | 1.003181 | 1.007753 | 0.986987 | 0.994936 |
| V13 (p.u.)                        | 0.95   | 1.1    | 1.018235 | 1.026852 | 1.027531 | 1.023421 | 1.033269 |
| Transformer tap ratio             |        |        | AEO  | EO  | GBO  | TFWO | CTFWO |
| T11 (p.u.)                        | 0.9    | 1.1    | 1.041081 | 1.037017 | 1.039456 | 1.016957 | 1.025889 |
| T12 (p.u.)                        | 0.9    | 1.1    | 0.906165 | 0.900177 | 0.900001 | 0.907931 | 0.9    |
| T15 (p.u.)                        | 0.9    | 1.1    | 0.960256 | 0.975119 | 0.975975 | 0.968549 | 0.985956 |
| T36 (p.u.)                        | 0.9    | 1.1    | 0.969779 | 0.968731 | 0.970034 | 0.970111 | 0.969488 |
| Capacitor bank                    |        |        | AEO  | EO  | GBO  | TFWO | CTFWO |
| QC10 (MVAr)                       | 0      | 5      | 4.081875 | 4.087516 | 1.027896 | 2.676166 | 1.742964 |
| QC12 (MVAr)                       | 0      | 5      | 1.911945 | 0.964742 | 2.500364 | 2.635314 | 1.827241 |
| QC15 (MVAr)                       | 0      | 5      | 2.438076 | 0.000256 | 0.000249 | 4.026815 | 0.007227 |
| QC17 (MVAr)                       | 0      | 5      | 3.247676 | 4.911974 | 1.68685  | 2.796258 | 3.506261 |
| QC20 (MVAr)                       | 0      | 5      | 3.134319 | 1.643454 | 1.376082 | 0        | 4.730291 |
| QC21 (MVAr)                       | 0      | 5      | 4.002702 | 4.998374 | 4.776548 | 4.999999 | 2.19 \times 10^{-6} |
| QC23 (MVAr)                       | 0      | 5      | 0.939362 | 0.04512  | 1.097063 | 0.803642 | 2.934356 |
| QC24 (MVAr)                       | 0      | 5      | 3.314184 | 1.963021 | 4.07833  | 1.928107 | 0.020467 |
| QC29 (MVAr)                       | 0      | 5      | 1.517154 | 1.885478 | 3.257629 | 0.001063 | 3.853446 |
| Objective function                |        |        | AEO  | EO  | GBO  | TFWO | CTFWO |
| VD (p.u.)                         | NA     | NA     | 0.123808 | 0.122428 | 0.122020 | 0.122065 | 0.12127  |
| Generator reactive power         |        |        | AEO  | EO  | GBO  | TFWO | CTFWO |
| QG1 (MVAr)                        | −29.8  | 59.6   | −29.799 | −27.7386 | −29.8  | −29.8  | −29.7778 |
| QG2 (MVAr)                        | −24    | 48     | 4.050136 | 6.40245  | −6.49091 | 0.917091 | −9.34062 |
| QG5 (MVAr)                        | −30    | 60     | 27.13802 | 30.35612 | 29.72286 | 29.12533 | 31.54037 |
| QG8 (MVAr)                        | −26.5  | 53     | 38.5871  | 40.69673 | 40.73791 | 45.66735 | 45.28808 |
| QG11 (MVAr)                       | −7.5   | 15     | 4.004549 | 1.949049 | 4.169385 | −5.75336 | −2.00473 |
| QG13 (MVAr)                       | −7.8   | 15.5   | 4.203959 | 10.50824 | 11.02679 | 7.990866 | 15.27388 |

The best values obtained are in bold.
Table 5. Results of the second objective function for the IEEE 30-bus system.

|       | AEO | EO  | GBO | TFWO | CTFWO |
|-------|-----|-----|-----|------|-------|
| Worst | 0.12811 | 0.12889 | 0.12655 | 0.12498 | 0.12365 |
| Best  | 0.12308 | 0.122428 | 0.12202 | 0.12206 | **0.12127** |
| Median | 0.1244 | 0.124771 | 0.12379 | 0.12367 | 0.122195 |
| Mean  | 0.124646 | 0.12517885 | 0.1238055 | 0.123365 | 0.122363 |
| Std. Deviation | 0.001245 | 0.00159252 | 0.00104612 | 0.000920 | 0.000794686 |

The best values obtained are in bold.

In Figure 7, the CTFWO algorithm gives the lowest values in the case of voltage deviation compared to the other algorithms in the 30-bus power system.

![Boxplots](image)

**Figure 7.** Boxplots for all algorithms for the 30-bus system in case 2.

The voltage profiles in p.u. for all algorithms with the 30 buses in this system are illustrated in Figure 8. The figure shows that the voltages magnitudes for all the buses are within the specified limits. However, the voltage profile in the case of using the proposed CTFWO technique has the better profile for most buses in the system than other algorithms. Figure 9 shows the reactive power values of the six generators for the 30-bus power system in case two, which simulates the voltage deviation, for all the algorithms.
Figure 8. Voltage profiles of load bus for the 30-bus system in case 2.

Figure 9. Representation of reactive power values of the generators for the 30-bus system in case 2.

Table 6 shows the generator voltage, transformer tap ratio, capacitor bank, and generator reactive power values for the power losses in the 57-bus power system.
Table 6. Results of case 3 for the IEEE 57-bus system.

| Parameters                     | Case 3 (Min Ploss) | AEO | EO  | GBO | TFWO | CTFWO |
|-------------------------------|-------------------|-----|-----|-----|------|-------|
| Generator voltage             |                   |     |     |     |      |       |
| V1 (p.u.)                     | 0.95              | 1.1 | 1.084262 | 1.088584 | 1.083097 | 1.088347 | 1.086947 |
| V2 (p.u.)                     | 0.95              | 1.1 | 1.073155 | 1.076589 | 1.072353 | 1.076389 | 1.076199 |
| V3 (p.u.)                     | 0.95              | 1.1 | 1.060508 | 1.061101 | 1.060881 | 1.060936 | 1.064546 |
| V6 (p.u.)                     | 0.95              | 1.1 | 1.054363 | 1.05593 | 1.054203 | 1.052998 | 1.055437 |
| V8 (p.u.)                     | 0.95              | 1.1 | 1.072266 | 1.074526 | 1.07583 | 1.069332 | 1.075181 |
| V9 (p.u.)                     | 0.95              | 1.1 | 1.043366 | 1.040742 | 1.04638 | 1.03933 | 1.043497 |
| V12 (p.u.)                    | 0.95              | 1.1 | 1.051094 | 1.043244 | 1.053073 | 1.044047 | 1.046439 |
| Transformer tap ratio         |                   |     |     |     |      |       |
| T19 (p.u.)                    | 0.9               | 1.1 | 19.89077 | 13.69412 | 7.408436 | 9.135741 | 8.562415 |
| T20 (p.u.)                    | 0.9               | 1.1 | 10.16505 | 15.49922 | 10.5197 | 10.15296 | 13.51124 |
| T31 (p.u.)                    | 0.9               | 1.1 | 11.50229 | 13.62317 | 10.5197 | 10.15296 | 13.51124 |
| T35 (p.u.)                    | 0.9               | 1.1 | 19.99983 | 4.99742 | 8.079208 | 8.39333 | 9.863767 |
| T36 (p.u.)                    | 0.9               | 1.1 | 3.869202 | 15.18321 | 12.87629 | 18.10179 | 8.393917 |
| T37 (p.u.)                    | 0.9               | 1.1 | 16.57872 | 10.01611 | 9.812319 | 10.48957 | 10.46434 |
| T41 (p.u.)                    | 0.9               | 1.1 | 15.42004 | 9.173277 | 9.720015 | 9.478536 | 9.601751 |
| T46 (p.u.)                    | 0.9               | 1.1 | 5.798275 | 3.498912 | 4.356667 | 5.942918 | 4.812247 |
| Capacitor bank                |                   |     |     |     |      |       |
| QC18 (MVAr)                   | 0                 | 20  | 24.44492 | 12.17391 | 8.35978 | 7.739999 | 12.36848 |
| QC25 (MVAr)                   | 0                 | 20  | 16.00438 | 14.4781 | 14.66842 | 16.74156 | 11.78276 |
| QC53 (MVAr)                   | 0                 | 20  | 16.51053 | 1.745298 | 15.49276 | 15.08808 | 14.34732 |
| Objective function            |                   |     |     |     |      |       |
| Ploss (MW)                    | NA                | NA  | 23.4554 | 23.68991 | 23.4998 | 23.3654 | 23.3235 |
| Generator reactive power      |                   |     |     |     |      |       |
| QG1 (MVAr)                    | −140              | 200 | 46.0987 | 64.86378 | 40.53132 | 62.32991 | 51.02177 |
| QG2 (MVAr)                    | −17               | 50  | 49.99321 | 49.89506 | 49.99514 | 50 | 49.99121 |
| QG3 (MVAr)                    | −10               | 60  | 28.60956 | 35.96237 | 42.07875 | 38.02165 | 45.49167 |
| QG6 (MVAr)                    | −8                | 25  | −3.05249 | 4.164812 | −2.94065 | 1.498686 | −3.36924 |
| QG8 (MVAr)                    | −140              | 200 | 60.07686 | 76.3103 | 66.07949 | 59.34457 | 69.22393 |
| QG9 (MVAr)                    | −3                | 9   | 8.999705 | 8.943546 | 8.996614 | 8.999999 | 8.999992 |
| QG12 (MVAr)                   | −150              | 155 | 64.08973 | 43.69682 | 65.40404 | 47.77938 | 49.32905 |

The best values obtained are in bold.

In Table 7, we observe that the CTFWO algorithm gives better, more optimal values in the case of power losses for the 57-bus system than those obtained from the other algorithms.

Table 7. Results of the first objective function for the IEEE 57-bus system.

| Parameters | AEO | EO  | GBO | TFWO | CTFWO |
|------------|-----|-----|-----|------|-------|
| Worst      | 24.1993 | 27.12346 | 23.8371 | 25.201 | 24.9111 |
| Best       | 23.4554 | 23.68991 | 23.4998 | 23.3654 | 23.3235 |
| Median     | 23.5902 | 25.03884 | 23.61985 | 23.7303 | 23.4988 |
| Mean       | 23.683825 | 25.368013 | 23.63577 | 23.833995 | 23.639485 |
| Std. Deviation | 0.24361589 | 1.055693 | 0.1022282 | 0.4940579 | 0.38384166 |

The best values obtained are in bold.
In Figure 10, we see that the CTFWO algorithm gives the best values at all individual runs in the case of power losses compared to the other algorithms for the 57-bus power system.

![Boxplots for all algorithms for the 57-bus system in case 3.](image1)

**Figure 10.** Boxplots for all algorithms for the 57-bus system in case 3.

The voltage profiles in p.u. for all the algorithms for the 57 buses in this system are illustrated in Figure 11. The figure shows that the voltages magnitudes for all the buses are within the specified limits. However, the voltage profile in the case of using the proposed CTFWO technique has the better profile for most buses in the system than the other algorithms. Figure 12 shows the reactive power values in the 57-bus power system in case three, which simulates voltage deviation, for all the algorithms.

![Voltage profiles of load bus for the 57-bus system in case 3.](image2)

**Figure 11.** Voltage profiles of load bus for the 57-bus system in case 3.
Table 8 illustrates the generator voltage, transformer tap ratio, capacitor bank and generator reactive power values for the case of voltage deviation in the 57-bus system.

### Table 8. Results of case 4 for the IEEE 57-bus system.

| Parameters | Min | Max  | AEO | EO | GBO | TFWO | CTFWO |
|------------|-----|------|-----|----|-----|------|-------|
| **Generator voltage** |     |      |     |    |     |      |       |
| V1 (p.u.) | 0.95 | 1.1  | 1.021242 | 1.013827 | 1.027151 | 1.031907 | 1.014437 |
| V2 (p.u.) | 0.95 | 1.1  | 1.009187 | 1.006551 | 1.016181 | 1.021767 | 1.006477 |
| V3 (p.u.) | 0.95 | 1.1  | 1.012401 | 1.009924 | 1.008498 | 1.014731 | 1.012832 |
| V6 (p.u.) | 0.95 | 1.1  | 1.001737 | 1.003425 | 1.003667 | 1.001059 | 1.008131 |
| V8 (p.u.) | 0.95 | 1.1  | 1.01807 | 1.023622 | 1.017704 | 1.003394 | 1.008705 |
| V9 (p.u.) | 0.95 | 1.1  | 0.998958 | 0.99855 | 0.998712 | 0.989075 | 1.008076 |
| V12 (p.u.) | 0.95 | 1.1 | 1.032864 | 1.018975 | 1.029294 | 1.034201 | 1.034201 |
| **Transformer tap ratio** |     |      |     |    |     |      |       |
| T19 (p.u.) | 0.9 | 1.1  | 15.41972 | 19.80841 | 4.345691 | 15.27412 | 10.61522 |
| T20 (p.u.) | 0.9 | 1.1  | 7.143219 | 7.227283 | 7.110257 | 7.249017 | 7.372825 |
| T31 (p.u.) | 0.9 | 1.1  | 19.65228 | 17.31838 | 12.17408 | 10.53058 | 17.76376 |
| T36 (p.u.) | 0.9 | 1.1  | 13.44046 | 19.99667 | 17.53055 | 19.99013 | 20 |
| T37 (p.u.) | 0.9 | 1.1  | 10.13173 | 11.21114 | 10.83356 | 9.719896 | 10.79664 |
| T41 (p.u.) | 0.9 | 1.1  | 10.82383 | 11.1787 | 9.627105 | 9.317074 | 10.74971 |
| T46 (p.u.) | 0.9 | 1.1  | 2.413594 | 3.985416 | 4.097224 | 1.68163 | 1.734963 |
| T54 (p.u.) | 0.9 | 1.1  | 0.032358 | 0.0 | 0.00183 | 2.26 × 10⁻⁶ | 0.0 |
| T58 (p.u.) | 0.9 | 1.1  | 3.247924 | 4.735199 | 2.983137 | 2.993189 | 2.95414 |
| T59 (p.u.) | 0.9 | 1.1  | 5.955591 | 6.472745 | 8.943067 | 5.794069 | 8.938434 |
| T65 (p.u.) | 0.9 | 1.1  | 9.137057 | 8.268309 | 10.09535 | 9.793917 | 11.07804 |
| T66 (p.u.) | 0.9 | 1.1  | 2.069724 | 0.419808 | 2.11 × 10⁻⁶ | 0.0 | 0.0 |
| T71 (p.u.) | 0.9 | 1.1  | 7.471875 | 5.29712 | 6.490749 | 4.988462 | 6.106468 |
| T73 (p.u.) | 0.9 | 1.1  | 5.314451 | 10.0823 | 9.159237 | 9.145331 | 10.33043 |
| T76 (p.u.) | 0.9 | 1.1  | 1.800253 | 0.0 | 4.71 × 10⁻⁵ | 0.0 | 0.0 |
| T80 (p.u.) | 0.9 | 1.1  | 9.097109 | 9.074298 | 8.345625 | 9.10713 | 10.86881 |
Table 8. Cont.

| Parameters               | Min  | Max  | Case 4 (Min VD) |
|--------------------------|------|------|-----------------|
|                          |      |      | AEO  | EO  | GBO  | TFWO | CTFWO |
| Capacitor bank           |      |      |      |     |      |      |       |
| QC18 (MVAr)              | 0    | 20   | 18.26974 | 19.07913 | 4.726816 | 9.512274 | 19.13888 |
| QC25 (MVAr)              | 0    | 20   | 22.14967 | 26.61433 | 23.11284 | 17.50151 | 21.75597 |
| QC53 (MVAr)              | 0    | 20   | 27.88595 | 27.89456 | 22.68993 | 28.56028 | 27.37095 |
| Objective function       |      |      |      |     |      |      |       |
| VD (p.u.)                | NA   | NA   | 0.60495 | 0.596804 | 0.60383 | 0.58588 | 0.58553 |
| Generator reactive power|      |      |      |     |      |      |       |
| QG1 (MVAr)               | −140 | 200  | 3.364011 | 13.2065 | 12.58937 | 23.46288 | 24.2855 |
| QG2 (MVAr)               | −17  | 50   | 31.87596 | 49.2699 | 47.99061 | 49.97456 | 43.33627 |
| QG3 (MVAr)               | −10  | 60   | 59.6576  | 58.89933| 43.98599 | 59.99735 | 58.95072 |
| QG6 (MVAr)               | −8   | 25   | −6.96418 | −7.98727| 6.681949 | 10.26215 | 7.99952 |
| QG8 (MVAr)               | −140 | 200  | 28.2041  | 44.74489| 28.10331 | 3.612073 | 44.07484 |
| QG9 (MVAr)               | −3   | 9    | 2.601341 | 8.979909| 8.692275 | 8.999975 | 8.999156 |
| QG12 (MVAr)              | −150 | 155  | 153.8968 | 127.2061| 140.3891 | 126.7261 | 152.9637 |

The best values obtained are in bold.

Table 9 shows that the CTFWO algorithm gives better and more optimal values for the 57-bus system in the case of voltage deviation compared with the other algorithms.

Table 9. Results of the second objective function for the IEEE 57-bus system.

|                | AEO  | EO  | GBO  | TFWO | CTFWO |
|----------------|------|-----|------|------|-------|
| Worst          | 0.68792 | 1.067937 | 0.72276 | 0.69456 | 0.61783 |
| Best           | 0.60495 | 0.596804 | 0.60383 | 0.58588 | 0.58553 |
| Median         | 0.64876 | 0.718362 | 0.63507 | 0.614465 | 0.593385 |
| Std. Deviation | 0.02736555 | 0.14116848 | 0.02654973 | 0.02774483 | 0.011368281 |

The best values obtained are in bold.

In Figure 13, the CTFWO algorithm gives the best values at 30 individual runs in the case of voltage deviation compared to the other algorithms in the 57-bus power system.

![Boxplots for all algorithms for the 57-bus system in case 4.](image-url)
The voltage profiles in p.u. for all the algorithms for the 57 buses in this system are illustrated in Figure 14. The figure shows that the voltages magnitudes for all the buses are within the specified limits. However, the voltage profile in the case of using the proposed CTFWO technique has the better profile for most buses in the system than the other algorithms. Figure 15 shows the reactive power values in the 57-bus power system in case four, which simulates voltage deviation, for all the algorithms.

**Figure 14.** Voltage profiles of load bus for the 57-bus system in case 4.

**Figure 15.** Representation of reactive power values of the generators for the 57-bus system in case 4.
In the case of the 30-bus power system and the 57-bus power system, we performed 30 different trials for each algorithm under study and recorded the best trial for each one and plotted them as shown in Figures 16–19.

Figure 16. Power loss ($P_{\text{loss}}$) with number of iterations for the 30-bus power system.

Figure 17. Voltage deviation (VD) with number of iterations for the 30-bus power system.
Figure 18. Power loss ($P_{\text{loss}}$) with number of iterations for the 57-bus power system.

Figure 19. Voltage deviation (VD) with number of iterations for the 57-bus power system.

Figures 16 and 17 illustrate the curves in the case of power loss and voltage deviation for the 30-bus power system, and from these we can see that the CTFWO algorithm achieves the best, most minimal, smoothest, lowest curve compared with the other algorithms.
Figures 18 and 19 illustrate the curves in the case of power loss and voltage deviation for the 57-bus power system and from these we can see that the CTFWO algorithm achieves the best, most minimal, smoothest, lowest curve compared with the other algorithms.

The values for power loss for the 30-bus system vary from 4.945 (in GBO) to 4.9449 (in TFWO); however, after using our algorithm (CTFWO), it becomes 4.9448. In addition, for the 57-bus system variation, it ranges from 23.68991 (in EO) to 23.3654 (in TFWO); however, after using our algorithm (CTFWO), it becomes 23.3235. Moreover, the values for voltage deviation for the 30-bus system is vary from 0.60495 (in AEO) to 0.58588 (in TFWO); however, after using our algorithm (CTFWO), it becomes 0.58553.

Table 10 illustrates that the best result for power loss for the 30-bus system is produced by the CTFWO algorithm when compared with the other algorithms, as shown in the table.

| Test System | Min     | Mean    |
|-------------|---------|---------|
| SF–DE [65]  | 4.946   | 4.947   |
| SP–DE [65]  | 4.947   | 4.9667  |
| EC–DE [65]  | 4.946   | 4.9467  |
| SR–DE [65]  | 4.946   | 4.9481  |
| ECHT–DE [65]| 4.947   | 4.9499  |
| ALC-PSO [20]| 5.1861  | -       |
| EB [40]     | 4.963   | -       |
| QODE [33]   | 5.2953  | -       |
| PSOGWO [68] | 5.0907  | -       |
| CKHA [54]   | 5.1163  | -       |
| GA [68]     | 5.0977  | -       |
| OGS [20]    | 5.1676  | -       |
| PSO [68]    | 5.1041  | -       |
| AEO         | 4.9449  | 4.945715|
| EO          | 4.944675| 4.945545|
| GBO         | 4.945   | 4.949695|
| TFWO        | 4.9449  | 4.945205|
| CTFWO       | 4.9448  | 4.944915|

In Table 11, we can observe that the best result for voltage deviation for the 30-bus system is produced by the CTFWO algorithm when compared with the other algorithms, as shown in the table.

| Test System | Min     | Mean    |
|-------------|---------|---------|
| SF–DE [65]  | 0.1231  | 0.1243  |
| SP–DE [65]  | 0.1224  | 0.1238  |
| EC–DE [65]  | 0.1217  | 0.1235  |
| SR–DE [65]  | 0.123   | 0.1241  |
| ECHT–DE [65]| 0.1229  | 0.1239  |
| PGS–PSO [26]| 0.1539  | 0.2189  |
| PSO–TVAC [26]| 0.2064 | 0.2376  |
| GA [68]     | 0.3732  | -       |
| PSO–TVAC [26]| 0.1354 | 0.1558  |
| PSO [68]    | 0.2816  | -       |
| SWT–PSO [26]| 0.1614  | 0.1814  |
| PSOGWO [68] | 0.278   | -       |
| PSO–CF [26] | 0.1287  | 0.1557  |
| AEO         | 0.12308 | 0.124646|
| EO          | 0.122428| 0.125179|
| GBO         | 0.12202 | 0.123806|
| TFWO        | 0.12206 | 0.123365|
| CTFWO       | 0.12127 | 0.122363|
Table 12 shows that the best result for power loss is produced by the CTFWO algorithm when compared with the other algorithms for the 57-bus system.

Table 12. Comparison of results for power loss in the 57-bus system.

| Test System      | Min  | Mean  |
|------------------|------|-------|
| SF–DE [65]       | 23.363 | 23.7164 |
| SP–DE [65]       | 23.35 | 23.6956 |
| EC–DE [65]       | 23.34 | 23.792 |
| SR–DE [65]       | 23.355 | 23.4392 |
| ECHT–DE [65]     | 23.396 | 23.4963 |
| PSO [44]         | 24.3826 | - |
| PGA [16]         | 23.836 | 24.5448 |
| MCBOA [44]       | 23.6943 | - |
| PSO-ICA [21]     | 24.1386 | - |
| BA [40]          | 24.9254 | - |
| BSO [69]         | 24.3744 | - |
| MOGA [43]        | 23.71544 | - |
| ALC-PSO [20]     | 23.39 | 23.41 |
| CSA [44]         | 24.4922 | - |
| ICA [21]         | 24.1607 | - |
| CSA [44]         | 24.2619 | - |
| MOALO [70]       | 26.593 | - |
| MFOM [40]        | 24.25293 | - |
| WCA [51]         | 24.82 | - |
| FPA [40]         | 24.8419 | - |
| AEO              | 23.4554 | 23.68383 |
| EO               | 23.68991 | 25.36801 |
| GBO              | 23.4998 | 23.63577 |
| TFWO             | 23.3654 | 23.8334 |
| CTFWO            | 23.3235 | 23.63949 |

Table 13 shows that the results of the CTFWO algorithm for voltage deviations in the 57-bus system are the best compared with the other techniques.

Table 13. Comparison of results for voltage deviation in the 57-bus system.

| Test System      | Min  | Mean  |
|------------------|------|-------|
| SF–DE [65]       | 0.586 | 0.6077 |
| SP–DE [65]       | 0.589 | 0.6085 |
| EC–DE [65]       | 0.59 | 0.6173 |
| SR–DE [65]       | 0.59 | 0.6069 |
| ECHT–DE [65]     | 0.588 | 0.6073 |
| ALC-PSO [20]     | 0.6634 | 0.6689 |
| NGWCA [51]       | 0.6501 | - |
| BA [71]          | 0.6434 | 0.6499 |
| OGSA [72]        | 0.6928 | - |
| CBA-III [71]     | 0.6413 | 0.644 |
| WCA [51]         | 0.6631 | - |
| ALO [73]         | 0.6666 | 0.7534 |
| CBA-IV [71]      | 0.6399 | 0.6424 |
| GBWCA [51]       | 0.6501 | - |
| AEO              | 0.60495 | 0.648972 |
| EO               | 0.596804 | 0.775162 |
| GBO              | 0.60383 | 0.639779 |
| TFWO             | 0.58588 | 0.622149 |
| CTFWO            | 0.58553 | 0.596695 |

The comparative Tables 10–13 show that from among the different optimized algorithms, the proposed algorithm (CTFWO) has clear advantages over the others, because it
achieves the best, most minimal values for power losses and voltage deviations, while also achieving the smoothest and lowest curves.

5. Conclusions

In this paper, several optimization algorithms; artificial ecosystem-based optimization, the equilibrium optimizer, the gradient-based optimizer, turbulent flow of water-based optimization, and proposed CTFWO are applied as tools to solve the ORPD problem by minimizing the voltage deviation (VD) and total transmission power loss ($P_{\text{loss}}$) in two standard power systems, a 30-bus system and a 57-bus system. For example, the values of power loss for the 30-bus system varied from 4.945 (in GBO) to 4.9449 (in TFWO), but after using our algorithm (CTFWO), it became 4.94480. Additionally, for the 57-bus system, there was variation from 23.68991 (in EO) to 23.3654 (in TFWO), but after using the proposed algorithm (CTFWO), it became 23.3235. Moreover, the values for voltage deviation in the 30-bus system varied from 0.12308 (in AEO) to 0.12206 (in TFWO); by using the proposed algorithm (CTFWO), it became 0.12127. For the 57-bus system variation, these values ranged from 0.60495 (in AEO) to 0.58588 (in TFWO); after using the proposed algorithm (CTFWO), it became 0.58553. From the all above results and discussions, we find that the CTFWO algorithm gives better voltage deviation and transmission power loss values than other algorithms, and that these results are also better than the results of other recently developed algorithms, such as the many modifications of the DE algorithm, PGSWT-PSO, OGSA, WCA, and GBWCA. The results that we obtained by using the proposed CTFWO algorithm are encouraging for future research. In the future, the proposed CTFWO can be used to solve ORPD problems for systems with a large number of buses, and also to study multi-objective ORPD problems.

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Abbreviations

| Abbreviation | Description                                |
|--------------|--------------------------------------------|
| ABC          | Artificial bee colony algorithm            |
| AEO          | Artificial ecosystem-based optimization    |
| ABC-FF       | ABC with firefly algorithm                 |
| AGA          | Adaptive genetic algorithm                 |
| CSA          | Cuckoo search algorithm                    |
| CSOA         | Crow search optimization algorithm         |
| EC           | E-constraint                               |
| ECHT         | Ensemble of constraint handling techniques |
| GA           | Genetic algorithm                          |
| ACO          | Ant colony optimization                    |
| ALC-PSO      | PSO with an aging leader and challengers   |
| ALO          | Ant lion optimizer                         |
| CKHA         | Chaotic krill herd algorithm               |
| CLPSO        | PSO with comprehensive learning            |
| DE           | Differential evolution                      |
| DE-AS        | Combination of DE and ant system method     |
| EO           | Equilibrium optimizer algorithm             |
| EMOA         | Exchange market optimization algorithm      |
| GBBWCA       | Gaussian bare-bones water cycle algorithm   |
GBTLBO | Gaussian bare-bones-based TLBO algorithm
---|---
GSA | Gravitational search algorithm
HFA-NMS | Hybrid firefly algorithm-based
HPSO | Hybrid PSO
HPSO-ICA | PSO hybrid and imperialist competitive algorithms
HAS | Harmony search algorithm
ICBO | Improved colliding bodies optimization
ICSA | Improved CSA
MFO | Moth–flame optimization technique
MOGWA | Multi-objective grey wolf algorithm
ORPD | Optimal reactive power dispatch
PSO | Particle swarm optimization
PSO-IPG | PSO with pseudo-gradient theory
QOTLBO | Quasi-oppositional teaching–learning-based optimization
SARCGA | Self-adaptive real coded genetic algorithm
Std. dev. | Standard deviation
SP | Self-adaptive penalty
TFWO | Turbulent flow of water-based optimization
P_{loss} | Active power losses
WOA | Whale optimization algorithm

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