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Optimal Reactive Power Dispatch Using Artificial Gorilla Troops Optimizer Considering Voltage Stability

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ABSTRACT- The power system has been expanded to supply and fulfil the consumers' requirements for reliability, affordability, and power quality. Power loss reduction and voltage stability enhancement are important points and have been considered interesting subjects for researchers and utilities. Furthermore, reactive power plays an important role in power system stability, security, and voltage improvement, and it is known as reactive power dispatch (RPD). In this paper, a newly developed meta-heuristic optimization technique that inspired the gorilla troop's social intelligence in nature is applied. It is named Artificial Gorilla Troop Optimization (GTO). In addition, GTO is utilized to solve the optimal reactive power dispatch (ORPD) problem, whose real active power and voltage deviation reduction are the objective functions of this study. Generator voltage, transformer tap-changers, and reactive power compensators are the controlled variables that are optimized for achieving the minimum real power loss and bus voltage deviation. To illustrate the efficiency and performance of the proposed algorithm, IEEE 14-bus and 30-bus systems are employed. Moreover, the obtained results are compared with those obtained with other three already existing optimization algorithms, including the genetic algorithm (GA), particle swarm optimization (PSO), and whale optimization algorithm (WOA). Obviously, the proposed approach can prove the optimal values of controlled variables in solving the ORPD problem by giving the minimum real power loss and voltage deviation than those from compared techniques with less computation time.

Keywords: Optimization, Reactive power, Real power loss, Voltage deviation.

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1. INTRODUCTION

In recent decades, electricity has played a very important role in the economy and modern society's development. An electrical power system is the combination of generating, transmitting, distribution, and consumption. Moreover, electricity is used in various aspects, including residential, industrial, and transportation uses. The increase in demand results in an increase in generation. Optimal power flow (OPF) has become popular since it was presented by a French scholar in the 1960s due to its significant efficiency in system reliability improvement and cost reduction. ORPD has been known as part of the OPF problem, and it has been considered a hot topic for researchers and utilities in today's grid modernization [1]. Moreover, insufficient reactive power in the system may cause system voltage instability, which can obviously minimize power system loss. ORPD is the way to identify the optimal value of controlling variables including reactive power injection, transformer tap-changer, and voltage magnitude [2]. It is considered a nonlinear optimization problem involving both discrete and continuous variables and satisfying both equality and inequality constraints. Reactive power compensator and power transformer tap setting are the discrete variables, and reactive power output from the generator with the voltage magnitude are the continuous variables [3]. It results in ORPD as a mixture of integer and nonlinear programming problems.

Many optimization methods, including conventional and intelligent search techniques, have been employed to overcome the ORPD problem, as reported in the literature. The well-known conventional optimization techniques were used in solving ORPD problems, such as Linear Programming [4], Dynamic Programming [5], Newton Method [6], Gradient Search [7], Interior Point Method [8], and Quadratic Programming [9]. Unfortunately, these conventional methods suffer from several drawbacks, including a long time of execution, insecure convergence properties, and the possibility of being trapped by local minima. Furthermore, they are also unable to handle nonlinear and non-convex problems [3]. In recent years, many optimization techniques have been improved and developed based on metaheuristic approaches to overcome the issues that conventional techniques have faced. Those novel methods have been applied to solve the OPF problem with extreme superiority. They could provide results that are near the global optimum point and are capable of handling non-convex and discontinuous objectives. Those techniques include Gravitational Search Algorithm (GSA) [10], Particle Swarm Optimization (PSO) [11], Artificial Bee Colony (ABC) [12], Harmony Search Algorithm (HSA) [13], Genetic Algorithm (GA) [14], Whale Optimization Algorithm (WOA) [15], Dingo Optimizer [16], Sine Cosine Algorithm (SCA) [17], Grey Wolf Optimizer (GWO) [18], Differential Evolution (DE) [19], Bacterial Foraging Optimization (BFO) [20], Hybrid Big Bang-Big Crunch [21], Linear Matrix Inequality [22], and Hybrid PSO [23]. However, some of these algorithms have limited capabilities in handling uncertainties, local minima, misleading global optima [24], etc. Emerging algorithms have been proposed to solve these difficulties.

Many intelligent search algorithms have been applied to handle ORPD problems in both single- and multi-objective functions. In [25], a moth-flame optimization algorithm was proposed to solve ORPD, for which IEEE 30, 57, and 118 bus systems were tested. A hybrid approach based on imperialist competitive algorithms (ICA) and PSO was applied to find solutions to ORPD in IEEE 57 and 118 buses systems [3]. Method proposed in [2] used ABC to solve ORPD for real power loss minimization and voltage stability improvement. IEEE 6 and 14 bus systems were tested with GA, PSO, and a combination of PSO and pattern search in handling reactive power optimization problems [26]. Seeker optimization algorithm (SOA) was applied on IEEE 57 and 118 bus systems to deal with ORPD, while power loss and voltage stability were the objective functions [27]. In [28], a multi-objective approach was used to reduce the ORPD problem of a system with integration with a wind farm. The controlled variables include shunt compensators, synchronous condensers, and under-load tap changers (ULTCs). Fuzzy adaptive heterogeneous comprehensive learning particle swarm optimization was presented to handle the ORPD problem in distribution systems [29]. In [30], the ant lion optimization (ALO) algorithm was used to solve ORPD with the aim of obtaining optimal values of controlled variables, including the number of switchable capacitor banks, generator voltage, and transformer tap-changer. WOA was presented to overcome the ORPD problem, in which real power and voltage deviation were the objective functions [31]. An algorithm for monitoring and enhancing voltage stability in power systems in both base-case and credible contingency conditions was introduced. It aimed to optimize the various control devices like generator excitation, switchable VAR compensators, and OLTC transformers, and the Indian power system was employed as the case study [32].

The PSO with time-varying acceleration coefficients (PSO-TVAC) algorithm was applied to solve ORPD. The performance of the proposed algorithm was tested on the IEEE 14 and 118 bus systems [33]. ORPD with flexible AC transmission systems (FACTS) was reported in [34]. A real-code genetic algorithm was proposed to solve multi-objective ORPD for loss minimization and maximization of voltage stability margin; moreover, terminal voltage, reactive power injection, and transformer tap changer were considered the controlled variables [35].

Referring to the no free lunch theorem [36], no specific optimization technique can handle all optimization problems. Hence, the ORPD problem can be solved by applying newly developed algorithms. In this research paper, a new nature-inspired metaheuristic optimization algorithm is proposed to solve ORPD problems. It is known as the artificial gorilla troop optimizer (GTO), which inspired the social intelligence of gorilla troops [37]. This paper is organized into 5 sections, and the next section describes the problem formulation of multi-objective ORPD problems whose objective function involves the minimization of active power loss and voltage deviation. The mathematical formulation and brief explanation of GTO are mentioned in *section 3*. Moreover, *section 4* illustrates the application of GTO to solving ORPD problems. Simulation results and discussions are shown in *section 5*. Last but not least, the conclusions of the research are presented in the *last section*.

2. PROBLEM FORMULATIONS

The main aims of this paper on ORPD are to minimize both the real power loss in transmission systems and voltage deviation while satisfying both equality and inequality constraints. Additionally, the complete mathematical formulation of the GTO can be found in [38], [39], [40]. The multi-objective function of power loss and voltage deviation can be formulated as:

$$\text{Minimize } \mathrm{f_i(x,u) i = 1,2,\ldots,N_{obj}, f_i} \tag{1}$$

$$\text{Subject to } \mathrm{g(x,u) = 0, h(x,u) \leq 0} \tag{2}$$

where f_i is the objective function i, N_{obj} is the number of objective functions, g is the equality constraints, h is the inequality constraints, x is the vector of dependent variables, and u is the vector of independent variables.

2.1. Real Power Loss Minimization

Power loss occurs during the operation of the power system, and more active power losses will increase the generated power costs. The active power loss minimization in transmission networks and voltage deviation are considered as the objective function of this paper. Moreover, the active power loss can be formulated by studying the flow of power between two bus systems, as described in *figure 1*.

Line current I_{ik} is measured at bus i and considered a positive position, and it can be formulated as:

$$I_{ik} = I_l + I_{i0} = y_{ik}(V_i - V_k) + y_{i0}V_i, \tag{3}$$

Similarly, line current I_{ki} is measured at bus k and considered as positive position and it can be given by:

$$I_{ki} = -I_l + I_{k0} = y_{ik}(V_k - V_i) + y_{i0}V_k, \tag{4}$$

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The complex power from bus i to bus k and from bus k to bus i can be expressed as:

$$S_{ik} = V_i I_{ik}^*, \tag{5}$$

$$S_{ki} = V_k I_{ki}^*, \tag{6}$$

As a result, the loss measured between two buses can be obtained by the algebraic sum of power flows,

$$S_{loss} = S_{ik} + S_{ki}. \tag{7}$$

The total power loss in a system is obtained by summing all the power flow of bus. The power loss in the slack bus can be obtained by summing the power flow at the terminated bus [17].

In this paper, the reactive power loss is neglected, so the objective function of total real power loss reduction is obtained as follows:

$$F_{Loss} = real(\sum_{i=1}^{n} S_{iloss}) \tag{8}$$

Where n is the number of bus branches S_{loss} and is the total complex power loss.

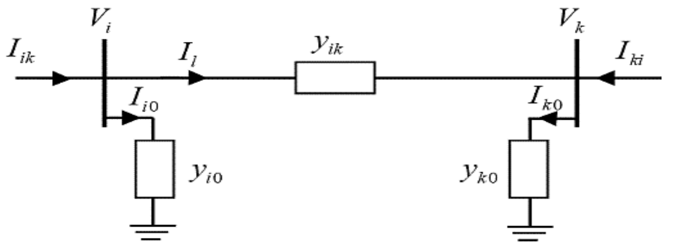

Figure 1. Transmission line model for line flow

2.2. Voltage Deviation Minimization

The voltage magnitude of the load bus should be maintained in the standard range; therefore, voltage deviation minimization is an important objective for improving the voltage system profile.

$$F_{VD} = \sum_{j=1}^{N_{Loadbus}} \left| V_j - V_{ref} \right| \tag{9}$$

Where $N_{Load\ bus}$ is the number of load buses in the system, V_j is the actual voltage magnitude at load bus j, and V_{ref} is the reference voltage magnitude at load bus j which it is considered V_{ref} = 1.0 p.u.

2.3. System Variable Constraints

System variable constraints are considered inequality constraints, which comprise real power injected (P_i), reactive power injected (Q_i), bus voltage magnitude ($|V_i|$), and transformer tap-changer position (T_i). These variables are optimized, and they are limited by the constraints during the optimization process. The system variable constraints are expressed as:

$$Pi_{imax\,imin} \tag{10}$$

$$Qi_{imax\,imin} \tag{11}$$

$$Ti_{imax\,imin} \tag{12}$$

$$Ti_{imax\,imin} \tag{13}$$

2.4. Power Balance Constraints

Power balance constraints are considered equality constraints that must fulfil the power flow equations, including real power, reactive power, and power.

$$P_{G,i} - P_{D,i} - P_{L,i} = 0, \tag{14}$$

$$Q_{G,i} - Q_{D,i} - Q_{L,i} = 0. \tag{15}$$

Where $P_{G,i}$ and $Q_{G,i}$ are real and reactive power generation at bus i, $P_{D,i}$ and $Q_{D,i}$ are real and reactive demands at bus i, $P_{L,i}$ and $Q_{L,i}$ are real and reactive power loss at bus i.

2.5. Overall Objective Function

Real power loss and voltage deviation minimization are considered the objective functions in this paper. Therefore, the overall objective function of the algorithm can be formulated as below: In the case of the combination of two objective functions, the best fitness value is the shortest vector from the origin, as illustrated in *figure 2*, for instance.

$$F_{overall} = F_{loss} + F_{VD} \tag{16}$$

Where F_{loss} and F_{VD} are the objective function of power loss and voltage deviation respectively.

3. ARTIFICIAL GORILLA TROOPS OPTIMIZER

The artificial gorilla troop optimizer is a novel optimization algorithm that draws inspiration from the lifestyle of a collective of gorillas. This algorithm has been recently developed. The term troop is used to refer to a social structure in which gorillas reside together as a cohesive unit. This collective unit consists of male gorillas, female gorillas, and their offspring. Furthermore, it is worth noting that male gorillas acquire the designation of silverbacks because of the distinctive hair growth on their backs during the onset of puberty. The silverback, on aver-age, surpasses 12 years of age and assumes the role of group leader. The silver-back assumes primary responsibility for various tasks and endeavours within the group, such as decision-making, conflict resolution, resource allocation, relocation, and group protection [35]. Male gorillas in their youth are commonly referred to as blackbacks due to their absence of silver-coloured back hairs, a characteristic typically observed between the ages of 8 and 12 years. The mathematical formulation of the GTO algorithm is derived from observations of the social dynamics exhibited by groups of gorillas in their natural habitat.

3.1. Exploration Phase

When gorillas disperse from their community to initiate a novel expedition, they traverse various locations, some of which may be unfamiliar to them. The entire population of gorillas can be classified as candidate solutions, with the silverback being regarded as the optimal candidate solution. During the exploration phase of position updates, three significant mechanisms are employed, namely transitioning to an unfamiliar position, transitioning to a familiar position, and transitioning to alternate gorillas. In addition, the equations governing the updates of position are formulated as follows:

$$GX(t+1) = \begin{cases} (UB - LB) \times r_1 + LB, r < p, \\ (r_2 - C) \times X_r(t) + L \times H, r \geq 0.5, \\ X(i) - L \times (L \times (X(t) - GX_r(t)) \\ r_3 \times (X(t) - GX_r(t)), r < 0.5. \end{cases} \quad (17)$$

In this context, r_1, r_2, r_3 represent random values within the range [0, 1]. The variable $GX(t+1)$ signifies the candidate positions for the subsequent iteration. UB and LB denote the upper and lower bounds of the controlled variables. The variable t represents the current iteration time. $X(t)$ represents the vector of the gorilla positions at the current time. Additionally, X_r and GX_r refer to two randomly selected gorilla positions within the current population. The values of C, L, and H can be determined by utilizing the equations provided below.

$$C = (cos(2 \times r_4) + 1) \times \left(1 - \frac{t}{MaxIt}\right), \quad (18)$$

$$L = C \times l, \quad (19)$$

$$H = Z \times X(t). \quad (20)$$

The cosine function, denoted as cos, is used in this context. The variable r_4 represents a random value within the range of 0 and 1. The notation $MaxIt$ represents the maximum number of iterations. The variable l is a random number that falls within the range of -1 and 1. Lastly, Z denotes a random value between -C and C.

3.2. Exploitation Phase

The silverback gorilla is the group's leader, organizing its movements, allocating food, and ensuring its safety. Silverback gorillas age and die. Black-backed guerillas are known to lead their groups. However, leadership does not always come without controversy. Mating with female gorillas and fighting other male gorillas may lead to leadership. The exploitation phase is characterized by two primary mechanisms: the tracking behaviour of silverback gorillas and the competition for adult female gorillas.

The W is utilized as a means of regulating the decision-making process between adhering to the leadership of the dominant male silverback or engaging in competition with adult females within a social group. If the value of C in *equation (18)* exceeds that of W, the silver back is chosen, and its characteristics can be represented by the following mathematical expressions.

$$GX(t+1) = \mathrm{L} \times \mathrm{M} \times (\mathrm{X}(t) - \mathrm{X}_{\mathrm{silverback}}) + \mathrm{X}(t), \quad (21)$$

$$\mathrm{M} = \left(\left|\frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{GX}_{\mathrm{i}}(t)\right|^{\mathrm{g}}\right)^{\frac{1}{\mathrm{g}}}, \quad (22)$$

$$\mathrm{g} = 2^{\mathrm{L}}. \quad (23)$$

The notation $X(t)$ represents the current position vector, $X_{silverback}$ represents the position vector of the silverback gorilla, $GX_i(t)$ represents the vector of each candidate gorilla, and N represents the total number of gorillas. In the event that the value of C is less than that of W, the selection process favors the adult female gorilla. The mathematical representation of this mechanism is presented below:

$$GX(i) = \mathrm{X}_{\mathrm{silverback}} - (\mathrm{X}_{\mathrm{silverback}} \times \mathrm{Q} - \mathrm{X}(t) \times \mathrm{Q}) \times \mathrm{A} \quad (24)$$

$$Q = 2 \times r_6 - 1, \quad (25)$$

$$A = \beta \times E, \quad (26)$$

$$E = \begin{cases} N_1, r_7 \geq 0.5, \\ N_2, r_7 < 0.5. \end{cases} \quad (27)$$

In the above equation, Q represents the impact factor, while r_6 and r_7 denote random numbers within the range of 0 to 1. A is a coefficient vector used to determine the degree of violence in a conflict, and β represents the parameter that is provided prior to the optimization process.

The optimal values of the latest iteration of $GX(t+1)$ are obtained during the final stages of the exploitation procedure. If $F(GX) < F(X)$ and GX are utilized in the subsequent optimization process, the resulting optimal value is referred to as the silverback $X_{silverback}$. The flowchart of the proposed algorithm is illustrated in *figure 2*. Moreover, the pseudocode of GTO is described in algorithm below.

1. *Initialize the size of population, number of maximum iterations, and population random* $X_i (i = 1,2, \dots. N)$
2. *Calculate the fitness value of the gorillas*
3. *While (stopping criteria is not met) do*
4. *update parameter C using equation 18*
5. *update parameter L using equation 20*
6. *for each gorilla* X_i *do % exploration*
7. *update the position of the current gorillas using equation 17*
8. *end for*
9. *Calculate the fitness value of the gorillas,*
10. *if GX is better than X, replace them and set* $X_{silverback}$ *as the position of silver back*
11. *for each gorilla* X_i *do % exploitation*
12. *if* $|C| \geq 1$ *then*
13. *update the position of gorillas using equation 21*
14. *else*
15. *Update the position of gorillas using equation 24*
16. *end if*
17. *end for*
18. *Calculate the best values of the gorillas, if the new solutions is better than the previous one, replace them and set* $X_{silverback}$ *as the position of the silverback (best position)*
19. *End while*
20. *Return* $X_{BestGorilla}$, $bestFitness$

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4. SIMULATION RESULTS AND DISCUSSIONS

In this section, the IEEE 14 and 30 buses test systems were employed to verify the effectiveness and performance of the proposed methods. Transmission system with 230 kV system voltage and a 100 MVA base applied to the proposed algorithm. Moreover, to compare the accuracy of the algorithm, four well-known optimization techniques comprising GA, PSO, WOA, and GTO were applied to solve the problems. To achieve the results and performances of the prepared program, all tested cases have been simulated by utilizing personal computer with MATLAB 2014a which was in Intel®, core i5-6200U, 2.8 GHz, RAM 8 GB.

Table 1. Controlled variables of the applied algorithms

Controlled variables		Limitations	
		Min	**Max**
Reactive power (Mvar)	*Q*	0	40
Bus voltage (p.u.)	*V*	0.95	1.05
Tap-changer (p.u.)	*T*	0.90	1.10

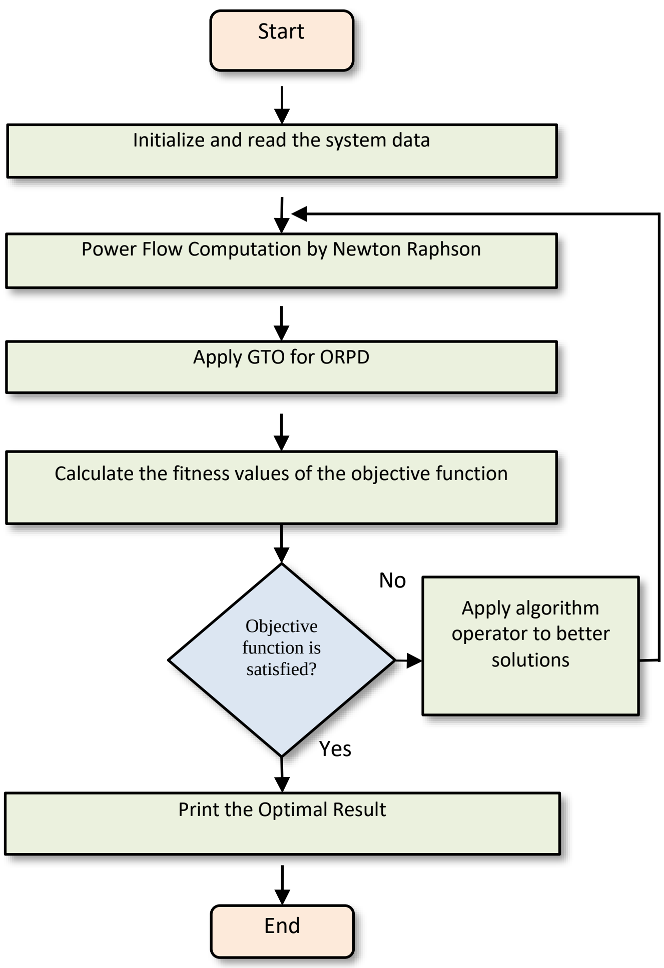

Figure 2. Flowchart of the proposed algorithm

All four algorithms were set to the same population and iteration to compare efficiency and performance. In addition, the maximum and minimum voltages of the bus with the installed capacitor were limited from 0.95 to 1.05 p.u. for controlling the voltage level in the standard range, while the tap changer of the power transformer was considered from 0.9 to 1.1 p.u. *Table 1* describes the limitations of controlled variables applied in the algorithms for the two case studies, including reactive power injection, bus voltage magnitude, and transformer tap-changer. Reactive power was set from 0 to 40 Mvar, while bus voltage and transformer tap-changer were limited from 0.95 to 1.05 p.u. and 0.90 to 1.1 p.u., respectively.

4.1. 14-Bus System

In this section, a 14-bus standard-tested system was employed with the proposed algorithm, and it can be found in [21]. Bus1 and 2 are considered the slack and voltage-controlled buses, respectively, while others are load buses. Moreover, buses 3, 6 and 8 are the locations for installing the reactive power compensator. In addition, the tested system has three power transformers with five tap changers, which are in branches 4–7, 4–9, 5–6, 7-8 and 7-9. *Table 2* shows the values of the setting parameters for the 14-bus system. Each method was set at 50 and 200 population and maximum iterations, respectively.

Table 2. Parameters values of each method of 14 bus system

Parameters	Algorithms			
	GA	**PSO**	**WOA**	**GTO**
Population	50	50	50	50
Max. iteration	200	200	200	200

The simulated results of the four methods are illustrated in *table 3*. It was observed that the power losses before the optimization implementation were 14.72 MW. After the optimization, the power losses were 13.95 MW, 13.99 MW, 13.99 MW and 13.94 MW, which were obtained from GA, PSO, WOA and GTO, respectively. In this case, GTO spent less time of computing which was 136.76s followed by WOA, GA and PSO which were 145.87 s, 210.45 s and 287.5 s, respectively.

Table 3. Simulated results of 14-bus system

Cases	Before optimization		After optimization						Computed time (s)
	Loss (MW)	**VD**	**Loss (MW)**	**VD**	**Loss Saving (MW)**	**VD reduction**	**Loss Deduction (%)**	**VD deduction (%)**	
GA	14.72	0.66	13.95	0.20	0.77	0.46	5.23	69.69	210.45
PSO			13.99	0.19	0.73	0.47	4.95	71.21	287.5
WOA			13.99	0.18	0.73	0.48	4.95	72.72	145.87
GTO			13.94	0.16	0.78	0.5	5.29	75.75	136.76

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Table 4. The obtained results of controlled variable of 14-bus system

Controlled variables		Bus	GA	PSO	WOA	GTO
Bus voltage (p.u.)	V_1 V_2 V_3	3 6 8	1.02 1.04 1.02	1.02 1.01 1.03	1.03 1.02 1.01	1.01 1.05 0.99
Reactive power (Mvar)	Q_1 Q_2 Q_3	3 6 8	8.42 26.19 21.30	3.19 31.47 16.57	5.00 28.16 15.00	9.93 33.08 14.62
Tap-changer (p.u.)	T_1 T_2 T_3 T_4 T_5	4-7 4-9 5-6 7-8 7-9	0.97 0.90 0.97 1.02 1.09	0.97 0.93 0.94 1.02 1.06	1.01 0.92 0.97 1.01 1.05	0.99 0.99 0.95 0.98 1.03

Furthermore, GTO could give the highest loss saving with amount of 0.78 MW while VD was reduced from 0.66 to 0.16 with higher deduction rate which up to 75.75 percent done by GTO. Despite low loss saving with amount of 5 percent in average, VD at every bus were significantly reduced. The obtained results of voltage magnitude, reactive power, and tap-changer were shown in *table 4*. Bus voltage at 3, 6 and 8 where the reactive power compensators installed are controlled; hence, the voltage magnitudes at those buses are in the limitation.

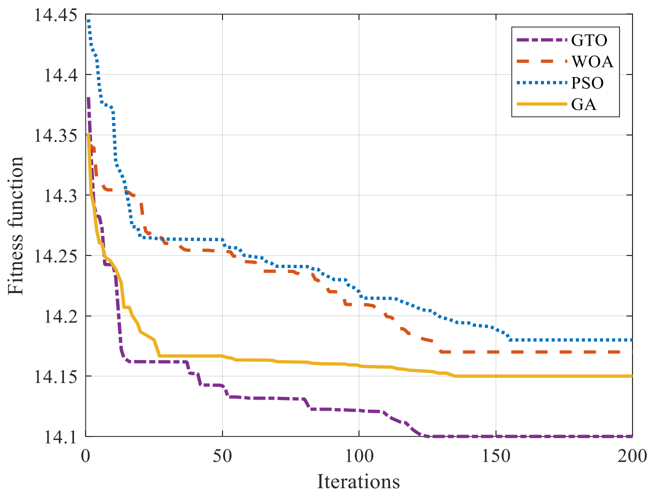

Figure 3. Graph of convergence of 14-bus system using different types of algorithms

The convergence graph in *figure 3* illustrates the performance of the GTO algorithm in solving the ORPD problem for a 14-bus power system. The graph displays the objective function value, which typically represents total real power losses (in MW) or the sum of voltage deviations, plotted against the number of iterations. Initially, the graph shows a steep decline in the objective value, indicating that the GTO algorithm rapidly identifies a promising solution space. As the number of iterations increases, the curve gradually flattens, signalling that the algorithm is converging towards an optimal or near-optimal solution. This convergence behaviour demonstrates the GTO's efficiency in minimizing power losses and improving voltage profiles within the system. The graph also compares the GTO's performance with other optimization techniques such as GA, PSO, and WOA, highlighting GTO's superior ability to achieve lower objective values more quickly. This underscores GTO's effectiveness in optimizing reactive power settings and enhancing the overall efficiency and stability of the power system.

4.2. 30-Bus System

30-bus standard-tested system was employed with the proposed algorithm and it can be found in [21]. Bus1 is the slack and bus 2, 5, 8,11 and 13 are voltage-controlled buses while others are load buses. Moreover, nine buses are the locations for installing the reactive power compensator. Furthermore, the system has four power transformers which are in branches 4–12, 6–9, 6–10 and 27-28. *Table 5* shows the values of the setting parameters for the 30-bus system. Each method was set at 100 and 400 population and maximum iterations, respectively for comparing their performances.

Table 5. Parameter values of each method of 30-bus system

Parameters	Algorithms			
	GA	PSO	WOA	GTO
Population	100	100	100	100
Max. iteration	400	400	400	400

The simulated results of the optimization algorithms are represented in *table 6*. Prior to the implementation of optimization, the power losses were observed to be 6.5 MW. The power losses derived from the optimization techniques were 6.16 MW, 6.20 MW, 6.17 MW, and 6.13 MW for GA, PSO, WOA and GTO, respectively. Controlled variable of the four algorithms comprising bus voltage, reactive power, and tap-changer after optimization are shown in the *table 7*.

Table 6. The obtained results of controlled variable of 30-bus system

Controlled variables		Bus	GA	PSO	WOA	DOA
Bus voltage (p.u.)	V_1	06	1.00	1.01	1.03	1.01
	V_2	07	1.02	1.04	1.02	1.05
	V_3	09	1.04	1.04	1.00	0.99
	V_4	11	1.01	1.02	1.01	1.02
	V_5	14	1.02	1.03	1.03	1.01
	V_6	15	1.01	1.01	0.99	1.00
	V_7	17	1.02	1.03	1.02	1.03
	V_8	18	1.04	1.04	1.03	1.04
	V_9	23	1.03	1.03	1.05	1.02
Reactive power (Mvar)	Q_1	06	0.35	3.19	0.08	0.00
	Q_2	07	0.22	1.47	1.24	0.00
	Q_3	09	0.77	2.57	2.95	0.00
	Q_4	11	0.09	1.67	1.15	0.00
	Q_5	14	1.34	2.62	3.73	3.13
	Q_6	15	1.57	1.52	0.17	3.66
	Q_7	17	0.66	0.87	0.17	1.39
	Q_8	18	8.02	6.43	0.00	8.11
	Q_9	23	2.4	4.32	0.27	3.06
Tap-changer (p.u.)	T_1	04-12	0.97	0.97	1.01	0.99
	T_2	06-09	0.90	0.93	0.92	0.99
	T_3	06-10	0.97	0.94	0.97	0.95
	T_4	27-28	1.02	1.02	1.01	0.98

Table 7. Simulated results of 30-bus system

Cases	Before optimization		After optimization						Computed time (s)
	Loss (MW)	VD	Loss (MW)	VD	Loss Saving (MW)	VD reduction	Loss Deduction (%)	VD deduction (%)	
GA	6.50	0.94	6.16	0.47	0.34	0.47	5.23	50.00	876.54
PSO			6.20	0.49	0.30	0.45	4.61	45.87	906.43
WOA			6.17	0.50	0.33	0.44	5.07	46.80	604.56
GTO			6.13	0.47	0.37	0.47	5.69	50.00	567.89

The simulation results of the 30-bus system are described in the *table 7*. Same to the previous case, GTO provided highest loss saving up to 0.37 MW followed by 0.34 MW, 0.33 MW, and 0.30 MW of GA, WOA and PSO, respectively. Furthermore, VD was reduced significantly up to 50% done by GTO and GA while WOA and PSO gave 46.80% and 45.87% respectively of VD reduction percentage. Also, GTO has less computation time compared to other three methods to get the optimal results.

Figure 4 compares the convergence of four algorithms—GTO, WOA, PSO, and GA—in solving the ORPD problem for a 30-bus system. GTO shows the fastest and most effective optimization, reaching the lowest fitness function value quickly. WOA and PSO also converge but are less effective than GTO. GA converges the slowest and to the highest fitness value, making it the least effective in this scenario. Overall, GTO outperforms the other algorithms in minimizing the objective function.

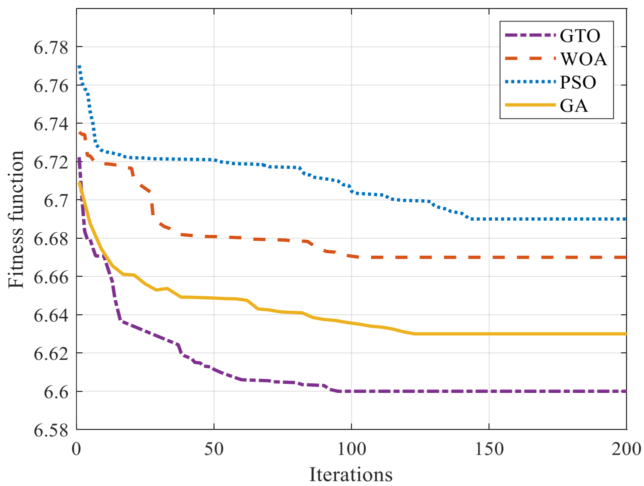

Figure 4. Graph of convergence of 30-bus system using different types of algorithms

5. CONCLUSIONS

Methods for solving ORPD problems with real power loss and VD as the objective function were described in this paper. The four algorithms GA, PSO, WOA, and GTO were used to solve the problem with a multi-objective for comparative purposes. With the algorithms, the IEEE of 14-bus and 30-bus systems were used to demonstrate the performance and efficiency. The obtained results were compared to those of each algorithm, and it was determined that the real power loss and VD were minimized along with the controlled variables. In addition, it was determined that GTO was the optimal method for resolving ORPD problem because it offered the optimal results with the quickest computation time. In addition, the simulation results demonstrated the efficiency and significance of the ORPD contribution in reducing power loss and increasing system voltage stability.

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