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Development and Application of a Leader Tasmanian Devil Optimizer for Solving the Optimal Reactive Power Dispatch Problem in Power Systems

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Abstract

The electric energy systems comprise the following three primary phases. These include generation, transmission and distribution. During the transmission of generated power, losses occur which is considered a major issue in any power system. To meet the continuous demand for electricity, power systems need to be efficient and economical while maintaining stability. The optimal reactive power dispatch (ORPD) problem is a complex and nonlinear optimization problem that involves control variables which are subject to both equality and inequality constraints. Solving the issue of the ORPD problem can help in achieving these goals. In this paper, the Leader Tasmanian Devil Optimization (LTDO) algorithm is proposed to address the ORPD problem and find the optimal solution. The objective functions of minimizing power loss and voltage deviation are implemented into the IEEE 30-bus and IEEE 57-bus tested power systems. The optimal control variables such as generator voltages, reactive power compensation and transformer tapings, are determined to achieve these goals. And so, comparisons are made between the outcomes of the suggested LTDO algorithm and other algorithms, such as the gradient-based optimizer (GBO), the equilibrium optimizer (EO) and the Tasmanian Devil Optimization (TDO) algorithm. Furthermore, the performance of the proposed LTDO algorithm is compared with the results of other well-known studied techniques in recent papers. The results show that the proposed LTDO algorithm outperforms the other algorithms in terms of accuracy, convergence rate and system stability. Therefore, the proposed LTDO algorithm deserves more attention as a potential solution for ORPD problems in the power system.

Keywords: Optimal Reactive Power Dispatch; Tasmanian Devil optimization algorithm; active power losses; voltage deviation.

1. Introduction

Optimization is a process that involves finding the best possible solution for a given problem while taking the constraints that apply to it **[1]**. These optimization problems can be classified into three main types based on the optimization techniques employed. These include single-variable functions, multi-variable functions without constraints and multi-variable functions with constraints. The constraints can be categorized as either equality or inequality constraints. The optimal power flow problem in energy systems comprises two sub-problems, the optimal reactive power dispatch (ORPD) problem and the economic dispatch problem **[2]**. The ORPD problem is a complex and nonlinear optimization problem that involves control variables which are subjected to both equality and inequality constraints. The power system has three main objectives, minimizing active power losses, minimizing voltage deviations and minimizing the L-index. All of which can be achieved by solving the ORPD problem.

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Solving the ORPD problem also provides values for control variables such as generator voltage ratings, transformer tap settings and shunt compensator outputs. These, in turn, can help the power system to operate more efficiently, stably and reliably **[3, 4]**.

Although the ORPD is a critical aspect of power systems, various optimization techniques have been employed to tackle this problem. Classical optimization methods, such as interior point (IP) **[5]**, gradient-based algorithm **[6]**, Newton-based method **[7]**, quadratic programming **[8]**, Lagrangian approach **[9]** and linear and nonlinear programming **[10, 11]**, were initially used to address ORPD. Regardless of the convergence characteristics of the classical optimization methods, these techniques may almost fail for obtaining the global solution due to difficulties of nonlinearity, and no convexity. However, these methods produced inaccurate results due to some limitations in solving the ORPD issue. Hence, novel optimization techniques, such as meta-heuristic algorithms (MA), have been developed and successfully applied to ORPD problems.

Several methodologies have been employed to address the ORPD issue, each proving effective in achieving optimal solutions. MAs offer an efficient and effective means of optimizing reactive power distribution in power systems, leading to enhanced system performance and reduced operational costs. The metaheuristic optimizations algorithms are inspired based on animals' behavior and physical phenomena have become widespread popular due to their flexibility, simplicity, and ability to get global solutions, and prevent local optimal solutions.

In a study referenced as **[12]**, the authors utilized the Grey Wolf Optimizer (GWO) algorithm to address the ORPD problem and compared its performance against other well-known optimization algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE). Also, a hybrid GWO-PSO method is proposed with the aim of enhancing optimization performance by leveraging the strengths of both the GWO and PSO algorithms. PSO is known for its fast convergence rate, while GWO excels in effective exploration capabilities. By combining these two techniques, the suggested hybrid algorithm achieves a balanced approach in exploring and utilizing the search space. Simulation tests conducted on IEEE 30-bus and 57-bus. The results of the suggested approach exhibit improved convergence and solution quality this shown in **[13]**. A unique metaheuristic optimization approach has been introduced to address ORPD problems in power systems. This approach draws inspiration from nature, specifically the social structure and hunting behavior of grey wolves and is based on GWO. The robustness of the utilized approach is demonstrated through a variety of ORPD problems on two tested power systems **[14]**.

In **[15]**, the specialized genetic algorithm (SGA) is examined and tested with the recommended constraint handling approach and the traditional penalization of deviations from feasible solutions. Several tests are run in the IEEE 30, 57, 118 and 300 bus test power systems. The results obtained with the proposed approach are compared to those offered by other metaheuristic techniques reported in the specialized literature Reference **[16]** shows that the PSO technique is utilized to determine the optimal values of reactive power sources in the system inspired by the social behavior of fish schools and flocks of birds. The suggested method is evaluated on widely used systems in power system optimization studies, namely the typical 30-bus and 57-bus test systems.

In reference **[17]**, the combination of fuzzy logic and PSO algorithms is proposed to enhance the performance of ORPD in bulk power systems. Fuzzy logic is utilized to dynamically adjust the parameters of the PSO technique during optimization, leading to improved convergence speed and solution quality. The objective function includes the reduction of overall actual power loss in the power system, along with considering VD as a penalty term. The proposed approach is tested on a 118-bus network to demonstrate its effectiveness in enhancing ORPD performance. But in **[18]**, the proposed PSO algorithm with aging leaders and challengers is tested on three different electric networks: the standard 14-bus, 30-bus, and 57-bus systems. In **[19]**, the suggested approach for handling constraints in the ORPD issue is based on the Penalty Function Method (PFM). The modified PFM approach is utilized to tackle the ORPD issue in the 30-bus and 118-bus power systems.

In **[20]**, the modified Social Spider Optimization (MSSO) algorithm is employed to solve the ORPD issue in electric networks with multiple objectives. The MSSO algorithm is an enhancement of the original SSO algorithm, which draws inspiration from the hunting behavior of social spiders. The accuracy of the developed MSSO approach is validated on the 33-bus and 69-bus systems with various objective functions including minimizing total power loss, reducing voltage variation, and a combination of both objectives. In reference **[21]**, the tight-and-cheap conic relaxation (TCCR) strategy was used to solve the ORPD. By tightly relaxing the ORPD problem using the TCCR technique. The authors evaluate their proposed methodology on several systems, including the 14-bus, 30-bus, and 118-bus typical networks.

In **[22]**, the suggested chaotic bat algorithm (CBA) incorporates a chaotic map to improve the algorithm's search ability and prevent it from getting stacked in a local optimum. The suggested CBA method is evaluated on the 14-bus, 30-bus, and 118-bus systems. In reference **[23]**, the authors propose an optimization method based on the moth-flame optimizer (MFO) to tackle ORPD issues in electric networks. The MFO algorithm imitates the behavior of moths and flames and utilizes the attraction mechanism between them to find the optimal solution. The efficacy of the proposed method is demonstrated on several ORPD challenges using a practical 135-bus system and a traditional 30-bus system.

In **[24]**, a novel methodology to solve the ORPD issue is proposed by utilizing an enhanced gravitational search algorithm (GSA) with two innovative constraint-handling strategies. The goodness of the incorporated method is validated on the IEEE 30-bus, 57-bus, and 118-bus standard networks. In reference **[25]**, a hybrid of artificial rabbits' optimization (ARO) and gradient-based optimization (GBO) (AROGBO) technique was applied to optimize the performance of the standard IEEE-30, IEEE-57, and IEEE-118 bus test systems. For each system, two objective functions were evaluated: minimizing total power loss and minimizing total VDs.

In reference **[26]**, a novel approach is proposed to address the ORPD issue in power systems by addressing load uncertainty. The methodology combines the DE technique and Monte Carlo simulation. The proposed methodology is extensively evaluated on both the standard 30-bus and enhanced 118-bus systems. In reference **[27]**, the authors present a unique approach to solving the ORPD issue incorporating an improved ant-lion optimization algorithm (IAOA). The article also includes a comprehensive evaluation of the suggested algorithm's performance on two different IEEE 30-bus systems and modified 118-bus networks. In reference **[28]**, a novel optimization technique called the Gaussian bare-bones water cycle (GBWC) algorithm is proposed to address the

RPD problem in electrical networks. The algorithm's performance is compared with several state-of-the-art optimization techniques on the 30-bus and 118-bus standard networks.

In reference **[29]**, the authors propose an improved Salp swarm algorithm (ISSA) that incorporates dynamic weight factors and a local search mechanism, along with additional features, to address both single-objective and multi-objective ORPD issues. The work considers benchmark issues in both single- and multi-objective ORPD on the 30-bus and 57-bus standard networks. In **[30]**, the authors propose a novel optimization technique called quasi-oppositional differential evolution (QODE) to tackle the RPD issue in electric networks. This technique combines opposing and quasi-opposing solutions to generate new candidate solutions. Standard IEEE 30 bus and 118 bus systems are incorporated for comparative analysis.

For instance, GA **[31]** and the hybrid loop-genetic-based algorithm **[32]** are some of the MA approaches used to address ORPD. The DE algorithm **[33]** has been integrated with other systems such as the Ant system (DE-AS) **[34]**, modified with other algorithms such as Modified teaching learning algorithm **[35]** chaotic turbulent flow of water-based optimization algorithm **[36]**.

In **[37]**, a novel non-probabilistic structural damage identification approach by developing a hybrid swarm intelligence technique based on Jaya and Tree Seeds Algorithm (TSA), taking into account the high-level uncertainties in the measurements and finite element modeling. To make the optimization algorithm more powerful and robust, a hybridization of the K-means clustering based Jaya and TSA is proposed. Jaya algorithm is taken as the core in the hybridization. The proposed hybridization algorithm is termed as "C-Jaya-TSA". To enhance the capacity of the proposed algorithm to consider uncertainties, a non-probabilistic method is also integrated to calculate the interval bound (lower and upper bounds) of the elemental stiffness changes by using the interval analysis method.

In **[38]**, the ORPD is solved using a new natural inspired algorithm called the marine predators' algorithm considering the uncertainties of the load demand and the output powers of wind and solar generation systems. The scenario-based method is applied to handle the uncertainties of the system by generating deterministic scenarios from the probability density functions of the system parameters. The proposed algorithm is applied to solve the ORPD of the IEEE-30 bus system to minimize the power loss and the system voltage devotions.

The Tasmanian Devil Optimization (TDO) algorithm has been found to be highly efficient and effective in solving real-world problems by striking a balance between exploration and exploitation. However, in this study, an effective version called the Leader Tasmanian Devil Optimization (LTDO) is presented to further enhance the accuracy of the solution to the ORPD problem. Our goal is to achieve a more stable grid and more accurate results. To achieve this, we applied three optimization methods (the gradient-based optimizer, equilibrium optimizer, and TDO algorithm) to two power systems (IEEE 30-bus and IEEE 57-bus) and tested two single objective functions (minimizing active power losses and minimizing voltage deviation). However, the results of these three algorithms did not meet our expectations, so we modified the TDO algorithm to create the LTDO algorithm. The LTDO algorithm was then used to solve the ORPD problem and compared to the results obtained by the other three techniques in both power systems. The simulation results showed that the LTDO algorithm outperformed the other three algorithms and led to a more stable and efficient power system.

The paper is structured as follows: Section 2 presents the mathematical equations for the ORPD problem. Section 3 describes the TDO optimization and the LTDO algorithm. Section 4 provides a detailed analysis of the results and a discussion of the findings. Finally, Section 5 presents the conclusions, the propositions, and the outcomes of the study.

2. Problem formulation

The power system network comprises various components, including generators (which produce electrical power and have parameters such as terminal voltage, output active power, and reactive power), transformers (which regulate voltage levels by increasing or decreasing voltage rate and adjusting tap changers), transmission lines (which transmit electricity from generators to loads), loads, and capacitors. When these components are controlled, the power system network operates stably and with high efficiency. The ORPD problem involves modeling objective functions and limitations, such as those pertaining to equality and inequality. There are three objective functions for the ORPD problem. The first objective is to minimize power losses (P_{Loss}), which is the primary objective. The second objective is to minimize voltage deviation (VD), and the third objective is to minimize the voltage stability index (L-index).

2.1. Objective Functions:

The main goals of the present study's ORPD problem are twofold: first, to minimize the active power loss (P_{Loss}), and second, to minimize the voltage deviation (VD) within the system being analyzed.

(1) Real Power Loss minimization (P_{Loss})

Minimizing active power loss (P_{Loss}) is a crucial objective function in power systems as it directly results in energy loss and increased energy prices. Mathematically, this function can be expressed as:

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

Where; P_{loss} is the active power loss, V_i signifies the voltage amplitude of the ith bus, V_j signifies the voltage amplitude of the ith bus, N_{TL} signifies the number of transmission lines, α_{ij} is phase angle between voltages of ith and the jth bus, and g_k is the conductance of the kth section.

(2) Voltage deviation minimization of (VD)

The second objective function in ORPD is the minimization of voltage deviation. Mathematically, this can be expressed as:

$$f_2 = VD = min\left(\sum_{i=1}^{N_L} |V_{li} - 1|\right) \quad (2)$$

where VD signifies the voltage deviation, V_{li} signifies the voltage at the i_{th} bus and N_L signifies the number of load buses **[38]**.

2.2. Constraints

(1) Equality Constraint

$$P_i - V_i \sum_{j=1}^{N_B} V_j \left[G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)\right] = 0 \tag{3}$$

Where; $P_i = (P_{Gi} - P_{Di})$ (4)

$$Q_i - V_i \sum_{j=1}^{N_B} V_j \left[G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)\right] = 0 \tag{5}$$

Where; $Q_i = (Q_{Gi} - Q_{Di})$ (6)

where P_i is the active power injected at ith bus, Q_i is the reactive power injected at ith bus, P_{Gi} is the active power generated at the bus i, Q_{Gi} is the reactive power generation of the ith bus, P_{Di} is the active load demand of the ith bus, Q_{Di} is the reactive power drawn from the ith bus, B_{ij} and G_{ij} signify the components of the bus admittance matrix, and N_B signifies the buses number.

(2) Inequality Constraints

- Generator Constraints

$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}$ *For i = 1, ………, N_G* (7)

$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}$ $For\ i = 1, \dots \dots \dots, N_G$ (8)

- Transformer Constraints

$T_i^{min} \leq T_i \leq T_i^{max}$ *For i = 1, ………, N_T* (9)

- Shunt VAR compensator Constraints

$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}$ *For i = 1, ………, N_C* (10)

- Transmission line and load Constraints

$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}$ *For i = 1,………, N_L* (11)

$S_{Li} \leq S_{Li}^{max}$ $For\ i = 1, \dots \dots \dots, N_L$ (12)

where: V_{Gi}^{max} is the maximum generator voltage of the ith bus V_{Gi}^{min} is the minimum generator voltage of the ith bus, Q_{Ci}^{max} is the minimum values of the reactive power injection of the ith shunt compensator, Q_{Ci}^{min} is the minimum values of the reactive power supplied by shunt compensator at the ith bus, T_i^{max} is the maximum tap adjusting values of the ith transformer, T_i^{min} is the minimum tap adjusting values of the ith transformer, N_C is the number of shunt compensators, N_G is the number of generators, N_T signifies the number of tap changers, V_{Li}^{min} signifies the minimum voltages of the ith load bus, V_{Li}^{max} signifies the maximum voltage of the ith load bus, Q_{Gi}^{min} signifies the minimum reactive power generation values of the ith generator bus, Q_{Gi}^{max} signifies the maximum reactive power generation values of the ith generator, and S_{Li}^{max} signifies the maximum apparent power flow through line i **[39]**.

3. Methodology

3.1 Optimization (TDO)

The TDO algorithm **[1]** is a metaheuristic method inspired by the natural foraging behavior of the Tasmanian devil. It simulates two main activities: attacking live prey and scavenging dead animals. The algorithm is structured around the Tasmanian devil's nutritional process, with a flowchart provided in Figure 1 illustrating the key steps of the methodology. In nature, the Tasmanian devil seeks food sources through a combination of active hunting and opportunistic feeding, whereas in the TDO algorithm, this behavior is translated into a structured search for the optimal solution to a given optimization problem.

The optimization process is divided into two main phases: exploration and exploitation mathematically represented by equations (13) to (21). In the context of the algorithm, exploration refers to the broad search across the solution space, analogous to the animal's search for food across various areas. Exploitation, on the other hand, represents the focused search within a confined region, similar to the devil's pursuit of prey in a specific area, and corresponds to the local refinement of potential solutions. The mathematical modeling of this nutritional behavior closely mirrors the design strategy employed to solve complex optimization problems **[1]**.

$$C_i = X_k \quad i=1,2\ldots N \quad, k \in \{1,2,\ldots\ldots N | k \neq i\}, \tag{13}$$

$$x_{i,j}^{new,s1} = \begin{cases} x_{i,j} + r.\left(C_{i,j} - I.x_{i,j}\right), F_{Ci} < F_i; \\ x_{i,j} + r.\left(x_{i,j} - C_{i,j}\right), otherwise; \end{cases} \tag{14}$$

$$X_i = \begin{cases} X_i^{new,s1}, & F_i^{new,s1} < F_i; \\ X_i, & otherwise; \end{cases} \tag{15}$$

$$P_i = X_k \quad i=1,2, \ldots\ldots N \quad, k \in \{1,2,\ldots\ldots N | k \neq i\}, \tag{16}$$

$$x_{i,j}^{new,s2} = \begin{cases} x_{i,j} + r.\left(P_{i,j} - I.x_{i,j}\right), F_{Pi} < F_i; \\ x_{i,j} + r.\left(x_{i,j} - P_{i,j}\right), otherwise; \end{cases} \tag{17}$$

$$X_i = \begin{cases} X_i^{new,s2}, & F_i^{new,s2} < F_i ; \\ X_i, & otherwise; \end{cases} \tag{18}$$

$$R=0.01(1- \frac{t}{T}), \tag{19}$$

$$x_{i,j}^{new} = x_{i,j} + (2r-1).R.x_{i,j} , \tag{20}$$

$$X_i = \begin{cases} X_i^{new}, & F_i^{new} < F_i ; \\ X_i, & otherwise, \end{cases} \tag{21}$$

where; *X* implies the size of population, X_i implies the *i*th solution, $x_{i,j}$ implies the value of *j*th variable for the *i*th solution , *N* implies the number of search agents, *Ci* implies the chosen carrion by *i*th devil, $X_i^{new,s1}$ implies the updated position of the *i*th devil according to the first strategy, $x_{i,j}^{new,s1}$ implies its value for the *j*th variable, $F_i^{new,s1}$ implies its fitness, F_{Ci}implies the fitness of chosen carrion, *r* implies an arbitrary number between[0; 1], and *I* implies a randomly produced number with a value of 1 or 2, P_i implies the defined prey by the *i*th devil, k implies a random number ranged from 1 to *N* and opposite *i*, $X_i^{new,s2}$implies the modified status of *i*th Devil according to the second strategy,; $x_{i,j}^{new,s2}$ implies the value for the *j*th variable, $F_i^{new,s2}$ implies its fitness, and F_{Pi} implies the fitness objective of defined prey, R implies the radius of the position of attack, t implies the current iteration, T implies the maximum iterations, x_i^{new} implies the updated status of the ith devil in neighborhood of X_i , $x_{i,j}^{new}$ implies its value for the jth variable, and F_i^{new}i implies its fitness value.

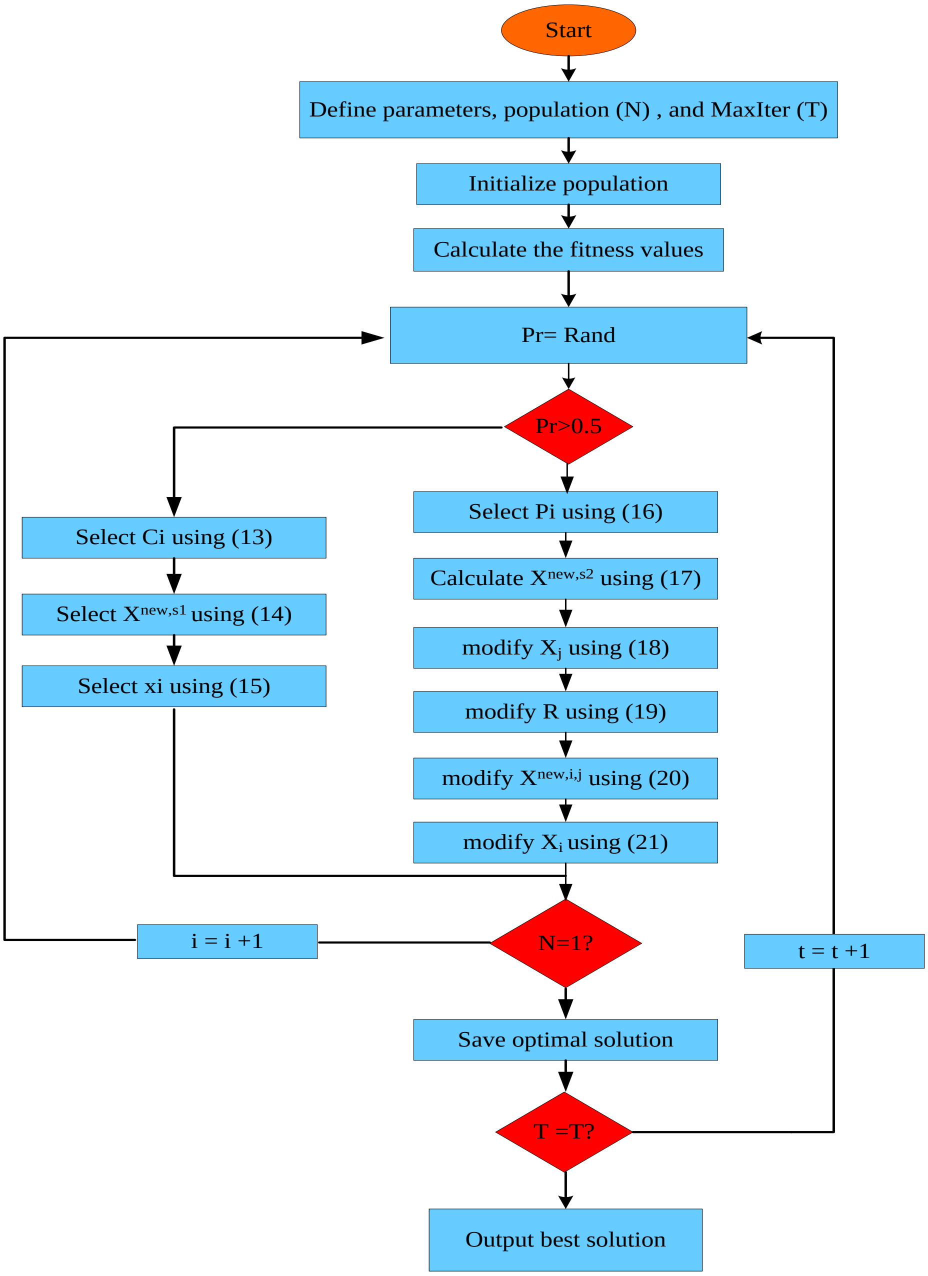

Fig. 1 Flowchart of the TDO technique

3.2 LTDO algorithm

Leader-based mutation selection is the term for the development **[43]**. This method was put up to address the potential for the ideal value to fall to a local minimum. This alteration is contingent upon the optimal location vector, x_{best}^t, based on the fitness value of the new location vector $x_i(new)$ between the number of population. The second-best position vector x_{best-1}^t and the third-best position vector x_{best-2}^t were determined. Next, the following gives the new mutation position vector $x_i(mut)$:

$$x_i(mut) = x_i(new) + 2 \times \left(1 - \frac{t}{\mathrm{Max\_}it}\right) \times (2 \times rand - 1)\left(2 \times x_{best}^{t} - \left(x_{best-1}^{t} + x_{best-2}^{t}\right)\right) + (2 \times rand - 1)\left(x_{best}^{t} - x_i(new)\right) \tag{22}$$

Then, the next location is modified as:

$$x_i(t+1) = \begin{cases} x_i(mut) & f\left(x_i(mut)\right) < f\left(x_i(new)\right) \\ x_i(new) & f\left(x_i(mut)\right) \geq f\left(x_i(new)\right) \end{cases} \tag{23}$$

Finally, the best solution is updated as follows:

$$x_{best} = \begin{cases} x_i(mut) & f\left(x_i(mut)\right) < f\left(x_{best}\right) \\ x_i(new) & f\left(x_i(new)\right) < f\left(x_{best}\right) \end{cases} \tag{24}$$

As seen in Figure 2, the flowchart of the LTDO technique includes the position of the proposed algorithm for Leader-based mutation selection. By employing the top three leaders for simultaneous crossover and mutation, this modification improves the evaluation of the modified LTDO approach.

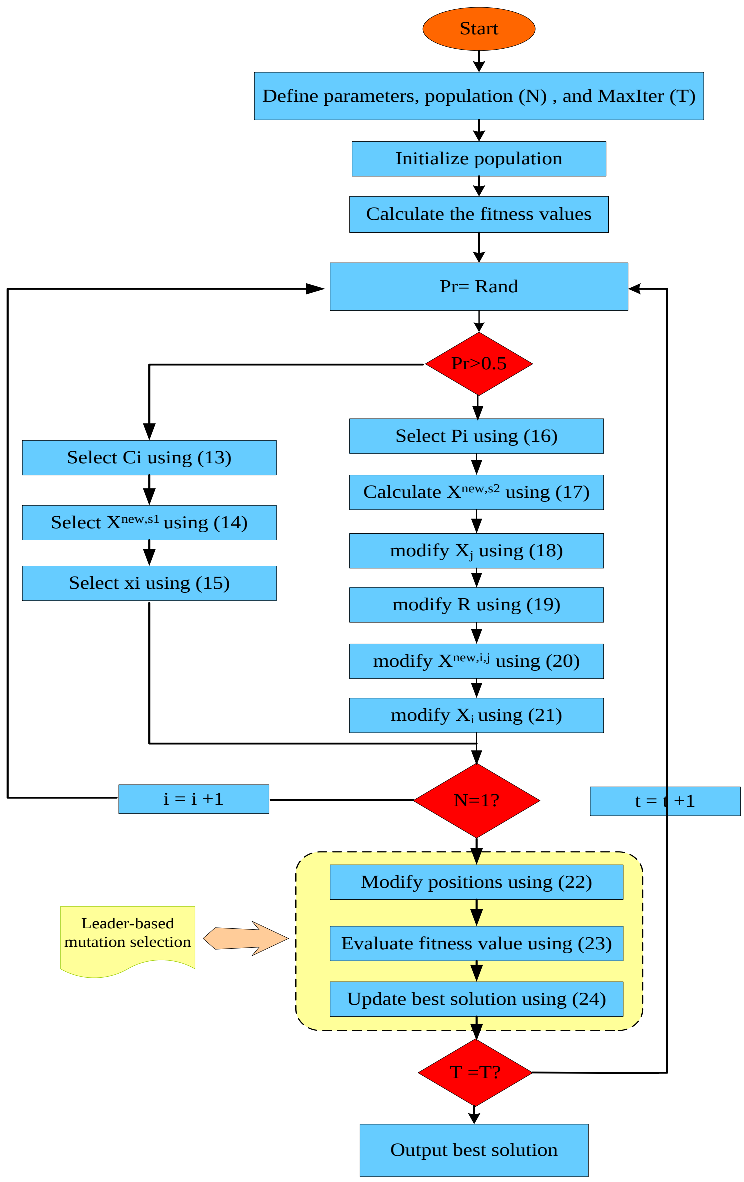

Fig. 2. Flowchart of the LTDO methodology

4. Results and Discussion

The study utilized four proposed algorithms, namely GBO, EO, TDO, and LTDO, to address the ORPD problem with two objective functions: minimizing active power losses (Ploss) and minimizing voltage deviation (VD). These algorithms were implemented on two power systems, namely IEEE 30-bus and IEEE 57-bus, as outlined in Table 1. Figure 3 shows the IEEE 30 bus system.

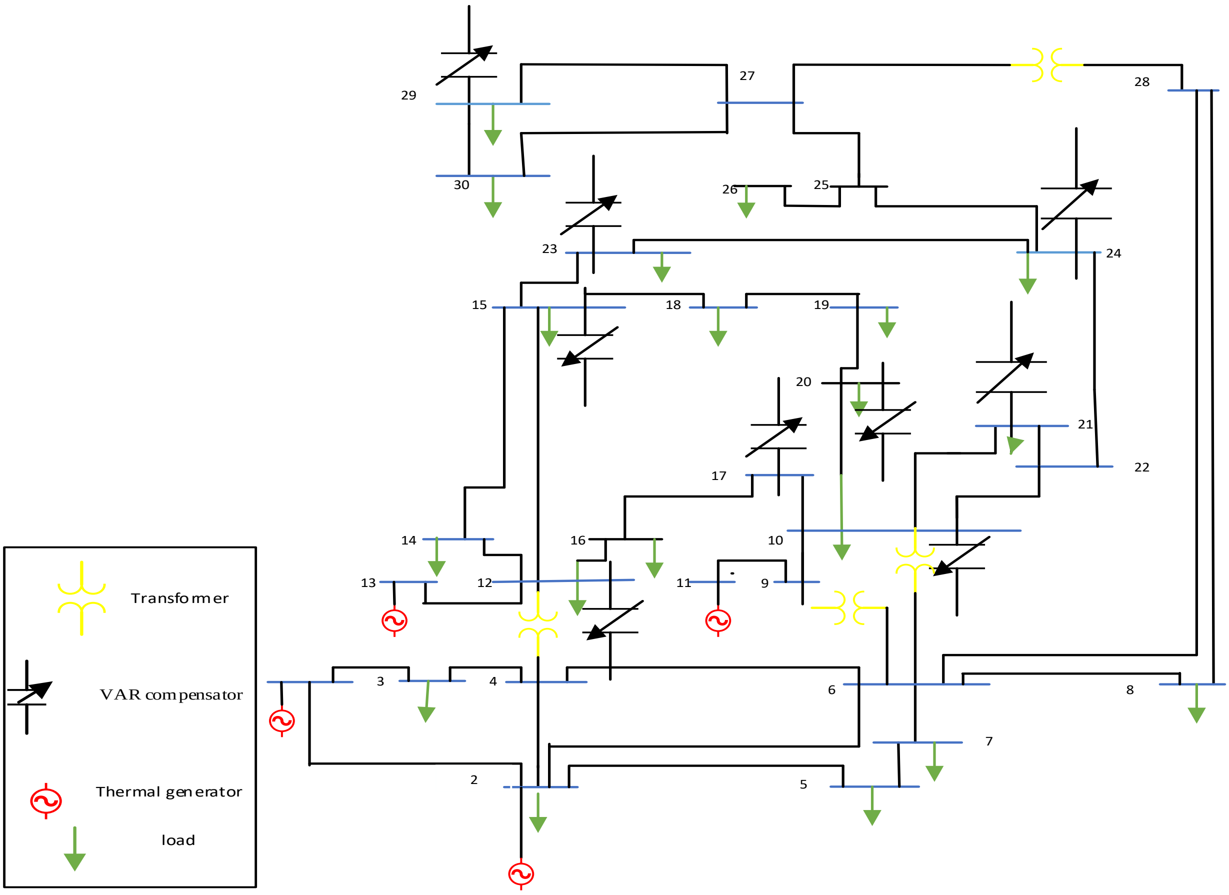

Figure 3. IEEE 30-bus system.

Table 1. Power systems specification.

Description	IEEE 30-bus	IEEE 57-bus
No. Of buses	30	57
No. Of generators	6	7
No. Of transformers	4	17
No. Of shunt compensators	9	3
No. Of branches	41	80
Equality constraints	60	114
Inequality constraints	125	245
Independent variables	19	27
Dependent variables	6	20
Base case for P_{loss}, MW	5.660	27.8637
Base case for TVD, p.u.	0.58217	1.23358

The MATLAB 2018 software program was used to implement the proposed algorithms on a computer with a 2.67 GHz core i5 processor and 4 GB RAM. The search agents were set to 50 and the maximum number of iterations was set to 500. In Case 1, where the objective was to minimize power losses (Ploss) in the IEEE 30-bus power system, the results presented in Table 2 demonstrate that the LTDO approach outperforms the other algorithms. The optimal control variable values that produced by our proposed algorithms are shown in Table 3.

Table 2. Control variables for IEEE 30-bus system case1 (P_{loss}).

Parameters	Min	Max	Proposed algorithms			
			GBO	EO	TDO	LTDO
Generator voltage (p.u.)						
V1	0.950	1.10	1.071032	1.071472	1.071237	1.071503
V2	0.950	1.10	1.061796	1.062185	1.062115	1.062354
V5	0.950	1.10	1.039846	1.039844	1.040064	1.040063
V8	0.950	1.10	1.039876	1.039817	1.040189	1.040193
V11	0.950	1.10	1.032475	1.036577	1.034406	1.036092
V13	0.950	1.10	1.062488	1.06159	1.061039	1.061222
Transformer tap ratio (p.u.)						
T11	0.90	1.10	1.01535	0.996542	1.015453	0.991399
T12	0.90	1.10	0.900161	0.926149	0.903146	0.932545
T15	0.90	1.10	0.984448	0.982578	0.981788	0.981728
T36	0.90	1.10	0.986786	0.986534	0.987736	0.987146
Capacitor bank (MVAr)						
QC10	0	5	0.521123	0.81860	0.487658	0.659298
QC12	0	5	0.260124	0	0.276267	0.118679
QC15	0	5	4.99989	4.9996	1.851999	2.465258
QC17	0	5	0.080239	0.000254	2.207969	0.750271
QC20	0	5	1.739245	0.327968	3.187559	3.482495
QC21	0	5	0.509966	4.687609	4.081412	4.965565
QC23	0	5	4.03902	2.5062	1.741715	2.518776
QC24	0	5	1.747189	4.962173	3.371643	1.345308
QC29	0	5	4.823309	3.6870039	1.341146	0.490049
Objective function						
Ploss (MW)	NA	NA	4.945	4.944876	4.944895	4.944845
Reactive power generation (MVAr)						
QG1	-29.80	59.6	-3.06773	-2.7178	-2.95516	-3.15886
QG2	-24	48	10.63886	11.25537	11.63162	11.12889
QG5	-30	60	1.953514	1.73356	1.808755	1.840262
QG8	-26.50	53	26.73682	26.5341	27.31009	26.74908
QG11	-7.50	15	-4.32984	-5.284388	-6.10067	-3.60406
QG13	-7.80	15.5	9.728283	9.03965	8.757492	8.619919

Table 3. Results of P_{loss} for IEEE 30-bus system.

Algorithm	TDO	LTDO	EO	GBO
Best	4.944895	4.944845	4.944875	4.945
Mean	4.945092	4.945399	4.945544	4.949695
Median	4.945068	4.945274	4.945375	4.94635
Worst	4.945444	4.947507	4.94658	4.9755
Std. Deviation	0.000137	0.000587	0.000519	0.007978

Figure 4 displays the comparison of minimum active power loss achieved by the LTDO algorithm and other algorithms. Figure 5 shows the reactive power of generators for all algorithms. Additionally, Figure 6 illustrates the voltage magnitudes for the 30 buses in the system for the proposed algorithms. The results indicate that the voltage profile achieved by the LTDO algorithm outperforms the other ones for most of the buses. In case 2, where the objective of minimizing (VD) in the IEEE 30-bus power system, Table 5 shows that the LTDO algorithm outperforms the other algorithms and achieves optimal values. Table 4 presents the optimal variables obtained by the four proposed algorithms.

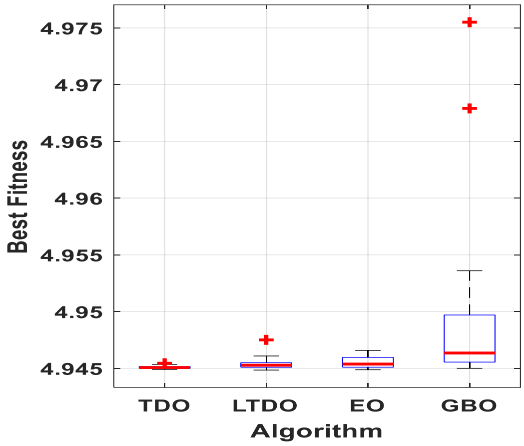

Figure 4. Boxplots based on suggested techniques for case 1.

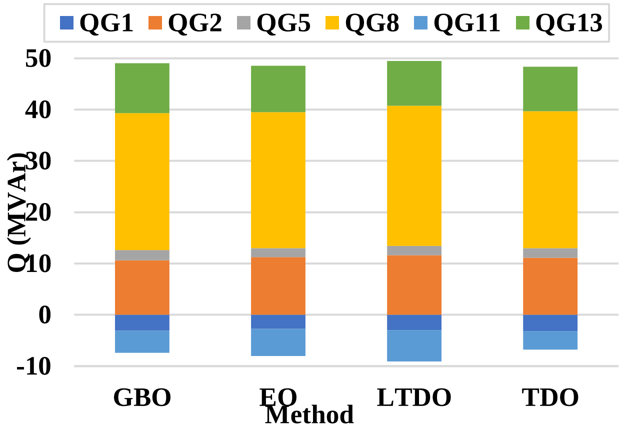

Figure 5. Representation of reactive power generation for case 1

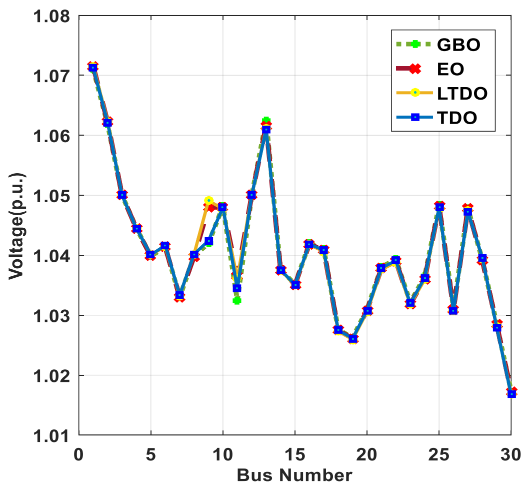

Figure 6. Voltage profiles for case-1.

Table 4. Optimized variables for IEEE 30-bus system case2 (VD).

Parameters	Min	Max	Proposed algorithms			
			GBO	**EO**	**TDO**	**LTDO**
Generator voltage (p.u.)						
V1	0.950	1.10	1.004141	1.004997	1.004435	1.00256
V2	0.950	1.10	1.004527	1.00445	1.004764	1.002462
V5	0.950	1.10	1.016646	1.017078	1.016912	1.017389
V8	0.950	1.10	1.005271	1.004935	1.005956	1.0056
V11	0.950	1.10	1.007753	1.003181	0.997502	0.998077
V13	0.950	1.10	1.027531	1.026852	1.02757	1.033196
Transformer tap ratio (p.u.)						
T11	0.90	1.10	1.039456	1.037017	1.028871	1.027832
T12	0.90	1.10	0.900001	0.900177	0.90497	0.900706
T15	0.90	1.10	0.975975	0.975119	0.975768	0.986791
T36	0.90	1.10	0.970034	0.968731	0.969534	0.970827
Capacitor bank (MVAr)						
QC10	0	5	1.027896	4.087516	2.886778	0.002281
QC12	0	5	2.500364	0.964742	1.869531	3.73286
QC15	0	5	0.000249	0.000256	2.491492	4.043346
QC17	0	5	1.68685	4.911974	1.78158	3.958112
QC20	0	5	1.376082	1.643454	0.860772	2.56869
QC21	0	5	4.776548	4.993874	2.488306	0.009062
QC23	0	5	1.097063	0.04512	3.170594	4.994962
QC24	0	5	4.074833	1.963021	3.072747	2.574953
QC29	0	5	3.257629	1.885478	1.787733	1.197623
Objective function						
VD (p.u.)	NA	NA	0.122024	0.122428	0.121902	**0.121539**
Reactive power generation (MVAr)						
QG1	-29.8	59.6	-29.8	-27.7386	-29.8	-29.5594
QG2	-24	48	-4.69091	-6.40245	-9.08833	-4.42821
QG5	-30	60	29.72286	30.35612	31.83225	29.94824
QG8	-26.5	53	40.73791	40.69673	43.04114	43.11959
QG11	-7.5	15	4.169385	1.949049	-0.50575	-0.77929
QG13	-7.8	15.5	11.02679	10.50824	15.34093	11.02194

Table 5. Results of VD for IEEE 30-bus test system.

Algorithm	**TDO**	**LTDO**	**EO**	**GBO**
Best	0.121902	0.121539	0.122428	0.12202
Mean	0.122639	0.122974	0.125179	0.123806
Median	0.122643	0.122985	0.124771	0.12379
Worst	0.123936	0.126764	0.128889	0.12655
Std. Deviation	0.000496	0.001286	0.001593	0.001046

Figure 7 displays the VD values of four algorithms studied for the 30-bus power system with a focus on minimizing VD. The LTDO technique demonstrates the best results. Figure 8 showcases the reactive power generation for other algorithms in case two. Figure 9 depicts the voltage profiles of the suggested techniques for the system of 30 buses. As demonstrated in the figure, the LTDO algorithm yields superior voltage profiles in most of the buses compared to the other algorithms.

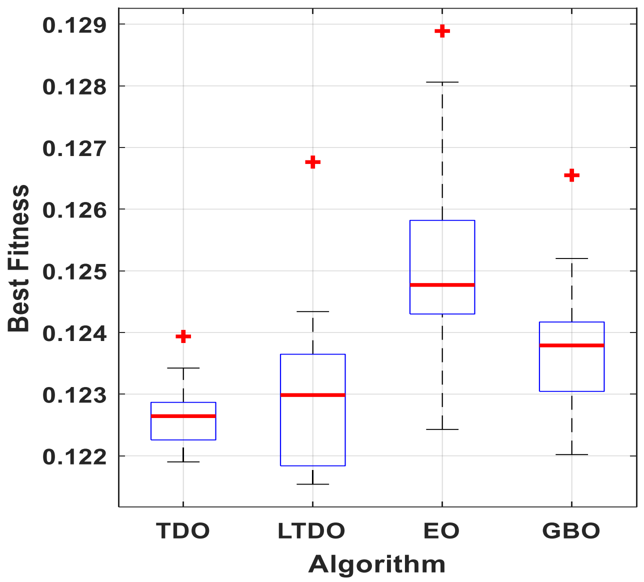

Figure 7. Boxplots based on suggested techniques for case-2.

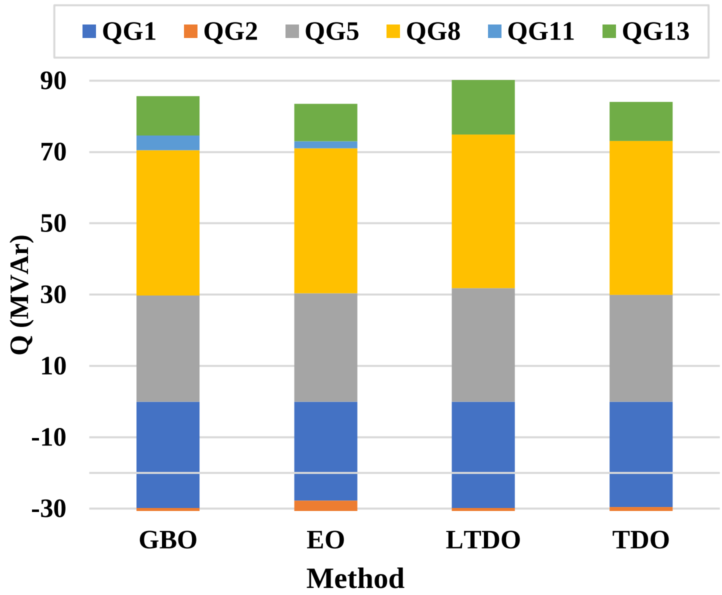

Figure 8. Representation of reactive power generation for case 2

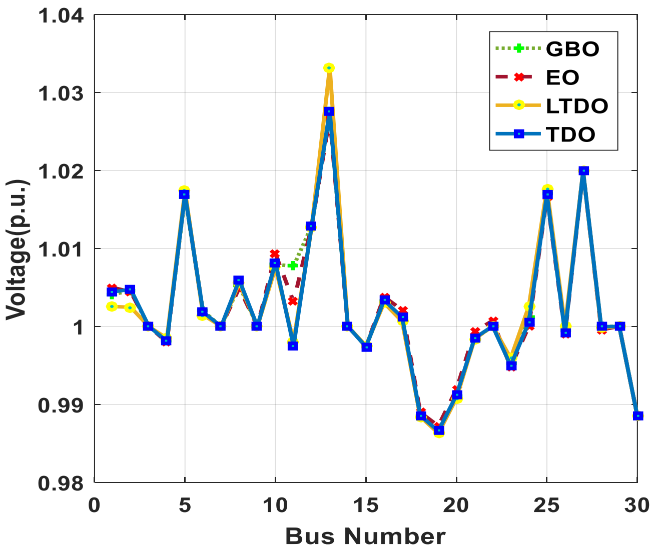

Figure 9. Voltage profiles for case-2.

In the case of the 57-bus power system, where the objective is to minimize Ploss in case 3, Table 6 lists the best control variable values. Table 7 demonstrates that the LTDO algorithm outperforms the other algorithms with regards to P_{loss} values.

Table 6. Control variables for IEEE 57-bus system case3 (P_{loss}).

Parameters	Min	Max	Proposed algorithms			
			GBO	EO	TDO	LTDO
Generator voltage (p.u.)						
V1	0.950	1.10	1.083097	1.088584	1.087669	1.08898
V2	0.950	1.10	1.072353	1.076589	1.075745	1.077138
V3	0.950	1.10	1.060881	1.061101	1.061423	1.062021
V6	0.950	1.10	1.054203	1.05593	1.04835	1.056823
V8	0.950	1.10	1.07583	1.074526	1.065384	1.071978
V9	0.950	1.10	1.046384	1.040742	1.037151	1.040515
V12	0.950	1.10	1.053073	1.043244	1.04478	1.04292
Transformer tap ratio (p.u.)						
T19	0	20	7.408436	13.69412	11.05833	10.81369
T20	0	20	10.68707	15.49922	11.55412	12.0325
T31	0	20	10.5197	13.62317	8.686563	11.05219
T35	0	20	8.079208	4.99742	15.03267	13.40578
T36	0	20	12.87629	15.18321	9.786959	7.360444
T37	0	20	9.812319	10.01611	11.23614	9.622633
T41	0	20	9.720015	9.173277	8.957711	9.675116
T46	0	20	4.356667	3.498912	6.247816	5.674863
T54	0	20	8.26881	0.000382	6.170274	12.20003
T58	0	20	8.255977	8.13231	8.628839	8.399063
T59	0	20	9.558948	8.03943	6.54122	7.049477
T65	0	20	10.26309	8.982809	7.636221	8.028192
T66	0	20	5.390395	4.778383	4.625574	6.249851
T71	0	20	6.989455	9.197826	5.953773	5.390506
T73	0	20	10.40507	1.179605	8.025692	12.69001
T76	0	20	6.67063	5.89709	10.63217	8.806221
T80	0	20	9.155039	7.510371	7.890874	7.832143
Capacitor bank (MVAr)						
QC18	1	30	8.353978	12.17391	15.98982	14.23534
QC25	1	30	14.66842	14.4781	15.25914	15.46344
QC53	1	30	15.49276	1.745298	15.06278	14.32887
Objective function						
Ploss (MW)	NA	NA	23.4998	23.6899	23.45493	**23.43204**
Generator reactive power (MVAr)						
QG1	-140	200	40.53132	64.86378	64.13694	60.95872
QG2	-17	50	49.99514	49.89506	49.9957	48.77168
QG3	-10	60	42.07875	35.96238	34.42213	39.26771
QG6	-8	25	-2.94065	4.164811	3.761811	-5.65749
QG8	-140	200	66.07949	76.3103	61.68105	57.50029
QG9	-3	9	8.999614	8.943546	8.999967	8.205503
QG12	-150	155	65.40404	43.69682	41.51389	52.5489

Table 7. Results of P_{loss} for IEEE 57-bus system.

Algorithm	TDO	LTDO	EO	GBO
Best	23.45493	23.40324	23.68991	23.4998
Mean	24.6249	23.88991	25.36801	23.63577
Median	24.45437	23.66876	25.03884	23.61985
Worst	25.87214	25.29229	27.12346	23.8371
Std. Deviation	0.715096	0.546281	1.055694	0.102224

For the 57-bus power system, where the objective is to minimize Ploss, Figure 10 indicates that the LTDO algorithm yields the lowest power losses compared to the other techniques. Figure 11 illustrates the reactive power generation in the power system, while Figure 12 displays the voltage profile achieved using the LTDO methodology, which outperforms the other studied techniques in most buses.

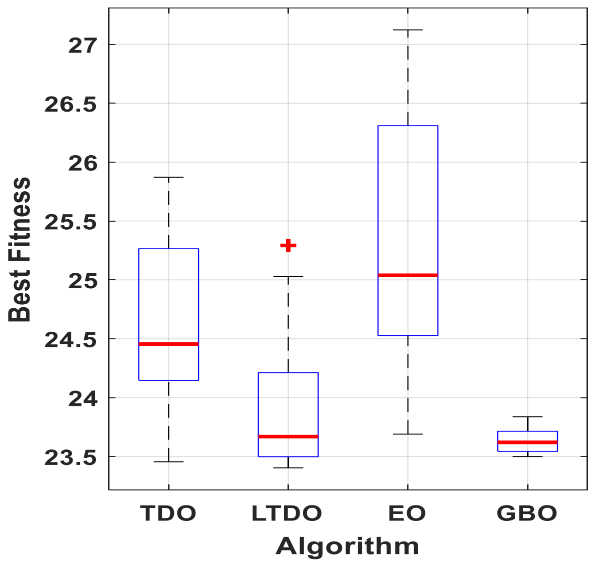

Figure 10. Boxplots based on suggested techniques for case-3.

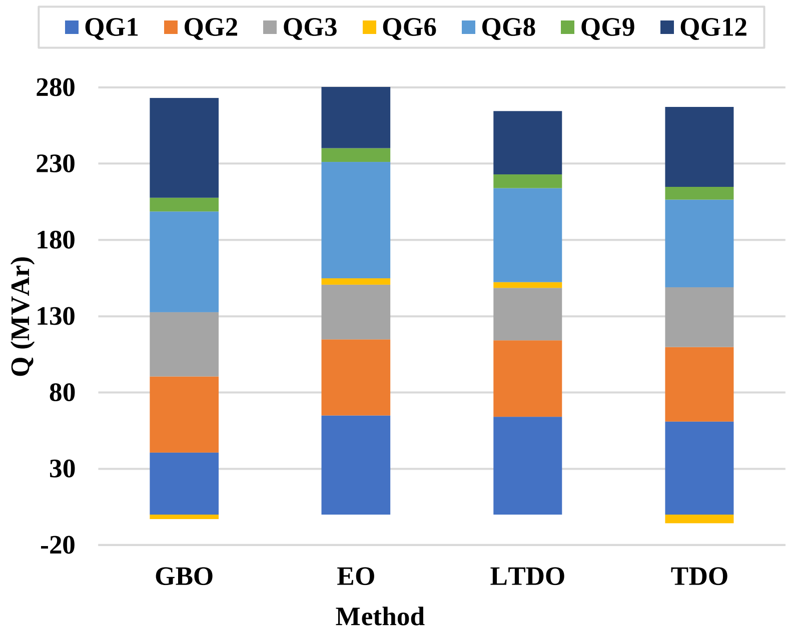

Figure 11. Representation of reactive power generation for case-3.

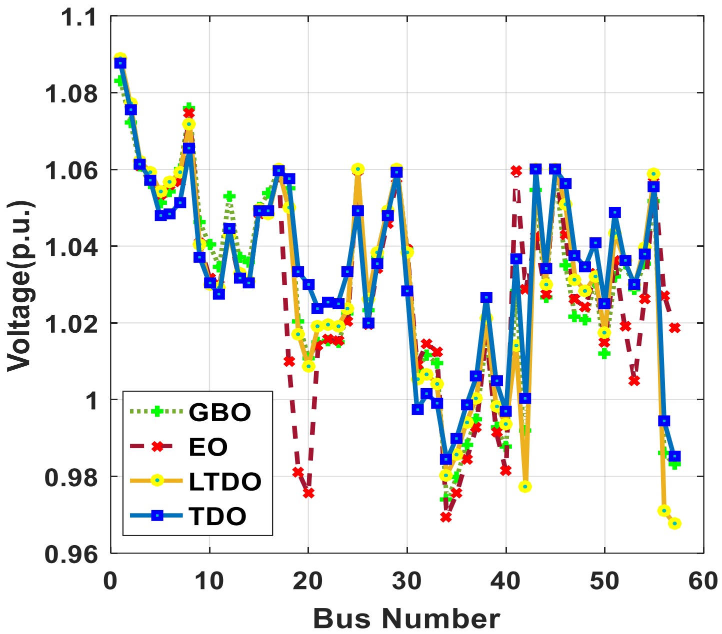

Figure 12. Voltage profiles for case-3.

Table 8 presents the optimal control variables for the IEEE 57-bus power system in case 4 with a focus on minimizing VD. The results obtained from the four proposed algorithms demonstrate that the LTDO methodology yields better values compared to the other algorithms under study. Also, Table 9 presents the statistical results of the proposed LTDO and other optimization algorithms to show the supremacy of the LTDO to solve the ORPD.

Figure 13 demonstrated that the LTDO algorithm provided the most optimal values for voltage deviation in the 57-bus power system. Figure 14 displayed the reactive power generation results for all algorithms examined; Figure 15 showcased the voltage profiles resulting from the suggested techniques. The results revealed that the LTDO algorithm outperformed the others for most buses in terms of voltage profile.

The proposed LTDO algorithm demonstrates superior convergence in power loss for case 1, as shown in Figure 16, achieving faster and more stable reduction compared to other techniques. In Figure 17, the algorithm exhibits enhanced convergence in voltage deviation for case 2, quickly reaching optimal values with minimal fluctuations. For case 3, Figure 18 highlights the LTDO algorithm's improved Ploss convergence, outperforming other methods by converging to a lower loss value more efficiently. Similarly, Figure 19 illustrates the algorithm's robust VD convergence for case 4, showcasing rapid stabilization and better performance than alternative approaches. Across all cases, the proposed LTDO technique consistently achieves faster and more reliable convergence, underscoring its effectiveness in optimizing power systems.

When compared with other recently developed techniques, Table 10 revealed that the proposed LTDO algorithm for the 30-bus system yielded the best results in minimizing power loss.

In the case of 30-bus system under minimizing VD, the best result has been given by using our proposed LTDO algorithm comparing with other recently techniques as provided in Table 11.

Table 8. Optimized control variables for case4 (VD).

Parameters	Min	Max	Proposed algorithms			
			GBO	EO	TDO	LTDO
Generator voltage (p.u.)						
V1	0.950	1.10	1.027151	1.013827	1.012717	1.019484
V2	0.950	1.10	1.016181	1.006551	1.00051	1.010841
V3	0.950	1.10	1.008498	1.009924	1.004001	1.009065
V6	0.950	1.10	1.003667	1.003425	0.995148	0.997159
V8	0.950	1.10	1.017704	1.023622	1.013968	1.017021
V9	0.950	1.10	0.998712	0.99855	0.994042	0.999751
V12	0.950	1.10	1.029294	1.018975	1.024702	1.032351
Transformer tap ratio (p.u.)						
T19	0	20	4.345691	19.80841	13.55167	7.148445
T20	0	20	13.30462	8.455433	10.09213	9.116505
T31	0	20	7.110257	7.227283	7.62836	8.369965
T35	0	20	12.17408	17.31383	10.22388	19.2655
T36	0	20	17.53505	19.99667	6.641036	13.05668
T37	0	20	10.83356	11.21114	11.04366	10.09138
T41	0	20	9.627105	11.1787	7.770522	9.715669
T46	0	20	4.097224	3.985416	3.260128	1.327637
T54	0	20	0.000183	0.00E+00	0.079764	1.01E-07
T58	0	20	2.983137	4.735199	2.318335	3.036027
T59	0	20	8.943067	6.472745	5.638287	7.350853
T65	0	20	10.09535	8.268309	9.332491	10.91834
T66	0	20	2.11E-06	0.419808	2.20E-02	0.32826
T71	0	20	6.490749	5.29712	5.795564	5.189964
T73	0	20	9.159237	10.0823	4.407124	9.961215
T76	0	20	4.71E-05	0	3.73E+00	0.212674
T80	0	20	8.345625	9.074298	9.124832	10.12272
Capacitor bank (MVAr)						
QC18	1	30	4.726816	19.07913	17.42691	10.49876
QC25	1	30	23.11284	26.64133	12.91723	19.42871
QC53	1	30	22.68993	27.89456	22.48519	27.86925
Objective function						
VD (p.u.)	NA	NA	0.603829	0.596804	0.640101	**0.588375**
Generator reactive power (MVAr)						
QG1	-140	200	12.58937	-13.2065	-9.60722	3.828022
QG2	-17	50	47.99061	49.2699	49.97487	31.72919
QG3	-10	60	43.98599	58.89933	58.29397	59.43659
QG6	-8	25	6.681949	-7.98727	-7.99008	-2.76365
QG8	-140	200	28.10331	44.74489	30.28082	39.46266
QG9	-3	9	8.692275	8.979909	8.989678	7.485923
QG12	-150	155	140.3891	127.2061	154.8105	151.1331

Table 9. Results of VD for IEEE 57-bus system.

Algorithm	TDO	LTDO	EO	GBO
Best	0.640101	0.588375	0.596804	0.60383
Mean	0.67912	0.638635	0.775162	0.639779
Median	0.671508	0.63068	0.718362	0.63507
Worst	0.786036	0.755152	1.067937	0.72276
Std. Deviation	0.041412	0.038656	0.141168	0.02655

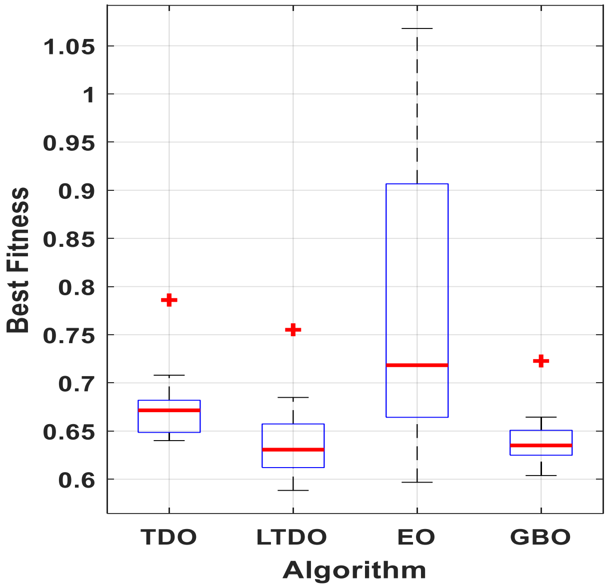

Figure 13. Boxplots based on suggested techniques for case-4.

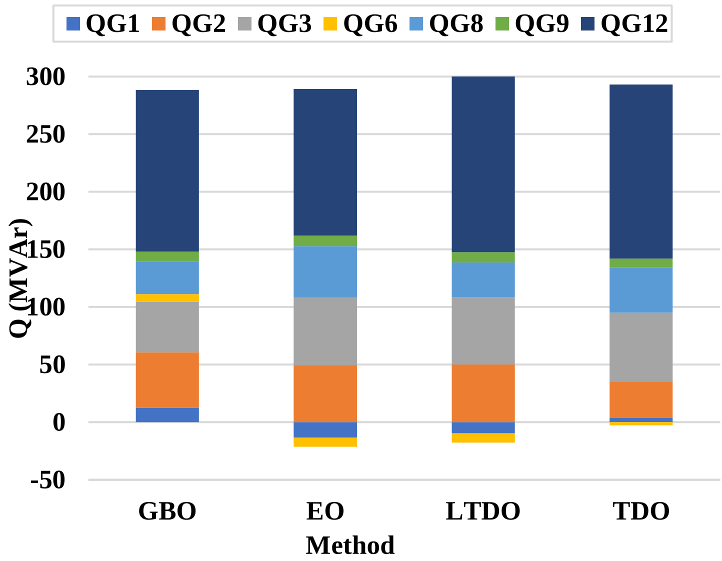

Figure 14. Representation of reactive power generation for case-4.

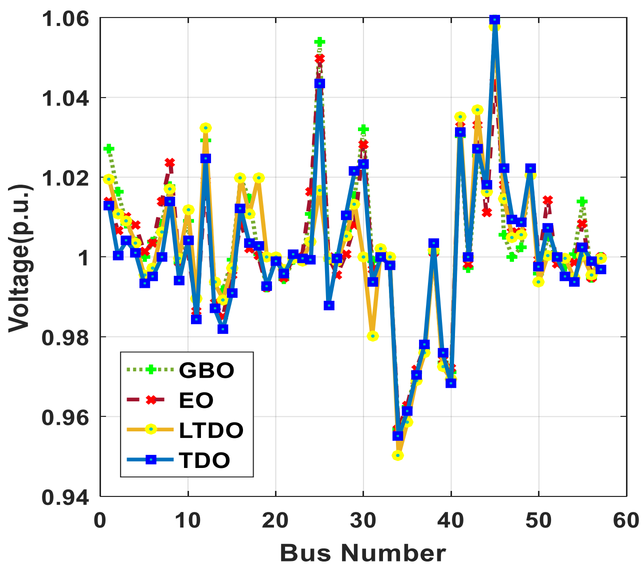

Figure 15. Voltage profiles for case 4.

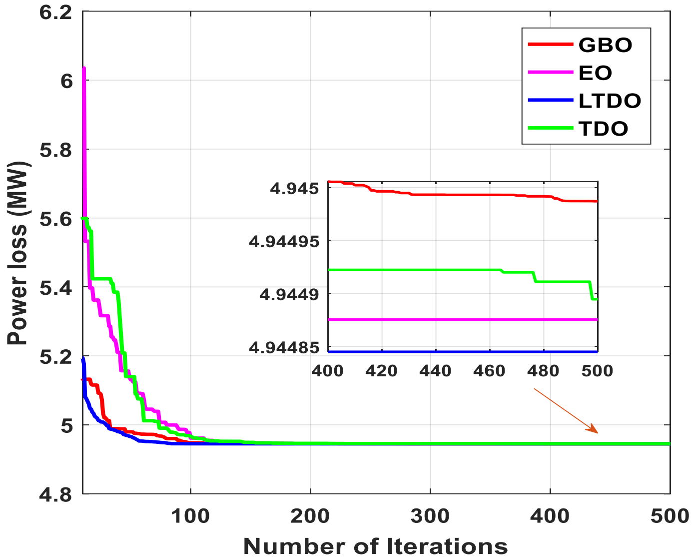

Figure 16. Power loss (Ploss) convergence trends for suggested techniques for case-1.

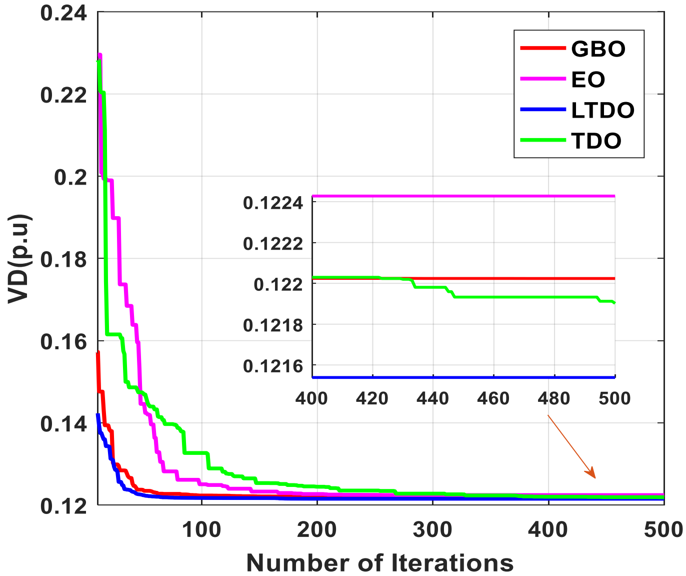

Figure 17. Voltage deviation (VD) convergence trends for suggested techniques for case-2.

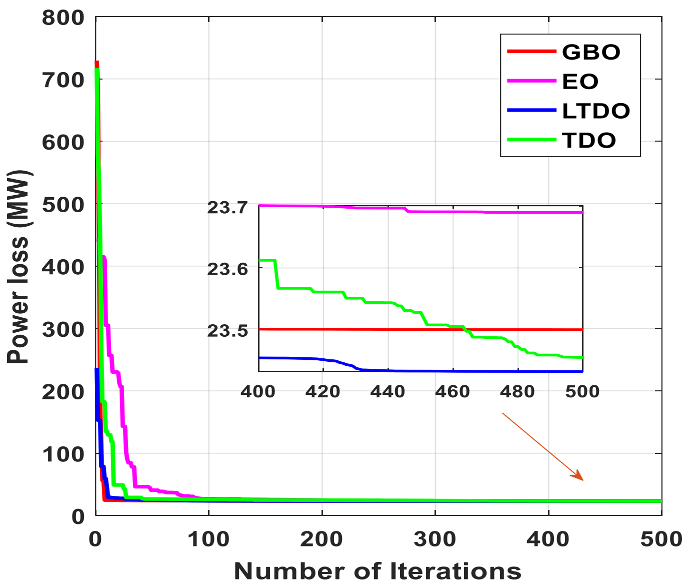

Figure 18. Power loss (Ploss) convergence trends for suggested technique for case-3.

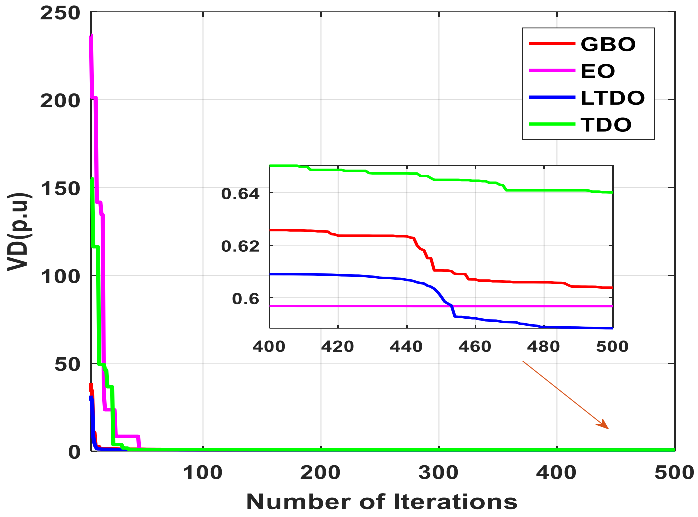

Figure 19. Voltage deviation (VD) convergence trends for suggested techniques for case-4.

Table 10. Comparison results of 30-bus power system for power loss.

Technique	Best	Mean
ECHT–DE [40]	4.947	4.9499
SP–DE [40]	4.947	4.9667
EC–DE [40]	4.946	4.9467
SR–DE [40]	4.946	4.9481
SF–DE [40]	4.946	4.9470
ICA-PSO [41]	5.1861	-
QODE [30]	5.2953	-
OGSA [24]	5.1676	-
PSOGWO [13]	5.09037	-
GA [31]	5.0977	**-**
TFWO [36]	4.9449	4.945205
AEO [36]	4.9449	4.945715
EO	4.944875	4.9455445
GBO	4.945	4.949695
TDO	**4.94490**	4.94509
LTDO	**4.94485**	4.9454

Table 11. Comparison results of VD for the 30-bus system

Technique	Best	Mean
ECHT–DE [40]	0.1229	0.1239
EC–DE [40]	0.12171	0.12352
SP–DE [40]	0.12240	0.12381
SR–DE [40]	0.1230	0.1241
SF–DE [40]	0.1231	0.1243
PSO [13]	0.2816	NA
PSOGWO [13]	0.27800	**-**
AEO [36]	0.12308	0.124646
TFWO [36]	0.12206	0.123365
EO	0.122427	0.12517885
GBO	0.122019	0.1238055
TDO	0.121902	0.122639
LTDO	0.121539	0.122974

From Table 12, it observed that the proposed LTDO algorithm produced the best result in the 57-bus power system under minimizing P_{loss} comparing with recent techniques.

Table 12. Comparison results of P_{loss} for the 57-bus system

Technique	Min	Mean
KHA [42]	23.41	NA
AEO [36]	23.4554	23.683825
GBO	23.4998	23.63577
EO	23.68991	25.368013
TDO	23.4549	24.6249
LTDO	23.4032	23.8899

Table 13 presents a comparison of algorithms for minimizing VD in the 57-bus power system, and the results indicate that our proposed LTDO algorithm performs better than other developed algorithms.

Table 13. Comparison results of VD for the 57-bus system

Technique	Min	Mean
SF–DE [40]	0.586	0.6077
SP–DE [40]	0.5891	0.60852
EC–DE [40]	0.590	0.61731
SR–DE [40]	0.590	0.6069
KHA [42]	0.6605	-
CKHA [42]	0.6484	NA
EO	0.596804	0.7751617
GBO	0.60383	0.639779
TDO	0.640101	0.67912
LTDO	0.588375	0.638635

5. Conclusion

In this paper, four different optimization techniques algorithms were applied, namely: the equilibrium optimizer (EO), the gradient-based optimizer (GBO), TDO algorithm, and the proposed algorithm, LTDO algorithm. These algorithms were tested to solve the ORPD problem in two standard power systems, a 30-bus system and a 57-bus system, with two objective functions: first, minimizing power loss and second, minimizing voltage deviation. The results of the simulations showed that the values of power loss were 4.944875 MW in the EO algorithm, 4.945 MW in the GBO algorithm, and 4.9449 MW in the TDO algorithm. However, after using the LTDO algorithm, the best value was achieved at 4.94485 MW. Similarly, the values of voltage deviation were 0.12202 p.u. in the GBO algorithm, 0.122428 p.u. in the EO algorithm, and 0.121902 p.u. in the TDO algorithm. After using the LTDO algorithm, the best value achieved was 0.121539 p.u.

In the case of the 57-bus system, the power loss values were 23.4998 MW in the GBO algorithm and 23.68991 MW in the EO algorithm. The power loss value in the TDO algorithm was 23.4549 MW, and by using the LTDO algorithm, the power loss value was improved to 23.4032 MW. Lastly, the voltage deviation values were 0.60383 p.u. in the GBO algorithm, 0.596804 p.u. in the EO algorithm, and 0.640101 p.u. in the TDO algorithm. However, after using the LTDO algorithm, the voltage deviation value was improved to 0.588375 p.u. From these simulation results, it can be concluded that the proposed LTDO algorithm produced the most satisfactory results compared to the other proposed algorithms. Not only that, but these results were also superior to the recently developed algorithms. In the future, these results are encouraging as they suggest that the proposed system can address multi-objective ORPD problems for large-scale energy systems.

6. References

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