Optimal Power Flow Incorporating Thyristor-Controlled Series Capacitors Using the Gorilla Troops Algorithm

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The optimal power flow issue (OPFI) can be solved in this work using the recently developed algorithm, gorilla troops algorithm (GTA). The goal of OPFI is to reduce numerous functions such as minimizing fuel costs, emissions, and power losses and improving the voltage stability related to electric power networks (EPNs). The GTA is inspired by gorillas' social habits, which include migration to a strange region, migration toward a specified spot, traveling to other gorillas, competing for adult females, and escorting the silverback. The developed GTA is tested with and without the inclusion of the Thyristor-Controlled Series Capacitor (TCSC) devices in the system. The proposed GTA is applied on a practical Egyptian West Delta-EPN (WD-EPN) and the standard IEEE 57-bus EPN and with and without the inclusion of the TCSC devices to appraise the GTA algorithm's performance in the OPFI. In addition, the proposed GTA is applied on a large-scale IEEE 118 bus system with higher out-performance compared to particle swarm optimization. The results illustrate that the fuel costs, emissions, voltage stability, and power losses are reduced for the standard IEEE 57-bus EPN with and without TCSC devices by a percentage of (18.847% and 18.818%), (59% and 58.97%), (13.405% and 11.507%), and (64.337% and 65.178%), respectively, while fuel costs, emissions, voltage stability, and power losses are reduced for WD-EPN with and without TCSC devices by a percentage of (8.547%, 8.565%), (13.641%, 13.6%), and (61.949%, 61.954%), respectively. A comparison study is conducted to demonstrate the GTA’s effectiveness when compared with other recently developed algorithms such as improved Salp Swarm Algorithm, quasi-reflection jellyfish search, Salp Swarm Algorithm, improved heap-based algorithm, bat search algorithm, social network search algorithm, electromagnetic field optimization, and other well-known algorithms as well. According to the comparison with these algorithms, the GTA demonstrates the best results among the attained results.

1. Introduction

The optimal power flow issue (OPFI) is considered a primary tool for managing electrical power networks, where it provides electrical power at the lowest possible cost while maintaining high quality [1, 2]. Its major goal is to optimize objective functions such as system losses, cost of fuel, and emissions with meeting a set of equality and inequality constraints such as generator bus voltage magnitude, valve-point constraints, generator real power, transformer taps, and reactive power of shunts while optimizing a given objective function [3].

A numerous optimization approaches were developed to solve the OPFI over the last few decades. Classic optimization methods and evolutionary algorithms are the two categories of optimization approaches [4, 5]. A plethora of mathematical approaches was addressed to tackle the OPFI such as programming based on semidefinite [6], linear [7, 8], fuzzy linear [9], nonlinear [10], and quadratic [11, 12] frameworks, sequential unconstrained minimization...
technique [13], Newton-based method [14, 15], and interior point approach [16–18]. Although these approaches have produced encouraging outcomes, they do have certain drawbacks.

Numerous researchers have turned for utilizing several nature-inspired algorithms to solve the shortcomings of traditional optimization methods [19, 20]. These algorithms do not require derivative information, and instead, they employ random probabilities for optimization rather than deterministic probabilities. It can be noticed that these nature-inspired algorithms are capable of solving large-scale nonlinear problems and jumping out of the local optimum. As a result, a variety of evolutionary algorithms have been used to solve OPF in recent years [21, 22].

Examples of the nature-inspired algorithms are electromagnetism-like mechanism [23], colliding bodies optimization algorithm [24], biogeography-based optimization (BBO) [25], particle swarm optimization (PSO) [26, 27], genetic algorithm (GA) [28], grey wolf optimization and differential evolution (DE) [29], simulated annealing optimization [30], and teaching-learning-based optimization [31]. Moreover, to get the optimal solution for the large-scale OPF, recent algorithms were elaborated such as chaotic salp swarm optimizer (CSSO) [32], quantum computing with moth flame technique (QMFT) [33], water cycle emerged with moth flame technique (WCEMFT) [34], and coyote optimization algorithm [35]. Several optimization algorithms have been characterized to tackle the OPF in recent years with numerous objective function formulations. Wind and solar power integration have become one of the most quickly developing forms of electricity generation [36, 37].

Various algorithm strategies have been demonstrated in the literature to identify the optimal OPF solution as illustrated in Table 1.

1.1. Research Gap and Contributions. Although these algorithms have been widely employed in the literature to deal with OPF, there is a lack of comparative analysis of these algorithms in terms of solution quality exists. This research investigates the computing efficiency of GTA on the standard IEEE 57-bus EPN and WD-EPN with and without the inclusion of the TCSC devices.

The active power losses throughout the system, fuel cost, and emissions are all factors in the objective function. There are two goals in this paper. The first is to use the gorilla troops algorithm (GTA) [51, 52], a recently developed metaheuristic optimization algorithm, to solve the OPF in EPNs with and without TCSC devices. The second goal is to solve the OPF with four different objectives which are fossil fuel cost, transmission losses, voltage stability, and emission. Simulations were run on normal and modified IEEE 57-bus EPN and WD-EPN, as well as comparative examinations of other approaches in the literature are conducted in this study. The simulation results demonstrated the GTA’s effectiveness in solving the OPF using TCSC devices. The key contributions of this work are summarized as follows:

(i) The GTA is adopted to handle the OPF including TCSC devices.

(ii) The GTA is utilized to reduce numerous functions such as minimizing the fuel rates, pollutant emissions, voltage deviation, and power losses related to EPNs.

(iii) The proposed GTA is applied on the standard IEEE 57-bus EPN and a WD-EPN with and without the inclusion of the TCSC devices. In addition, the proposed GTA is applied on a large-scale IEEE 118 bus system with higher outperformance than the particle swarm optimization (PSO).

(iv) The OPF, including TCSC devices, is solved with diverse objective functions which are minimizing thermal generation cost, voltage stability, transmission power loss, and emission.

(v) A comparative study is conducted between the proposed GTA and recently developed algorithms such as ISSA, QRJFS, SSA, IHBA, SNSA, EFO, and MICA.

The remainder of the work is divided into the following sections: the OPF construction is elaborated in Section 2, while Section 3 characterizes the intended GTA for OPF. In addition, Section 4 contains the simulated findings and comments, while Section 5 has the concluding notes.

2. OPF Formulation considering TCSC Devices Incorporation

In OPF, the reactive power injections of switching capacitors and reactors and the generators’ real power output are denoted by \((Q_{cr1}, Q_{cr2}, \ldots, Q_{cr_Nqr})\) and \((P_{gr1}, P_{gr2}, \ldots, P_{gr_Ngr})\), respectively. The voltages of the generators and the tap changer settings are designated by \((V_{gr1}, V_{gr2}, \ldots, V_{gr_Ngr})\) and \((T_{p1}, T_{p2}, \ldots, T_{pNtr})\), respectively. Here, \(N_{qr}\), \(N_{tr}\), and \(N_{gr}\) represent the number of reactive power sources, on-load tap changers, and generators, respectively. The dependent variables are load bus voltage magnitudes, generator reactive power outputs, and transmission flow limits, as shown by \((V_{L1}, \ldots, V_{LNTP})\), \((Q_{gr1}, Q_{gr2}, \ldots, Q_{gr_Ngr})\), and \((S_{P1}, \ldots, S_{PNE})\), where \(N_{L}\) and \(N_{TP}\) represent the number of transmission lines and load buses, respectively. This problem can be expressed numerically as follows:

\[
\text{Min } OJF = \{OJF_1(l,x), OJF_2(l,x), \ldots, OJF_n(l,x)\}. \tag{1}
\]

Subject to

\[
C(l,x) = 0, \quad D(l,x) \leq 0, \tag{2}
\]

where \(OJF\) characterizes the modeled objective function of numerous \(u\) aims and the symbols \((l, x)\) denote the control and state variables, whereas \(C(l,x)\) and \(D(l,x)\) illustrate the equality and inequality constraints of the OPF, respectively.

2.1. Modelling of TCSC Devices. The TCSC is one of the most prominent series of FACTS devices, with several advantages such as high performance, quick reaction, and inexpensive cost. It offers several benefits over series capacitors. TCSC
devices have two reactive operational modes which are inductive and capacitive. In both modes, the reactance of the corresponding transmission line can be, accordingly, lowered or raised.

Figure 1 depicts TCSC modeling in power systems that are connected in series with a line. Therefore, the reactance of the TCSC is represented as a function of the transmission-line reactance ($X_{\text{line}}$). The needed value of the TCSC device ($X_{\text{TCSC}}$) to avoid transmission line overcompensation may be computed using the following equation [53, 54]:

$$-0.5X_{\text{TCSC}} \leq X_{\text{LINE}} \leq 0.5X_{\text{TCSC}}.$$  

(3)

2.2. Objectives

2.2.1. Aim 1: Fuel Cost. The goal of (Aim 1) is to keep costs down while meeting electricity demands. A quadratic relationship exists between fuel cost and generated power ($OJ_{F1}$) which can be expressed in dollars per hour and formulated as follows:

$$OJ_{F1} = \sum_{p=1}^{N_{gr}} A_p + B_p P_{gr_p} + C_p P_{gr_p}^2,$$  

(4)

where $A_p$, $B_p$, and $C_p$ elaborate the cost coefficients of generator $p$.

2.2.2. Aim 2: Emissions. The goal of (Aim 2) is to reduce emissions produced by the power plants. The emissions ($OJ_{F2}$) can be expressed in ton/h and formulated as follows:

$$OJ_{F2} = \sum_{p=1}^{N_{gr}} \xi_p \left(B_{pp} P_{gr_p} + \frac{\gamma_p P_{gr_p}^2 + \beta_p P_{gr_p} + \alpha_p}{100}\right),$$  

(5)

where $\gamma_p$, $\beta_p$, $\alpha_p$, $\xi_p$, and $\lambda_p$ designate the emission coefficients of generator $p$.

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**Table 1: Various algorithm strategies for OPFI.**

| Ref. | Year | Applied algorithm | Feature |
|------|------|-------------------|---------|
| [38] | 2021 | Adaptive constraint differential evolution | It has been introduced to solve the 30-bus system with different objectives which are voltage stability, real active power losses, voltage deviation, fuel cost considering the valve-point effect, and emission. However, it has been used without the inclusion of the TCSC devices |
| [39] | 2020 | Improved adaptive differential evolution (IADE) | It has been applied to the OPFI with the self-adaptive penalty constraint technique. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [40] | 2020 | Manta-ray foraging algorithm | It has been employed on EPNs with/without combination with voltage source converter stations to optimize the fuel costs, emissions, and losses |
| [41] | 2018 | Quasi-oppositional-based learning with Jaya Algorithm | It has been used to support exploration capability and convergence properties for the OPFI solution. However, it has been used without the inclusion of the TCSC devices |
| [42] | 2019 | Improved social spider optimizer | It has been manifested to reduce fuel costs, power losses, and emissions. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [43] | 2020 | Emended moth swarm algorithm (EMSA) | It has been introduced to modify quasi-oppositional-based learning and applied to the OPFI. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [44] | 2016 | Adaptive group search technique (AGST) | It has been applied on emission, fuel cost, and losses with diverse constraints. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [45] | 2019 | An improved NSGA-III | It is developed by decreasing the selection attempts and was proposed to optimize the objectives of fuel costs, emission, and losses. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [46] | 2019 | Modified JAYA | It has been demonstrated to solve OPFI with various objectives on IEEE 30-bus, 57-bus, and 118-bus systems. However, it has been used without practical systems and the inclusion of the TCSC devices |
| [47] | 2021 | Fuzzy adaptive-based selfadaptive differential evolution and particle swarm optimization (FAHSDE-PSO) | It has been proposed with nine operational cases with different objective functions and applied on IEEE 30-bus, 57-bus, and 118-bus test systems. However, it has been used without practical systems and the inclusion of the TCSC devices |
| [48] | 2017 | An improved-strength Pareto evolutionary algorithm (ISPEA) | It has been applied on emission, fuel cost, and losses with diverse constraints. However, it has been used without voltage stability and the inclusion of the TCSC devices |
| [49] | 2020 | Multiobjective evolutionary algorithm with superiority of feasible solutions based on decomposition (MOEA/SF-D) | It has been demonstrated to solve OPFI with various objectives on IEEE 30-bus, 57-bus, and 118-bus systems. However, it has been used without practical systems and the inclusion of the TCSC devices |
| [50] | 2018 | Multiobjective dimension-based firefly algorithm (MODFA) | It has been manifested to reduce fuel costs, power losses, and emissions. However, it has been used without voltage stability and the inclusion of the TCSC devices |
2.2.3. Aim 3: Losses. The goal of (Aim 3) is to reduce the overall transmission system power loss. The emissions (OJF3) can be formulated as follows [55]:

\[ OJ_3 = \sum_{p=1}^{Npq} Npq G_{pq} \left( V_p^2 + V_q^2 - 2V_p V_q \cos(\theta_p - \theta_q) \right), \]  

(6)

where \( G_{pq} \) illustrates the transfer conductance between buses \( p \) and \( q \). \( V \) is the voltage; \( N_{pq} \) is the number of buses, and \( \theta \) refers to the phase angle.

2.2.4. Aim 4: Voltage Stability. The goal of (Aim 4) is to improve voltage stability by minimizing the maximum voltage stability index (L-index) that is illustrated in Reference [56]. To illustrate, the L-index for each bus \( j \) \((L_j)\) can be mathematically formulated as follows:

\[ L_j = \left| 1 - \sum_{i=1}^{N_j} F_{ji} V_i \right| \left( \theta_{ij} + \delta_i - \delta_j \right), \]  

(7)

\[ F_{ji} = -[Y_{LL}]^{-1} [Y_{LG}]. \]  

(8)

The voltage stability of the system can be maximized using the maximum L-index, and this index can be mathematically formulated as follows:

\[ OI_4 = L_{\text{max}} = \text{Max}(L_j), \quad j = 1, 2, \ldots, N_j. \]  

(9)

2.3. System Constraints. The equality constraints are as follows:

\[ P_{grj} - PL_j - V_{grj} \sum_{p=1}^{N_{pq}} V_{grp} (G_{jp} \cos \theta_{jp} + B_{jp} \sin \theta_{jp}) = 0, \]  

\[ j = 1, \ldots, N_{pq}, \]  

(10)

\[ Q_{grj} + Q_{c} - QL_j - V \sum_{i=1}^{N_{pq}} V_{ip} (G_{jp} \sin \theta_{jp} - B_{jp} \cos \theta_{jp}) = 0, \]  

\[ j = 1, 2, \ldots, N_{pq}, \]

where \( QL \) and \( PL \) illustrate the consumed power consumption of its reactive and active components, respectively. Furthermore, \( G_{jk} \) and \( B_{jk} \) characterize the mutual conductance and susceptance of a transmission line connected between buses \( j \) and \( k \).

The inequality constraints are as follows:

\[ P_{grp_{\text{min}}} \leq P_{grj} \leq P_{grp_{\text{max}}}, \quad p = 1, 2, \ldots, N_{gr}, \]  

(11)

\[ T_{P_{\text{min}}} \leq T_{P_{tr}} \leq T_{P_{\text{max}}}, \quad Tr = 1, 2, \ldots, N_t, \]  

(12)

\[ Q_{grp_{\text{min}}} \leq Q_{grj} \leq Q_{grp_{\text{max}}}, \quad p = 1, 2, \ldots, N_{gr}, \]  

(13)

\[ V_{grp_{\text{min}}} \leq V_{grj} \leq V_{grp_{\text{max}}}, \quad p = 1, 2, \ldots, N_{gr}, \]  

(14)

\[ V_{L_{j_{\text{min}}}} \leq V_{L_{j}} \leq V_{L_{j_{\text{max}}}}, \quad j = 1, 2, \ldots, N_{pq}, \]  

(15)

\[ Q_{C_{\text{VAR}}} \leq Q_{C_{\text{VAR}}} \leq Q_{C_{\text{VAR}}}, \quad \text{VAR} = 1, 2, \ldots, N_{q}, \]  

(16)

\[ |S_{fl}| \leq S_{\text{max}}, \quad fl = 1, 2, \ldots, N_f, \]  

(17)

where \( S_{fl} \) illustrates the power flow via line \( fl \) and \( V L_{j} \) signifies the load voltage at bus \( j \).

3. Gorilla Troops Optimization Technique

The gorilla troops algorithm (GTA) relies on gorillas’ group dynamics throughout five strategic options. Such strategic options involve movement with other gorilla, migrating to an unknown place, migrating toward an established site, competing for female adults, and accompanying the silverback. These strategic options can be categorized into two stages which are the exploration and exploitation stages as explained in the next paragraphs.

3.1. Exploration Stage. In the exploratory stage, three distinct tendencies are characterized: the first tendency is to advance GTA exploration which is called (movement to an unknown destination), while the second tendency is to augment the consistency between exploratory and exploitation which is called (movement of other gorillas). Moreover, the third tendency is to promote GTA capabilities to determine myriads of computation spaces which are called (gorilla’s movement in the path of a familiar destination). These three tendencies can be mathematically represented as depicted in equation (17). In this equation, the movement to an unknown destination tendency is chosen once a factor \( (Pr) \) is greater than a random value. Furthermore, the tendency of (movement in the path of an identifiable place) is chosen once a random value is more than or equal to 50%, whilst the tendency of (a movement in the path of a recognized site) is selected once a random value is less than 50%.
where $X$ $(Itr)$ and $GoX$ $(Itr+1)$ describe the entire and prospective vectors of gorilla location in the next iterations, respectively, whereas $rv$, $rv_1$, $rv_2$, and $rv_5$ signify random values between $[0, 1]$. The factor $(Pr)$ represents the likelihood of selecting a migrating method to an undetermined location and can be given in the range $[0:1]$. The variables $X_r$ and $GoXr$ depict a gorilla among the current group and a candidate position that can be arbitrarily assigned, accordingly. The variables’ minimum and maximum bounds are denoted by $LB$ and $UB$, correspondingly. Equations (2)–(5), consecutively, could be used to describe the variables $D$ and $Q$ mathematically. The terms $(Itr)$ and $(MxItr)$ signify the present and maximum iteration number of the optimizing process, respectively, and $rd4$ denotes a random value inside the bound $[0:1]$. Moreover, the abbreviations $(s)$ and $Z$ indicate random values between $[−1:1]$ and $[−(D × (1 − Itr/MxItr)), D × (1 − Itr/MxItr)]$, respectively.

3.2. Exploitation Stage. According to the factor $D × (1 − Itr/MxItr)$ and by comparing it to the variable $(Y)$, two tendencies could be determined. To manifest, if the value of $D × (1 − Itr/MxItr)$ is greater than or equal to the value of $Y$, the approach of the silverback that can direct the others to sources of food could be chosen. This can be illustrated in equation (22) that can be used to exemplify this tendency as follows:

$$GoX(Itr+1) = Q × R(Itr) × (X(Itr) − X_{\text{silverback}}) + X(Itr), \quad (22)$$

$$R(Itr) = \left( \left( \frac{1}{\text{Nog}} \sum_{i=1}^{\text{Nog}} GoX_i(Itr) \right)^{20} \right)^{(1/20)}. \quad (23)$$

$X$ $(Itr)$ is the vector of gorilla location, and $X_{\text{silverback}}$ indicates the best solution which is the silverback. Furthermore, $GoX(Itr)$ represents the location of each potential gorilla vector in iteration $Itr$, while $\text{Nog}$ represents the population of gorillas.

If the term $D × (1 − Itr/MxItr)$ is less than $Y$, the approach of competing for female adults could be chosen [57]. This can be illustrated in equation (22) which can be used to exemplify this tendency as follows:

$$GX(Itr) = X_{\text{silverback}} - (X_{\text{silverback}} × L - X(Itr) × L) × A, \quad (24)$$

$$L = 2 × rv_5 - 1, \quad (25)$$

$$A = \beta × E, \quad (26)$$

$L$ represents the force of impact, which could be expressed as in equation (23), whereas $rv_5$ represents random value within bound $[0:1]$. The factor $(A)$ indicates a vector that provides the level of violence in a fight and may be calculated by equation (26). From that equation, $\beta$ refers to a preoptimization value, and $E$ is utilized to mimic the violence efficacy.

If the cost of $GoX(Itr)$, at the end of the exploitation stage, is less than $X(Itr)$, the $GoX(Itr)$ solution will replace $X(Itr)$. Figure 2 illustrates the key procedures of the GTA [52].

3.3. Proposed Solution-Based GTA for OPFI in EPNs. The Newton–Raphson Approach (NRA) could be utilized to meet the equality principles that describe power flow balancing models. It meets the balance restrictions and illustrates the operation of electric grids in a steady state. As a result, MATPOWER uses the NRA as a crucial framework for demonstrating three-phase systems [58]. Also, the dependent/independent variable constraints must be maintained. The following are the operational limits of the independent variables:

$$GoX_m = \begin{cases} 
GoX_{\text{min}} & \text{if } GoX_m \leq GoX_{\text{min}}, \\
GoX_{\text{max}} & \text{if } GoX_m \geq GoX_{\text{max}}, 
\end{cases} \quad (27)$$

$m = 1, 2, \ldots, \text{Dim.}$
As can be seen, the variables dramatically continue to reach their limits, and if one of them exceeds the ratings, it is regenerated at random within the necessary bounds. Furthermore, the target cost objective widens and penalizes the restrictions of the second category. Consequently, in the next round, if the gorilla’s location surpasses any of the proper limitations, it will be discarded.

4. Simulation Results

First of all, the performance analysis of GTA for standard well-known mathematical functions is performed and compared with well-known established optimization algorithms such as the particle swarm optimization (PSO) [59] and grey wolf optimization (GWO) [60] as illustrated in Table 2 in the Appendix. It is manifested from this table that the proposed GTA has a higher performance and efficiency than PSO and GWO in the tested mathematical functions which verify the robustness of GTA in obtaining the optimal solution of these mathematical functions. In the next subsections, the proposed GTA is applied to three test EPNs with different scenarios.

Firstly, the standard IEEE 57-bus EPN is considered as described in Figure 3, whereas a practical Egyptian WD-EPN is manifested in Figure 4. In addition to that, the proposed GTA is applied to the large-scale IEEE 118-bus EPN. Thirty simulation runs are conducted using the proposed GTA with gorillas’ group of 50 members and peak iterations of 500. The first EPN involves 17 on-load tap changing transformers; 57 buses; three capacitive sources on buses 18, 25, and 53; and seven generators on buses 1, 2, 3, 6, 8, 9, and 12, 80 lines. The data of this test system are extracted from [63]. For this EPN, two TCSC devices are considered to be installed on lines 8 and 15 [54]. Secondly, the WD-EPN involves 52 buses with voltages in the ranges between 1.06 and 0.94 p.u. For this EPN, two TCSC devices are considered to be installed on buses 1, 2, 3, 6, 8, 9, and 12, 80 lines. Lastly, the standard IEEE 118-bus EPN is considered which has 118 buses, 9 on-load tap transformers, 186 routes, 14 capacitor devices, and 54 generators [64]. Therefore, the proposed GTA is applied for 130 decision variables where each gorilla position comprises a vector of 130 elements.

![Flowchart of the main stages of the proposed GTA.](image-url)
| Function | Mathematical representation | Dimension | Range       | $F_{\text{min}}$ | GTA | GWO | PSO |
|----------|-----------------------------|-----------|-------------|------------------|-----|-----|-----|
| F1       | $f(x) = \sum_{i=1}^{d} x_i^2$ | 30        | $[-100, 100]^d$ | 0                | 0.0000 E+00 | 1.3068E-01 | 2.4635E+03 |
| F2       | $f(x) = \max_{i} \{|x_i|, 1 \leq i \leq d\}$ | 30        | $[-100, 100]^d$ | 0                | 0.0000 E+00 | 2.4126E-01 | 3.5154E+03 |
| F3       | $f(x) = \sum_{i=1}^{d} |100(x_i - x_i^*)^2 + (x_i - 1)^2|$ | 30        | $[-30, 30]^d$ | 0                | 0.0000 E+00 | 2.4126E+00 | 8.6534E-01 |
| F4       | $f(x) = -20 \exp(-0.2 \sqrt{\sum_{i=1}^{d} x_i^2}) - \exp(-\sum_{i=1}^{d} \cos(2 \pi x_i)) + 20 + e$ | 30        | $[-32, 32]^d$ | 0                | 0.0000 E+00 | 1.2771E-10 | 1.7638E+01 |
| F5       | $f(x) = \frac{1}{1000} \sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} \cos(x_i / \sqrt{i}) + 1$ | 30        | $[-600, 600]^d$ | 0                | 0.0000 E+00 | 1.2159E-01 | 1.7776E+03 |
| F6       | $f(x) = \left[\frac{1}{500} + \sum_{i=1}^{d} \frac{1}{i} + \sum_{i=1}^{d} \frac{x_i - a_{i,j}}{b_{i,j}}\right]^{-1}$ | 2         | $[-65, 65]^d$ | 1                | 0.0000 E+00 | 3.1647E-02 | 4.6628E+01 |
| F7       | $f(x) = \sum_{i=1}^{d} \left[ a_i - x_i \right] \left( b_i + b_j x_i \right) \left( b_i + b_j x_i + x_i \right)^2$ | 4         | $[-5, 5]^d$ | -1.0316          | 0.0000 E+00 | 1.2671E+01 | 5.9288E+00 |
| F8       | $f(x) = \left[ 1 + (x_1 + x_2 + 1)^2 \left( 19 - 14x_1 - 3x_2^2 - 14x_2 + 6x_1 x_2 + 3x_2^2 \right) \right] \times \left[ 30 + (2x_1 - 3x_2^2)^2 + (18 - 32x_1 + 12x_2^2 + 48x_2 - 36x_1 x_2 + 27x_2^2) \right]$ | 2         | $[-2, 2]^d$ | 3                | 0.0000 E+00 | 5.7000E+00 | 3.0000E+00 |
| F9       | $f(x) = \sum_{i=1}^{d} a_i \exp(-\sum_{j=1}^{d} b_j (x_j - p_{ij})^2)$ | 3         | $[1, 3]^d$ | -3.86            | 0.0000 E+00 | 8.4000E+00 | 3.0000E+00 |
| F10      | $f(x) = \sum_{i=1}^{d} \left[ (X - a_i)(X - a_i)^T + c_i \right]^{-1}$ | 4         | $[0, 10]^d$ | -10.1532         | 0.0000 E+00 | 4.3099E-04 | 2.4049E-03 |

**Table 2: Performance analysis of GTA for standard mathematical functions in comparison with metaheuristic technique.**
Figure 3: IEEE 57-bus power system [61].

Figure 4: Real WD-EPN [9, 62].
The simulation runs were conducted using MATLABR2017b with 8 GB of RAM and CPU of Core (TM) i7-7200U - (2.5 GHz) Intel(R).

4.1. Outcomes of the GTA Applications for the First EPN. For this EPN, four scenarios are examined with and without considering the TCSC devices:

(i) Scenario 1: O1 minimization described in equation (4)
(ii) Scenario 2: O2 minimization described in equation (5)
(iii) Scenario 3: O3 minimization described in equation (6)
(iv) Scenario 4: O4 minimization described in equation (7)

4.1.1. Minimization of the Fuel Costs (Scenario 1). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices. The results are shown in Table 3. Furthermore, Figure 5 depicts the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the fuel costs from 51345 $/h in the initial scenario to 41668.02 $/h with a reduction percentage of 18.847%. In the second case by considering the TCSC devices, the suggested GTA reduces the fuel costs from 51345 $/h in the initial scenario to 41682.64 $/h with a reduction percentage of 18.818%. For these reasons, the suggested GTA is operating the TCSC devices on lines 8 and 15 at compensation levels of −32.768% and 49.9686%, respectively.

In addition, Figure 6 shows the comparisons of the outcomes of Scenario 1 with numerous alternative techniques without considering the TCSC devices. The described results are reported to be related to social spider optimization (SSO) [42], real-coded biogeography-based optimization (RCBBO) [25], improved Salp Swarm Algorithm (ISSA) [65], jellyfish search (JFS) [66], quasi-reflection jellyfish search (QRJFS) [66], Salp Swarm Algorithm (SSA) [67], differential search algorithm (DSA) [68], heap-based algorithm (HBA) [69], enhanced heap-based algorithm (IHBA) [69], bat search algorithm (BSA) [70], genetic algorithm (GA) [45], improved genetic algorithm (IGA) [45], social network search algorithm (SNSA) [71], electromagnetic field optimization (EFO) [72], and modified imperialist competitive algorithm (MICA) [73]. As shown, the proposed GTA provides the superior performance in minimizing the fuel costs with the least value of 41668.02 $/h. On the other side, the minimum costs related to SNSA [71], IGA [45], GA [45], SSO [42], enhanced SSO [42], MICA [73], TLBO [63], JFS [66], and QRJFS [66] are, respectively, 1.0375, 1.0830, 1.1210, 1.0393, 1.7024, 1.2246, 1.0772, 1.0473, 1.0410, and 1.0377 ton/h.

4.1.2. Minimization of the Emissions (Scenario 2). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices in order to minimize the produced emissions, and the results are shown in Table 4. Furthermore, Figure 7 illustrates the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the produced emissions from 2.528 ton/h in the initial scenario to 1.036393 ton/h with a reduction percentage of 59%. In the second case by considering the TCSC devices, the suggested GTA reduces the produced emissions from 2.528 ton/h in the initial scenario to 1.03715 ton/h with a reduction percentage of 58.97%. For this case, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of −24.486% and 19.6084%, respectively.

In addition, Figure 8 shows the comparisons of the outcomes of Scenario 1 with numerous alternative techniques without considering the TCSC devices. The described results are reported to be related to SNSA [71], IGA [45], GA [45], SSO [42], enhanced SSO [42], MICA [73], teaching-learning based optimization (TLBO) [63], JFS [66], and QRJFS [66].

As shown, the proposed GTA provides the superior performance in minimizing the produced emissions with the least value of 1.036393 ton/h. On the other side, the minimum costs related to SNSA [71], IGA [45], GA [45], SSO [42], enhanced SSO [42], MICA [73], TLBO [63], JFS [66], and QRJFS [66] are, respectively, 1.0375, 1.0830, 1.1210, 1.0393, 1.7024, 1.2246, 1.0772, 1.0473, 1.0410, and 1.0377 ton/h.

4.1.3. Minimization of the Power Losses (Scenario 3). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices in order to minimize the power losses, and the results are shown in Table 5. Furthermore, Figure 9 depicts the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the power losses from 27.835MW in the initial scenario to 9.92662MW with a reduction percentage of 64.337%. In the second case by considering the TCSC devices, the suggested GTA reduces the power losses from 27.835MW in the initial scenario to 9.692474MW with a reduction percentage of 65.178%. For this case, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of 49.9995% and 34.7962%, respectively.

In addition, Figure 10 shows the comparisons of the outcomes of Scenario 3 with numerous alternative techniques without considering the TCSC devices. The described results are reported to be related to SNSA [71], differential evolution (DE) [74], SSO [42], SSA [67], MICA [73], GA [45], IGA [45], and Stud Kril Herd Algorithm (SKHA) [75]. As shown, the proposed GTA provides the superior performance in minimizing the power losses with the least value of 9.92662 MW. On the other side, the minimum costs related to SNSA [71], IGA [45], GA [45], SSO [42], enhanced SSO [42], MICA [73], TLBO [63], JFS [66], and QRJFS [66] are, respectively, 10.1952, 10.558, 11.320, 11.883, 11.0772, 11.0473, 11.0410, and 11.0377 ton/h.

4.1.4. Minimization of the $L_{\text{max}}$ (Scenario 4). (1) $L_{\text{max}}$ Minimizing (Scenario 4). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices in order to improve the voltage stability by minimizing the index ($L_{\text{max}}$), and the results are shown in Table 6.
Furthermore, Figure 11 illustrates the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the stability index from 0.3000 in the initial scenario to 0.259785 with a reduction percentage of 13.405%. In the second case by considering the TCSC devices, the suggested GTA reduces the stability index from 0.3000 in the initial scenario to 0.265479 with a reduction percentage of 11.507%. For this case, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of 24.1205% and -50%, respectively.

4.2. Outcomes of the GTA Applications for the Second EPN.

For this EPN, three scenarios are examined with and without considering the TCSC devices:

- Scenario 5: OJ1 minimization described in equation (4)
- Scenario 6: OJ3 minimization described in equation (6)
- Scenario 7: OJ4 minimization described in equation (7)

4.2.1. Minimization of the Fuel Costs (Scenario 5). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices, and the results are shown in Table 7. Furthermore, Figure 12 depicts the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the fuel costs from 25098.70 $/h in the initial scenario to 22953.42 $/h with a reduction percentage of 8.547%. In the second case by considering the TCSC devices, the suggested GTA reduces the fuel costs from 25098.70 $/h in the initial scenario to 22948.95 $/h with a reduction percentage of 8.565%. For these reasons, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of $-45.836%$ and $-35.71%$ respectively. In addition, Figure 13 shows the comparisons of the outcomes of Scenario 5 with numerous alternative techniques without considering the TCSC devices. The described results are reported to be related to the grey wolf algorithm (GWA) [76], SSA [77], novel bat algorithm (NBA) [78], improved

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|---------------------|------------------|
| Vg       |                  |                     |                  |
| 1        | 1.01000          | 1.06000             | 1.059982         |
| 2        | 1.01000          | 1.058412            | 1.057758         |
| 3        | 1.01000          | 1.052555            | 1.050591         |
| 6        | 1.01000          | 1.059722            | 1.0589           |
| 8        | 1.01000          | 1.06                | 1.06             |
| 9        | 1.01000          | 1.039867            | 1.043105         |
| 12       | 1.01000          | 1.045733            | 1.052959         |
| 4-18     | 0.97000          | 0.987484            | 1.023022         |
| 4-18     | 0.97800          | 1.024632            | 1.099982         |
| 21-20    | 1.04300          | 0.989194            | 1.081332         |
| 24-25    | 1.00000          | 1.009996            | 1.022684         |
| 24-25    | 1.00000          | 1.017643            | 1.028921         |
| 24-26    | 1.04300          | 1.012815            | 1.017326         |
| 7-29     | 0.96700          | 0.952325            | 0.964552         |
| 34-32    | 0.97500          | 0.957575            | 0.983804         |
| Tap      |                  |                     |                  |
| 11-41    | 0.95500          | 0.900002            | 0.944872         |
| 15-45    | 0.95500          | 0.948576            | 0.939975         |
| 14-46    | 0.90000          | 0.942201            | 0.931681         |
| 10-51    | 0.93000          | 0.948434            | 0.940966         |
| 13-49    | 0.89500          | 0.923079            | 0.914197         |
| 11-43    | 0.95800          | 0.928728            | 0.936011         |
| 40-56    | 0.95800          | 0.99208             | 1.02062          |
| 39-57    | 0.98000          | 0.939661            | 1.044991         |
| 9-55     | 0.94000          | 0.971423            | 0.960974         |
| 18       | 10.00000         | 28.57187            | 24               |
| Qc       |                  |                     |                  |
| 25       | 5.90000          | 14.59395            | 15.5             |
| 53       | 6.30000          | 13.11964            | 27.5             |
| 1        | 478.63500        | 143.3567            | 142.7673         |
| 2        | 0.00000          | 92.27242            | 90.00291         |
| 3        | 40.00000         | 44.79782            | 44.8337          |
| Pg       |                  |                     |                  |
| 6        | 0.00000          | 69.64632            | 72.30513         |
| 8        | 450.00000        | 458.7721            | 459.0071         |
| 9        | 0.00000          | 96.91842            | 95.24292         |
| 12       | 310.00000        | 359.8742            | 361.6572         |
| TCSC8 compensation % | —             | —                  | -32.768          |
| TCSC15 compensation % | —             | —                  | 49.9686          |
| Fuel costs | 51345          | 41668.02            | 41682.64         |
| Losses   | 27.83500         | 14.838              | 15.16592         |
4.2.2. Minimization of the Power Losses (Scenario 6). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices in order to minimize the power losses, and the results are shown in Table 8. Furthermore, Figure 14 depicts the convergent properties of the suggested GTA for this scenario considering both cases. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the power losses from 19.015 MW in the initial scenario to 7.233531 MW with a reduction percentage of 61.949%. In the second case by considering TCSC devices, the suggested GTA reduces the power losses from 19.015 MW in the initial scenario to 7.234384 MW. For this case, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of $-18.215\%$ and $34.398\%$, respectively.

4.2.3. Minimization of the $L_{max}$ (Scenario 7). Using such a situation, the suggested GTA is used both with and without the inclusion of the TCSC devices in order to improve the voltage stability by minimizing the index ($L_{max}$), and the results are shown in Table 9. As illustrated, the suggested GTA reduces, in the first case without considering the TCSC devices, the stability index from 0.173 in the initial scenario to 0.149417 with a reduction percentage of 13.641%. In the second case by considering the TCSC devices, the suggested
GTA reduces the stability index from 0.173 in the initial scenario to 0.149417. For this case, the suggested GTA is operating the TCSC devices at lines 8 and 15 at compensation levels of 6.0923% and -28.321%, respectively.

4.3. Outcomes of the GTA Applications for the Third EPN. For the IEEE 118-bus large-scale network, the proposed GTA is applied in comparison to the PSO technique, which is one of the well-established algorithms to deal with such OPF problems, for minimizing the fuel costs. Based on those circumstances, the obtained results using the proposed GTA and PSO techniques are tabulated in Table 10, while the regarding convergence properties are described in Figure 15. As illustrated, the proposed GTA achieves lower fuel cost value of 129752.2 $/hr than the implemented PSO that achieves fuel costs of 129990.8 $/hr. Also, Table 11 describes a comparison with reported results of well-established techniques of the differential algorithm [74] and PSO [81]. As shown, the proposed GTA provides better performance than the differential algorithm [74] and PSO [81], which obtain fuel costs of 130518.5 and 130288.21 $/h, respectively.
3.95
3.45
2.95
2.45
1.95
1.45
0.95

1
20
39
58
77
96
115
134
153
172
191
210
229
248
267
286
305
324
343
362
381
400
419
438
457
476
495

Iterations

Emissions

Without TCSC
With TCSC

Figure 7: Convergent characteristics of the proposed GTA for Scenario 1 with and without considering the TCSC devices.

Figure 8: Comparisons for Scenario 2 without considering the TCSC devices.

Table 5: Outcomes of the proposed GTA for Scenario 3 with and without considering the TCSC devices.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|---------------------|------------------|
| Vg       | 1.01000          | 1.06                | 1.059989         |
|          | 1.01000          | 1.054638            | 1.054609         |
|          | 1.01000          | 1.06                | 1.059987         |
|          | 1.01000          | 1.059419            | 1.057453         |
|          | 1.01000          | 1.059867            | 1.06             |
|          | 1.01000          | 1.042316            | 1.042094         |
|          | 1.01000          | 1.04939             | 1.048461         |
Table 5: Continued.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|----------------------|------------------|
| Tap      |                  |                      |                  |
| 4-18     | 0.97000          | 0.92458              | 0.927146         |
| 4-18     | 0.97800          | 1.1                  | 0.96848          |
| 21-20    | 1.04300          | 1.014906             | 0.985473         |
| 24-25    | 1.00000          | 1.1                  | 0.985075         |
| 24-25    | 1.00000          | 1.001276             | 1.036794         |
| 24-26    | 1.04300          | 1.095381             | 1.000235         |
| 7-29     | 0.96700          | 1.037725             | 0.955372         |
| 34-32    | 0.97500          | 0.977432             | 0.949085         |
| Tap      |                  |                      |                  |
| 11-41    | 0.95500          | 0.934873             | 0.901312         |
| 15-45    | 0.95500          | 0.947282             | 0.944165         |
| 14-46    | 0.90000          | 0.929635             | 0.944992         |
| 10-51    | 0.93000          | 0.936895             | 0.946334         |
| 13-49    | 0.89500          | 0.904858             | 0.931824         |
| 11-43    | 0.95800          | 0.926142             | 1.021098         |
| 40-56    | 0.95800          | 1.003019             | 1.002755         |
| 39-57    | 0.98000          | 1.024649             | 0.984054         |
| 9-55     | 0.94000          | 1.027027             | 0.950339         |
| Qc       |                  |                      |                  |
| 18       | 10.00000         | 30                   | 5.5              |
| 25       | 5.90000          | 18.14239             | 15               |
| 53       | 6.30000          | 19.5735              | 15               |
| 1        | 478.63500        | 204.4293             | 202.4207         |
| 2        | 0.000000         | 5.74E-08             | 1.189606         |
| 3        | 40.000000        | 140                  | 140              |
| Pg       |                  |                      |                  |
| 6        | 0.000000         | 100                  | 100              |
| 8        | 450.000000       | 307.6783             | 306.8823         |
| 9        | 0.000000         | 100                  | 100              |
| 12       | 310.000000       | 410                  | 409,9999         |
| TCSC 4 compensation % | —         | —                  | 49.9995           |
| TCSC 15 compensation % | —         | —                  | 34.7962           |
| Fuel costs | 51345      | 45058.35             | 45027.8           |
| Emissions | 2.528       | 1.552649             | 1.554878         |
| Losses   | 27.835       | 9.92662              | 9.692474         |

Figure 9: Convergent characteristics of the proposed GTA for Scenario 3 with and without considering the TCSC devices.
Figure 10: Comparisons for Scenario 3 without considering the TCSC devices.

Table 6: Outcomes of the proposed GTA for Scenario 4 with and without considering the TCSC devices.

| Variable | Initial scenario | Without TCSC device | With TCSC devices |
|----------|------------------|---------------------|------------------|
| Vg       |                  |                     |                  |
| 1        | 1.01000          | 1.059983            | 1.035626         |
| 2        | 1.01000          | 1.043359            | 1.022417         |
| 3        | 1.01000          | 1.034003            | 1.029037         |
| 6        | 1.01000          | 1.032652            | 1.032039         |
| 8        | 1.01000          | 1.057631            | 1.045406         |
| 9        | 1.01000          | 1.029484            | 1.031654         |
| 12       | 1.01000          | 1.02379             | 1.06             |
| 4-18     | 0.97000          | 0.961106            | 0.975022         |
| 4-18     | 0.97800          | 0.985939            | 1.092986         |
| 21-20    | 1.04300          | 1.009005            | 0.994966         |
| 24-25    | 1.00000          | 1.010756            | 1.037913         |
| 24-25    | 1.00000          | 1.099964            | 1.046319         |
| 24-26    | 1.04300          | 0.979306            | 1.037111         |
| 7-29     | 0.96700          | 0.956764            | 0.928224         |
| 34-32    | 0.97500          | 0.9                | 0.9              |
| Tap      |                  |                     |                  |
| 11-41    | 0.95500          | 0.993953            | 1.098315         |
| 15-45    | 0.95500          | 0.926515            | 0.912823         |
| 14-46    | 0.90000          | 0.903968            | 1.029298         |
| 10-51    | 0.93000          | 0.949356            | 0.966277         |
| 13-49    | 0.89500          | 0.9                | 0.90774          |
| 11-43    | 0.95800          | 0.900097            | 0.923992         |
| 40-56    | 0.95800          | 1.099446            | 1.099903         |
| 39-57    | 0.98000          | 1.013967            | 0.939561         |
| 9-55     | 0.94000          | 0.955748            | 1.097816         |
| 18       | 10.00000         | 1.155637            | 30               |
| Qc       |                  |                     |                  |
| 25       | 5.90000          | 18.1075             | 17.5             |
| 53       | 6.30000          | 29.94176            | 30               |
| 1        | 478.63500        | 371.9249            | 314.0687         |
| 2        | 0.00000          | 0.000499            | 4.95E-08         |
| 3        | 40.00000         | 12.98833            | 0.063139         |
| Pg       |                  |                     |                  |
| 6        | 0.00000          | 0.741333            | 0.168514         |
| 8        | 450.00000        | 371.9531            | 549.7923         |
| 9        | 0.00000          | 100                | 2.71E-09         |
| 12       | 310.00000        | 409.7994            | 409.7321         |
| TCSC₄ compensation % | —          | —                  | 24.1205          |
| TCSC₁₅ compensation % | —          | —                  | -50              |
| Fuel costs | 51345      | 46728.3            | 45264.89         |
| Lmax     | 0.30000         | 0.259785            | 0.265479         |
| Losses   | 27.835          | 16.60758            | 23.02473         |
Table 7: Outcomes of the proposed GTA for Scenario 4 with and without considering the TCSC devices.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|---------------------|------------------|
| Vg       |                  |                     |                  |
|          | 1 1.00           | 1.060               | 1.060            |
|          | 2 1.00           | 1.060               | 1.060            |
|          | 3 1.00           | 1.060               | 1.060            |
|          | 4 1.00           | 1.060               | 1.060            |
|          | 5 1.00           | 1.060               | 1.060            |
|          | 6 1.00           | 1.060               | 1.060            |
|          | 7 1.00           | 1.045558            | 1.045459         |
|          | 8 1.00           | 189.5708            | 1.05167          |
|          | 1 85.6900        | 1.051726            | 190.7962         |
|          | 2 157.400        | 10                  | 10               |
|          | 3 139.3100       | 214.6983            | 214.3116         |
|          | 4 113.6900       | 180.419             | 180.024          |
|          | 5 166.4800       | 10                  | 10               |
|          | 6 31.7100        | 234.0315            | 233.908          |
|          | 7 92.0           | 56.29898            | 56.17319         |
|          | 8 122.490        | 32.18592            | 32.03292         |
| Pg       |                  |                     |                  |
|          | 1 10.00          | 25098.70            | 22953.42         |
|          | 2 10.00          | 22948.95            | 22948.95         |

TCSC 4 compensation % — — -45.836
TCSC 9 compensation % — — -35.71
Fuel costs 25098.70 22953.42 22948.95
Losses 19.0150 37.45454 37.49588

Figure 11: Convergent characteristics of the proposed GTA for Scenario 4.
Figure 12: Convergent characteristics of proposed GTA for scenario 5.

Figure 13: Comparisons for scenario 5 without considering the TCSC devices.

Table 8: Outcomes of the proposed GTA for scenario 6 with and without considering the TCSC devices.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|-----------------|---------------------|-----------------|
| Vg       | 1.00            | 1.059589            | 1.059058        |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
|          | 1.00            | 1.060               | 1.060           |
Table 8: Continued.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|----------------------|------------------|
| 1        | 85.6900          | 60.46196             | 60.63965         |
| 2        | 157.400          | 58.81879             | 58.64809         |
| 3        | 139.3100         | 180.6457             | 180.6514         |
| 4        | 113.6900         | 130.7557             | 130.7599         |
| 5        | 166.4800         | 117.9838             | 117.9631         |
| 6        | 31.7100          | 156.5708             | 156.5706         |
| 7        | 122.4900         | 86.27631             | 86.27771         |
| TCSC 4 compensation % | —               | —                    | -18.215          |
| TCSC 9 compensation % | —               | —                    | 34.398           |
| Fuel costs | 25098.70       | 24773.08             | 24771.64         |
| Losses   | 19.0150          | 7.235351             | 7.234384         |

Figure 14: Convergent characteristics of the proposed GTA for scenario 6 with and without considering the TCSC devices.

Table 9: Outcomes of the proposed GTA for Scenario 4 with and without considering the TCSC devices.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|----------------------|------------------|
| 1        | 1.00             | 1.060                | 1.050446         |
| 2        | 1.00             | 1.060                | 0.958485         |
| 3        | 1.00             | 1.060                | 1.060            |
| 4        | 1.00             | 1.060                | 1.060            |
| 5        | 1.00             | 1.060                | 0.957001         |
| 6        | 1.00             | 1.060                | 0.950365         |
| 7        | 1.00             | 1.060                | 0.974183         |
| 8        | 1.00             | 1.060                | 1.037331         |
Table 9: Continued.

| Variable | Initial scenario | Without TCSC device | With TCSC device |
|----------|------------------|----------------------|------------------|
| 1        | 85.690           | 235.3035            | 164.5225         |
| 2        | 157.40           | 15.24983            | 250              |
| 3        | 139.3100         | 29.63804            | 10               |
| 4        | 113.6900         | 250                 | 10               |
| Pg       |                  |                      |                  |
| 5        | 166.4800         | 375                 | 10               |
| 6        | 31.7100          | 31.21698            | 10               |
| 7        | 92.000           | 14.97695            | 250              |
| 8        | 122.4900         | 15.20074            | 250              |
| TCSC ± compensation % | — | — | 6.0923 |
| TCSC γ compensation % | — | — | —28.321 |
| Fuel costs | 25098.70 | 27031.11 | 28299.95 |
| $I_{max}$ | 0.173 | 0.149417 | 0.149417 |

Table 10: Optimal results of the proposed GTA and PSO for the third EPN.

| Variable | Proposed GTA | Proposed GTA | Variable | Proposed GTA | Proposed GTA |
|----------|--------------|--------------|----------|--------------|--------------|
| V G1     | 0.978501     | 1.014395     | V G100  | 1.020345     | P G26        |
| V G4     | 1.012648     | 1.044675     | V G103  | 1.02287     | P G27        |
| V G6     | 1.009743     | 1.032677     | V G104  | 1.019259     | P G31        |
| V G8     | 1.06         | 1.06         | V G105  | 1.015793     | P G32        |
| V G10    | 1.06         | 1.06         | V G107  | 1.01894     | P G34        |
| V G12    | 1.001782     | 1.028617     | V G110  | 1.006949     | P G36        |
| V G15    | 0.998521     | 1.022519     | V G111  | 1.014302     | P G40        |
| V G18    | 1.008914     | 1.030823     | V G112  | 1.000718     | P G42        |
| V G19    | 1.001008     | 1.024811     | V G113  | 1.007193     | P G46        |
| V G24    | 0.996245     | 1.043987     | V G116  | 1.06         | P G49        |
| V G25    | 1.021984     | 1.058359     | TP R 5  | 1.029612     | P G54        |
| V G26    | 1.004594     | 1.06         | TP 26-25 | 1.034384     | P G55        |
| V G27    | 1.002232     | 1.041299     | TP 30-17 | 1.00146     | P G56        |
| V G31    | 0.994091     | 1.031925     | TP 38-37 | 1.012302     | P G59        |
| V G32    | 0.992677     | 1.038484     | TP 63-59 | 1.04127     | P G61        |
| V G33    | 0.999019     | 1.035797     | TP 64-61 | 0.991775     | P G62        |
| V G36    | 0.991777     | 1.033989     | TP 65-66 | 0.981633     | P G65        |
| V G40    | 0.982977     | 1.029688     | TP 68-69 | 1.020788     | P G66        |
| V G42    | 0.98163      | 1.036631     | TP 81-80 | 1.030669     | P G67        |
| V G44    | 1.000725     | 1.038833     | QC 9    | 1.900194     | P G70        |
| V G49    | 1.024589     | 1.051785     | QC 100  | 1.07205     | P G72        |
| V G51    | 1.004102     | 1.032799     | QC 110  | 1.119056     | P G73        |
| V G55    | 1.000234     | 1.031209     | QC 144  | 1.739739     | P G74        |
| V G56    | 1.002218     | 1.031322     | QC 146  | 3.724853     | P G76        |
| V G59    | 1.028498     | 1.043654     | QC 146  | 3.569582     | P G77        |
| V G61    | 1.06         | 1.042242     | QC 148  | 1.421501     | P G80        |
| V G62    | 1.051388     | 1.036809     | QC 148  | 3.710799     | P G85        |
| V G65    | 1.06         | 1.06         | QC 179  | 3.861601     | P G87        |
| V G66    | 1.052957     | 1.054528     | QC 182  | 1.829246     | P G89        |
| V G69    | 1.030315     | 1.06         | QC 183  | 2.049816     | P G90        |
| V G70    | 0.985261     | 1.036728     | QC 185  | 2.862461     | P G91        |
| V G72    | 0.983634     | 1.034832     | QC 187  | 1.326682     | P G92        |
| V G73    | 0.982136     | 1.029527     | QC 190  | 2.905878     | P G99        |
| V G74    | 0.970282     | 1.019137     | P G1    | 27.326       | P G100       |
| V G76    | 0.960648     | 1.011218     | P G4    | 61.59694     | P G103       |
| V G77    | 0.989506     | 1.034381     | P G5    | 3.512879     | P G104       |
| V G80    | 1.003065     | 1.045973     | P G8    | 0            | P G105       |
| V G85    | 1.002084     | 1.040072     | P G10  | 388.7673     | P G107       |
| V G87    | 1.037667     | 1.052759     | P G12  | 83.82445     | P G110       |
| V G89    | 1.02058      | 1.06         | P G15  | 25.60050     | P G111       |
| V G90    | 1.014289     | 1.033737     | P G18  | 18.48071     | P G112       |
| V G91    | 1.012734     | 1.025402     | P G19  | 21.02219     | P G113       |
| V G92    | 1.004339     | 1.041442     | P G24  | 1.531488     | P G116       |
| V G99    | 1.022844     | 1.027761     | P G25  | 187.9791     | P G117       |

Fuel Costs | 25098.70 | 27031.11 | 28299.95 |
5. Conclusion

This research investigates a new nature-inspired algorithm called the gorilla troops algorithm (GTA) to solve the OPFI with and without the inclusion of the Thyristor-Controlled Series Capacitor (TCSC) devices in the system. Numerous objective functions are minimized throughout regulating the generator bus voltage magnitude, generator real power, reactive power of shunts, and transformer taps. Seven scenarios with and without the inclusion of the TCSC devices in the system are evaluated, and each scenario involves the goal function of transmission losses, fuel costs, voltage stability, and emissions. The efficiency of the GTA has been verified using the standard IEEE 57-bus EPN and a practical Egyptian West Delta-EPN (WD-EPN) with and without the inclusion of the TCSC devices to appraise the GTA algorithm’s performance in the OPFI. In addition to that, the proposed GTA is applied on the large-scale IEEE 118-bus EPN. The simulation findings demonstrate that integrating TCSC devices in an OPFI framework can significantly improve voltage stability and reduce the operation cost, active power losses, and emissions. In addition to this, the findings obtained by the GTA have outperformed the recently developed powerful and well-known algorithms in the literature.

The proposed GTA can be investigated in the future for resolving the OPFI in power grids with high renewable energy penetration. The future extension can be added for the GTA improvement and the possible network limitations under competitive systems.

Data Availability

The complete data of this IEEE 30-bus EPS are extracted from [1, 40, 61], while the data for Real WD-EPNs are extracted from [1, 9, 62]. Y. Liu, D. Gong, J. Sun, and Y. Jin, “A Many-Objective Evolutionary Algorithm Using A One-by-One Selection Strategy,” IEEE Trans. Cybern, vol. 47, no. 9, pp. 2689–2702, 2017, doi: 10.1109/TCYB.2016.2638902.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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