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RESEARCH ARTICLE

Optimal Tuning of Power System Stabilizers for a Multi-Machine Power Systems Using Hybrid Gorilla Troops and Gradient-Based Optimizers

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ABSTRACT This work discusses the production of a novel hybrid algorithm by combining the gorilla troops optimizer (GTO) with the gradient-based optimizers (GBO) approach. The novel approach is called GTO-GBO, it is offered as a useful tool for optimizing the power system stabilizer (PSS) used in the IEEE four-generator, two-area multi-machine power system subjected to a three-phase short-circuit fault. MATLAB/Simulink software was utilized to carry out the assessments. The suggested approach is initially evaluated using multiple benchmark functions with unimodal and multimodal properties. The results are then compared to other competing algorithms (artificial ecosystem optimizer, artificial rabbits optimizer, Coati Optimization Algorithm, and northern goshawk optimization). The comparisons with various algorithms reveal the developed hybrid GTO-GBO algorithm's considerable promise. This demonstrates the GTO-GBO algorithm's improved balance of global and local search stages. The proposed GTO-GBO algorithm's performance is also evaluated by developing an optimum performing PSS for further examination, allowing observation of its capabilities for difficult real-world engineering challenges. To illustrate the applicability and superior performance of the suggested hybrid algorithm for such a complicated real-world engineering problem, the PSS damping controller is formulated as an optimization problem, and the developed GTO-GBO algorithm is used to search for optimal controller parameters. The latter case's findings are compared to the competitive optimization algorithms where the GTO-GBO demonstrates the efficiency and robustness of this suggested optimization algorithm to enhance power system stability.

INDEX TERMS Low-frequency oscillations, multi-machine power system, power system stabilizer, GTO-GBO.

NOMENCLATURE

PSS:	Power system stabilizer.
CPSS:	Conventional PSS (i.e., lead-lag PSS).
AVR:	Automatic voltage regulator.
σ:	The real part of the eigenvalues.
$T_{1,2,3,4}$:	Stabilizer time constants.
GTO:	Artificial Gorilla Troops Optimizer.
GBO:	Gradient-based optimizer.
FF:	Fitness function.
ω:	The imaginary part of the eigenvalues.
K_{PSS}:	PSS gain.

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I. INTRODUCTION

A. BACKGROUND

Because of the indispensability of this type of energy, the rising demand for electrical energy poses a significant difficulty. As a result of power interchanges across different zones of these networks, power systems grow increasingly complicated and huge in scale. Underdamped low-frequency oscillations may appear to impact the entire system in this condition. Therefore, power system engineers must accept responsibility for providing consumers with consistent, high-quality power. Furthermore, the integration of various power systems may result in rotor oscillations in the 0.2-3 Hz range [1]. If these oscillations are not effectively managed, they may increase, impact the entire system, and restrict power transmission capabilities. Damping controllers are thus necessary to dampen these oscillations and enhance the electrical system's dynamic performance. PSSs are often employed to offer supplemental control action via the excitation system. However, these controllers use local measurements as inputs, which are insufficient to dampen inter-area oscillations [2].

B. LITERATURE REVIEW

The primary method for improving PSS resilience is to deploy new tactics to provide adequate dampening of electromechanical oscillations. Traditional control and metaheuristic optimization approaches are among these strategies. Traditional control methods include optimum adaptive and intelligent control. There are several unique intelligent control design approaches, such as artificial neural networks [3] and fuzzy logic [4], [5], have been researched. As per literature there are so many used metaheuristic optimization algorithms for the optimum tuning of PSS like Particle Swarm Optimization [6], [7], JAYA Algorithm [8], Improved Moth Flame [9], whale optimization algorithm [10], sine cosine algorithm [11], A hybrid modified grey wolf optimization-sine cosine algorithm [12], modified Sperm Swarm Optimization [13], Improved Salp Swarm Optimization Algorithm [14], Adaptive Rat Swarm Optimization [15], improved particle swarm optimization [16], Bat Algorithm [17], Runge Kutta optimizer [18], Quantum Artificial Gorilla Troops Optimizer [19], Cuckoo Search Optimization Algorithm [20], slime mould algorithm [21], honey bee mating optimization [22], Backtracking Search Algorithm [23], kidney-inspired algorithm [24], henry gas solubility optimization algorithm [25], modified arithmetic optimization algorithm [26],Water Cycle-Moth Flame Optimization [27], modified sine cosine algorithm [28], non-dominated sorting genetic algorithm [29], Improved Harris Hawk Optimizer [30], genetic algorithm-neural network techniques [31].

As an alternative approach, the researchers presented numerous innovative PSS structures to increase power system stability, such as multi-input PSS [32], fuzzy logic-based PID PSS [33],multi-band PSS [34], Decentralized nonlinear model predictive control [35], a nonlinear autoregressive model with exogenous input neural network [36]. In comparison to the power system stabilizer, these proposed approaches have proved the ability to dampen power system oscillations. Furthermore, these techniques enable the construction of a PSS while accounting for the power system's parameter uncertainty and non-linearity, as well as providing the greatest signal efficiency for a wide range of loading situations [30]. Despite the presence of numerous PSS structures, most power utilities still choose the traditional fixed structure lead-lag PSS (CPSS). It might be related to the simplicity of online adjustment and the lack of certainty about the stability of particular variables [37].

A linearized power system model is used to tackle the traditional PSS parameter selection issue. The damping of electromechanical oscillations, particularly inter-area modes, is heavily influenced by changes in loading circumstances and the topology of the power system. PSS cannot give good damping properties under these conditions. Numerous research works have concentrated on resilient PSS using innovative design methodologies or various PSS architectures [38].

C. MOTIVATION

In the last few periods, hybrid techniques have been applied by numerous researchers to solve many optimization problems. These hybrid techniques have presented a superior performance in comparison to their counterparts in solving several complex problems. In [39], a genetic algorithm (GA) has been hybridized with a particle swarm optimizer (PSO) for global optimization. In this article, the researchers have employed the GAPSO to produce individuals not only from the crossover and mutation operators but also by global and local search operators of PSO. In [40], the grey wolf optimizer (GWO) is hybridized with the hybrid differential evolution (DE) algorithm to improve the convergence characteristics of the hybrid GWODE algorithm for solving continuous global optimization problems. Tawhid and Ali [41] proposed a novel method that hybridized the GWO and GA algorithms and applied the proposed technique to decrease the energy function of a simplified model of the molecule. In another paper, the exploration ability of GWO is hybridized with the capability of exploitation in PSO in order to enhance the strength of the hybrid GWOPSO algorithm [42]. Newly, to improve the performance of complex optimization problems, the GWO algorithm is hybridized with an artificial bee colony (ABC) and used to optimize the parameters [43]. This article focused on applying the bee's information-sharing strategy of the ABC technique to achieve exploration as well as the exploitation ability of the GWO algorithm. In [44], BBO and GWO algorithms are hybridized composed of stability exploration and exploitation and to attain better performance than BBO and GWO individually. Hassanein et al. proposed hybridized CSA algorithm with a rough searching scheme to handle the impreciseness and roughness of the present information concerning the global optimum solution and finally enhance the performance of CSA [45]. These studies approve that the hybrid techniques prove the best performance in comparison to local or global search techniques.

D. CONTRIBUTION

The Artificial Gorilla Troops Optimizer (GTO) algorithm is considered a metaheuristic optimization algorithm inspired by gorilla troops' social intelligence in nature [46]. The GTO algorithm has the benefits of rapid convergence and high performance. Moreover, GTO is characterized by its simplicity, easy implementation, and speed convergence but it still stagnated in local optima [47]. In order to decrease the probability of escaping from local optima and improve the accuracy of the results, the hybrid GTO with Gradient-based optimizer (GBO) algorithm which is one of the more effective algorithms is proposed in this article. The hybrid GTO-GBO technique is an enhancement to the GTO algorithm to enhance the balance between global search or exploration and increase the strength of the proposed GTO-GBO technique for several high-dimensional optimization problems. The main contribution of this paper can be summarized as follows:

1) The introduction of a novel hybrid optimization algorithm GTO-GBO.
2) Validation of the proposed optimizer with the well-known benchmark functions.
3) Proofing the efficiency of the GTO-GBO optimization algorithm when employed to the well-known benchmark functions.
4) Utilizing the GTO-GBO optimization algorithm for the optimum tuning of power system stabilizer of multimachine power systems.

E. PAPER ORGANIZATION

The rest of this work is structured as follows: Section II presents the mathematical formulation of the PSS optimum tuning as well as the model of a multi-machine power system. Section III explains the GTO-GBO optimization algorithm. Section IV illustrates the GTO-GBO performance characteristics on the well-known benchmark function and PSS optimum tuning as a real-world optimization problem. Finally, Section V summarizes the study's findings and future work

II. MATHEMATICAL MODELING AND FORMULATIONS

In power systems, synchronous generators are the primary source of electric energy. The main issue with power system stability is keeping networked synchronous machinery in synchronism. As a result, reliable modeling of the dynamic characteristics of these generators is critical for studying power system stability. The i^th machine's model differential equations are expressed as follows [48]:

$$\dot{\delta}_i = \omega_b (\omega_i - 1) \tag{1}$$

$$\dot{\omega}_i = \frac{1}{M_i} (T_{mi} - T_{ei} - D_i (\omega_i - 1)) \tag{2}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}} \left[E_{fdi} - E'_{qi} - (x_{di} - x'_{di})\, i_{di} \right] \tag{3}$$

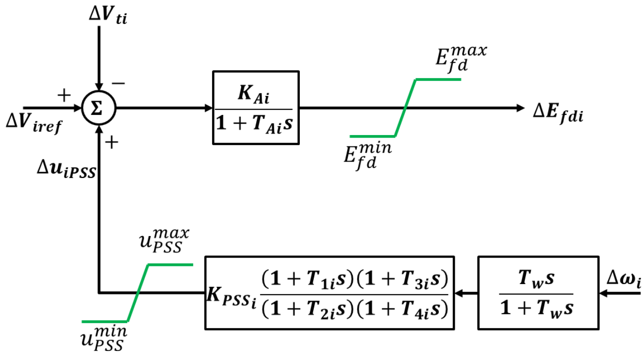

FIGURE 1. Power system stabilizer structure.

where δ, ω denotes the rotor angle and angular speed, respectively, the mechanical torque is T_m, the electrical torque is T_e, and the damping coefficient is D. T'_{do} is the open circuit time constant of the d-axis, x_d is the d-axis transient reactance.

Exciters are commonly found in synchronous generators. An excitation system's main role is to supply the DC current to the synchronous machine field winding. Furthermore, the excitation system controls the field voltage and hence the field current, which is critical to the power system's operation. Control functions include voltage and reactive power flow regulation, as well as system stability enhancement. The protection functions ensure that the synchronous machines, excitation systems, and other equipment's capability limits are not exceeded. Figure 1 shows the conventional IEEE type-ST1 exciter model utilized in this research which can be described as:

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}} \left[K_{Ai} (v_{ref-i} - v_{ti} + u_{PSS}) - E_{fdi} \right] \tag{4}$$

where v_{ref-i} is the steady-state value of the terminal voltage v_{ti} of machine-i, E_{fdi} represents the e.m.f. owing to d-axis flux and K_{Ai}, T_{Ai} represents the regulator gain and time constant respectively. The PSS stabilization signal is expressed by u_{PSS}

A power system stabilizer's primary duty is to dampen the oscillations of the generator rotor by managing its excitation with auxiliary stabilizing impulses. The automatic voltage regulator (AVR), which controls the generator stator terminal voltage, is enhanced with a PSS that modifies the AVR input signal by using stabilizing feedback signals such as shaft speed. PSS must generate an electrical torque component that is in phase with the rotor speed variations to damp low-frequency oscillations.

An eigenvalue-based fitness function FF is suggested below to increase system damping to electromechanical modes oscillation. The variable ζ represents the minimum damping ratio. The optimum tuning problem can be mathematically defined as follows:

$$FF = Max.(\zeta);\ \zeta = -\frac{\sigma}{\sqrt{\sigma^2 + \omega^2}}$$
$$\text{Subjected to}: \ K_{PSS_{min}} \le K_{PSS} \le K_{PSS_{max}}$$

$$T_{1_{min}} \leq T_1 \leq T_{1_{max}}$$
$$T_{2_{min}} \leq T_2 \leq T_{2_{max}}$$
$$T_{3_{min}} \leq T_3 \leq T_{3_{max}}$$
$$T_{4_{min}} \leq T_4 \leq T_{4_{max}} \quad (5)$$

III. THE PROPOSED OPTIMIZATION ALGORITHM

This section presents the process of the hybrid GTO-GBO technique. The proposed GTO-GBO algorithm

A. ARTIFICIAL GORILLA TROOPS OPTIMIZER (GTO)

B. EXPLORATION PHASE

Three different operators were used in the exploration phase: Move to an unknown location to further explore the GTO algorithm [46]. The second factor, the transition to other gorillas, increases the balance between exploration and exploitation. The third factor is in the exploration phase, that is, migrating to a known position significantly rises the capability of the GTO algorithm to search for different development spaces. These different operators can be represented using the following equation:

$$GX(t+1) = \begin{cases} (ub - lb) \times r_1 + lb, & rand < z \\ (r_2 - C) \times X_r(t) + D \times B, & rand \geq 0.5 \\ X(i) - D \times (D \times (X(t) - GX_r(t)) + r_3 \times (X(t) - GX_r(t))), & rand < 0.5 \end{cases}$$
$$C = (cos(2\times r_4) + 1) \times \left(1 - \frac{it}{Maxit}\right)$$
$$D = C \times k$$
$$B = E \times X(t)$$
$$E = [-C, C] \quad (6)$$

where, $GX(t+1)$ is the gorilla candidate position in the next iteration. lb and ub denote the lower and upper bounds of the variables, respectively. r_1, $rand$, r_2, r_3, and r_4 are random values ranging from 0 to 1. z represents a parameter that has a range from 0 to 1. $X(t)$ denotes the current vector of the gorilla position while $X_r(t)$ is a member of the gorillas randomly chosen from the entire gorillas and also $GX_r(t)$ .k denotes a random value ranging from -1 to 1.

C. EXPLOITATION PHASE

Two behaviors are applied in the exploitation phase. Two strategies are applied in the exploitation phase. the first strategy is Follow the silverback and it is applied when $C \geq W$. W denotes a parameter to be set before the optimization operation. The first strategy can be mathematically calculated as follows [19]:

$$GX(t+1) = D \times M \times (X(t) - X_{silverback}) + X(t)$$
$$M = \left(\left|\frac{1}{N}\sum_{i=1}^{N} GX_i(t)\right|^g\right)^{\frac{1}{g}}$$
$$g = 2^D \quad (7)$$

where $X_{silverback}$ denotes the best solution, N is the total number of gorillas.

The second mechanism is the Competition for adult females, and it is applied when $C < W$. This mechanism is calculated using the following equation:

$$GX(i) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A$$
$$Q = 2 \times r_5 - 1$$
$$A = \beta \times H$$
$$H = \begin{cases} N_1, & rand \geq 0.5 \\ N_2, & rand < 0.5 \end{cases} \quad (8)$$

where β is a parameter to be given value before the optimization operation. r_5 is a random value ranging from 0 to 1.

D. GRADIENT BASED OPTIMIZER (GBO)

The conventional GBO algorithm [49], combines gradient and population-based approaches, it employs Newton's method that requires the search direction to observe the search domain with the use of a collection of vectors and two main operators, namely gradient search rule (GSR) and local escaping operators (LEO).

1) GRADIENT SEARCH RULE (GSR) PROCESS

In the GBO technique, GSR is according to the gradient-based method where the target of using the GSR is exploration tendency development and increasing the convergence rate. Therefore, the new position X_{n+1} can be defined as [50]:

$$X_{n+1} = X_n - \frac{2\Delta x \times f(X_n)}{f(X_n + \Delta x) - f(X_n - \Delta x)} \quad (9)$$

Eq. (9) will be adjusted to contain the population-based search theory that is presented by Eq. (10).

$$GSR = randn \times \frac{2\Delta x X_n}{(x_{worst} - x_{best} + \varepsilon)} \quad (10)$$

where $randn$ denotes a random number with a normal distribution, x_{worst}, x_{best} are the worst and best solutions attained through the procedure of optimization, ε is a small number within the interval [0, 0.1], and Δx denotes the change in location at each iteration. From the previous Eqs., the GSR is defined as:

$$GSR = randn \times \rho_1 \times \frac{2\Delta x X_n}{(x_{worst} - x_{best} + \varepsilon)} \quad (11)$$

where ρ_1 is the randomly produced parameter and it can be calculated as below:

$$\rho_1 = (2 \times rand \times \alpha) - \alpha \quad (12)$$
$$\alpha = \left|\beta \sin\left(\frac{3\pi}{2} + \sin\left(\beta\frac{3\pi}{2}\right)\right)\right| \quad (13)$$
$$\beta = \beta_{min} + (\beta_{min} - \beta_{min})\left(1 - \left(\frac{m}{M}\right)^3\right)^2 \quad (14)$$

where α is a sine function for the transference from exploration to exploitation, β_{min} and β_{max} represent constant values 0.2 and 1.2, respectively, m denotes the current number of

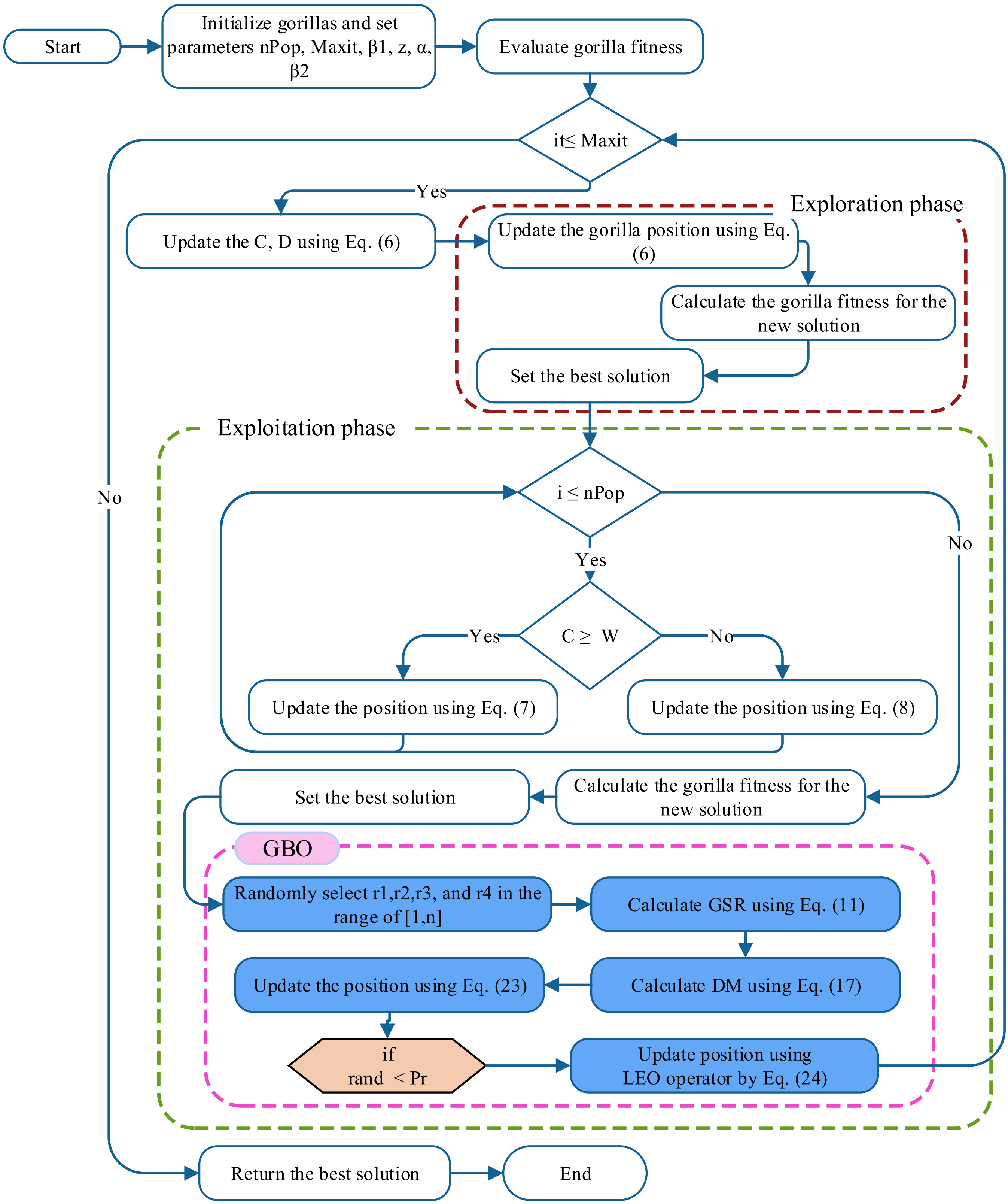

FIGURE 2. Flowchart of hybrid GTO-GBO algorithm.

iterations, and M refers to the total number of iterations. The change Δx between the best solution x_{best} and a randomly selected location x_{r1}^m can be given by [51]:

$$\Delta x = rand\,(1:N) \times |step| \tag{15}$$

$$step = \frac{\left(x_{best} - x_{r1}^m\right) + \delta}{2} \tag{15-1}$$

$$\delta = 2 \times rand \times \left(\left|\frac{x_{r1}^m + x_{r2}^m + x_{r3}^m + x_{r4}^m}{4}\right| - x_n^m\right) \tag{15-2}$$

where $rand(1{:}N)$ is a random vector with N dimensions, $r1, r2, r3$, and $r4 (r1 \neq r2 \neq r3 \neq r4 \neq n)$ represent different integers randomly selected from [1, N], $step$ is a step size. The new location X_{n+1} is updated based on the GSR from the following equation:

$$X_{n+1} = X_n - GSR \tag{16}$$

The direction of movement (DM) is added for better exploitation of the nearby area of X_n which is calculated as follows:

$$DM = rand \times \rho_2 \times (x_{best} - x_n) \tag{17}$$

$$\rho_2 = (2 \times rand \times \alpha) - \alpha \tag{17-1}$$

Consequently, the new location $X1_n^m$ can be calculated after considering the GSR and DM from the following equation:

$$X1_n^m = x_n^m - \mathrm{GSR} + \mathrm{DM} \tag{18}$$

$$X1_n^m = x_n^m - randn \times \rho_1 \times \frac{2\Delta x \times x_n^m}{(x_{\text{worst}} - x_{best} + \varepsilon)} + rand \times \rho_2 \times (x_{best} - x_n^m) \tag{19}$$

The GBO used another location to increase the local search by putting the best-so-far solution (x_{best}) rather than the location x_n^m. The new location ($X2_n^m$) can be calculated as below:

$$X2_n^m = x_{\text{best}} - randn \times \rho_1 \times \frac{2\Delta x \times x_n^m}{(yp_n^m - yq_n^m + \varepsilon)} + rand \times \rho_2 \times (x_{r1}^m - x_{r2}^m) \tag{20}$$

where

$$yp_n = rand \times \left(\frac{[z_{n+1}+x_n]}{2} + rand \times \Delta x\right) \tag{21}$$

$$yq_n = rand \times \left(\frac{[z_{n+1}+x_n]}{2} - rand \times \Delta x\right) \tag{22}$$

Based on the locations $X1_n^m, X2_n^m$, and the current location (X_n^m), the new location at the next iteration (x_n^{m+1}) is formulated as:

$$x_n^{m+1} = r_a \times \left(r_b \times X1_n^m + (1 - r_b) \times X2_n^m\right) + (1 - r_a) \times X3_n^m \tag{23}$$

$$X3_n^m = X_n^m - \rho_1 \times (X2_n^m - X1_n^m) \tag{23-1}$$

2) LOCAL ESCAPING OPERATOR (LEO)

The LEO is applied to improve the performance of the GBO algorithm and to escape the local solutions for solving complex problems. The LEO produces a suitable solution (X_{LEO}^m) by using numerous solutions that include x_{best}, the solutions $X1_n^m$, and $X2_n^m$, two random solutions x_{r1}^m and x_{r2}^m, and a new randomly generated solution (x_k^m). The solution X_{LEO}^m is given as:

$$
\begin{aligned}
&\textit{if } rand < pr\\
&\quad \textit{if } rand < 0.5\\
&\qquad X_{LEO}^m = X_n^{m+1} + f_1 \times \left(u_1 \times x_{\text{best}} - u_2 \times x_k^m\right)\\
&\qquad\qquad + f_2 \times \rho_1 \times \left(u_3 \times (X2_n^m - X1_n^m)\right.\\
&\qquad\qquad \left. + u_2 \times (x_{r1}^m - x_{r2}^m)\right)/2\\
&\quad X_n^{m+1} = X_{LEO}^m\\
&\quad \text{Else}\\
&\qquad X_{LEO}^m = x_{\text{best}} + f_1 \times \left(u_1 \times x_{\text{best}} - u_2 \times x_k^m\right)\\
&\qquad\qquad + f_2 \times \rho_1 \times \left(u_3 \times (X2_n^m - X1_n^m)\right.\\
&\qquad\qquad \left. + u_2 \times (x_{r1}^m - x_{r2}^m)\right)/2\\
&\quad X_n^{m+1} = X_{LEO}^m\\
&\quad \text{End}\\
&\text{End}
\end{aligned} \tag{24}
$$

where f_1 is a uniformly distributed random number in the range of $[-1, 1]$, f_2 denotes a random number from a normal distribution with a mean of 0 and a standard deviation of 1, pr refers to the probability, and u_1, u_2, and u_3 are random values produced as below [52]:

$$u_1 = \begin{cases} 2 \times rand & \textit{if } \mu_1 < 0.5 \\ 1 & \textit{otherwise} \end{cases} \tag{25}$$

$$u_2 = \begin{cases} rand & \textit{if } \mu_1 < 0.5 \\ 1 & \textit{otherwise} \end{cases} \tag{26}$$

$$u_3 = \begin{cases} rand & \textit{if } \mu_1 < 0.5 \\ 1 & \textit{otherwise} \end{cases} \tag{27}$$

where $rand$ is a random number in the range of [0, 1], and μ_1 represents a number in the range of [0, 1]. The above equations are simply clarified as follows:

$$u_1 = L_1 \times 2 \times rand + (1 - L_1) \tag{28}$$

$$u_2 = L_1 \times rand + (1 - L_1) \tag{29}$$

$$u_3 = L_1 \times rand + (1 - L_1) \tag{30}$$

where L_1 is a binary parameter with a value of 0 or 1. If parameter $\mu_1 < 0.5$, the value of $L_1 = 1$, otherwise, $L_1 = 0$. The solution x_k^m is created as below:

$$x_k^m = \begin{cases} x_{rand} & \textit{if } \mu_2 < 0.5 \\ x_p^m & \textit{otherwise} \end{cases} \tag{31}$$

$$x_{rand} = X_{min} + rand\,(0, 1) \times (X_{max} - X_{min}) \tag{32}$$

where x_{rand} refers to a randomly generated solution, x_p^m is a randomly selected solution of the population ($p \in$

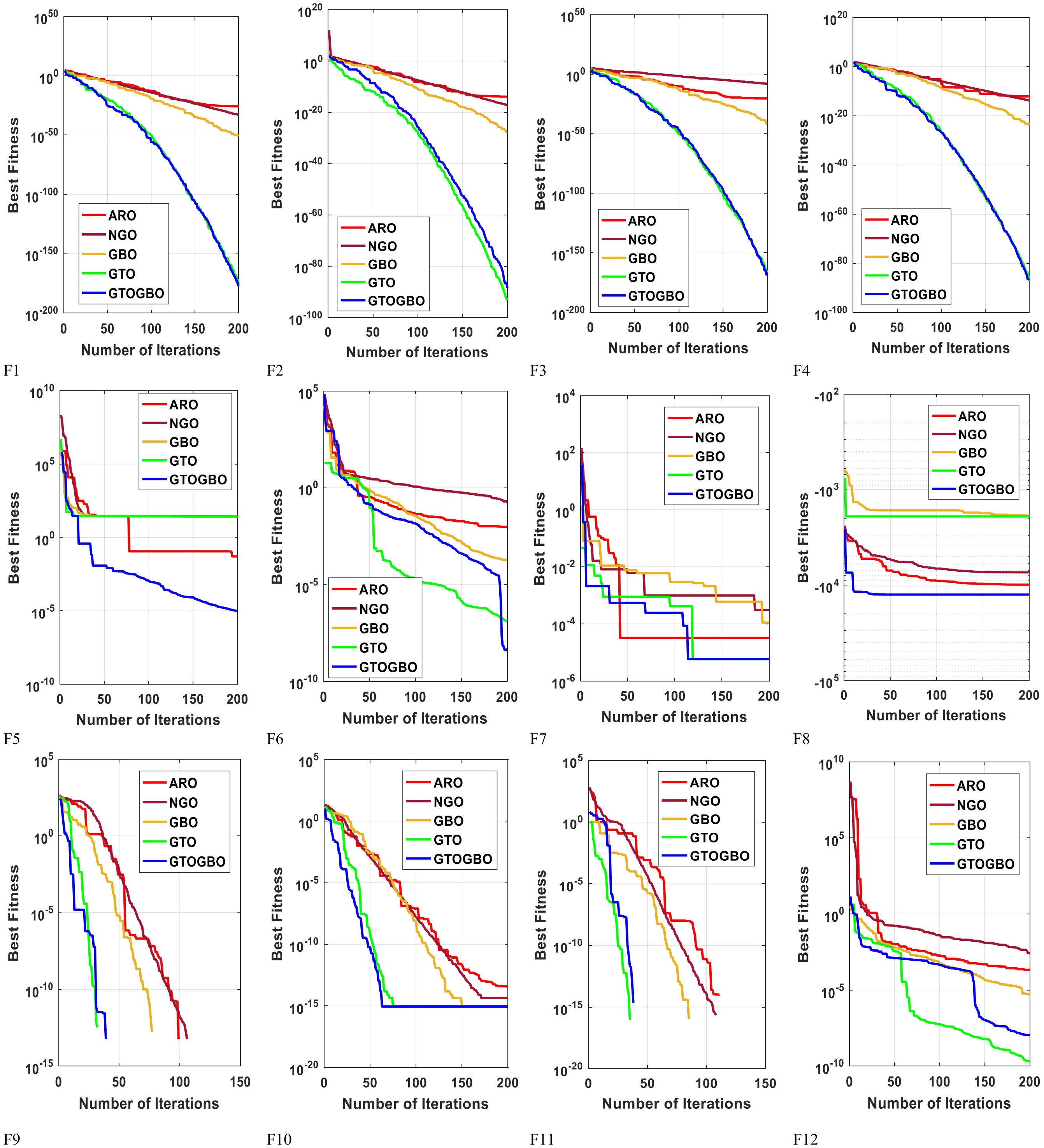

FIGURE 3. The convergence curves of all algorithms for 23 benchmark functions.

[1, 2, . . . , N]), and μ_2 denotes a random number in the range of [0, 1]. Eq. (31) is simplified as:

$$x_k^m = L_2 \times x_p^m + (1 - L_2) \times x_{rand} \tag{33}$$

where L_2 refers to a binary parameter with a value of 0 or 1. If $\mu_2 < 0.5$, the value of $L_2 = 1$, otherwise, $L_2 = 0$. The flowchart of the hybrid GTO-GBO algorithm is shown in Figure 2.

IV. SIMULATION RESULTS AND DISCUSSION

A. BENCHMARK FUNCTIONS VALIDATION

In this subsection, the supremacy of the hybrid GTO-GBO technique is demonstrated using 23 benchmark

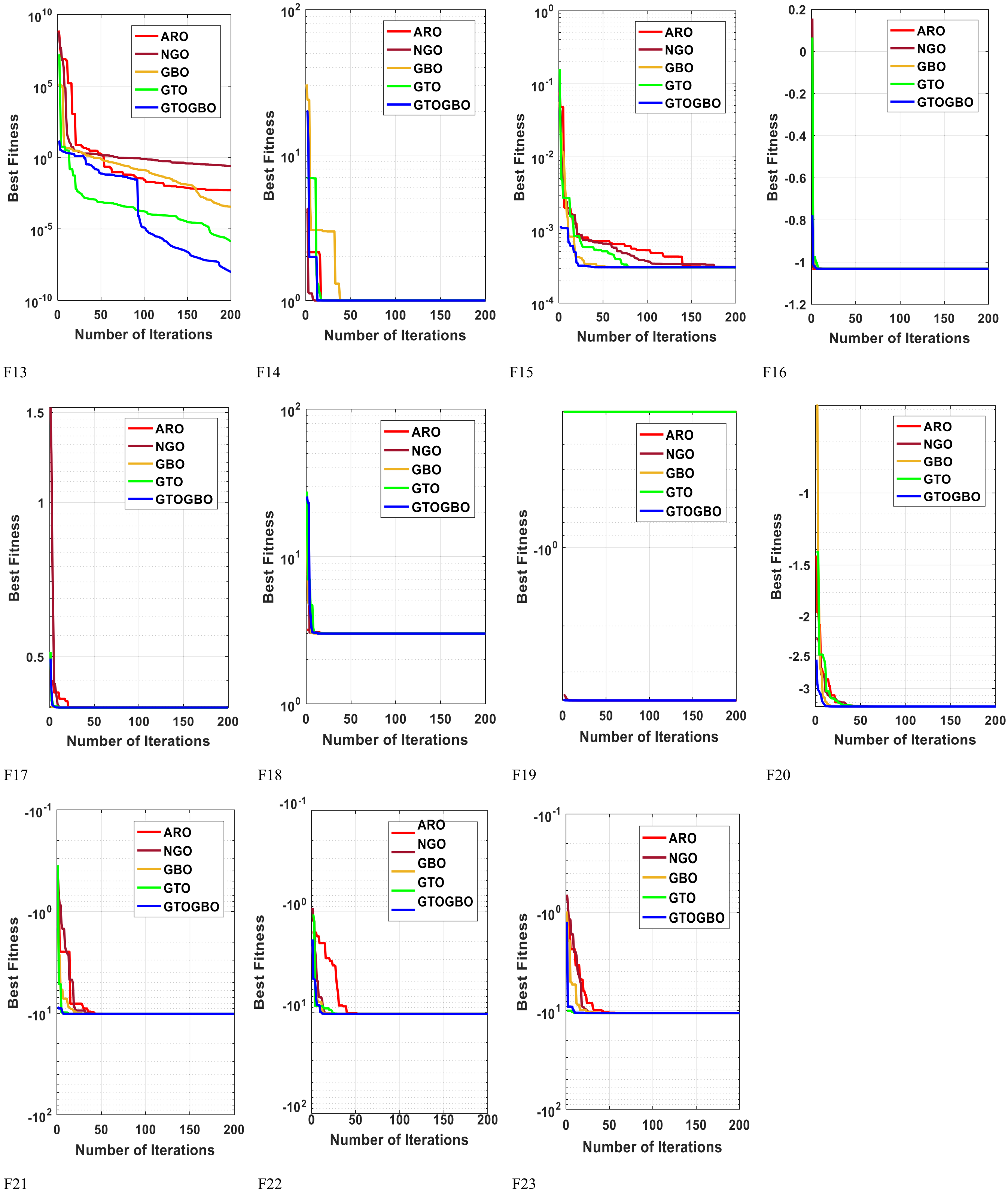

FIGURE 3. *(Continued.)* **The convergence curves of all algorithms for 23 benchmark functions.**

functions [53]. All the experiments of the 23 benchmark functions are implemented by MATLAB (R2016a) on a computer with Intel(R) Core i5-4210U CPU 2.40 GHz with an 8GB RAM environment. In this study, 23 well-known benchmark test functions have been used to evaluate the proposed GTO-GBO technique's performance. The maximum number of

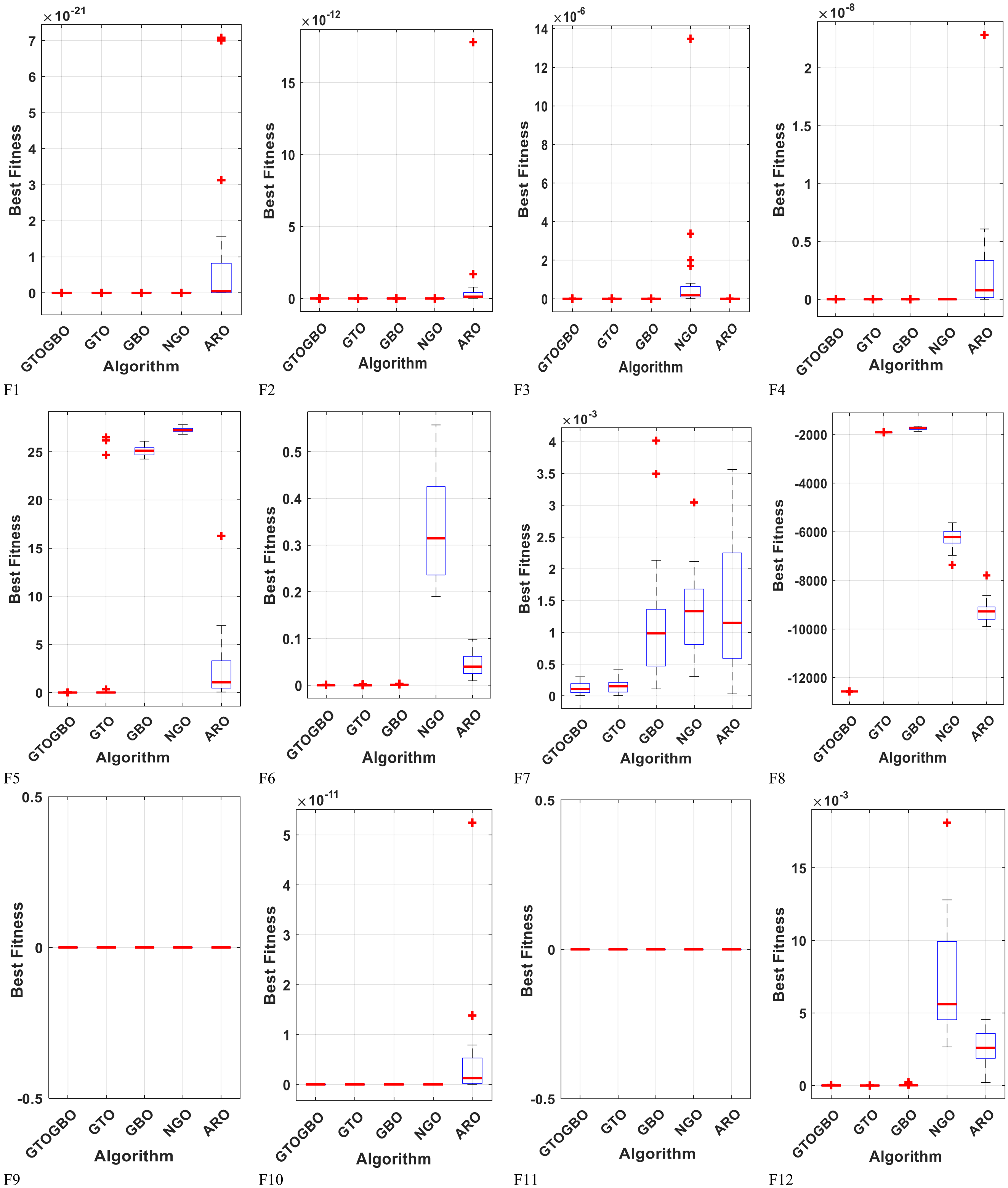

FIGURE 4. Boxplots for all algorithms for 23 benchmark functions.

iterations considered for all applied techniques is 200 and the number of populations is 50. In this subsection, the hybrid GTO-GBO algorithm is compared with several recent algorithms such as conventional GTO, GBO, artificial rabbits optimization (ARO) [54], and northern goshawk optimization (NGO) [55], [56] and the superiority of the achieved solution

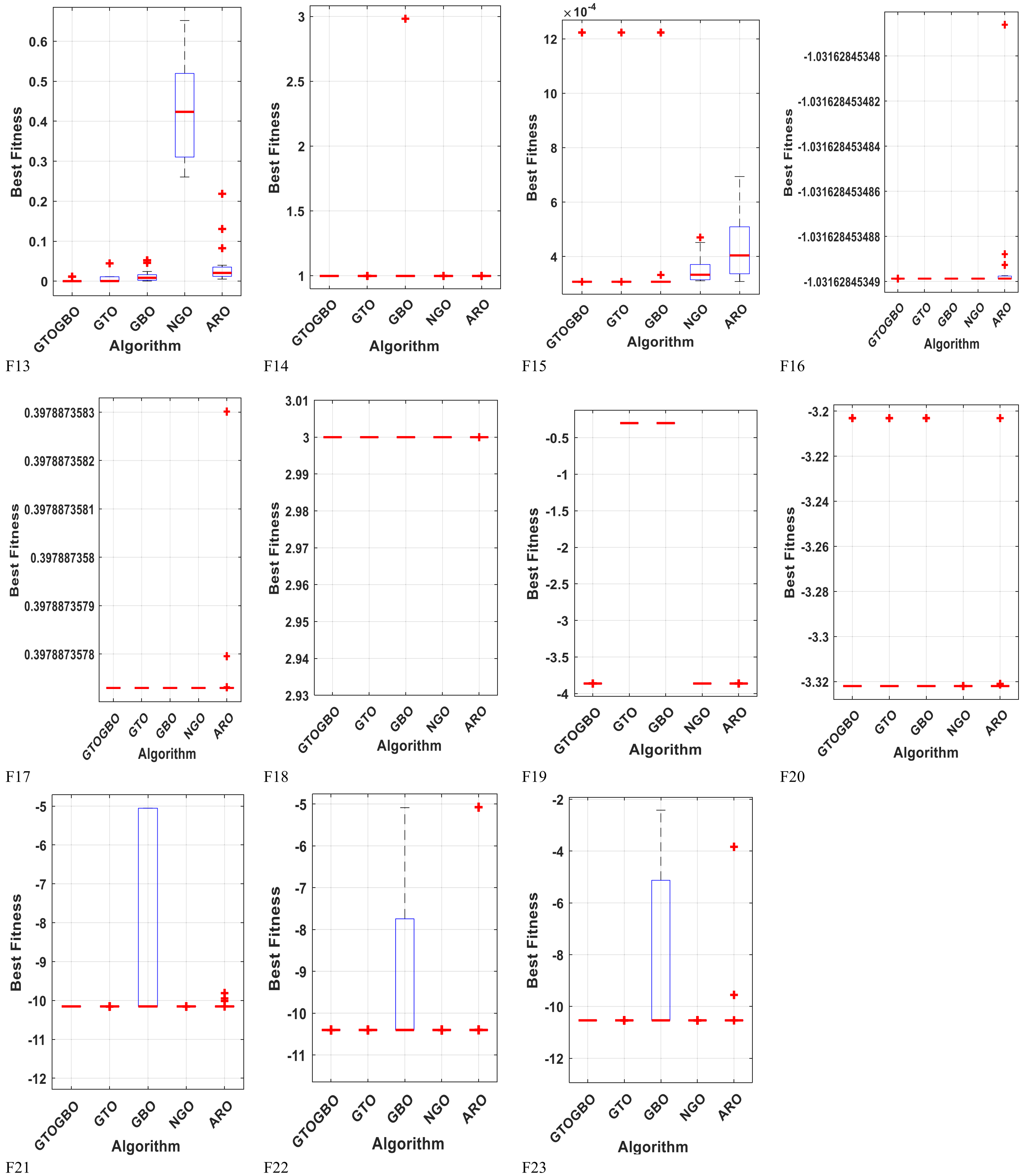

FIGURE 4. ***(Continued.)*** **Boxplots for all algorithms for 23 benchmark functions.**

is tested using mean value and standard deviation (std). The technique with a lesser mean value and std can be considered a technique with strong global optimization competence and more stability. the statistical results achieved by the hybrid GTO-GBO algorithm and these recent techniques for solving 23 benchmark functions in terms of mean value and std are shown in Table 1. From this table, the GTO-GBO algorithm is superior to the compared algorithms in 16 benchmark

TABLE 1. The statistical Results of benchmark functions using the proposed GTO-GBO algorithm and other recent algorithms.

Function		GTO-GBO	GTO	GBO	ARO	NGO
F1	Best	8E-178	1.3E-176	9.06E-52	1.59E-26	5.01E-34
	Mean	1.7E-161	9.1E-152	4.1E-46	1.07E-21	7.16E-33
	Median	4.1E-167	4.2E-170	1.73E-49	4.68E-23	4.24E-33
	Worst	1.6E-160	1.8E-150	4.79E-45	7.08E-21	3.02E-32
	std	4.6E-161	4.1E-151	1.27E-45	2.18E-21	8.77E-33
	Rank	1	2	3	5	4
F2	Best	3.51E-89	2.96E-85	2.03E-28	1.34E-14	6.6E-18
	Mean	3.88E-79	1.44E-80	1.95E-24	1.15E-12	1.65E-17
	Median	3.08E-82	5.06E-82	1.77E-25	1.22E-13	1.58E-17
	Worst	7.22E-78	9.29E-80	1.95E-23	1.78E-11	3.85E-17
	std	1.61E-78	2.93E-80	4.64E-24	3.94E-12	7.66E-18
	Rank	2	1	3	5	4
F3	Best	3.9E-169	3.8E-167	3.42E-42	4.28E-21	1.04E-08
	Mean	4.7E-151	3.9E-149	2.56E-38	5.08E-15	1.19E-06
	Median	6E-158	9.3E-157	5.51E-40	6.99E-17	1.85E-07
	Worst	7.1E-150	7.4E-148	2.05E-37	6.41E-14	1.35E-05
	std	1.6E-150	1.7E-148	5.68E-38	1.51E-14	3.02E-06
	Rank	1	2	3	4	5
F4	Best	2.2E-87	8.11E-88	1.54E-24	8.35E-13	1.39E-14
	Mean	3.12E-77	1.3E-80	8.59E-22	2.6E-09	3.71E-14
	Median	2.82E-84	8.8E-83	1.22E-22	7.79E-10	3.34E-14
	Worst	6.25E-76	1.37E-79	1.08E-20	2.28E-08	7.08E-14
	std	1.4E-76	3.51E-80	2.47E-21	5.09E-09	1.77E-14
	Rank	2	1	3	5	4
F5	Best	9.18E-06	4.82E-05	24.25387	0.048127	26.83203
	Mean	0.004094	3.890629	25.13063	2.57084	27.31122
	Median	0.000772	0.003429	25.117	1.069097	27.2574
	Worst	0.019565	26.5186	26.10917	16.26736	27.8186
	std	0.006564	9.448749	0.565603	3.783419	0.253381
	Rank	1	3	4	2	5
F6	Best	3.9E-09	1.28E-07	0.00018	0.009568	0.189623
	Mean	0.000154	0.000152	0.00108	0.044563	0.337336
	Median	7.1E-05	2.01E-05	0.000875	0.039666	0.314621
	Worst	0.000837	0.001805	0.002836	0.098375	0.557148
	std	0.00023	0.0004	0.000702	0.026373	0.115208
	Rank	2	1	3	4	5
F7	Best	5.85E-06	5.83E-06	0.000111	3.22E-05	0.000308
	Mean	0.00012	0.000168	0.001192	0.001407	0.001318
	Median	0.00011	0.000152	0.000985	0.00115	0.001333
	Worst	0.000301	0.000421	0.004017	0.003564	0.003044
	std	9.05E-05	0.00012	0.001008	0.001071	0.000676
	Rank	1	2	3	5	4
F8	Best	-12569.5	-1909.05	-1872.79	-9902.5	-7365.87
	Mean	-12569.5	-1909.05	-1743.83	-9268.23	-6275.83
	Median	-12569.5	-1909.05	-1732.31	-9276.94	-6222.66
	Worst	-12569.5	-1909.05	-1659.76	-7798.04	-5610.59

TABLE 1. *(Continued.)* **The statistical Results of benchmark functions using the proposed GTO-GBO algorithm and other recent algorithms.**

	std	3.17E-05	0.000616	58.4135	494.4779	454.4917
	Rank	1	4	5	2	3
F9	Best	0	0	0	0	0
	Mean	0	0	0	0	0
	Median	0	0	0	0	0
	Worst	0	0	0	0	0
	std	0	0	0	0	0
	Rank	1	1	1	1	1
F10	Best	8.88E-16	8.88E-16	8.88E-16	3.29E-14	4.44E-15
	Mean	8.88E-16	8.88E-16	8.88E-16	5.19E-12	6.04E-15
	Median	8.88E-16	8.88E-16	8.88E-16	1.26E-12	4.44E-15
	Worst	8.88E-16	8.88E-16	8.88E-16	5.25E-11	7.99E-15
	std	0	0	0	1.17E-11	1.81E-15
	Rank	1	1	1	5	4
F11	Best	0	0	0	0	0
	Mean	0	0	0	0	0
	Median	0	0	0	0	0
	Worst	0	0	0	0	0
	std	0	0	0	0	0
	Rank	1	1	1	1	1
F12	Best	1.08E-08	2.01E-10	5.1E-06	0.000211	0.002656
	Mean	7.72E-06	6.7E-07	3.6E-05	0.002555	0.007196
	Median	3.87E-06	7.98E-08	2.19E-05	0.002594	0.005604
	Worst	4E-05	4.23E-06	0.000217	0.004551	0.018111
	std	1.02E-05	1.09E-06	4.68E-05	0.001218	0.003978
	Rank	2	1	3	4	5
F13	Best	1.02E-08	1.42E-06	0.000369	0.005253	0.260517
	Mean	0.00115	0.005645	0.014006	0.038605	0.424609
	Median	1.56E-05	0.000236	0.008366	0.020631	0.423517
	Worst	0.011469	0.044505	0.052319	0.218513	0.651846
	std	0.003483	0.010476	0.016889	0.051532	0.123586
	Rank	1	2	3	4	5
F14	Best	0.998004	0.998004	0.998004	0.998004	0.998004
	Mean	0.998004	0.998004	1.097209	0.998004	0.998004
	Median	0.998004	0.998004	0.998004	0.998004	0.998004
	Worst	0.998004	0.998004	2.982105	0.998004	0.998004
	std	1.61E-16	8.82E-17	0.443659	2.97E-16	6.83E-14
	Rank	1	1	5	3	4
F15	Best	0.000307	0.000307	0.000307	0.000308	0.000311
	Mean	0.000445	0.000399	0.000446	0.000441	0.000349
	Median	0.000307	0.000307	0.000307	0.000404	0.000333
	Worst	0.001223	0.001223	0.001223	0.000694	0.00047
	std	0.000335	0.000282	0.000335	0.000131	4.52E-05
	Rank	4	2	5	3	1
F16	Best	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163
	Mean	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163
	Median	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163
	Worst	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163

TABLE 1. ***(Continued.)*** **The statistical Results of benchmark functions using the proposed GTO-GBO algorithm and other recent algorithms.**

	std	2.16E-16	1.69E-16	1.61E-16	2.5E-12	1.35E-16
	Rank	1	1	1	5	1
F17	Best	0.397887	0.397887	0.397887	0.397887	0.397887
	Mean	0.397887	0.397887	0.397887	0.397887	0.397887
	Median	0.397887	0.397887	0.397887	0.397887	0.397887
	Worst	0.397887	0.397887	0.397887	0.397887	0.397887
	std	0	0	0	1.28E-10	0
	Rank	1	1	1	5	1
F18	Best	3	3	3	3	3
	Mean	3	3	3	3	3
	Median	3	3	3	3	3
	Worst	3	3	3	3	3
	std	1.45E-15	1.5E-15	1.56E-15	1.16E-15	1.52E-15
	Rank	4	1	1	1	5
F19	Best	-3.86278	-0.30048	-0.30048	-3.86278	-3.86278
	Mean	-3.86278	-0.30048	-0.30048	-3.86278	-3.86278
	Median	-3.86278	-0.30048	-0.30048	-3.86278	-3.86278
	Worst	-3.86278	-0.30048	-0.30048	-3.86278	-3.86278
	std	2.19E-15	1.14E-16	1.14E-16	3.73E-15	2.13E-15
	Rank	1	4	4	3	1
F20	Best	-3.322	-3.322	-3.322	-3.322	-3.322
	Mean	-3.29822	-3.29822	-3.29822	-3.31597	-3.322
	Median	-3.322	-3.322	-3.322	-3.322	-3.322
	Worst	-3.2031	-3.2031	-3.2031	-3.2031	-3.322
	std	0.048793	0.048793	0.048793	0.026567	2.01E-10
	Rank	3	3	3	2	1
F21	Best	-10.1532	-10.1532	-10.1532	-10.1532	-10.1532
	Mean	-10.1532	-10.1532	-7.8591	-10.1187	-10.1532
	Median	-10.1532	-10.1532	-10.1532	-10.1532	-10.1532
	Worst	-10.1532	-10.1532	-5.0552	-9.81141	-10.1532
	std	2.51E-15	2.41E-15	2.602111	0.090338	5.69E-06
	Rank	1	1	5	4	3
F22	Best	-10.4029	-10.4029	-10.4029	-10.4029	-10.4029
	Mean	-10.4029	-10.4029	-9.07412	-10.1364	-10.4029
	Median	-10.4029	-10.4029	-10.4029	-10.4029	-10.4029
	Worst	-10.4029	-10.4029	-5.08767	-5.07631	-10.4029
	std	3.43E-15	3.8E-15	2.36137	1.191013	1.38E-06
	Rank	1	1	5	4	3
F23	Best	-10.5364	-10.5364	-10.5364	-10.5364	-10.5364
	Mean	-10.5364	-10.5364	-8.37899	-10.1522	-10.5364
	Median	-10.5364	-10.5364	-10.5364	-10.5364	-10.5364
	Worst	-10.5364	-10.5364	-2.42173	-3.83543	-10.5364
	std	2.61E-15	2.41E-15	3.074069	1.502943	1.09E-07
	Rank	1	1	5	4	3
Average Rank		**1.521739**	1.652174	3.086957	3.521739	3.173913
Final ranking		**1**	2	3	5	4

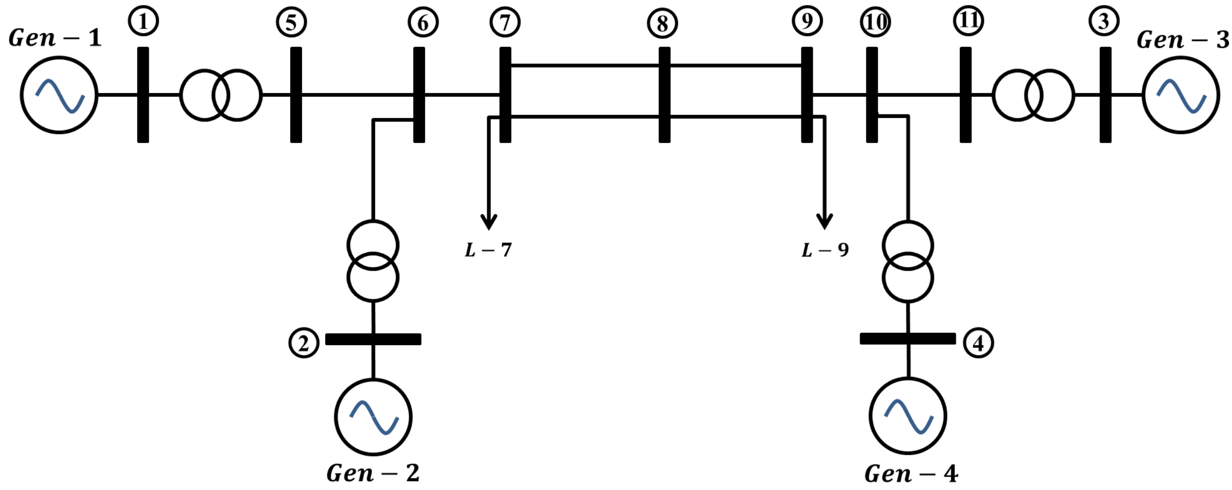

FIGURE 5. Single-line diagram of Four-machine power system.

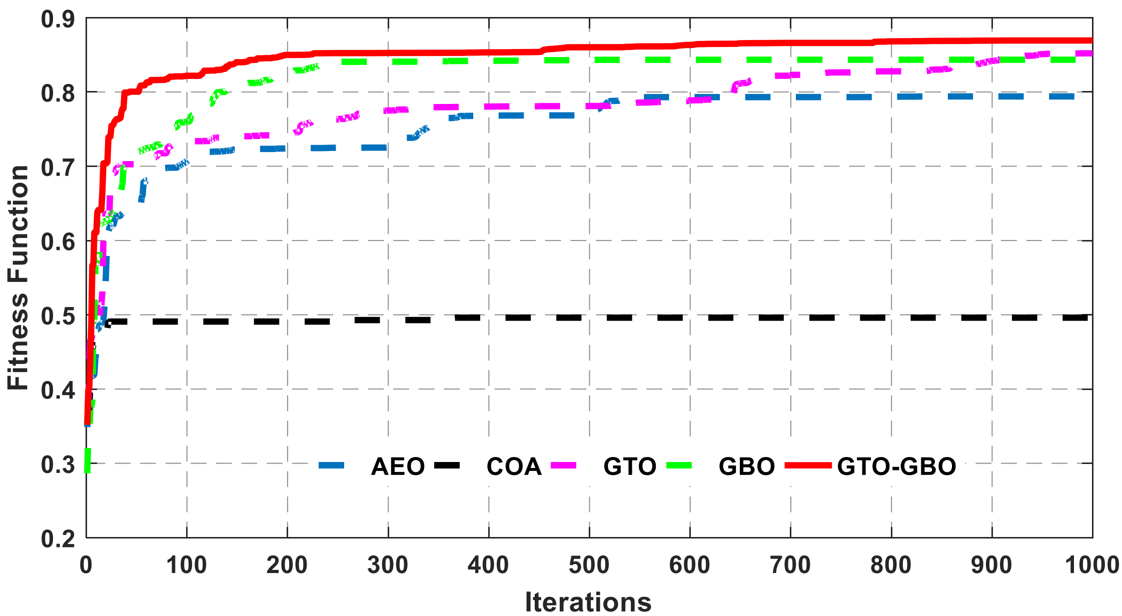

FIGURE 6. Convergence curves of twenty distinct runs.

functions in terms of the average value (F1, F3, F5, F7, F8, F9, F10, F11, F13, F14, F16, F17, F19, F21, F22, F23). It is clear from these results that the GTO-GBO algorithm can attain better solutions compared to several newly proposed algorithms in solving numerous of the benchmark functions. This discussion proves that the hybrid GTO-GBO technique is very effective. Also from this table, the GTO and GBO display strong efficiency, which are the second and third best. It is concluded that the hybrid GTO-GBO technique is an effective algorithm for solving these types of problems.

Furthermore, the convergence curves of these algorithms for each of the 23 benchmark functions are shown in Fig.3. Each benchmark function is implemented over 20 independent trials. It is also seen from Fig.3 that the proposed GTO-GBO technique has a much better convergence curve compared with the original GTO, GBO, ARO, and NGO algorithms. From this figure, the GTO-GBO technique is superior to the compared algorithms in 20 benchmark functions in terms of the convergence characteristics (F1, F3, F4, F5, F6, F7, F8, F9, F10, F11, F13, F14, F15, F16, F17, F18, F19, F21, F22, F23). It is shown that it can be analyzed that the proposed GTO-GBO algorithm tends to demonstrate a faster convergence rate in comparison to other algorithms in the first quarter of optimization. This fast convergence capability makes the GTO-GBO algorithm a capable and promising algorithm to solve several real-world optimization problems. The underlying reason for the superior performance of the proposed algorithm is that it is able to locate high-performing

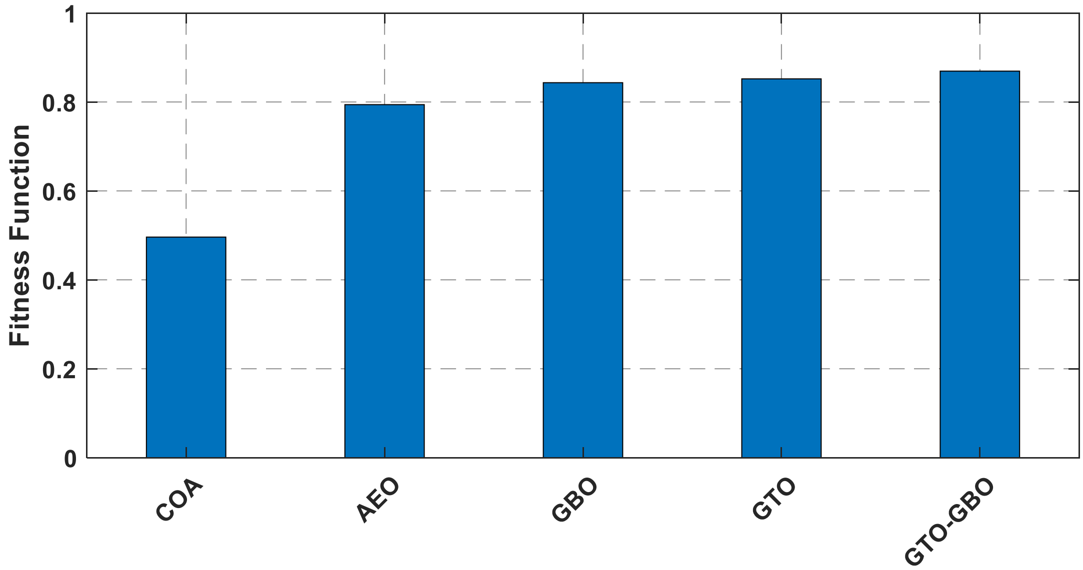

FIGURE 7. Bar plot for the attained fitness function using various optimization algorithms.

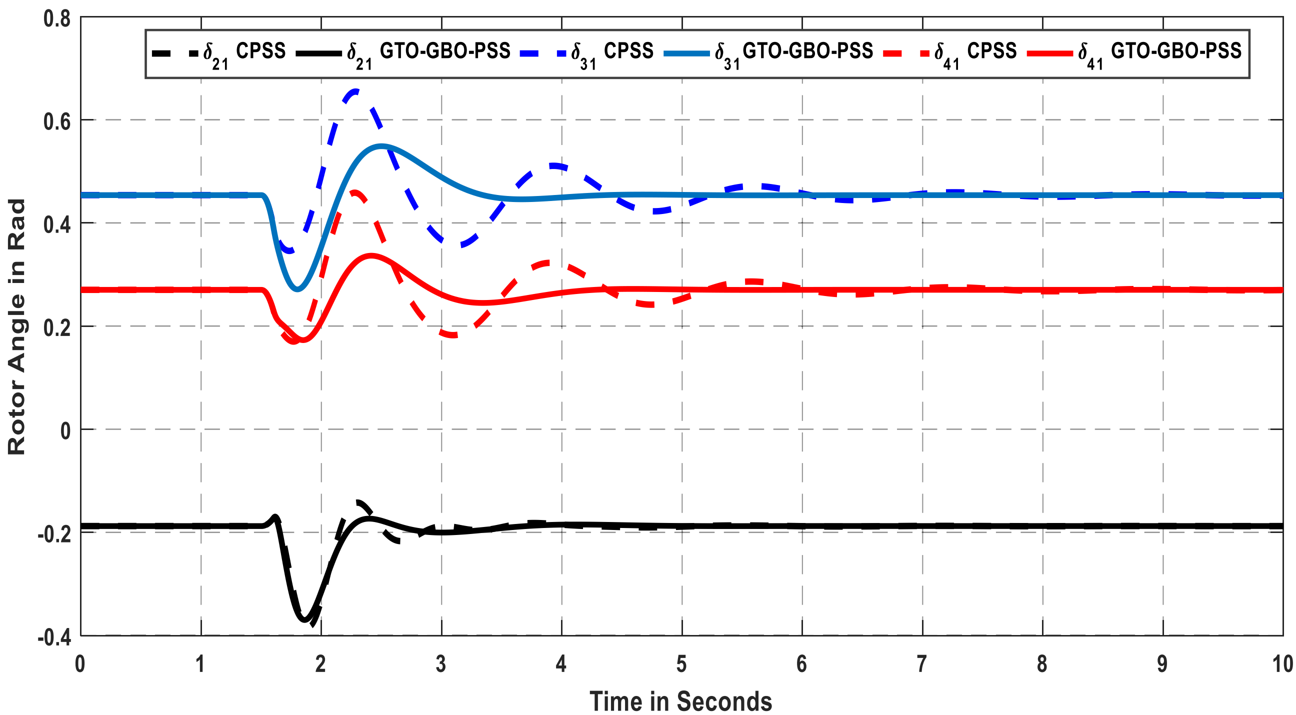

FIGURE 8. Generators rotor angle under a 6-cycle, 3-phase fault disturbance at bus 7.

regions in the search space of the function optimization problem at hand. The box plot of numerical data represents the pattern of different optimal values obtained in different runs corresponding to an algorithm. To investigate the attained results, the boxplot for 23 benchmark functions with the numerical data obtained from the considered algorithms for 30 individual runs is presented in Figure 10. Since boxplots represent the data distribution, they are outstanding plots to highlight the accord between data. From Fig.4, it is clear that the boxplots of the proposed GTO-GBO technique for most of the functions are narrow and amongst the lowest values. These figures are the graphical tool for the performance analysis of the nonlinear system and give a clear comparison between different techniques, and the proposed algorithm outperforms the other algorithms.

B. OPTIMUM TUNING OF PSS

The two-area weakly-connected multi-machine power system is the subject of this research. Figure 5 depicts the system's one-line diagram. The information about the system data used, as well as load flow findings, can be found in [10]. This system is made up of two identical regions. Each

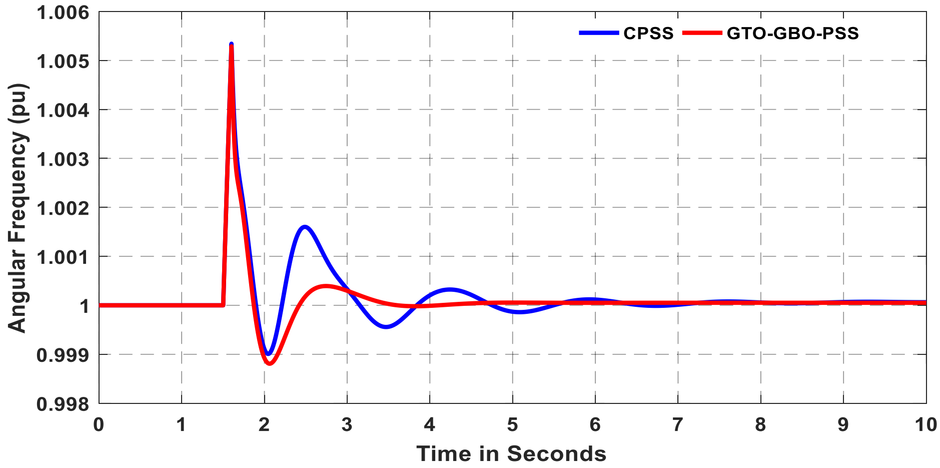

FIGURE 9. Machine-1 angular speed under a 6-cycle, 3-phase fault disturbance at bus 7.

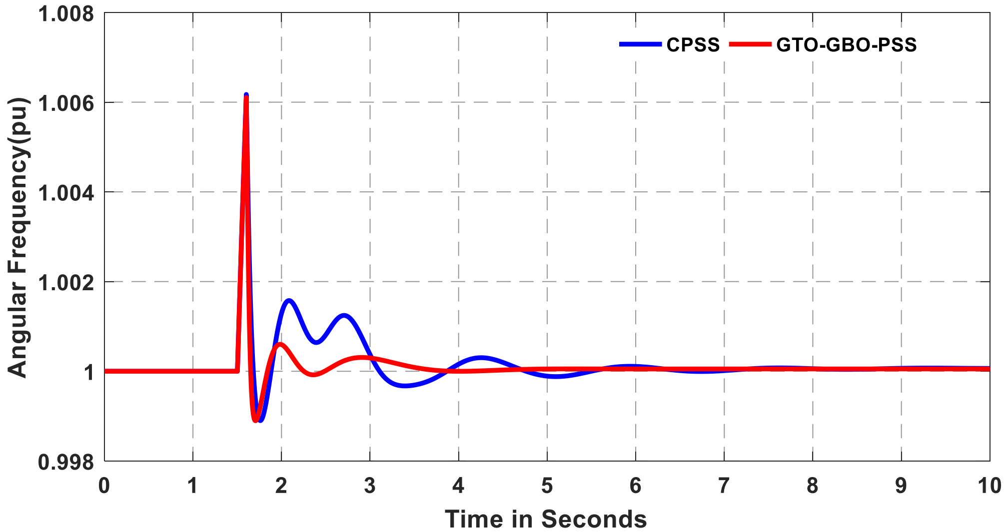

FIGURE 10. Machine-2 angular speed under a 6-cycle, 3-phase fault disturbance at bus 7.

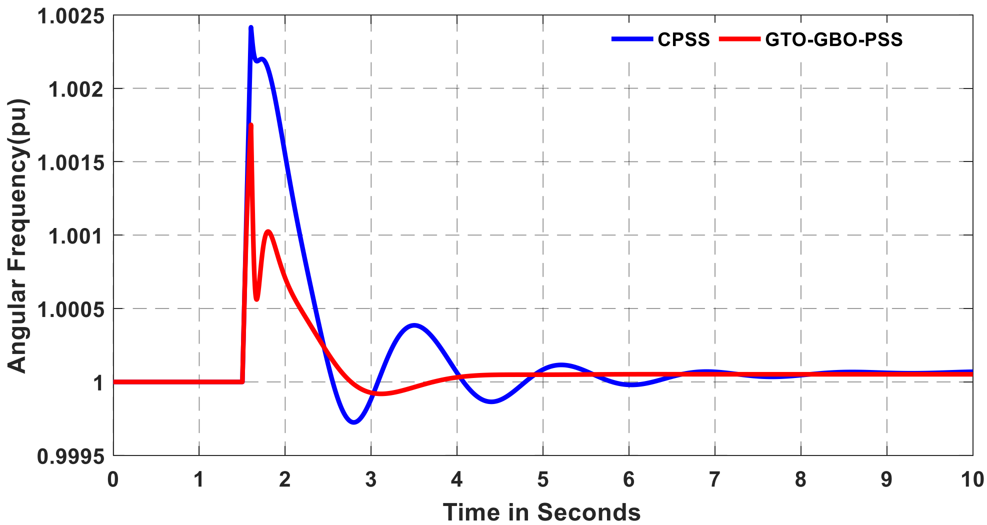

FIGURE 11. Machine-3 angular speed under a 6-cycle, 3-phase fault disturbance at bus 7.

zone has two generating units each rated 900 MVA with rapid static exciters. The same dynamic model represents all four generating units. Power is transferred from Area 2 to Area 1 through a single tie line. At time $t = 1.5$s,

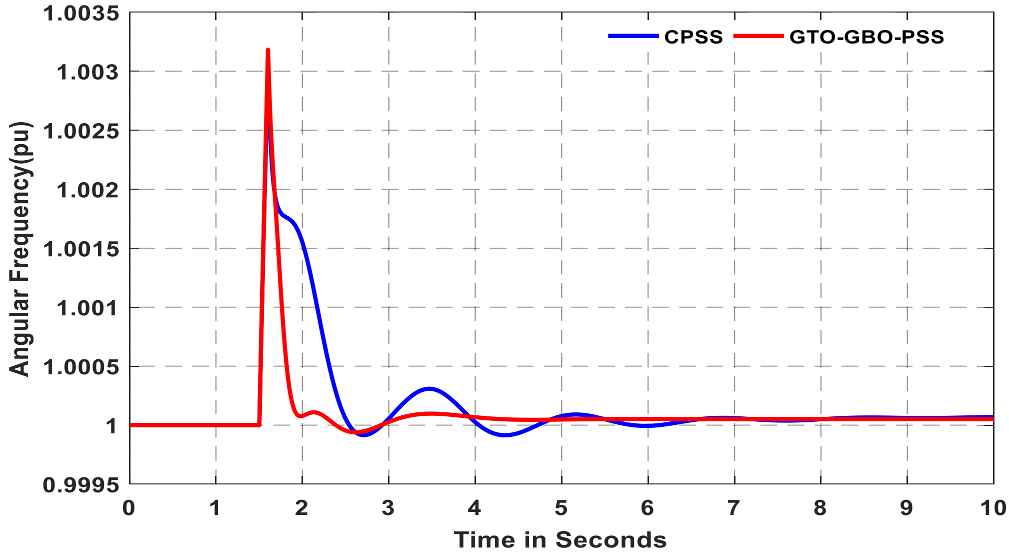

FIGURE 12. Machine-4 angular speed under a 6-cycle, 3-phase fault disturbance at bus 7.

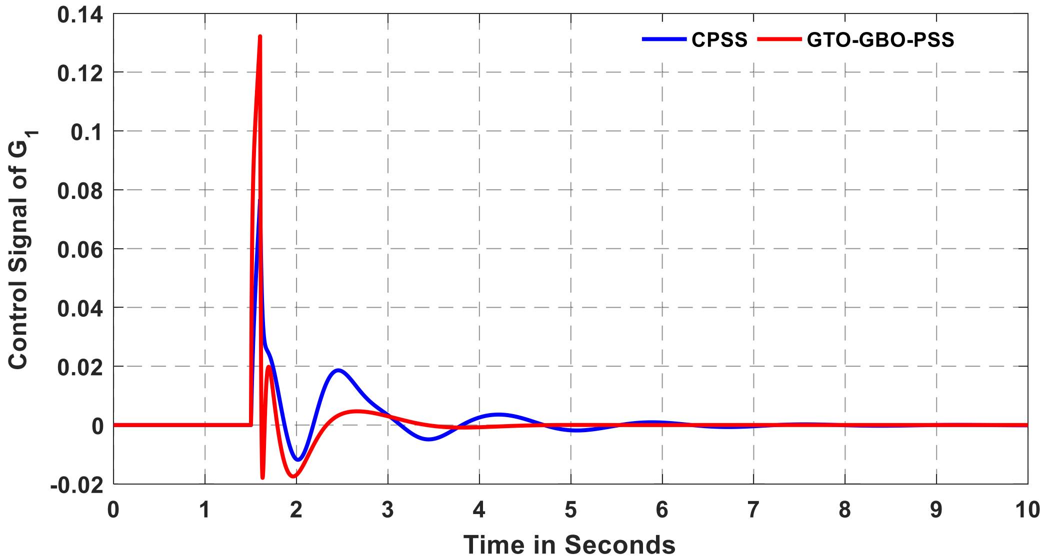

FIGURE 13. PSS control signal of machine-1 under a 6-cycle, 3-phase fault disturbance at bus 7.

a 6-cycle, 3-phase fault disturbance at bus 7 is applied to the system to evaluate the effectiveness of the optimized stabilizer parameters. The simulation findings for GTO-GBO-based PSS were compared to those for GTO, GBO, AEO, COA-based PSS, and conventional PSS. The population size and the maximum number of iterations for both GTO-GBO and other competitive algorithms are set to 50, and 1000, respectively. The washout time constant is set to 10s. The optimum parameter ranges were [0.0 to 50.0] for K_{PSS} and [0.01 to 1.00] for T_1, T_2, T_3 and T_4.

The changes in the goal function (maximizing damping ratio) for twenty distinct runs regarding a predefined number of iterations while improving lead-lag PSS are shown in Fig. 6. The graph shows the level of confidence in the proposed GTO-GBO strategy when each run ends at a certain value (0.86935) of the objective function. As a result, despite the beginning population, the GTO-GBO optimizer was able to locate the global optimal solution, proving the robustness of the suggested technique which is supported by Fig. 7.Figure 8 depicts the fluctuations in rotor angles of generators 2,3, and 4 concerning the reference angle of G-1 for the same fault. This figure demonstrates that the GTO-GBO-based optimized PSS stabilizes the oscillations whereas the traditional PSS requires more time. Also, the settling time for GTO-GBO is substantially shorter than for CPSS. For GTO-GBO-based PSS, the percentage of overshoot is also lower.

Figures 9, 10, 11, and 12 show the angular frequency of all generators. According to all figures, the settling time for GTO-GBO-based tuned PSS is less than for others. Also, the control signal concerning the time of G1 and G4 is shown in Figs 13,14. The size of the control signals is likewise less for the GTO-GBO-based optimizers, indicating that it performs

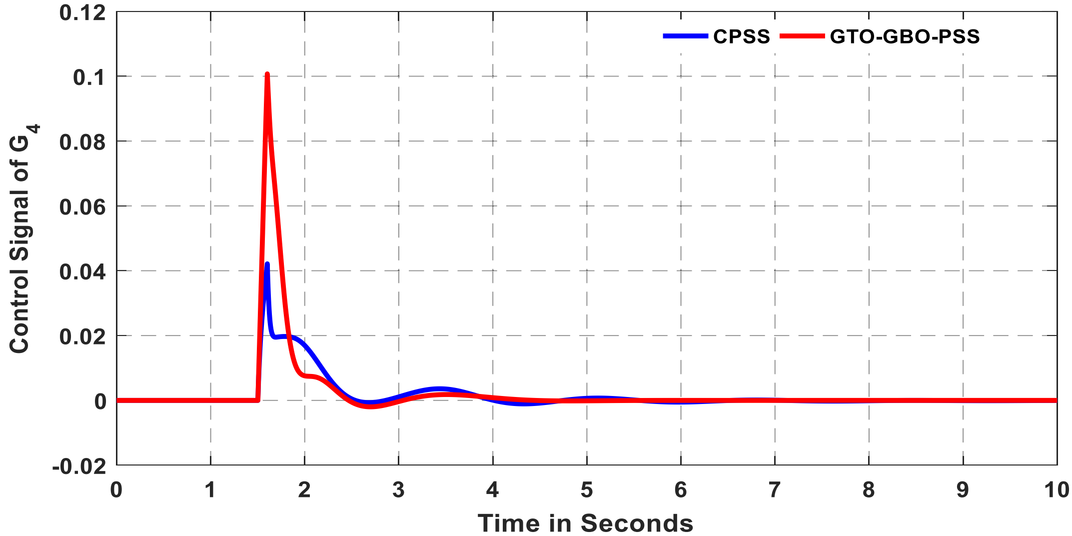

FIGURE 14. PSS control signal of machine-4 under a 6-cycle, 3-phase fault disturbance at bus 7.

TABLE 2. Optimum parameters of all machines PSS.

Generator	Algorithms	K_G	T_1	T_2	T_3	T_4
	COA	49.543	0.134	0.989	0.992	0.010
	AEO	41.883	0.995	0.370	0.045	0.015
G1	**GTO**	49.984	0.114	0.198	0.093	0.011
	GBO	49.873	1.000	0.010	0.046	0.401
	GTO-GBO	16.874	0.148	0.402	0.232	0.010
	COA	12.454	0.055	0.992	0.439	0.677
	AEO	18.748	0.558	0.389	0.336	0.543
G2	**GTO**	49.874	0.089	0.032	0.022	0.010
	GBO	22.401	0.598	0.010	0.010	0.732
	GTO-GBO	23.658	0.109	0.010	0.698	0.669
	COA	49.567	0.276	0.977	0.930	0.011
	AEO	20.880	0.189	0.119	0.190	0.276
G3	**GTO**	47.679	0.055	0.028	0.044	0.010
	GBO	40.009	0.086	0.010	0.834	0.682
	GTO-GBO	42.221	0.528	0.010	0.041	0.159
	COA	15.305	0.010	0.614	0.705	0.011
	AEO	39.376	0.155	0.010	0.632	0.828
G4	**GTO**	50.000	0.122	0.010	0.067	0.083
	GBO	48.898	0.710	0.012	0.095	0.962
	GTO-GBO	43.321	0.010	0.516	0.365	0.010

TABLE 3. Maximum attained cost function using various optimization algorithms.

	COA	AEO	GTO	GBO	GTO-GBO
Min. damping ratio	0.49611	0.79402	0.85203	0.84342	0.86935

better for multi-machine power system networks than the competitive optimization techniques.

Table 2 tabulates the optimum attained parameter values, whereas Table 3 shows the maximum damping ratio for conventional, COA, AEO, GTO, GBO, and GTO-GBO-based improved PSS.

V. CONCLUSION

A deviation in the electrical power system can have several negative consequences for its stability. As a result, maintaining its stability under such operating conditions has been a continual concern for power engineers. Power system stabilizers (PSSs) are one of the suggested solutions that operate as auxiliary controllers to alleviate the instabilities induced by disturbances. This research paper presents a thorough study of optimum parameter tuning of PSS utilizing unique hybrid gorilla troops and gradient-based optimizers. The suggested algorithm's validity is demonstrated using well-known benchmark functions. The suggested innovative optimization technique outperforms the gorilla troops optimizer, gradient-based optimizer, and compatible optimization algorithms. As a future work, the optimum coordination between PSS and a series compensated series capacitor will be considered. Moreover, the obtained results of GTO-GBO motivate the application of it in complex power system optimization problems like energy management, optimum reactive power dispatch, and optimum power flow.

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