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Artificial gorilla troops optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems

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Abstract

Metaheuristics play a critical role in solving optimization problems, and most of them have been inspired by the collective intelligence of natural organisms in nature. This paper proposes a new metaheuristic algorithm inspired by gorilla troops' social intelligence in nature, called Artificial Gorilla Troops Optimizer (GTO). In this algorithm, gorillas' collective life is mathematically formulated, and new mechanisms are designed to perform exploration and exploitation. To evaluate the GTO, we apply it to 52 standard benchmark functions and seven engineering problems. Friedman's test and Wilcoxon rank-sum statistical tests statistically compared the proposed method with several existing metaheuristics. The results demonstrate that the GTO performs better than comparative algorithms on most benchmark functions, particularly on high-dimensional problems. The results demonstrate that the GTO can provide superior results compared with other metaheuristics.

KEYWORDS

gorilla troops optimizer, metaheuristic algorithms, optimization

1 | INTRODUCTION

Optimization denotes finding the best possible or desirable solution(s) to a problem commonly encountered in a wide range of fields. Optimization algorithms may show two types of behaviors when optimizing problems: deterministic and stochastic.[1] Deterministic algorithms typically require complicated calculations, which makes them less practical and applicable. The performance of such methods also degrades substantially proportional to the size of an optimization problem. Stochastic or randomized algorithms show stochastic behavior and make educated decisions to search "wise regions" of a search space in an optimization problem. This allows them to better cope with the difficulties of challenging optimization problems.

Using nature-inspired, stochastic algorithms with efficient computations rather than deterministic methods and algorithms has been suggested.[1,2] Heuristic and metaheuristic algorithms fall under approximate methods to solve optimization problems, seek optimal solutions in a reasonable time, and use appropriate computational resources. However, these algorithms do not guarantee to find the best possible solutions in one try. This originates from the stochastic search mechanism of such algorithms.

Metaheuristics have become very popular in engineering applications[3,4] due to several reasons. First, they have relatively simple concepts and are easy to implement. Second, they outperform local search algorithms. Third, they can be used in a wide range of applications. Finally, there is no need for derivative function information. Nature-inspired metaheuristic algorithms solve optimization problems by imitating biological or physical phenomena. These algorithms can be categorized into five main categories, nature-based methods, physics-based methods, swarm-based methods, human-based methods, and animal-based methods. Of course, all metaheuristic optimization algorithms benefit from these advantages despite the differences. In Figure 1, the classification of metaheuristic algorithms is provided.

Studies have demonstrated that most of the suggested metaheuristic algorithms have been inspired by animals' search and prey behavior in nature. However, there is still no work that

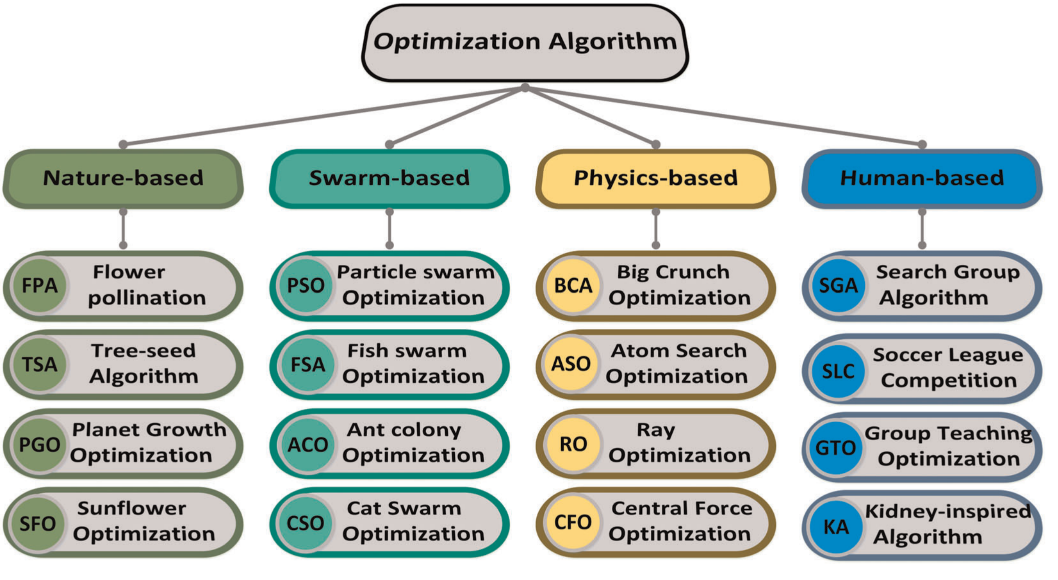

FIGURE 1 Classification of metaheuristic algorithms [Color figure can be viewed at wileyonlinelibrary.com]

mimics gorilla troops' lifestyle to design and develop a metaheuristic algorithm. This motivated our attempts to provide a mathematical model of gorillas' behavior and proposed Gorilla Troops Optimizer (GTO). We first intend to investigate the unique aspect of gorilla troops and then provide several mathematical models based on the proposed GTO.

In the rest of this study, Section 2 provides a literature review of nature-inspired metaheuristic algorithms. Section 3 describes the biological principles and social lives of the gorilla. Section 4 proposes the GTO algorithm, which includes a proposed algorithm theory and its flowchart and formulation. Section 5 deals with testing the GTO's performance using standard benchmark functions, and the results are displayed in separate graphical diagrams. Conclusions and future works are given in Section 6.

2 | RELATED WORKS

There are various categories for metaheuristic algorithms in the literature. Despite different categories, one would argue that most of these algorithms have been inspired by animals' collective behavior and hunting processes in nature. This section aims to explore nature-inspired metaheuristic algorithms and study the basic algorithms proposed to solve optimization problems.

Genetic Algorithm (GA) is the first and most popular method for solving optimization problems that Holland proposed in 1992, inspired by the Darwinian evolutionary concepts. This algorithm has been widely used in most optimization problems with two recombination and mutation operators and is seen as one of the successful algorithms,[5] with various improved and recombination versions already presented.[6] In 2001, the Harmony Search (HS) algorithm, derived from the musicians' search process following the best state of harmony, was introduced by Geem et al.[7] After the initial version of this algorithm was introduced in many optimization problems, it was used mainly because of its simplicity. In the following, we will describe several new metaheuristic algorithms inspired by nature. A new HS algorithm for discrete optimization was developed to study the truss structure.[8] The recombined HS algorithm follows a new approach for improvisation: Although the algorithm retains the harmony memory and screw adjustment functions, the randomization functions replace the HS algorithm with neighborhood search and the universal best particle swarm search. The efficiency of the HS algorithm was tested on six truss structure optimization problems under different loading conditions. The HS algorithm usually outperforms other optimization methods in terms of optimal solution and convergence ability. The HS algorithm provides an optimal balance between exploration and exploitation and converges faster relative to other methods. It achieves a result much better in almost all design samples than other methods as it requires less structural analysis.

Particle swarm optimization (PSO)9 was introduced in 1995 based on animals' swarming behavior in nature, such as birds and fish. Since then, PSO has become the focus of attention, forming an exciting research topic called swarm intelligence. It has been used in almost all optimization areas, including computational intelligence and designing/planning applications. In 2005, Karaboga proposed an algorithm based on the bees' collective behavior called the artificial bee colony (ABC)10 algorithm. The ABC algorithm simulates employed bees, onlooker bees, and scout bees and provides mathematical formulas for each step. This algorithm, like any metaheuristic algorithms, had its weaknesses, with improved versions introduced later. In 2008, Yang introduced an algorithm inspired by the luminosity of fireflies.[11] In this algorithm, the amount of light intensity and attractiveness of each firefly was formulated, in a way that each firefly is compared with other fireflies in terms of brightness or light, with low-light fireflies moving towards brighter fireflies. Of course, fireflies sometimes fly randomly, which led to an improved version of the algorithm.

Yang introduced an algorithm inspired by bat behavior in 2010,12 which is based on the behavior of bats' acoustic resonance at different pulse rates and loudness. In Reference [13], an optimization algorithm based on gravity and mass interactions is proposed called the gravitational search algorithm (GSA). Search agents are a set of masses that interact with each other based on the Newtonian law of gravity and motions. Agents are seen as objects, and their mass measures their function. All of these objects are attracted to each other by the gravity forces, which causes all objects to move towards heavier objects universally. Hence, the masses cooperate through gravity using the direct form of communication. Heavy masses corresponding to reasonable solutions move slower and lighter, as this step ensures the algorithm's efficiency. In GSA, each mass (agent) is characterized by four issues: position, inertial mass, active gravity mass, and passive gravity mass. The mass's position relates to the problem solution, and its gravitational and inertial masses are determined using an appropriate fitness function.

In 2013, a new metaheuristic algorithm for optimization problems called the hunter-seeker algorithm was proposed.[14] In this algorithm, randomly generated solutions serve as a hunter, and the seeker is assigned depending on their performance in the objective function. Their performance can be determined numerically, and that is called the survival rate. Spider Monkey Optimization (SMO) algorithm[15] is proposed for numerical optimization, where a new model for numerical optimization using spider monkey feeding behavior modeling is proposed. Spider monkeys are classified as animals based on the "fission and fusion" social structure. These animals transfer themselves from more prominent groups to smaller groups due to lack of food and vice versa.

In 2014, Oveis Abedinia et al. proposed a new metaheuristic algorithm based on Shark Smell Optimization (SSO).[16] This algorithm is based on the shark's ability, the superior hunter in nature, to hunt prey, derived from the shark's sense of smell and its movement towards the smell source. The shark's various behaviors in the search area, that is, seawater, have been mathematically modeled in the proposed optimization method. The Symbiotic Organisms Search (SOS) algorithm is one of the newest methods to solve optimization problems based on interacting organisms in nature. This algorithm considers three stages of mutualism, parasitism, and commensalism in nature that may benefit or harm each other.[17] However, the chaos-integrated SOS (CSOS) algorithm was developed for global optimization in Reference [18]. The chaotic local search is embedded in the proposed algorithm, strengthening the search process around the best solution as the most promising search space area. It increases the probability of maintaining a better solution and ultimately improves the quality of the solution. Besides, the proposed algorithm performs better in multidimensional test functions, implying a proper balance between exploration and exploitation, so CSOS can be considered an up-and-coming optimization tool for solving complex nonlinear engineering optimization problems.

Moth–flame optimization (MFO)[19] algorithm is a new exploratory model inspired by moths' traverse orientations. Moths fly at night at a constant angle to the moon, as there is a very effective mechanism for traveling in a straight line for long distances. However, these fantasy insects are trapped in a useless and deadly spiral path around artificial light, as this behavior is mathematically modeled for optimization. In the proposed MFO algorithm, it is assumed that the solutions to the problem are a moth, and the problem variables are the position of the butterflies in the search space. Therefore, butterflies can fly in one-, two-, and three-dimensional spaces or very high spaces by changing their position vector.

A new metaheuristic algorithm based on hierarchical gray wolf behavior was introduced in 2014,[3] named Gray Wolf Optimization (GWO). In this algorithm, ordinary wolves have named omega, following three wolves: alpha, beta, and delta. In the simulation, the three best solutions include alpha, beta, and delta wolves, respectively, and the remaining solutions are considered ordinary wolves.

A metaheuristic algorithm based on butterflies' life was proposed in 2017, in which two groups of Artificial Butterfly Optimization (ABO) were placed between exploration and exploitation of the search space.[20] However, this algorithm's authors provided two versions of ABO1 and ABO2 using three different flight types. The modified ABC algorithm was introduced based on a highly improved general approach and limited adaptive strategy for universal optimization.[21] The modified ABC was named IGAL-ABC based on the highly improved universal approach and limited adaptive strategy for optimization problems. The exploration and exploitation capacity of the ABC algorithm was balanced and improved in this search process. The optimization of the proposed algorithm was tested on single- and multi-state standard functions. Comparisons results suggested that the proposed algorithm on multidimensional standard functions had better efficiency, generating better convergence and optimization features.

The Sine–Cosine Algorithm (SCA) for solving optimization problems was introduced in Reference [22], generating several initial random candidate solutions and seeking the best solutions using a cosine and sine functions-based mathematical model. The efficiency of the proposed method was examined in three phases. The findings revealed that the proposed algorithm could explore different search space areas, avoid local optimization, move towards general optimization, exploit the search space areas optimally, and converge quicker than other algorithms. This algorithm proves very useful in solving real problems with unknown and limited search space.

Teaching Learning Based Optimization (TLBO)[26] algorithm was developed and inspired by the learner and teaching methods to solve optimization problems where TLBO has used a new inertia weight strategy in the learning phase to increase learning capacity. Random topological order is adopted using energy weight, so the learner improves their search ability. This adaptive learning-teaching algorithm is used to select genes by proposing newly updated mechanisms to solve optimization problems in real-world applications.

The Farmland Fertility Algorithm (FFA) was developed to solve ongoing problems,[2] which is inspired by the fact that farmland is divided into several parts, with each sector's solutions becoming optimized with optimal efficiency, both internal and external memory. Simulation findings reveal that farmland fertility often performs better than other metaheuristic algorithms. In Reference [23], the self-adaptive fruit fly optimization algorithm for universal optimization was developed, as it was provided to solve high-dimensional optimization problems. The proposed self-adaptive method significantly improves the capability to search for the fruit fly in promising areas that depend on the search process and the problem and is seen as a string and good algorithm for universal optimization.

We just reviewed only a few major metaheuristic algorithms; however, there are other metaheuristic optimization algorithms, such as Golden Ball (GB) algorithm,[24] Cuckoo Search (CS),[25] Simulated Annealing (SA) algorithm,[26] Gravitational Optimization,[27] Biogeography-Based Optimization (BBO),[28] Galaxy-based Search Algorithm (GbSA),[29] Group Counseling Optimizer (GCO),[30] Clonal Selection Algorithm (CSA),[31] Bird Mating Optimizer (BMO),[32] Social Spider Optimization (SSO),[33] Imperialist Competitive Algorithm (ICA),[34] Intelligent Water Drops (IWD) algorithm,[35] Colliding Bodies Optimization (CBO),[36] League Championship Algorithm (LCA),[37] Differential Evolution (DE),[38] Charged System Search (CSS) algorithm,[39] Ray Optimization algorithm (RO),[40] Water Evaporation Optimization (WEO) algorithm,[41] Glowworm Swarm Optimization (GSO),[42] Dolphin echolocation optimization (DEO),[43] and Water Cycle Algorithm (WCA).[44]

Generally, the No Free Lunch (NFL) Theorems[45,46] states that, on average, all nonsampling optimization algorithms perform equally well in solving almost all optimization problems.[47] This hypothesis also states that all black box search algorithms and optimization algorithms have the same function in all possible target functions in a fixed search space. On the other hand, however, there is no algorithm to solve all real-world problems accurately and well.[48] For this reason, in NLF theory, an algorithm has been aligned with the problem. NLF has also introduced a scenario where an existing algorithm can even be better than a random search. Problem subset knowledge of a random search can also often be precious; one of the most important reasons is simple execution and good performance. This is an important principle where the NFL does not apply. However, when and why can researchers ignore the NFL? That is unlikely.

It appears that the researcher intends to make a specific claim about an algorithm that performs moderately compared with a set of possible problems in space, that is, (original NFL), a CUP set (SNFL), focus set (FNFL), or restricted set (RMNFL). However, it is clear that under such a situation, one cannot ignore NFL, and it is impossible to see any improvements in the random search. This is why a researcher may create a super algorithm better than a random one in all real-world problems. This could yield promising results, though NFL results cannot prevent this as researchers can also ignore NFL. In the end, a researcher hoping to have a super algorithm to be better than a random one in solving all problems may be neutralized by an NFL.[49]

3 | GORILLA TROOPS

Gorillas, like other apes, have feelings, make and use tools, establish strong family bonds, and think about their past and future.[50,51] Some researchers argue that gorillas also have inner feelings or religious inclinations.[50,51] On average, gorillas perform such activities as taking rest, traveling, and eating during the day. Gorilla diets vary from species to species. Mountain gorillas are primarily herbivores and feed on substances, such as leaves, stems, kernels, and twigs, while fruits account for a tiny portion of their meals.[52–54]

Gorillas live in groups called troops, consisting of an adult male or silverback gorilla group (see Figure 2) and several adult female gorillas and their offspring.[55–57] However, there are groups, including several male gorillas.[56] A silverback usually lives over 12 years and takes its name because of the silver-colored hair that grows on its backs during puberty.

FIGURE 2 Silverback gorilla [Color figure can be viewed at wileyonlinelibrary.com]

Moreover, silverbacks have enormous canines that reappear during puberty. Both male and female gorillas tend to migrate from their born.[55–58] Gorillas usually migrate and move on to new groups.[57] Also, male gorillas tend to abandon their groups and form new groups by attracting female gorillas who have migrated. However, male gorillas sometimes remain in the same group they were born and are included in the silverback group. If the silverback gorilla dies, these gorillas may dominate the group or engage with the silverback to dominate it.[56,59,60]

On the other hand, male gorillas engage in fierce competition for adult females. They get engaged in violent fights with other males to expand and form their groups over females, as the fights may sometimes last for several days.[61–66] In groups where only one gorilla lives, female gorillas and offspring disperse and seek new groups for themselves.[58,67] Without silverback gorillas to protect baby gorillas, baby gorillas may fall victim to infanticide, thereby attempting to join new groups as a solution to this problem.[58,67,68]

Silverback is the focus of a group.[69] It makes all the decisions, mediates the fights, determines group movements, directs the gorillas to food sources, and takes responsibility for the group's safety well-being. Young male gorillas, called blackbacks, follow silverbacks and serve as backup protectors for the group. The blackbacks are between 8 and 12 years old and have no silver hairs on their backs.[69] The link between silverback and female gorillas forms the heart of gorillas' social life. This bond is maintained by grooming and staying close to each other.[57,70] Female gorillas form strong relationships with male gorillas to preserve the mating situation and protect themselves from predators.[57,70,71] Male gorillas have poor social relationships, especially in groups with several male gorillas with clear hierarchies. Also, there is a fierce rivalry in these groups to find a mate.

Although male gorillas in all-male groups tend to form friendly relationships by playing, grooming, staying together, and sometimes engaging in homosexual engagements,[58,59,67–71] extreme violence in stable groups is rare. However, when two mountain gorilla groups meet each other, the silverbacks can create deep wounds and fissures on their rivals' bodies using their canines.[68] Male gorillas are not diligent in caring for newborns but play a role in setting associations with other gorillas.[72] Silverback gorillas have a strong supportive relationship with the newborns and protect them from intragroup invasions.[72] Gorillas are known to have 25 different songs, many of which are mainly used for group communication. Voices classified as grunts and barks are most often heard when traveling, indicating group members' presence.[73] These songs may also be used during social interactions when discipline is required. Screams and roars are warning signs often produced by the silverback gorillas.

This paper provides a new algorithm called GTO, using the gorilla troop's behavior to solve optimization problems; we will explain this in detail in Section 4.

3.1 | Artificial gorilla troops optimization algorithm (GTO)

In this section, inspired by gorillas' group behaviors, we provided a new metaheuristic algorithm called GTO, where specific mathematical mechanisms are presented to explain the two phases of exploration and exploitation fully. In the GTO algorithm, five different operators are used for optimization operations (exploration and exploitation) simulated based on gorilla behaviors.

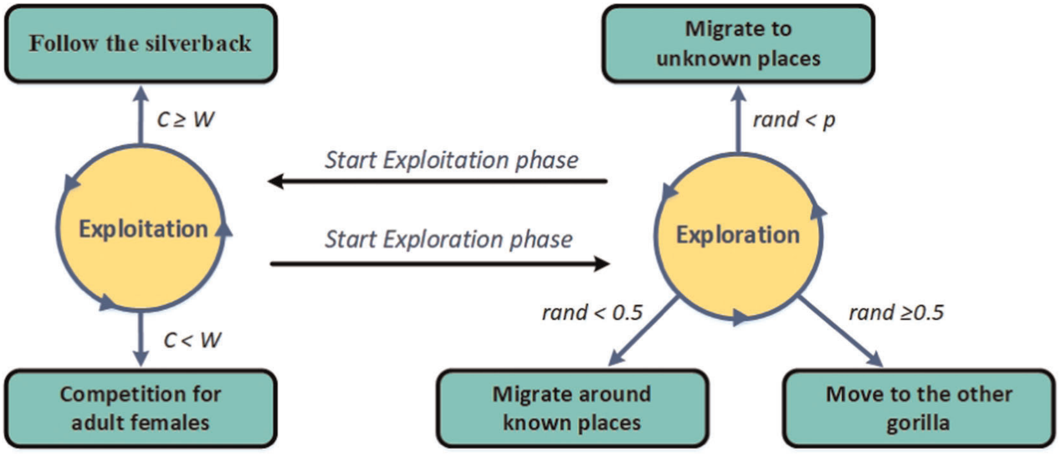

FIGURE 3 Different phases of Gorilla Troops Optimizer [Color figure can be viewed at wileyonlinelibrary.com]

Three different operators have been used in the exploration phase: migration to an unknown place to increase GTO exploration. The second operator, a movement to the other gorillas, increases the balance between exploration and exploitation. The third operator in the exploration phase, that is, migration towards a known location, significantly increases the GTO capability to search for different optimization spaces. On the other hand, two operators are used in the exploitations phase, which significantly increases the search performance in exploitation. In GTO, a different method is used for the phase change procedure of exploration and exploitation, as shown in Figure 3, in which an overview of the optimization operation procedure in the GTO algorithm is illustrated.

GTO generally follows the following several rules to search for a solution:

1. The GTO algorithm's optimization space contains three types of solutions, where the X is known as the gorillas' position vector, and the GX as the gorilla candidate position vectors created in each phase and operates should it performs better than the current solution. Finally, the silverback is the best solution found in each iteration.
2. Only one silverback in the entire population when considering the number of search agents selected for optimization operations.
3. Three types of X, GX, and silverback solutions simulate the gorillas' social life in nature accurately.
4. Gorillas can increase their power by finding better food sources or positioning in a fair and robust group. In GTO, solutions are created in each iteration known as GX in the GTO algorithm. If the solution found is new (GX), it replaces the current solution (X). Otherwise, it remains in memory (GX).
5. The tendency to a communal life among gorillas prevents them from living individually. Thus they look for food as a group and continue to live under a silverback leader, who makes all the group decisions. In our formulation phase, assuming that the worst solution in the population is the weakest member of the gorilla group, the gorillas attempt to turn away from the worst solution and get closer to the best solution (silverback), improving all the gorilla's positions.

Considering the basic concepts of gorilla group life when finding food and their group life together, given GTO's unique features in many optimization problems, the algorithms can be widely used. For better understanding, the GTO flowchart is shown in Figure 4, and each step of the formulation algorithm is fully introduced.

The GTO algorithm uses various mechanisms for optimization operations, which are described below.

3.1.1 | Exploration phase

In this subsection, the mechanisms applied in the exploration phase in GTO are examined. If we consider the nature of gorillas' group life, we conclude that they live in nature in groups under the domination of a silverback, as he is obeyed; there are times when gorillas leave their group. Upon leaving the group, the gorillas will migrate to different places in nature, which they may or may not have met in the past. In the GTO algorithm, all gorillas are seen as candidate solutions, and the best candidate solution at each optimization operation stage is considered a silverback gorilla. We used three different mechanisms for the exploration phase, that is, migration to an unknown location, migration towards a known location, and moving to other gorillas. Each of these three mechanisms is selected according to a general procedure.

A parameter called p was used to select the mechanism of migration to an unknown location. The first mechanism is selected when $rand < p$. However, if $rand \geq 0.5$, the mechanism of movement towards other gorillas is selected. However, if $rand < 0.5$, the mechanism of migration to a known location is selected. According to the mechanisms used, each of the mechanisms gives an excellent ability to the GTO algorithm. The first mechanism makes it possible for the algorithm to monitor the entire problem space well, the second mechanism improves the GTO exploration performance, and finally, the third mechanism reinforces the GTO in escaping from local optimal points. Equation (1) has been used to simulate the three mechanisms used in the exploration phase.

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

In Equation (1), $GX(t+1)$ is the gorilla candidate position vector in the next t iteration. $X(t)$ is the current vector of the gorilla position. Moreover, r_1, r_2, r_3, and $rand$ is random values ranging from 0 to 1 updated in each iteration. p is a parameter that must be given a value before the optimization operation and has a range of 0–1; this parameter determines the probability of selecting the migration mechanism to an unknown location. UB and LB represent the upper and lower bounds of the variables, respectively. X_r is one member of the gorillas in the group randomly selected from the entire population and also GX_r. One of the vectors of gorilla candidate positions randomly selected and includes the positions updated in each phase. Finally, C, L, and H are calculated using Equations (2), (4), and (5), respectively.

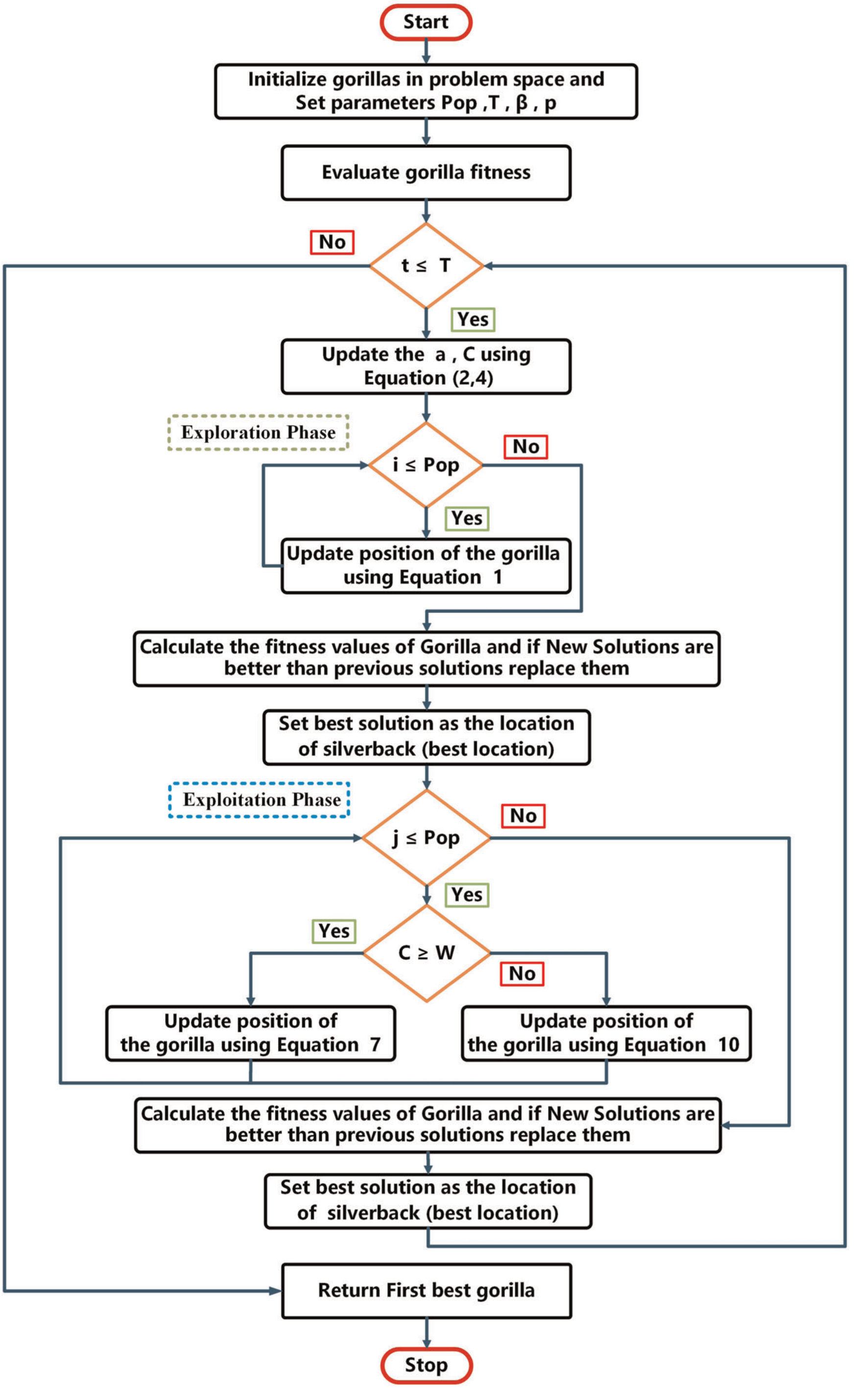

FIGURE 4 Flowchart of Gorilla Troops Optimizer [Color figure can be viewed at wileyonlinelibrary.com]

$$C = F \times \left(1 - \frac{It}{MaxIt}\right), \tag{2}$$

$$F = cos\,(2 \times r_4) + 1, \tag{3}$$

$$L = C \times l. \tag{4}$$

In Equation (2), *It* is the current iteration value, *MaxIt* is the total value of iterations to perform the optimization operation, and *F* is calculated using Equation (3). In Equation (3), *cos* indicates the cosine function and r_4 is random values ranging from 0 to 1 updated in each iteration. According to Figure 5, in Equation (2), values with sudden changes over a large interval are generated in the early stages of the optimization operation, but this interval of change decreases in the final stages. *L* is calculated using Equation (4), where *l* is a random value in the range of −1 and 1. Equation (4) is used to simulate the silverback leadership. In the real world, the silverback gorilla may not make the right decisions to find food or control the group due to a lack of sufficient experience in the early stages of group leadership; however, it achieves enough experience obtaining enough experience good stability in his leadership. The changes in the values generated in the two independent implementations using Equations (2) and (4) are illustrated in Figure 5.

Also, in Equation (1), *H* is calculated using Equation (5), while in Equation (5), *Z* is calculated using Equation (6), where Z is a random value in the problem dimensions and the range of $-C$, C.

$$H = Z \times X\,(t), \tag{5}$$

$$Z = [-C, C]. \tag{6}$$

Figure 6 illustrates how the position of search agent vectors changes in the exploration phase.

At the end of the exploration phase, a group formation operation is done. At the end of the exploration phase, the cost of all *GX* solutions is calculated, and if the cost is $GX\,(t) < X\,(t)$, the $GX(t)$ solution is used as the $X(t)$ solution. Thus, the best solution generated in this phase is also considered as a silverback.

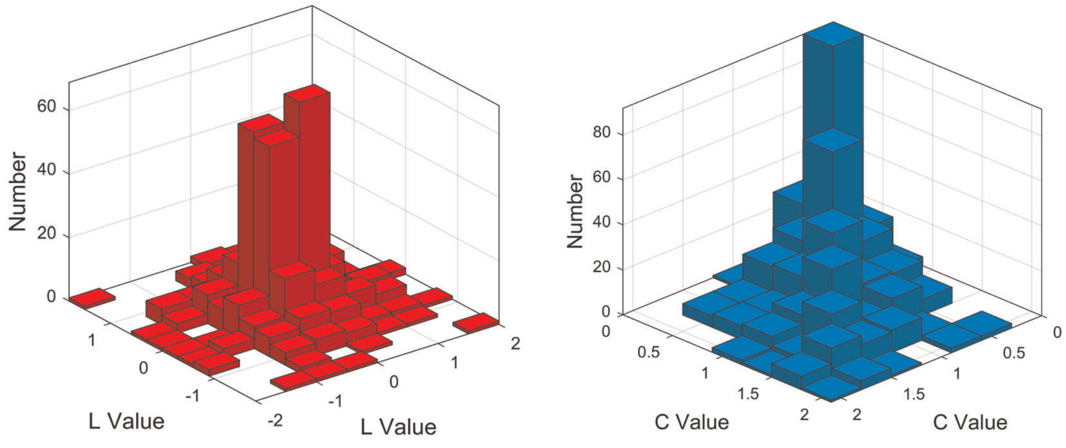

FIGURE 5 Value of *C*, *L* during two runs and 500 iterations [Color figure can be viewed at wileyonlinelibrary.com]

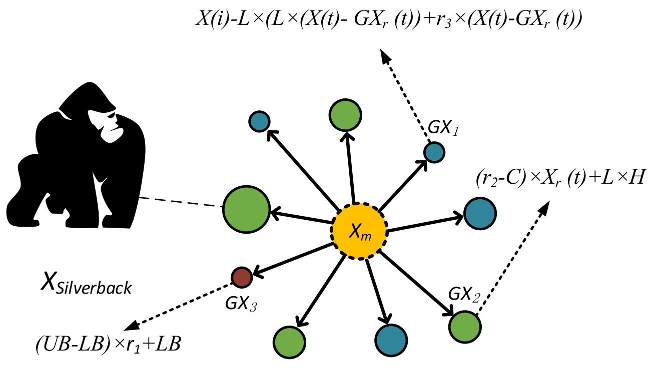

FIGURE 6 Example of overall vectors in the case of an exploration phase [Color figure can be viewed at wileyonlinelibrary.com]

3.1.2 | Exploitation phase

In the GTO algorithm's exploitation phase, two behaviors of Follow the silverback and Competition for adult females are applied. The silverback gorilla leads a group, makes all the decisions, determines the group's movements, and directs the gorillas towards the food sources. It is also responsible for the group's safety and well-being, and all gorillas in the group follow all silverback decisions. On the other hand, silverback gorilla may weaken and get old and eventually die, with the black back in the group may become the group leader, or other male gorillas may engage the silverback gorilla and dominated the group. As described with the two mechanisms used in the exploitation phase, it is possible to select either Follow the silverback or Competition for adult females using the C value in Equation (2). If $C \geq W$, the follow the silverback mechanism is selected, but if $C < W$, adult females' Competition is taken. W is a parameter to be set before the optimization operation.

Follow the silverback

With the group newly formed, the silverback is young and healthy, and the other male gorillas in the group are young and follow the silverback well. They also follow all the silverback orders to go to various areas to find food sources and follow silverback. Also, the members can affect all group members on group movement. This strategy is selected when the $C \geq W$ value is selected. Equation (7) is used to simulate this behavior. Figure 7 is also used to illustrate this mechanism.

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t), \tag{7}$$

$$M = \left(\left| \frac{1}{N} \sum_{i=1}^{N} GX_i(t) \right|^g \right)^{\frac{1}{g}}, \tag{8}$$

$$g = 2^L. \tag{9}$$

In Equation (7), $X(t)$ is the gorilla position vector, and $X_{silverback}$ is the silverback gorilla position vector (best solution). Moreover, L is calculated using Equation (4) and M using

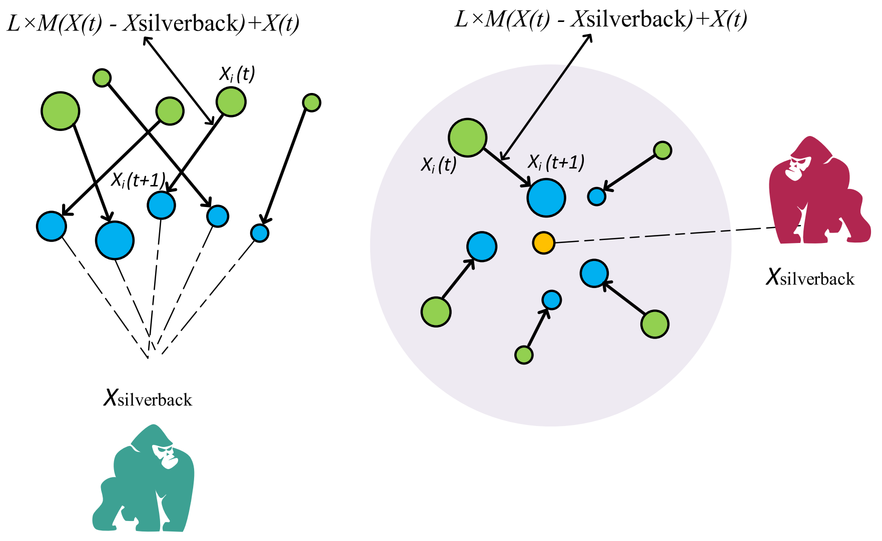

FIGURE 7 Example of overall vectors follows the silverback in 2D and 3D space [Color figure can be viewed at wileyonlinelibrary.com]

Equation (8). In Equation (8), $GX_i(t)$ shows each candidate gorilla's vector position in iteration t. N represents the total number of gorillas. g is also estimated using Equation (9), and in Equation (9), L is also calculated using Equation (4).

Competition for adult females

If $C < W$, the second mechanism is selected for the exploitation phase. After a while, when young gorillas reach puberty, they fight with other male gorillas expanding their group on choosing adult females, and this competition is often violent. These fights can last for days and involve group members. Equation (10) is used to simulate this behavior.

$$GX(i) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A, \tag{10}$$

$$Q = 2 \times r_5 - 1, \tag{11}$$

$$A = \beta \times E, \tag{12}$$

$$E = \begin{cases} N_1, & rand \geq 0.5, \\ N_2, & rand < 0.5. \end{cases} \tag{13}$$

In Equation (10), $X_{silverback}$ is the *silverback* position vector (best solution) and $X(t)$ is the current gorilla position vector. Q is seen to simulate the impact force, calculated using Equation (11). In Equation (11), r_5 is random values ranging from 0 to 1. A coefficient vector to determine the degree of violence in conflicts is calculated using Equation (12). In Equation (12), β is a parameter to be given value before the optimization operation, and E is valued using Equation (13) while being used to simulate the effect of violence on the dimensions of solutions. If $rand \geq 0.5$, the E's value of E will be equal to random values in the normal

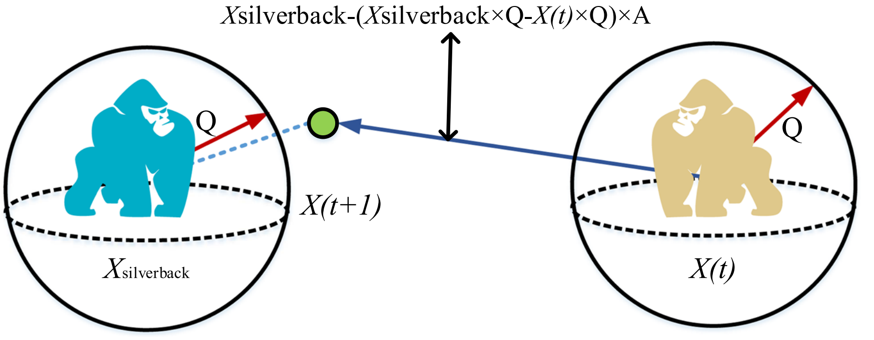

FIGURE 8 Example of overall vectors in the competition for adult females [Color figure can be viewed at wileyonlinelibrary.com]

distribution and the problem's dimensions, but if $rand < 0.5$, E will be equal to a random value in the normal distribution. $rand$ is also a random value between 0 and 1. Figure 8 is used to indicate how the solutions change.

At the end of the exploitation phase, a group formation operation is conducted, in which the cost of all GX solutions is estimated, and if the cost of $GX(t) < X(t)$, the $GX(t)$ solution is used as the $X(t)$ solution and the best solution obtained among the whole population is seen as a silverback. The proposed pseudocode for the proposed algorithm is given in Algorithm 1.

Pseudocode of GTO: The pseudocode of the GTO is described in Algorithm 1.

Algorithm 1. Pseudocode of GTO

% GTO setting
Inputs: The population size N and maximum number of iterations T and parameters β and p
Outputs: The location of Gorilla and its fitness value
% initialization
Initialize the random population $\boldsymbol{X_i}$ $\boldsymbol{(i = 1, 2, \ldots, N)}$
Calculate the fitness values of Gorilla
% Main Loop
while (stopping condition is not met) **do**
  Update the C using Equation (2)
  Update the L using Equation (4)
  % Exploration phase
  for (each Gorilla ($\boldsymbol{X_i}$)) **do**
  Update the location Gorilla using Equation (1)
  end for
  % Create group
  Calculate the fitness values of Gorilla
  if GX is better than X, replace them

(Continues)

Set $X_{silverback}$ as the location of *silverback* (best location)
% Exploitation phase
for (each Gorilla ($\boldsymbol{X_i}$)) **do**
if ($|C| \geqslant 1$) then
Update the location Gorilla using Equation (7)
Else
Update the location Gorilla using Equation (10)
End if
end for
% Create group
Calculate the fitness values of Gorilla
if New Solutions are better than previous solutions, replace them
Set $X_{silverback}$ as the location of *silverback* (best location)
end while
Return $X_{BestGorilla}$, *bestFitness*

3.2 | Computational complexity

The GTO algorithm's computational complexity depends on three main processes: initialization, fitness evaluation, and updating of vultures. Because there is an N gorilla, the computational complexity in the initialization process is equal to $O(N)$. On the other hand, the computational complexity in the update mechanism process is based on two phases of exploration and exploitation. In each of the phases, an updating operation is performed on all the solutions in the optimization space, and the best solution is performed, which is equal to $O(T \times N) + O(T \times N \times D) \times 2$. Where T represents the maximum value of iterations, and D is the dimensions of the problems. Therefore, the GTO algorithm's computational complexity is $O(N \times (1 + T + TD) \times 2)$.

4 | RESULT AND DISCUSSION

4.1 | Benchmark set and compared algorithms

A set of different and diverse benchmark functions[77,78] includes three different unimodal (UM), multimodal (MM), and composite (CM) groups. Using the UM benchmark functions (F1–F7), which has only one of the global best, each optimization algorithm's exploitative capacities (intensification) can be revealed. The exploration capacities (diversification) optimization algorithms are revealed using MM criterion functions (F8–F23). The UM and MM standard functions' mathematical formulas and properties are illustrated in Tables A1–A3 in Appendix A.

For the third group, the benchmark functions (F24–F52) available in CEC2017 competition are used, involving hybrid composite, rotated and shifted MM cases. These benchmarks are used in many articles that can be used to appraise optimization algorithms' performance because to solve these problems. There is a need for balance in exploration and exploitation and

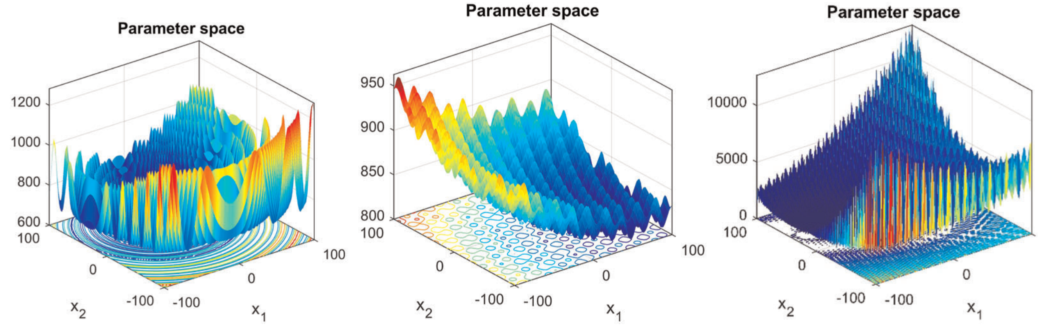

FIGURE 9 Parameter space representation of the benchmark functions C6, C8, and C9 [Color figure can be viewed at wileyonlinelibrary.com]

the ability to escape local optimal points in optimization algorithms. Details of the benchmark functions are given in Table A4 in Appendix A.

Results and Performance of GTO with other types of optimization algorithms PSO,[28] GWO,[3] WOA,[4] MFO,[19] TSA,[74] MVO,[75] SCA,[22] and GSA[13] have been compared. This comparison is based on the best solution, the worst solution, standard deviation (STD), and average mean (AVG) results. The MFO, WOA, GWO, MVO, SCA, PSO, SHO, GSA, and TSA optimization algorithms are selected as powerful and novel optimization algorithms, while PSO and GSA algorithms are chosen since they are used a lot in the optimization context. Also, for better evaluation, such as Derrac et al.,[76] a Wilcoxon statistical test with a significance level of 5% was performed to detect significant differences concerning the results of GTO compared with other optimization methods (Figure 9).

4.2 | Parameter settings

The GTO has been tested and executed using the Matlab 9.2 (R2017R) laptop computer running Windows 10 Enterprise 64-bit with an Intel Core i7-4510U 2.6 GHz processor and 8.00 GB RAM, and all tests performed to check the performance of the GTO were carried out using 30 populations in a maximum of 500 iterations. All results are stored based on the average of 30 independent run results and are compared using the obtained results. The settings of PSO,[28] GWO,[3] WOA,[4] MFO,[19] TSA,[74] MVO,[75] SCA,[22] and GSA[13] are used from the settings presented in the original work. These algorithms cover both recently proposed techniques, such as SCA, MVO, TSA, MFO, WOA, GWO, and the most utilized optimizers in the field like the PSO and GSA algorithms.

We used to set three parameters of the GTO algorithm as presented in Reference [77]. This method has been used for parameter tuning in many researches.[78–80] Each parameter is set according to three levels of different values of the low, medium, and high. A total of 3^3 models are generated from a combination of parameters for each level. This paper has tested for this evaluation of the benchmark functions 1–13 with dimensions 30 and different combinations of parameters. Finally, the best performance of the combination of parameters is used to evaluate the following steps, shown in Table 1.

The parameter settings of the optimization algorithms are shown in Table 1.

TABLE 1 Parameter settings of optimization algorithms for comparison and evaluation of the GTO

Algorithm	Parameter	Value
GTO	β	3
	W	0.8
	p	0.03
GWO	Convergence constant a	[2 0]
TSA	Parameter P_{min}	1
	Parameter P_{max}	4
PSO	Inertia factor	0.3
	$vMax$	6
	c_1	2
	c_2	2
MVO	Existence probability	[0.2 1]
	Traveling distance rate	[0.6 1]
MFO	Convergence constant a	[−2 −1]
	Spiral factor b	1
WOA	Convergence constant a	[2, 0]
	Spiral factor b	1
SCA	A	2
GSA	α	20
	G_0	100
	Power of R	1

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

4.3 | Qualitative results of GTO

Evaluations of qualitative results of GTO nine standard unimodal and multimodal standard functions are used. This evaluation is also done using four different criteria: search history, convergence behavior, the average fitness of the population, and the trajectory of the first Gorilla. The search history diagram illustrates some locations in the optimization space that artificial gorillas would visit. The convergence behavior diagram demonstrates the best silverback gorilla's fitness value as the best solution during the optimization process. The population diagram's average fitness diagram shows how the average fitness of the whole population changes in various optimization stages. Finally, the first gorilla diagram trajectory shows how the first gorilla changes' first variable during the optimization process. Studying the search history diagrams in Figure 10, one would argue that GTO has shown a similar pattern in the wake of various optimization problems. According to the diagrams demonstrated in Figure 10, the gorillas were found to have performed exploration operations in different

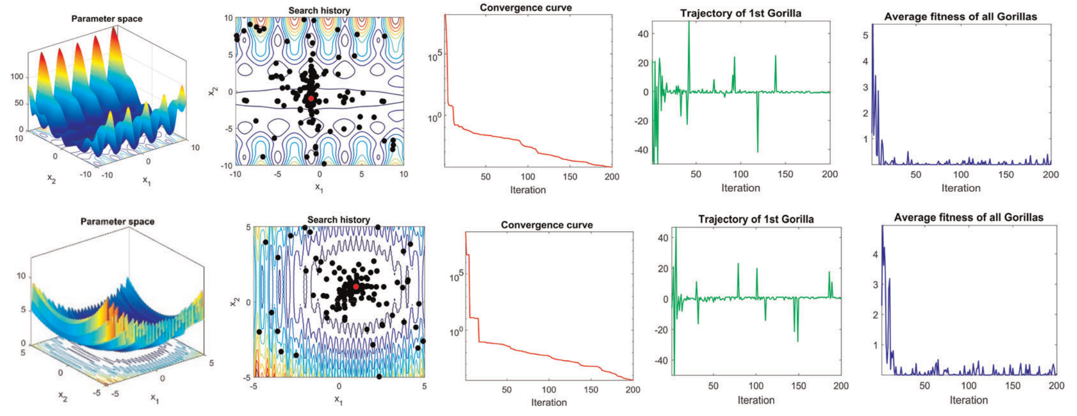

FIGURE 10 Qualitative results for the F1, F3, F4, F7, F8, F9, F10, F12, and F13 functions [Color figure can be viewed at wileyonlinelibrary.com]

optimization space areas and continued the exploitation operations near the best solution. Finally, it is determined that the GTO algorithm goes through almost the entire optimization space well and has an adequate capacity in the exploration and exploitation phases. Convergence diagrams illustrate the silverback gorilla's average fitness in different optimization stages, as shown in Figure 10. It is concluded that there is a rapid and continuous descending pattern in all convergence diagrams. Looking at the convergence diagrams, it is easy to conclude that GTO has a rapid convergence trend.

According to the average fitness of the population criterion, which shows the average fitness of the entire population in various optimization stages and is shown in Figure 10, it is said that GTO has found various solutions by performing random movements in search agents. Moreover, these solutions have had less fitness, resulting in descending trends. On the other hand, looking at the diagrams shown in Figure 10, one would conclude that GTO has an excellent ability to improve all gorillas in at least half of the iterations. On the other hand, in all the diagrams, there is a pattern of rapidly descending curves. Also, as iterations increase, the range of fitness changes decreases, but these changes still exist with a small range due to GTO's exploration at different optimization stages. Finally, such movements result from the GTO focusing more on promising areas during the optimization phase. Finally, the first gorilla diagram trajectory shows the first gorilla's behavior searching for different optimization space areas. The first gorilla is selected as representing other gorillas. This diagram provides a good understanding of the gorillas' behavior to explore new search space solutions. Looking at the trajectory diagrams, it is evident that the first gorilla has gone through sudden changes in the early stages, with minor changes and fluctuations in the other optimization stages. According to[81] developed by Van Den Bergh and Engel Brecht, it is argued that such activities cause a *P*-metaheuristic to finally converge at one point and perform exploitation operations from that area.

On the other hand, in different optimization stages, it is seen that there are fluctuations. Such movements also make GTO have an excellent ability to escape from optimal local locations because there is no guarantee for the search agents to locate next to the optimal global location in the premature optimization stages. In Figure 10, the first gorilla had sudden and significant movements in the early stages of optimization, but in the later stages, it only went through sudden movements in some stages, ranging from half of the search space. This feature suggests an excellent ability to explore GTO at different optimization stages. Also, in the later stages of the search operation, the range of the fluctuations had almost slightly changed and decreased. This indicates that GTO has finally stabilized the first gorilla movement, indicating that GTO seeks to be exploitative in promising areas.

4.4 | Quantitative results and discussion

In this subsection, to investigate the GTO performance, other optimization algorithms were compared. Various benchmark functions were used, where F1–F13 with 30, 100, 500, and 1000 dimensions were applied to evaluate the GTO scalability. Also, benchmark functions (F14–F52) MM and CM were used to appraise the GTO performance further. The GTO test aims to use significant problems to examine the GTO's ability to solve significant problems and scalability. On the other hand, it determines how GTO performs in producing solutions and what quality in the face of problems under different dimensions.

On the other hand, it reveals whether GTO can retain its search features when encountered with large-scale issues. This test was evaluated using the results obtained from 30 independent implementations in 500 stored iterations and four different average error criteria of AVG, Worst, Best, and STD. Figure 11 and Tables 2–5 illustrate the results of the scalability test. Tables 6 and 7 illustrate the GTO performance and the results obtained in different benchmark functions (F14–F52) compared with other optimizers.

According to the results in Tables 2–5 and Figure 11, it is concluded that GTO has an excellent ability to achieve good results and acceptable performance in all dimensions; this is while GTO has, via increasing dimensions, managed to meet an acceptable level of search capabilities. It also has a significant advantage over other optimizers in (F1–F13) in all comparable dimensions because other comparable optimizers significantly reduce their performance as the dimensions increase. On the basis of scalability testing, it is clear that GTO has an excellent ability to balance exploration and exploitation capabilities in the face of large-scale problems.

Table 2 shows that GTO can obtain better and more significant results in the benchmark functions (F1–F13) than most optimization algorithms under comparison. Also, Table 3 shows the results from benchmark functions with 100 dimensions. In this test, GTO also generated significant performance compared with most optimization algorithms under comparison and obtained reasonable-quality solutions. On the other hand, Table 4 illustrates the results from evaluating the (F1–F13) with 500 dimensions. Table 4, GTO can find reasonable-quality solutions, producing significant performance compared with competitive optimizers. Finally, Table 5 demonstrates the GTO test results and other optimizers using the benchmark functions (F1–F13) with 1000 dimensions. According to these results, it is easily determined that GTO is still highly capable of finding high-quality solutions and achieves results almost similar to those achieved at lower dimensions. By evaluating GTO using functions (F14–F23), it is tested and compared with competitive optimizers.

The results in Table 6 show that GTO has also performed well in fixed-dimension benchmark functions (F14–F23), and they indicate a very competitive or better performance for GTO in solving some MM test cases. The results related to benchmark functions (F16–F17) and PSO, GSA, and MFO algorithms were funded to be very competitive, and these optimization algorithms had an excellent ability to obtain high-quality results. On the other hand, in the GSA benchmark function,

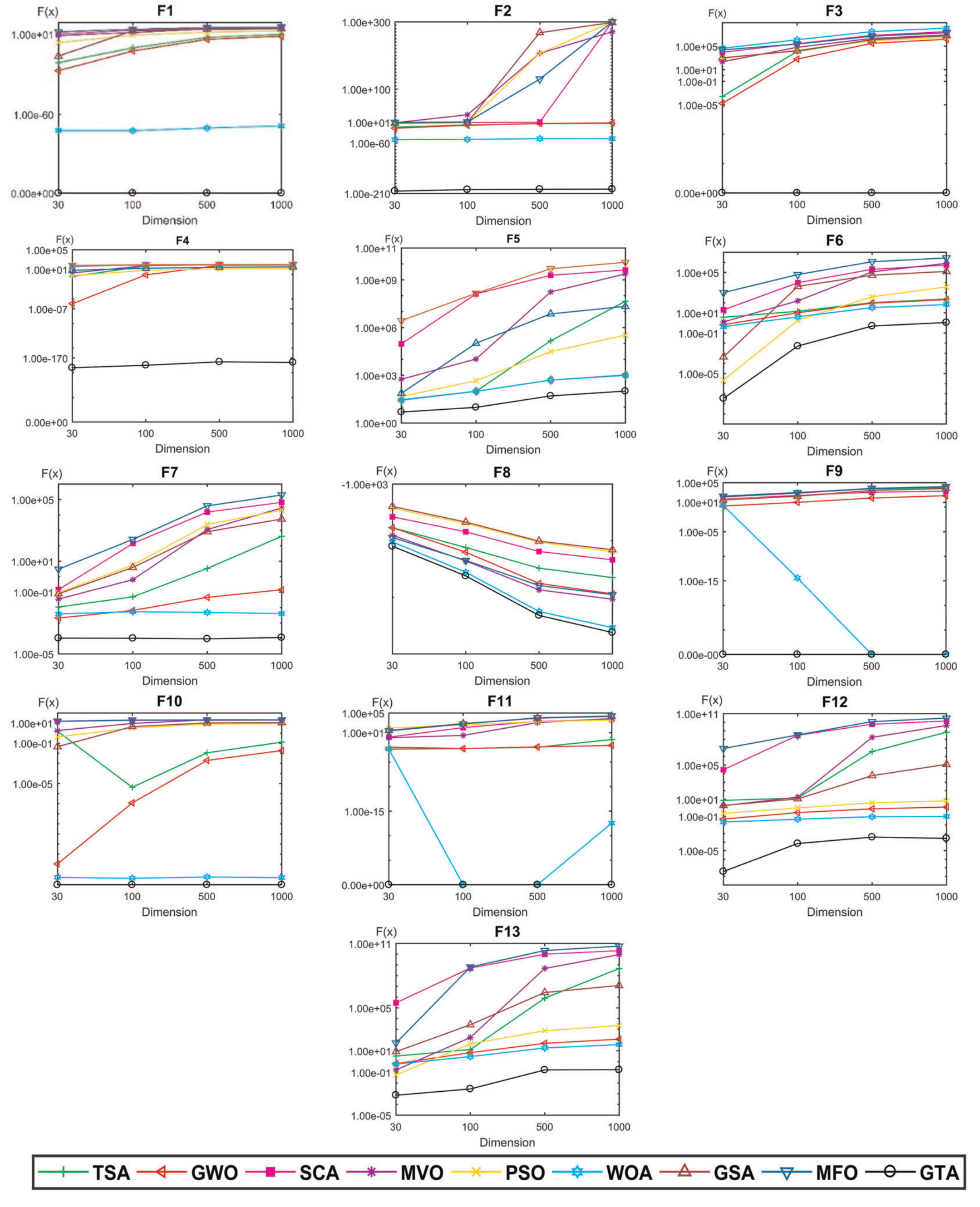

FIGURE 11 Results of GTO scalability evaluation against other optimization algorithms in F1–F13 functions in different dimensions. GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Results of benchmark functions (F1–F13), with 30 dimensions

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F1	Best	**0.0000E+00**	1.4368E−23	3.3533E−29	3.9005E−03	8.3647E−01	4.6711E−09	1.5095E−89	1.1440E−16	9.5597E−01
	Worst	**0.0000E+00**	1.5016E−20	1.6202E−26	1.4236E+02	1.8630E+00	6.3732E−05	1.2874E−71	4.2911E−16	1.0005E+04
	Mean	**0.0000E+00**	2.3061E−21	1.7091E−27	1.4523E+01	1.1070E+00	4.7058E−06	5.5002E−73	2.3532E−16	6.7289E+02
	STD	**0.0000E+00**	4.3365E−21	3.2809E−27	3.0107E+01	2.7820E−01	1.1926E−05	2.3708E−72	9.1916E−17	2.5361E+03
F2	Best	**8.0420E−220**	5.3213E−15	1.3643E−17	2.7766E−04	5.4848E−01	3.7884E−06	1.0074E−58	5.4248E−08	5.2060E−01
	Worst	**2.3838E−202**	7.8343E−13	4.3580E−16	2.1884E−01	2.3333E+00	1.8728E−02	2.6524E−49	2.4036E+00	9.0003E+01
	Mean	**1.0211E−203**	1.1565E−13	1.2365E−16	2.5643E−02	8.4484E−01	3.6477E−03	9.6725E−51	1.2500E−01	3.1246E+01
	STD	**0.0000E+00**	1.6225E−13	1.0931E−16	4.5382E−02	4.3868E−01	4.9417E−03	4.8401E−50	4.8061E−01	1.9907E+01
F3	Best	**0.0000E+00**	4.9700E−09	3.8126E−08	6.6862E+02	6.5143E+01	1.2301E+01	1.1829E+04	4.5802E+02	3.1181E+03
	Worst	**0.0000E+00**	3.3065E−03	1.9122E−04	1.9865E+04	4.0876E+02	4.3861E+03	8.0571E+04	1.6428E+03	4.6219E+04
	Mean	**0.0000E+00**	2.6060E−04	1.8580E−05	8.8051E+03	2.1883E+02	7.9186E+02	4.3601E+04	9.8887E+02	2.2994E+04
	STD	**0.0000E+00**	6.5035E−04	4.1272E−05	5.2670E+03	9.9175E+01	1.1616E+03	1.4048E+04	3.2842E+02	1.2222E+04
F4	Best	**2.1404E−210**	1.5499E−02	8.1138E−08	1.1681E+01	1.1783E+00	2.7605E−01	8.0883E−03	2.5876E+00	4.6091E+01
	Worst	**2.7688E−196**	1.9585E+00	7.9629E−06	7.4047E+01	2.9982E+00	2.5435E+00	8.5122E+01	1.2506E+01	8.4318E+01
	Mean	**1.0449E−197**	3.6686E−01	1.1296E−06	3.8649E+01	1.9398E+00	5.7113E−01	4.9909E+01	6.7621E+00	6.6329E+01
	STD	**0.0000E+00**	4.1234E−01	1.5496E−06	1.4645E+01	5.5471E−01	4.7769E−01	2.7878E+01	2.1010E+00	9.4383E+00
F5	Best	**7.9224E−08**	2.6213E+01	2.5787E+01	4.9381E+01	3.8449E+01	2.0183E+01	2.6923E+01	1.6046E+01	2.1360E+02
	Worst	**2.4608E+01**	2.8902E+01	2.8748E+01	1.5111E+06	2.9294E+03	3.3744E+02	2.8757E+01	5.8272E+02	8.0033E+07
	Mean	**4.8493E+00**	2.8359E+01	2.6993E+01	9.4594E+04	5.6504E+02	4.5709E+01	2.7935E+01	7.3227E+01	2.6909E+06
	STD	**9.8652E+00**	7.4575E−01	8.0766E−01	2.8920E+05	8.8406E+02	5.9492E+01	5.3679E−01	1.1786E+02	1.4608E+07

(Continues)

TABLE 2 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F6	Best	**4.6778E−12**	1.7989E+00	7.7955E−05	4.1260E+00	8.0166E−01	6.3996E−09	7.7984E−02	1.0342E−16	1.1135E+00
	Worst	**3.4783E−07**	5.5347E+00	1.2630E+00	1.4647E+02	1.7881E+00	2.1075E−05	9.9711E−01	1.3162E−02	1.0101E+04
	Mean	**3.4157E−08**	3.6958E+00	6.8931E−01	2.0045E+01	1.2963E+00	2.1819E−06	4.3282E−01	4.3874E−04	1.0022E+03
	STD	**6.5676E−08**	8.0031E−01	3.5603E−01	2.9239E+01	2.8293E−01	4.7464E−06	2.3830E−01	2.4031E−03	3.0397E+03
F7	Best	**2.6158E−06**	2.7697E−03	3.5203E−04	3.6638E−03	1.6213E−02	4.4480E−02	2.0010E−04	2.2990E−02	7.6178E−02
	Worst	**4.5937E−04**	2.3775E−02	4.4746E−03	8.5922E−01	9.5213E−02	1.8912E−01	1.7971E−02	1.9154E−01	1.9040E+01
	Mean	**1.0512E−04**	1.0797E−02	2.0936E−03	1.4483E−01	3.5576E−02	9.0402E−02	3.8493E−03	7.7579E−02	3.0785E+00
	STD	**1.0581E−04**	5.3721E−03	1.0777E−03	1.9743E−01	1.9754E−02	3.4907E−02	4.3432E−03	4.5161E−02	5.4242E+00
F8	Best	**−1.2569E+04**	−7.3162E+03	−7.2007E+03	−4.4667E+03	−9.5122E+03	−3.4688E+03	−1.2567E+04	−3.5277E+03	−1.0475E+04
	Worst	**−1.2569E+04**	−4.6233E+03	−3.4153E+03	−3.3228E+03	−7.2117E+03	−2.0919E+03	−7.0495E+03	−1.7384E+03	−6.9838E+03
	Mean	**−1.2569E+04**	−5.8828E+03	−5.9014E+03	−3.7930E+03	−8.0292E+03	−2.6741E+03	−1.0522E+04	−2.4884E+03	−8.8188E+03
	STD	**1.8775E−04**	6.1166E+02	7.6410E+02	2.9567E+02	6.7539E+02	3.5924E+02	1.8162E+03	4.3288E+02	8.1531E+02
F9	Best	**0.0000E+00**	1.0304E+02	5.6843E−14	3.1313E−03	8.9042E+01	2.1889E+01	0.0000E+00	1.7909E+01	9.8520E+01
	Worst	**0.0000E+00**	2.7225E+02	9.7855E+00	1.0631E+02	2.0363E+02	6.1687E+01	7.3952E+01	4.2783E+01	2.4718E+02
	Mean	**0.0000E+00**	1.8400E+02	1.7682E+00	4.6123E+01	1.2356E+02	3.7709E+01	2.4651E+00	3.0280E+01	1.6932E+02
	STD	**0.0000E+00**	4.4655E+01	3.0413E+00	3.4456E+01	3.0144E+01	1.0036E+01	1.3502E+01	6.3234E+00	4.2520E+01
F10	Best	**8.8818E−16**	1.3580E−12	7.1942E−14	1.3046E−01	1.1340E+00	3.0002E−06	8.8818E−16	8.6779E−09	1.4836E+00
	Worst	**8.8818E−16**	3.7125E+00	1.3589E−13	2.0374E+01	2.9430E+00	2.6608E+00	7.9936E−15	1.3404E+00	1.9963E+01
	Mean	**8.8818E−16**	1.5625E+00	1.0404E−13	1.4513E+01	1.8003E+00	4.1633E−01	4.7962E−15	4.4681E−02	1.5169E+01
	STD	**0.0000E+00**	1.6076E+00	1.3791E−14	8.1063E+00	4.7857E−01	8.5605E−01	2.8529E−15	2.4473E−01	6.8139E+00

TABLE 2 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F11	Best	**0.0000E+00**	0.0000E+00	0.0000E+00	3.0943E−01	7.9821E−01	6.4046E+01	0.0000E+00	1.9133E+01	6.0102E−01
	Worst	**0.0000E+00**	8.9366E−02	2.7677E−02	3.0726E+00	9.9129E−01	1.1028E+02	1.3763E−01	5.5310E+01	2.7093E+02
	Mean	**0.0000E+00**	1.0987E−02	4.4610E−03	1.1399E+00	8.9914E−01	8.5935E+01	4.5878E−03	2.8310E+01	2.2089E+01
	STD	**0.0000E+00**	1.7120E−02	8.7510E−03	5.2740E−01	5.3427E−02	8.9650E+00	2.5128E−02	7.6542E+00	5.6315E+01
F12	Best	**2.7740E−11**	3.4138E−01	1.4121E−02	9.1971E−01	6.7568E−02	5.7347E−11	6.5012E−03	5.2386E−01	2.1152E+00
	Worst	**2.6005E−07**	1.8043E+01	1.5857E−01	5.3384E+05	4.1350E+00	1.2555E+00	6.1329E−02	3.4070E+00	2.5600E+08
	Mean	**3.6895E−08**	7.5149E+00	4.7988E−02	2.8034E+04	1.8157E+00	2.2526E−01	2.2071E−02	1.9135E+00	8.5336E+06
	STD	**5.4173E−08**	4.4181E+00	3.1123E−02	1.0072E+05	1.4051E+00	3.6070E−01	1.2612E−02	7.7171E−01	4.6739E+07
F13	Best	**7.8752E−11**	1.8834E+00	2.2815E−01	2.5119E+00	3.8911E−02	5.0062E−11	6.7885E−02	1.7135E−01	2.4142E+00
	Worst	**1.0988E−02**	4.8076E+00	1.1927E+00	3.2766E+06	2.9693E−01	1.6087E+00	1.2649E+00	3.0698E+01	9.3419E+02
	Mean	**7.3420E−04**	3.2360E+00	6.2308E−01	2.9465E+05	1.6759E−01	5.6211E−02	5.8120E−01	8.4765E+00	5.3251E+01
	STD	**2.7872E−03**	6.1605E−01	2.3309E−01	7.7295E+05	7.0790E−02	2.9326E−01	2.8742E−01	6.5773E+00	1.6722E+02

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 3 Results of benchmark functions (F1–F13), with 100 dimensions

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F1	Best	**0.0000E+00**	4.3745E−11	3.2223E−13	7.6341E+02	1.2629E+02	3.4891E−01	6.6470E−88	2.6529E+03	3.4523E+04
	Worst	**0.0000E+00**	1.5602E−09	5.2187E−12	3.3116E+04	2.1038E+02	1.3724E+01	7.0325E−72	5.5277E+03	1.2436E+05
	Mean	**0.0000E+00**	3.8145E−10	1.5011E−12	1.2555E+04	1.8245E+02	1.9267E+00	3.5572E−73	4.0160E+03	6.0081E+04
	STD	**0.0000E+00**	4.4179E−10	1.1956E−12	7.8229E+03	2.4141E+01	2.7296E+00	1.3165E−72	7.3515E+02	1.9837E+04
F2	Best	**8.6580E−213**	5.8471E−08	1.3117E−08	8.6795E−01	2.9588E+04	1.1179E+00	4.6167E−55	9.9745E+00	1.6953E+02
	Worst	**5.9582E−198**	8.4608E−07	8.3604E−08	1.6535E+01	7.8941E+24	6.9342E+00	9.6057E−49	3.5919E+01	3.6393E+02
	Mean	**2.5890E−199**	2.4816E−07	4.0127E−08	6.4652E+00	5.7119E+23	3.0410E+00	4.1365E−50	1.9359E+01	2.3980E+02
	STD	**0.0000E+00**	2.0743E−07	1.4356E−08	4.5167E+00	2.0315E+24	1.1479E+00	1.7649E−49	5.4089E+00	4.2589E+01
F3	Best	**0.0000E+00**	1.7497E+03	5.4350E+01	1.5488E+05	5.2760E+04	4.3888E+03	6.7617E+05	9.3091E+03	1.5333E+05
	Worst	**0.0000E+00**	2.7387E+04	3.5225E+03	3.4417E+05	7.4132E+04	7.8068E+04	1.8385E+06	3.2503E+04	3.6077E+05
	Mean	**0.0000E+00**	1.2330E+04	6.3184E+02	2.6040E+05	6.4830E+04	2.0501E+04	1.1967E+06	1.5937E+04	2.2479E+05
	STD	**0.0000E+00**	6.9693E+03	7.3824E+02	4.5331E+04	6.0225E+03	1.6123E+04	3.0569E+05	5.1043E+03	5.8877E+04
F4	Best	**1.0044E−209**	3.1582E+01	7.8209E−02	8.0178E+01	5.0232E+01	4.8039E+00	2.4640E+01	1.4425E+01	8.7002E+01
	Worst	**6.0946E−193**	8.7166E+01	2.8610E+00	9.5109E+01	7.1352E+01	8.0438E+00	9.6764E+01	2.2952E+01	9.5947E+01
	Mean	**3.3959E−194**	5.3289E+01	8.1032E−01	8.8694E+01	6.0339E+01	6.6532E+00	7.9260E+01	1.7738E+01	9.2932E+01
	STD	**0.0000E+00**	1.5108E+01	7.6359E−01	3.1603E+00	6.2794E+00	8.7633E−01	2.0802E+01	1.8232E+00	2.0311E+00
F5	Best	**3.6576E−07**	9.6448E+01	9.6630E+01	4.0077E+07	3.2487E+03	2.7617E+02	9.7534E+01	3.1327E+04	3.5622E+07
	Worst	**9.4902E+01**	9.8696E+01	9.8545E+01	2.4510E+08	3.1873E+04	6.5160E+02	9.8409E+01	2.3289E+05	2.6711E+08
	Mean	**9.5133E+00**	9.8264E+01	9.7984E+01	1.2995E+08	1.0425E+04	4.5377E+02	9.8158E+01	1.0284E+05	1.4217E+08
	STD	**2.8905E+01**	5.1945E−01	5.9335E−01	6.0439E+07	9.3257E+03	9.1540E+01	2.2169E−01	5.0943E+04	5.4204E+07

TABLE 3 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F6	Best	**5.7588E−06**	1.2171E+01	8.2118E+00	2.5497E+03	1.1761E+02	2.9039E−01	2.0601E+00	2.8476E+03	2.7690E+04
	Worst	**2.6158E−02**	1.6824E+01	1.2106E+01	2.3493E+04	1.9653E+02	1.1422E+01	7.1318E+00	6.1903E+03	1.0361E+05
	Mean	**5.1516E−03**	1.4264E+01	1.0252E+01	9.5915E+03	1.5338E+02	1.8094E+00	4.0446E+00	4.1147E+03	6.1069E+04
	STD	**6.3310E−03**	1.2294E+00	1.1122E+00	6.0050E+03	2.3128E+01	2.4744E+00	1.1772E+00	8.7754E+02	1.7189E+04
F7	Best	**7.6254E−06**	2.3419E−02	1.6825E−03	2.3358E+01	2.6043E−01	2.2197E+00	4.6665E−05	1.6157E+00	5.4901E+01
	Worst	**4.5520E−04**	9.2439E−02	1.3277E−02	3.2039E+02	9.4876E−01	1.9939E+01	2.5268E−02	7.9360E+00	6.3587E+02
	Mean	**1.0238E−04**	4.9408E−02	6.4748E−03	1.4188E+02	6.4617E−01	5.6669E+00	5.4548E−03	3.9681E+00	2.6049E+02
	STD	**1.0619E−04**	1.9827E−02	2.3799E−03	7.7993E+01	1.7818E−01	3.5655E+00	6.4975E−03	1.3930E+00	1.3063E+02
F8	Best	**−4.1898E+04**	−1.5035E+04	−1.9513E+04	−7.9229E+03	−2.5696E+04	−6.6500E+03	−4.1898E+04	−6.5083E+03	−2.6234E+04
	Worst	**−4.1895E+04**	−1.1637E+04	−5.2781E+03	−5.6589E+03	−2.0415E+04	−3.0482E+03	−2.4827E+04	−3.5562E+03	−1.8669E+04
	Mean	**−4.1898E+04**	−1.3204E+04	−1.6025E+04	−6.9765E+03	−2.2881E+04	−4.9691E+03	−3.5969E+04	−4.7038E+03	−2.2385E+04
	STD	**8.3095E−01**	1.0233E+03	2.4115E+03	5.8043E+02	1.6663E+03	7.6092E+02	5.6258E+03	8.0790E+02	1.8572E+03
F9	Best	**0.0000E+00**	7.2721E+02	7.4692E−11	6.0801E+01	5.3700E+02	1.1142E+02	0.0000E+00	1.2374E+02	7.5427E+02
	Worst	**0.0000E+00**	1.1544E+03	2.9368E+01	4.8717E+02	8.7310E+02	2.3035E+02	1.1369E−13	2.2889E+02	9.9996E+02
	Mean	**0.0000E+00**	9.9019E+02	9.4659E+00	2.5354E+02	7.1314E+02	1.5999E+02	3.7896E−15	1.7647E+02	8.7778E+02
	STD	**0.0000E+00**	9.1744E+01	8.6083E+00	1.1244E+02	8.8002E+01	2.6130E+01	2.0756E−14	2.5022E+01	6.9373E+01
F10	Best	**8.8818E−16**	3.8914E−07	5.1723E−08	8.2704E+00	4.2388E+00	2.0932E+00	8.8818E−16	3.6880E+00	1.9575E+01
	Worst	**8.8818E−16**	1.7234E−05	2.6265E−07	2.0686E+01	2.0249E+01	6.2428E+00	7.9936E−15	5.9216E+00	1.9963E+01
	Mean	**8.8818E−16**	4.2338E−06	1.1814E−07	1.8848E+01	9.1430E+00	3.1808E+00	3.9672E−15	4.4641E+00	1.9903E+01
	STD	**0.0000E+00**	3.5786E−06	5.0343E−08	4.0766E+00	6.8589E+00	9.2895E−01	2.7572E−15	5.4120E−01	8.9166E−02

(Continues)

TABLE 3 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F11	Best	**0.0000E+00**	6.2403E−12	1.2446E−13	1.9296E+01	1.9984E+00	2.7754E+02	**0.0000E+00**	5.9878E+02	2.8124E+02
	Worst	**0.0000E+00**	3.9800E−02	4.4613E−02	2.7897E+02	3.0392E+00	3.6336E+02	**0.0000E+00**	7.6172E+02	8.1021E+02
	Mean	**0.0000E+00**	5.6575E−03	5.5354E−03	1.0325E+02	2.5740E+00	3.3598E+02	**0.0000E+00**	6.7162E+02	5.5946E+02
	STD	**0.0000E+00**	1.2978E−02	1.3163E−02	6.8312E+01	3.2546E−01	1.7042E+01	**0.0000E+00**	4.2890E+01	1.2589E+02
F12	Best	**1.2274E−10**	5.9311E+00	1.7035E−01	2.7122E+07	1.2233E+01	1.9822E−01	2.5426E−02	5.8755E+00	9.9734E+07
	Worst	**4.5135E−04**	2.5840E+01	4.8755E−01	6.6708E+08	3.0268E+01	2.2760E+00	7.5791E−02	1.8677E+01	1.1297E+09
	Mean	**6.9514E−05**	1.4256E+01	2.8446E−01	3.0081E+08	1.8116E+01	9.9461E−01	4.6775E−02	1.1223E+01	3.3380E+08
	STD	**1.1401E−04**	5.3756E+00	7.8656E−02	1.6533E+08	5.3798E+00	5.6330E−01	1.5897E−02	3.4655E+00	1.9426E+08
F13	Best	**5.2669E−07**	9.0494E+00	5.8342E+00	1.2090E+08	1.4305E+02	4.9141E+00	1.3121E+00	1.6306E+02	1.5049E+08
	Worst	**3.7673E−02**	1.8865E+01	7.6615E+00	8.9827E+08	2.2023E+02	8.6882E+01	4.8376E+00	2.4589E+04	1.6634E+09
	Mean	**2.8296E−03**	1.3106E+01	6.8300E+00	5.1265E+08	1.7296E+02	4.5033E+01	2.9166E+00	2.6429E+03	6.3494E+08
	STD	**7.7068E−03**	2.2122E+00	4.8020E−01	2.0445E+08	2.1961E+01	2.3441E+01	8.2925E−01	5.2405E+03	3.7801E+08

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 4 Results of benchmark functions (F1–F13), with 500 dimensions

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F1	Best	**0.0000E+00**	3.9560E−03	6.6965E−04	5.4429E+04	1.0108E+05	2.4798E+02	4.4134E−82	4.5957E+04	1.0806E+06
	Worst	**0.0000E+00**	6.9541E−02	2.7993E−03	3.4888E+05	1.2842E+05	7.5508E+02	8.6466E−70	5.9391E+04	1.2190E+06
	Mean	**0.0000E+00**	3.3903E−02	1.4509E−03	2.1389E+05	1.1899E+05	4.1854E+02	3.1481E−71	5.2706E+04	1.1477E+06
	STD	**0.0000E+00**	1.7024E−02	5.1598E−04	7.8042E+04	7.2207E+03	1.1329E+02	1.5776E−70	3.6249E+03	3.4308E+04
F2	Best	**2.6963E−214**	2.5553E−03	7.4946E−03	3.9088E+01	1.4513E+146	1.4812E+02	1.5485E−57	2.6697E+02	8.8480E+75
	Worst	**4.4229E−197**	1.3638E−02	1.5640E−02	2.1944E+02	8.0920E+207	1.9263E+02	1.6467E−46	3.1868E+269	2.3500E+131
	Mean	**2.5844E−198**	7.0192E−03	1.0670E−02	1.0193E+02	5.9867E+206	1.6429E+02	8.7863E−48	1.2361E+268	7.8333E+129
	STD	**0.0000E+00**	2.9923E−03	2.1801E−03	4.1878E+01	Inf	1.3636E+01	3.2049E−47	Inf	4.2905E+130
F3	Best	**0.0000E+00**	8.8185E+05	1.7206E+05	3.6517E+06	1.6141E+06	2.4182E+05	1.5733E+07	3.6984E+05	3.5091E+06
	Worst	**0.0000E+00**	1.7466E+06	4.5015E+05	1.0427E+07	2.5157E+06	2.8206E+06	7.0624E+07	3.5203E+06	6.8987E+06
	Mean	**0.0000E+00**	1.3570E+06	3.0508E+05	6.6787E+06	2.1117E+06	8.2904E+05	3.0098E+07	1.1329E+06	4.8240E+06
	STD	**0.0000E+00**	2.3510E+05	6.3185E+04	1.6460E+06	2.4168E+05	5.7559E+05	1.1821E+07	6.2456E+05	7.0979E+05
F4	Best	**5.7867E−206**	9.8370E+01	5.2558E+01	9.8509E+01	9.2032E+01	1.1371E+01	3.4048E+01	2.4025E+01	9.7363E+01
	Worst	**4.9921E−189**	9.9606E+01	7.8509E+01	9.9498E+01	9.6253E+01	1.4971E+01	9.9266E+01	3.5637E+01	9.9417E+01
	Mean	**1.6724E−190**	9.9163E+01	6.6077E+01	9.9155E+01	9.4276E+01	1.3467E+01	8.5823E+01	2.7805E+01	9.8841E+01
	STD	**0.0000E+00**	3.0766E−01	5.4071E+00	2.3316E−01	1.3414E+00	7.7605E−01	1.6408E+01	2.3633E+00	4.4627E−01
F5	Best	**6.0311E−06**	1.4303E+04	4.9753E+02	1.1139E+09	1.3713E+08	2.2554E+04	4.9544E+02	5.4336E+06	4.4020E+09
	Worst	**4.9340E+02**	5.7146E+05	4.9888E+02	2.7805E+09	2.4214E+08	3.9044E+04	4.9712E+02	9.7750E+06	5.4984E+09
	Mean	**5.0118E+01**	1.4598E+05	4.9809E+02	1.9327E+09	1.7223E+08	3.0855E+04	4.9617E+02	7.1942E+06	4.9881E+09
	STD	**1.5010E+02**	1.1587E+05	3.5353E−01	4.8046E+08	3.3038E+07	4.4688E+03	3.9636E−01	1.1225E+06	2.5974E+08

(Continues)

TABLE 4 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F6	Best	**1.3871E−03**	9.8734E+01	8.8316E+01	7.4445E+04	1.0555E+05	2.3158E+02	1.9722E+01	4.2972E+04	1.0994E+06
	Worst	**1.8175E+00**	1.0637E+02	9.6325E+01	3.0597E+05	1.3277E+05	5.5803E+02	4.7188E+01	5.9536E+04	1.2234E+06
	Mean	**4.9894E−01**	1.0260E+02	9.1667E+01	2.0710E+05	1.1554E+05	3.8808E+02	3.2980E+01	5.3015E+04	1.1581E+06
	STD	**4.6877E−01**	1.8822E+00	1.9816E+00	5.1880E+04	8.0632E+03	8.4844E+01	8.5784E+00	3.6469E+03	3.2364E+04
F7	Best	**6.5992E−06**	1.1804E+00	2.7350E−02	6.6861E+03	8.4147E+02	1.5408E+03	1.2734E−04	6.2024E+02	3.3078E+04
	Worst	**4.0011E−04**	7.2526E+00	8.0187E−02	2.1078E+04	1.3956E+03	3.2398E+03	2.5790E−02	1.0682E+03	4.4810E+04
	Mean	**9.3845E−05**	3.4194E+00	4.5572E−02	1.5259E+04	1.1371E+03	2.3926E+03	4.7984E−03	8.2011E+02	3.8656E+04
	STD	**1.0466E−04**	1.5552E+00	1.3763E−02	3.2438E+03	1.4419E+02	3.7904E+02	5.9384E−03	1.2175E+02	2.3822E+03
F8	Best	**−2.0949E+05**	−3.6264E+04	−6.8972E+04	−1.8235E+04	−8.3356E+04	−1.3589E+04	−2.0936E+05	−1.5317E+04	−7.1489E+04
	Worst	**−2.0939E+05**	−2.4922E+04	−4.9024E+04	−1.3277E+04	−6.5288E+04	−7.4799E+03	−1.0868E+05	−7.3612E+03	−5.7310E+04
	Mean	**−2.0948E+05**	−3.0578E+04	−5.6970E+04	−1.5521E+04	−7.4143E+04	−1.0613E+04	−1.7810E+05	−1.0173E+04	−6.2107E+04
	STD	**2.0361E+01**	2.3541E+03	5.0704E+03	1.1725E+03	4.9435E+03	1.6249E+03	3.3168E+04	1.7550E+03	4.2467E+03
F9	Best	**0.0000E+00**	4.1472E+03	2.6623E+01	2.6720E+02	6.1693E+03	2.1598E+03	**0.0000E+00**	2.4150E+03	6.6583E+03
	Worst	**0.0000E+00**	6.7721E+03	1.3167E+02	2.2344E+03	6.8161E+03	2.7581E+03	**0.0000E+00**	2.9123E+03	7.3658E+03
	Mean	**0.0000E+00**	5.5376E+03	7.1224E+01	1.0817E+03	6.4058E+03	2.4376E+03	**0.0000E+00**	2.6954E+03	6.9741E+03
	STD	**0.0000E+00**	6.2108E+02	2.4092E+01	4.4975E+02	1.7839E+02	1.3789E+02	**0.0000E+00**	1.2631E+02	1.7055E+02
F10	Best	**8.8818E−16**	4.8050E−03	1.2897E−03	9.7539E+00	2.0726E+01	6.8186E+00	8.8818E−16	9.7337E+00	2.0047E+01
	Worst	**8.8818E−16**	2.8829E−02	2.5546E−03	2.0835E+01	2.0909E+01	8.8899E+00	7.9936E−15	1.0576E+01	2.0465E+01
	Mean	**8.8818E−16**	1.1216E−02	1.9672E−03	1.8671E+01	2.0836E+01	7.7665E+00	5.2699E−15	1.0235E+01	2.0285E+01
	STD	**0.0000E+00**	5.1528E−03	3.2084E−04	3.9157E+00	4.9099E−02	4.4145E−01	2.2242E−15	2.1885E−01	1.3999E−01

TABLE 4 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F11	Best	**0.0000E+00**	4.8899E−04	6.5815E−05	6.1575E+02	9.5641E+02	1.6806E+03	**0.0000E+00**	7.7653E+03	9.8341E+03
	Worst	**0.0000E+00**	1.6651E−01	1.1380E−01	3.7589E+03	1.1843E+03	1.8915E+03	**0.0000E+00**	8.9367E+03	1.0979E+04
	Mean	**0.0000E+00**	1.0639E−02	1.2159E−02	2.0122E+03	1.0719E+03	1.7776E+03	**0.0000E+00**	8.5757E+03	1.0355E+04
	STD	**0.0000E+00**	2.9727E−02	3.1647E−02	7.7251E+02	7.5775E+01	4.6628E+01	**0.0000E+00**	2.3837E+02	3.3259E+02
F12	Best	**9.8793E−12**	5.7627E+05	6.6568E−01	3.9643E+09	9.4411E+07	2.2294E+00	2.8082E−02	3.8321E+01	1.0565E+10
	Worst	**4.6529E−03**	1.3045E+07	9.2436E−01	7.7107E+09	2.3943E+08	5.7086E+00	1.7943E−01	1.8065E+04	1.3022E+10
	Mean	**3.7955E−04**	3.8079E+06	7.6761E−01	5.9041E+09	1.7199E+08	3.9439E+00	9.1032E−02	5.7877E+03	1.1784E+10
	STD	**9.9661E−04**	3.4247E+06	5.6579E−02	1.1005E+09	4.3412E+07	7.4974E−01	3.6962E−02	5.6640E+03	5.7768E+08
F13	Best	**1.5099E−04**	9.7440E+04	4.7168E+01	6.3484E+09	3.4209E+08	5.8809E+02	8.8398E+00	1.5441E+06	1.9839E+10
	Worst	**1.6580E+00**	2.5135E+06	5.4158E+01	1.2178E+10	6.2665E+08	8.7066E+02	3.7606E+01	5.7846E+06	2.5181E+10
	Mean	**1.6720E−01**	8.0758E+05	5.0275E+01	9.8697E+09	4.7357E+08	7.5158E+02	1.8407E+01	2.6717E+06	2.1917E+10
	STD	**3.3179E−01**	7.7246E+05	1.3109E+00	1.5823E+09	8.1781E+07	6.5251E+01	6.5833E+00	8.7124E+05	1.2045E+09

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 5 Results of benchmark functions (F1–F13), with 1000 dimensions

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F1	Best	**0.0000E+00**	8.3482E−01	1.3068E−01	8.9858E+04	7.4867E+05	2.4635E+03	3.5027E−78	1.1278E+05	2.6694E+06
	Worst	**0.0000E+00**	2.1216E+01	4.2039E−01	8.3308E+05	8.7248E+05	4.8032E+03	4.2387E−68	1.3478E+05	2.7967E+06
	Mean	**0.0000E+00**	5.8069E+00	2.4126E−01	4.4114E+05	8.0535E+05	3.5154E+03	1.5101E−69	1.2511E+05	2.7334E+06
	STD	**0.0000E+00**	4.9022E+00	6.9701E−02	1.6162E+05	3.3743E+04	6.1530E+02	7.7304E−69	5.1680E+03	3.4145E+04
F2	Best	**2.4266E−209**	5.8490E−03	2.2670E−01	1.0000E+300	4.9254E+203	7.1393E+02	9.6113E−55	1.8916E+258	1.0000E+300
	Worst	**1.8437E−196**	7.8520E−02	2.1375E+00	1.0000E+300	3.8712E+271	1.0000E+300	6.5641E−47	2.1923E+299	1.0000E+300
	Mean	**1.0098E−197**	2.7039E−02	6.4334E−01	1.0000E+300	2.6660E+270	1.0000E+300	5.5849E−48	7.3077E+297	1.0000E+300
	STD	**0.0000E+00**	1.6976E−02	3.7341E−01	1.0000E+300	1.0000E+300	1.0000E+300	1.6168E−47	1.0000E+300	1.0000E+300
F3	Best	**0.0000E+00**	4.2454E+06	9.9816E+05	1.7727E+07	7.0988E+06	9.3878E+05	7.1384E+07	2.3625E+06	1.2164E+07
	Worst	**0.0000E+00**	7.6531E+06	2.4071E+06	5.4917E+07	8.9303E+06	9.1543E+06	2.3891E+08	1.2445E+07	2.9589E+07
	Mean	**0.0000E+00**	5.7375E+06	1.4940E+06	3.0052E+07	7.9011E+06	3.0005E+06	1.2016E+08	6.0920E+06	1.9612E+07
	STD	**0.0000E+00**	9.7986E+05	3.5552E+05	7.6664E+06	5.7369E+05	2.0975E+06	3.6240E+07	2.1045E+06	3.7418E+06
F4	Best	**1.0392E−204**	9.9250E+01	7.2506E+01	9.9276E+01	9.5893E+01	1.3764E+01	1.5379E+00	2.8898E+01	9.9152E+01
	Worst	**2.5843E−189**	9.9772E+01	8.5165E+01	9.9786E+01	9.8933E+01	1.7638E+01	9.9575E+01	3.5298E+01	9.9742E+01
	Mean	**1.2771E−190**	9.9577E+01	7.8413E+01	9.9610E+01	9.7606E+01	1.5660E+01	7.8392E+01	3.2847E+01	9.9551E+01
	STD	**0.0000E+00**	1.2110E−01	3.3976E+00	1.0754E−01	7.2257E−01	8.6534E−01	2.5060E+01	1.5336E+00	1.3934E−01
F5	Best	**2.5289E−04**	1.3523E+07	1.0197E+03	1.7727E+09	2.0251E+09	2.4927E+05	9.9262E+02	1.8336E+07	1.1612E+10
	Worst	**9.8841E+02**	9.5928E+07	1.1400E+03	6.6390E+09	2.6641E+09	4.4661E+05	9.9675E+02	2.4859E+07	1.3278E+10
	Mean	**1.0147E+02**	4.4624E+07	1.0555E+03	4.1389E+09	2.3725E+09	3.3299E+05	9.9406E+02	2.1407E+07	1.2499E+10
	STD	**3.0070E+02**	2.1372E+07	3.1904E+01	9.9639E+08	1.9624E+08	5.0670E+04	9.1931E−01	1.7819E+06	4.0469E+08

TABLE 5 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F6	Best	**3.7165E−03**	2.2555E+02	1.9652E+02	2.9666E+05	7.2503E+05	2.7081E+03	3.3327E+01	1.1729E+05	2.6129E+06
	Worst	**3.3921E+00**	2.4641E+02	2.0755E+02	8.9968E+05	8.5012E+05	4.9081E+03	9.9718E+01	1.3311E+05	2.8015E+06
	Mean	**1.1147E+00**	2.3491E+02	2.0279E+02	5.2718E+05	7.8921E+05	3.6446E+03	6.6643E+01	1.2584E+05	2.7348E+06
	STD	**9.6315E−01**	5.0550E+00	2.5997E+00	1.5724E+05	3.6771E+04	5.5579E+02	1.6649E+01	3.6788E+03	3.9399E+04
F7	Best	**1.1982E−05**	7.8081E+01	1.0699E−01	4.0231E+04	2.2217E+04	1.6648E+04	5.4700E−05	4.5809E+03	1.7760E+05
	Worst	**3.7004E−04**	8.3688E+02	2.0425E−01	9.9845E+04	3.3152E+04	2.6003E+04	1.8211E−02	6.4409E+03	2.1363E+05
	Mean	**1.1591E−04**	4.1201E+02	1.4151E−01	6.5161E+04	2.8074E+04	2.0704E+04	4.0616E−03	5.3877E+03	1.9613E+05
	STD	**8.7652E−05**	2.1052E+02	2.5082E−02	1.3534E+04	2.8097E+03	2.5684E+03	4.9539E−03	4.6217E+02	7.2124E+03
F8	Best	**−4.1898E+05**	−4.9824E+04	−9.9463E+04	−2.5086E+04	−1.1290E+05	−2.0619E+04	−4.1887E+05	−2.0305E+04	−1.0562E+05
	Worst	**−4.1870E+05**	−3.9010E+04	−1.9154E+04	−1.9437E+04	−9.9410E+04	−1.1943E+04	−2.3384E+05	−1.0929E+04	−8.1676E+04
	Mean	**−4.1895E+05**	−4.4899E+04	−8.7079E+04	−2.1762E+04	−1.0817E+05	−1.5677E+04	−3.4394E+05	−1.4485E+04	−8.9969E+04
	STD	**5.6761E+01**	2.7841E+03	1.3376E+04	1.7287E+03	3.7498E+03	2.1340E+03	6.4239E+04	2.5838E+03	5.7312E+03
F9	Best	**0.0000E+00**	5.4952E+03	1.4223E+02	7.6823E+02	1.4247E+04	5.9056E+03	**0.0000E+00**	6.1952E+03	1.5163E+04
	Worst	**0.0000E+00**	1.3116E+04	5.2886E+02	3.9540E+03	1.4955E+04	7.1027E+03	**0.0000E+00**	6.9938E+03	1.5837E+04
	Mean	**0.0000E+00**	9.6317E+03	2.2177E+02	1.9316E+03	1.4595E+04	6.4470E+03	**0.0000E+00**	6.5838E+03	1.5535E+04
	STD	**0.0000E+00**	2.1203E+03	7.5592E+01	8.0283E+02	2.4206E+02	3.0401E+02	**0.0000E+00**	1.7472E+02	1.7392E+02
F10	Best	**8.8818E−16**	2.6172E−02	1.2469E−02	9.4061E+00	2.0949E+01	7.8819E+00	8.8818E−16	1.0560E+01	2.0026E+01
	Worst	**8.8818E−16**	8.7354E−01	2.−4657E−02	2.0886E+01	2.1019E+01	9.5002E+00	7.9936E−15	1.1181E+01	2.0695E+01
	Mean	**8.8818E−16**	1.2690E−01	1.8284E−02	1.9903E+01	2.0988E+01	8.6221E+00	4.5593E−15	1.0885E+01	2.0409E+01
	STD	**0.0000E+00**	1.5112E−01	2.6578E−03	2.8383E+00	2.3613E−02	3.0715E−01	2.7174E−15	1.8625E−01	2.1664E−01

(Continues)

TABLE 5 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F11	Best	**0.0000E+00**	8.2300E−02	1.0870E−02	1.7364E+03	6.3239E+03	3.4947E+03	0.0000E+00	2.0001E+04	2.3799E+04
	Worst	**0.0000E+00**	1.0574E+00	2.3040E−01	7.8590E+03	7.5367E+03	3.7675E+03	1.1102E−16	2.1149E+04	2.5467E+04
	Mean	**0.0000E+00**	3.8167E−01	2.5458E−02	4.2058E+03	7.1021E+03	3.5881E+03	3.7007E−18	2.0550E+04	2.4492E+04
	STD	**0.0000E+00**	2.6010E−01	3.9153E−02	1.5832E+03	3.0834E+02	5.4933E+01	2.0270E−17	3.1159E+02	3.8192E+02
F12	Best	**5.3797E−09**	1.4692E+08	9.7371E−01	9.4555E+09	3.5107E+09	4.9507E+00	3.2476E−02	2.1126E+04	2.8568E+10
	Worst	**2.7047E−03**	2.0570E+09	2.2587E+00	1.9237E+10	5.5082E+09	8.3249E+00	2.3904E−01	4.2617E+05	3.3148E+10
	Mean	**2.7031E−04**	6.9381E+08	1.2517E+00	1.4129E+10	4.1836E+09	6.4110E+00	1.0000E−01	1.2193E+05	3.0711E+10
	STD	**5.5534E−04**	3.9588E+08	3.2471E−01	2.5907E+09	5.1906E+08	8.9298E−01	4.2739E−02	9.7186E+04	1.1132E+09
F13	Best	**1.0353E−05**	1.4507E+08	1.1022E+02	1.2010E+10	8.1387E+09	1.7132E+03	1.4103E+01	7.7569E+06	5.1672E+10
	Worst	**1.1775E+00**	1.1303E+09	1.4460E+02	2.9456E+10	1.2072E+10	4.4767E+03	6.8057E+01	1.8448E+07	5.8610E+10
	Mean	**1.7370E−01**	4.5791E+08	1.2083E+02	2.1265E+10	9.1269E+09	2.2499E+03	3.7591E+01	1.2277E+07	5.5609E+10
	STD	**2.8391E−01**	2.4115E+08	7.2282E+00	4.4422E+09	1.0247E+09	5.2335E+02	1.5478E+01	2.8423E+06	1.7930E+09

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 6 Results of benchmark functions (F14–F23)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F14	Best	**9.9800E−01**	9.9800E−01	9.9800E−01	9.9800E−01	9.9800E−01	9.9800E−01	9.9800E−01	9.9800E−01	9.9800E−01
	Worst	**9.9800E−01**	1.8304E+01	1.2671E+01	2.9821E+00	9.9800E−01	5.9288E+00	1.0763E+01	1.2193E+01	7.8740E+00
	Mean	**9.9800E−01**	8.1307E+00	4.2305E+00	2.0238E+00	9.9800E−01	1.6270E+00	2.6971E+00	4.8545E+00	2.3481E+00
	STD	**0.0000E+00**	5.7947E+00	4.0855E+00	9.9084E−01	2.6200E−11	1.1164E+00	3.2933E+00	2.7988E+00	1.9439E+00
F15	Best	**3.0749E−04**	3.0790E−04	3.0810E−04	5.3498E−04	5.4649E−04	3.0749E−04	3.1170E−04	7.0949E−04	6.4325E−04
	Worst	**1.2232E−03**	8.8541E−02	2.0363E−02	1.7269E−03	2.0363E−02	2.0363E−02	2.2519E−03	1.2866E−02	2.0363E−02
	Mean	**3.9905E−04**	7.5060E−03	3.7814E−03	1.0261E−03	3.4291E−03	1.1453E−03	7.5887E−04	4.1780E−03	1.8103E−03
	STD	**2.7940E−04**	1.7318E−02	7.5471E−03	3.7296E−04	6.8812E−03	3.6434E−03	4.8856E−04	3.1142E−03	3.5415E−03
F16	Best	**−1.0316E+00**	−1.0316E+00	−1.0316E+00	−1.0316E+00	−1.0316E+00	**−1.0316E+00**	−1.0316E+00	**−1.0316E+00**	**−1.0316E+00**
	Worst	**−1.0316E+00**	−1.0000E+00	−1.0316E+00	−1.0315E+00	−1.0316E+00	**−1.0316E+00**	−1.0316E+00	**−1.0316E+00**	**−1.0316E+00**
	Mean	**−1.0316E+00**	−1.0285E+00	−1.0316E+00	−1.0316E+00	−1.0316E+00	**−1.0316E+00**	−1.0316E+00	**−1.0316E+00**	**−1.0316E+00**
	STD	**6.7752E−16**	9.6515E−03	2.3057E−08	4.2030E−05	1.9966E−07	**6.7752E−16**	1.8661E−09	**6.7752E−16**	**6.7752E−16**
F17	Best	**3.9789E−01**	3.9789E−01	3.9789E−01	3.9797E−01	3.9789E−01	**3.9789E−01**	3.9789E−01	**3.9789E−01**	**3.9789E−01**
	Worst	**3.9789E−01**	3.9822E−01	3.9821E−01	4.0861E−01	3.9789E−01	**3.9789E−01**	3.9795E−01	**3.9789E−01**	**3.9789E−01**
	Mean	**3.9789E−01**	3.9794E−01	3.9790E−01	4.0085E−01	3.9789E−01	**3.9789E−01**	3.9789E−01	**3.9789E−01**	**3.9789E−01**
	STD	**0.0000E+00**	6.7526E−05	5.7899E−05	2.8817E−03	3.8452E−07	**0.0000E+00**	1.1259E−05	**0.0000E+00**	**0.0000E+00**
F18	Best	**3.0000E+00**	3.0000E+00	3.0000E+00	3.0000E+00	3.0000E+00	3.0000E+00	3.0000E+00	3.0000E+00	3.0000E+00
	Worst	**3.0000E+00**	8.4001E+01	8.4000E+01	3.0006E+00	3.0001E+00	3.0000E+00	3.0018E+00	4.2286E+00	3.0000E+00
	Mean	**3.0000E+00**	2.4600E+01	5.7000E+00	3.0001E+00	3.0000E+00	3.0000E+00	3.0001E+00	3.0410E+00	3.0000E+00
	STD	**7.1892E−16**	3.4300E+01	1.4789E+01	1.2351E−04	2.0705E−05	1.7337E−15	3.2667E−04	2.2431E−01	1.8895E−15

(Continues)

TABLE 6 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F19	Best	**−3.8628E+00**	−3.8628E+00	−3.8628E+00	−3.8623E+00	−3.8628E+00	−3.8628E+00	−3.8628E+00	−3.8628E+00	−3.8628E+00
	Worst	**−3.8628E+00**	−3.8549E+00	−3.8609E+00	−3.8504E+00	−3.8628E+00	−3.8549E+00	−3.7435E+00	−3.8628E+00	−3.8549E+00
	Mean	**−3.8628E+00**	−3.8618E+00	−3.8626E+00	−3.8542E+00	−3.8628E+00	−3.8620E+00	−3.8529E+00	−3.8628E+00	−3.8625E+00
	STD	**2.7101E−15**	2.3278E−03	4.3099E−04	2.6025E−03	1.3946E−06	2.4049E−03	2.1866E−02	2.2873E−06	1.4390E−03
F20	Best	−3.3220E+00	−3.3208E+00	−3.3220E+00	−3.1214E+00	−3.3220E+00	−3.3220E+00	−3.3219E+00	**−3.3220E+00**	−3.3220E+00
	Worst	−3.2031E+00	−3.1350E+00	−3.0867E+00	−1.7911E+00	−3.1996E+00	−3.0867E+00	−2.8400E+00	**−3.3220E+00**	−3.1376E+00
	Mean	−3.2705E+00	−3.2601E+00	−3.2641E+00	−2.9024E+00	−3.2896E+00	−3.2753E+00	−3.2296E+00	**−3.3220E+00**	−3.2295E+00
	STD	5.9923E−02	7.2163E−02	7.0831E−02	3.7287E−01	5.5667E−02	7.6210E−02	1.3905E−01	**1.6840E−15**	6.5249E−02
F21	Best	**−1.0153E+01**	−1.0069E+01	−1.0153E+01	−8.2648E+00	−1.0153E+01	−1.0153E+01	−1.0153E+01	−1.0153E+01	−1.0153E+01
	Worst	**−1.0153E+01**	−2.6007E+00	−2.3316E+00	−4.9728E−01	−2.6304E+00	−2.6305E+00	−2.6248E+00	−2.6305E+00	−2.6305E+00
	Mean	**−1.0153E+01**	−6.3088E+00	−9.3828E+00	−2.7594E+00	−6.6184E+00	−5.3115E+00	−7.8525E+00	−5.2274E+00	−5.7977E+00
	STD	**6.5642E−15**	3.1079E+00	2.0417E+00	2.1285E+00	3.1271E+00	3.3425E+00	2.9069E+00	3.5542E+00	3.2848E+00
F22	Best	**−1.0403E+01**	−1.0293E+01	−1.0402E+01	−6.7740E+00	−1.0403E+01	−1.0403E+01	−1.0400E+01	−1.0403E+01	−1.0403E+01
	Worst	**−1.0403E+01**	−1.8302E+00	−5.0876E+00	−9.0261E−01	−2.7659E+00	−1.8376E+00	−2.7617E+00	−6.7587E+00	−2.7519E+00
	Mean	**−1.0403E+01**	−6.3959E+00	−1.0224E+01	−3.7007E+00	−7.6237E+00	−5.9104E+00	−7.1870E+00	−1.0182E+01	−6.4147E+00
	STD	**7.3759E−16**	3.6566E+00	9.7016E−01	1.5485E+00	3.1657E+00	3.5717E+00	3.1381E+00	8.4434E−01	3.4084E+00
F23	Best	**−1.0536E+01**	−1.0473E+01	−1.0536E+01	−8.1004E+00	−1.0536E+01	−1.0536E+01	−1.0535E+01	−1.0536E+01	−1.0536E+01
	Worst	**−1.0536E+01**	−2.4110E+00	−1.0533E+01	−9.4483E−01	−2.4273E+00	−1.6766E+00	−2.4158E+00	−2.4273E+00	−2.4217E+00
	Mean	**−1.0536E+01**	−7.6980E+00	−1.0535E+01	−4.0835E+00	−9.4802E+00	−7.3484E+00	−7.6994E+00	−9.9670E+00	−7.6010E+00
	STD	**1.2342E−15**	3.4985E+00	8.5960E−04	1.7790E+00	2.7874E+00	3.7524E+00	3.3809E+00	1.9251E+00	3.6977E+00

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 7 Results of benchmark functions (F23–F52)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F24	Best	**1.0584E+02**	6.3089E+06	1.8768E+04	4.2284E+08	6.5078E+03	1.0403E+02	1.8119E+06	5.5814E+03	1.1776E+02
	Worst	**1.3145E+04**	7.1515E+09	5.6688E+08	2.5357E+09	7.8330E+04	3.4517E+09	5.7113E+07	7.6879E+04	2.1175E+09
	Mean	**2.3996E+03**	2.5725E+09	1.8943E+07	1.2404E+09	3.4690E+04	2.7729E+08	1.7777E+07	2.9419E+04	2.8761E+08
	STD	**3.0872E+03**	2.3675E+09	1.0349E+08	4.8379E+08	2.4736E+04	8.6181E+08	1.2834E+07	1.3362E+04	5.8274E+08
F25	Best	**3.0000E+02**	4.2713E+02	3.6514E+02	5.8872E+02	3.0016E+02	3.0000E+02	1.3525E+03	1.4805E+04	3.3001E+02
	Worst	**3.0001E+02**	3.0971E+04	1.3714E+04	1.2232E+04	3.0065E+02	1.0168E+04	1.4469E+04	3.7765E+04	3.0950E+04
	Mean	**3.0000E+02**	1.2595E+04	4.9310E+03	3.7761E+03	3.0035E+02	2.1079E+03	5.3221E+03	2.7146E+04	8.7341E+03
	STD	**1.0376**E−**03**	8.0998E+03	3.4963E+03	1.9342E+03	1.4960E−01	2.7280E+03	3.0010E+03	5.6587E+03	8.9352E+03
F26	Best	4.0000E+02	4.0150E+02	4.0077E+02	4.1879E+02	4.0028E+02	4.0001E+02	4.0707E+02	**4.0001E+02**	4.0494E+02
	Worst	4.3810E+02	2.7005E+03	4.4014E+02	5.8680E+02	4.3811E+02	2.4461E+03	5.9839E+02	**4.1392E+02**	5.1756E+02
	Mean	4.1310E+02	8.0640E+02	4.2528E+02	4.8139E+02	4.1621E+02	6.1832E+02	4.7927E+02	**4.0106E+02**	4.4410E+02
	STD	1.8021E+01	6.5143E+02	1.6946E+01	4.0557E+01	1.8567E+01	4.8112E+02	5.3013E+01	**3.1886E+00**	2.7976E+01
F27	Best	**5.0597E+02**	5.3249E+02	5.0302E+02	5.3007E+02	5.0996E+02	5.3144E+02	5.2992E+02	5.3482E+02	5.0796E+02
	Worst	**5.4079E+02**	6.1590E+02	5.4212E+02	5.8668E+02	5.5673E+02	5.9213E+02	6.0367E+02	5.8159E+02	5.6200E+02
	Mean	**5.1912E+02**	5.6824E+02	5.2117E+02	5.5406E+02	5.2301E+02	5.5373E+02	5.5534E+02	5.6096E+02	5.2936E+02
	STD	**8.4503E+00**	1.9209E+01	1.0923E+01	1.1270E+01	1.3192E+01	1.4954E+01	2.0769E+01	1.3315E+01	1.2771E+01
F28	Best	**6.0000E+02**	6.0875E+02	6.0010E+02	6.1790E+02	6.0023E+02	6.1019E+02	6.2094E+02	6.2303E+02	6.0000E+02
	Worst	**6.0678E+02**	6.8558E+02	6.0731E+02	6.3771E+02	6.2943E+02	6.4289E+02	6.7704E+02	6.5087E+02	6.1421E+02
	Mean	**6.0088E+02**	6.3583E+02	6.0102E+02	6.2717E+02	6.0412E+02	6.2536E+02	6.4118E+02	6.3419E+02	6.0247E+02
	STD	**1.7453E+00**	1.6244E+01	1.3902E+00	4.8424E+00	7.4697E+00	7.8174E+00	1.3859E+01	7.2540E+00	3.4067E+00

(Continues)

TABLE 7 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F29	Best	7.2142E+02	7.5562E+02	7.1554E+02	7.6677E+02	**7.1725E+02**	7.2226E+02	7.4840E+02	7.1699E+02	7.1118E+02
	Worst	7.5250E+02	8.7913E+02	7.7412E+02	8.4006E+02	**7.4184E+02**	8.4773E+02	8.6015E+02	7.6508E+02	7.6507E+02
	Mean	7.3320E+02	8.1258E+02	7.3993E+02	7.9711E+02	**7.2772E+02**	7.7544E+02	8.0093E+02	7.3280E+02	7.4003E+02
	STD	8.6658E+00	3.2524E+01	1.6261E+01	1.7445E+01	**7.7712E+00**	3.1404E+01	2.8069E+01	1.1118E+01	1.2232E+01
F30	Best	8.0796E+02	8.2209E+02	**8.0709E+02**	8.3471E+02	8.0797E+02	8.2428E+02	8.1734E+02	8.2786E+02	8.1691E+02
	Worst	8.4875E+02	8.9347E+02	**8.4689E+02**	8.8325E+02	8.4080E+02	8.8733E+02	8.8647E+02	8.7860E+02	8.5424E+02
	Mean	8.2339E+02	8.6438E+02	**8.2155E+02**	8.5592E+02	8.2309E+02	8.4904E+02	8.4999E+02	8.5499E+02	8.2816E+02
	STD	1.0463E+01	1.6646E+01	**1.1402E+01**	9.0694E+00	8.6113E+00	1.8164E+01	2.0530E+01	1.0902E+01	7.9486E+00
F31	Best	**9.0000E+02**	9.5355E+02	9.0002E+02	1.1124E+03	9.0001E+02	1.0203E+03	1.0234E+03	1.0027E+03	9.0000E+02
	Worst	**1.1661E+03**	5.4453E+03	1.0391E+03	1.8136E+03	3.4924E+03	2.8990E+03	5.0582E+03	2.2357E+03	2.1432E+03
	Mean	**9.2701E+02**	1.9449E+03	9.3495E+02	1.3403E+03	1.1136E+03	1.6064E+03	2.1755E+03	1.5848E+03	1.1207E+03
	STD	**6.1707E+01**	1.0062E+03	3.7637E+01	1.7023E+02	6.7570E+02	4.3166E+02	8.3097E+02	3.4361E+02	2.7193E+02
F32	Best	1.1374E+03	1.4538E+03	**1.0626E+03**	2.1724E+03	1.2551E+03	1.6799E+03	1.7489E+03	1.3526E+03	1.1408E+03
	Worst	2.3032E+03	2.6170E+03	**2.5902E+03**	2.7314E+03	2.0871E+03	3.0538E+03	3.1614E+03	2.5877E+03	2.8327E+03
	Mean	1.6845E+03	2.0634E+03	**1.6117E+03**	2.4584E+03	1.6319E+03	2.4529E+03	2.2695E+03	1.9022E+03	1.9322E+03
	STD	3.3734E+02	3.1149E+02	**4.0326E+02**	1.7544E+02	2.4605E+02	3.0102E+02	3.2707E+02	2.9607E+02	4.1286E+02
F33	Best	**1.1010E+03**	1.1303E+03	1.1176E+03	1.1998E+03	1.1066E+03	1.1160E+03	1.1991E+03	1.1683E+03	1.1013E+03
	Worst	**1.1385E+03**	6.3816E+03	1.3505E+03	1.4800E+03	1.2196E+03	1.3052E+03	1.7010E+03	1.5848E+03	1.4925E+03
	Mean	**1.1101E+03**	1.7907E+03	1.1839E+03	1.3042E+03	1.1626E+03	1.1788E+03	1.3845E+03	1.4258E+03	1.1611E+03
	STD	**1.0082E+01**	1.2440E+03	5.7173E+01	8.3902E+01	3.2767E+01	5.3310E+01	1.4405E+02	8.2326E+01	8.7233E+01

TABLE 7 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F34	Best	**1.6898E+03**	1.8502E+04	8.1101E+03	1.6703E+06	1.6366E+05	1.6597E+03	8.8291E+04	6.8468E+04	1.5370E+03
	Worst	**2.3579E+04**	3.4037E+08	3.6164E+06	3.3079E+07	3.0563E+06	3.2018E+04	1.4866E+07	2.4313E+06	9.8607E+06
	Mean	**9.5634E+03**	4.6322E+07	5.9286E+05	8.4845E+06	9.6656E+05	1.2711E+04	2.9321E+06	1.0994E+06	8.3268E+05
	STD	**5.3047E+03**	8.7422E+07	1.0730E+06	7.0682E+06	7.3858E+05	7.6356E+03	3.1526E+06	6.8897E+05	1.8411E+06
F35	Best	**1.3240E+03**	2.6863E+03	1.8704E+03	2.0275E+04	1.4357E+03	1.4233E+03	2.3708E+03	3.0453E+03	1.3494E+03
	Worst	**4.8401E+03**	3.2656E+04	7.0840E+04	7.3188E+05	1.9949E+04	1.7429E+04	5.7614E+04	1.2726E+04	3.0492E+04
	Mean	**1.8270E+03**	1.5708E+04	1.1700E+04	1.7975E+05	6.6548E+03	6.5754E+03	1.4664E+04	7.3242E+03	1.0554E+04
	STD	**6.7442E+02**	8.8235E+03	1.2850E+04	1.8296E+05	6.0344E+03	4.9235E+03	1.3157E+04	2.1970E+03	7.9650E+03
F36	Best	**1.4100E+03**	1.4613E+03	1.4690E+03	1.6102E+03	1.4412E+03	1.4320E+03	1.5939E+03	3.5617E+03	1.4795E+03
	Worst	**1.7592E+03**	8.5736E+03	8.0954E+03	7.6976E+03	2.8169E+04	7.6149E+03	9.6049E+03	1.1797E+04	1.6856E+04
	Mean	**1.4796E+03**	3.5069E+03	4.1693E+03	3.5497E+03	6.4874E+03	2.7364E+03	3.5721E+03	6.2936E+03	4.2006E+03
	STD	**7.3138E+01**	2.7583E+03	2.3604E+03	1.9726E+03	8.3434E+03	1.7338E+03	2.2551E+03	2.1628E+03	3.6721E+03
F37	Best	**1.5074E+03**	1.7343E+03	1.7424E+03	2.4373E+03	1.5523E+03	1.5438E+03	1.6640E+03	2.5084E+04	1.8108E+03
	Worst	**1.7375E+03**	8.4734E+04	8.7138E+04	7.5449E+04	1.2105E+04	6.7568E+04	3.6357E+04	6.1849E+04	1.6771E+05
	Mean	**1.5721E+03**	3.9358E+04	2.2007E+04	8.0718E+03	3.2544E+03	1.4031E+04	1.0719E+04	3.9068E+04	1.6030E+04
	STD	**5.3792E+01**	3.6262E+04	2.3404E+04	1.4260E+04	3.2845E+03	1.8356E+04	1.1768E+04	9.4007E+03	3.2828E+04
F38	Best	**1.6016E+03**	1.6377E+03	1.6050E+03	1.6685E+03	1.6213E+03	1.6014E+03	1.6179E+03	1.7312E+03	1.6019E+03
	Worst	**1.8406E+03**	2.1564E+03	1.8257E+03	2.0631E+03	1.8725E+03	2.1149E+03	2.5948E+03	2.4600E+03	2.0927E+03
	Mean	**1.6775E+03**	1.8381E+03	1.7088E+03	1.8056E+03	1.7479E+03	1.8253E+03	1.8901E+03	2.0868E+03	1.7818E+03
	STD	**7.0705E+01**	1.1504E+02	6.2221E+01	9.8415E+01	8.6990E+01	1.4774E+02	2.1005E+02	2.0805E+02	1.3603E+02

(Continues)

TABLE 7 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F39	Best	**1.7086E+03**	1.7324E+03	1.7190E+03	1.7669E+03	1.7262E+03	1.7262E+03	1.7809E+03	1.7431E+03	1.7203E+03
	Worst	**1.8416E+03**	2.0074E+03	1.8951E+03	1.9358E+03	1.9044E+03	1.9870E+03	2.0226E+03	2.3540E+03	2.0041E+03
	Mean	**1.7442E+03**	1.8716E+03	1.7621E+03	1.8186E+03	1.8072E+03	1.7873E+03	1.9086E+03	1.9952E+03	1.8105E+03
	STD	**2.9039E+01**	8.0155E+01	3.4523E+01	3.8315E+01	5.6798E+01	5.3636E+01	6.9762E+01	1.8061E+02	8.2465E+01
F40	Best	**1.8345E+03**	7.5758E+03	2.4914E+03	1.6767E+04	4.5945E+03	2.0703E+03	3.0710E+03	3.9320E+03	3.3601E+03
	Worst	**2.3457E+03**	7.1481E+08	9.1720E+04	1.1126E+06	9.5313E+04	8.0204E+04	1.0096E+05	2.4359E+04	6.5721E+06
	Mean	**1.9553E+03**	2.4494E+07	2.7893E+04	2.3836E+05	2.7002E+04	2.4421E+04	5.2613E+04	1.1299E+04	4.8851E+05
	STD	**1.0014E+02**	1.3042E+08	1.7539E+04	2.3865E+05	3.0200E+04	2.4474E+04	3.7991E+04	5.2008E+03	1.6531E+06
F41	Best	**1.9055E+03**	2.2795E+03	1.9713E+03	2.2105E+03	1.9064E+03	1.9201E+03	2.1985E+03	1.0553E+05	2.0445E+03
	Worst	**2.0449E+03**	1.4130E+06	1.2518E+06	1.9760E+04	6.7077E+03	1.2805E+04	2.4005E+06	1.4838E+06	4.5944E+04
	Mean	**1.9576E+03**	3.4726E+05	6.8507E+04	7.9774E+03	3.2506E+03	3.9208E+03	3.6259E+05	5.2067E+05	1.3363E+04
	STD	**4.1818E+01**	5.0787E+05	2.2983E+05	4.2194E+03	1.3163E+03	2.4442E+03	6.9117E+05	4.0297E+05	1.3292E+04
F42	Best	**2.0043E+03**	2.0477E+03	2.0229E+03	2.0635E+03	2.0272E+03	2.0750E+03	2.0535E+03	2.2194E+03	2.0216E+03
	Worst	**2.0850E+03**	2.4561E+03	2.2434E+03	2.2549E+03	2.2256E+03	2.3155E+03	2.3154E+03	2.5885E+03	2.2104E+03
	Mean	**2.0401E+03**	2.2016E+03	2.0744E+03	2.1205E+03	2.0911E+03	2.1574E+03	2.1761E+03	2.4022E+03	2.0923E+03
	STD	**1.9792E+01**	1.0099E+02	4.7632E+01	3.8545E+01	6.4332E+01	6.3037E+01	6.9976E+01	9.5365E+01	5.2051E+01
F43	Best	**2.2000E+03**	2.2164E+03	2.2149E+03	2.2142E+03	2.2000E+03	2.2030E+03	2.2115E+03	2.2171E+03	2.2000E+03
	Worst	**2.2096E+03**	2.3907E+03	2.3441E+03	2.3571E+03	2.3473E+03	2.4033E+03	2.3874E+03	2.3613E+03	2.3634E+03
	Mean	**2.2003E+03**	2.3349E+03	2.3115E+03	2.2391E+03	2.2908E+03	2.2973E+03	2.3166E+03	2.3107E+03	2.2943E+03
	STD	**1.7553E+00**	4.9653E+01	2.7263E+01	3.5588E+01	5.7583E+01	5.5574E+01	6.4080E+01	2.9737E+01	5.6643E+01

TABLE 7 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F44	Best	**2.3000E+03**	2.3118E+03	2.3025E+03	2.3788E+03	2.3030E+03	2.3260E+03	2.3106E+03	2.3000E+03	2.3000E+03
	Worst	**2.3361E+03**	3.7741E+03	3.2135E+03	2.5734E+03	3.3660E+03	4.4978E+03	3.7673E+03	3.8154E+03	2.6450E+03
	Mean	**2.3073E+03**	2.8093E+03	2.3862E+03	2.4418E+03	2.4681E+03	3.1151E+03	2.6047E+03	2.7754E+03	2.3311E+03
	STD	**8.8348E+00**	4.5365E+02	2.3356E+02	5.1593E+01	3.4503E+02	7.8387E+02	4.7085E+02	6.3360E+02	7.0478E+01
F45	Best	**2.3000E+03**	2.6414E+03	2.6113E+03	2.6482E+03	2.6168E+03	2.6331E+03	2.6291E+03	2.6610E+03	2.6144E+03
	Worst	**2.6377E+03**	2.7596E+03	2.6438E+03	2.6739E+03	2.6730E+03	2.8430E+03	2.7049E+03	2.8399E+03	2.6542E+03
	Mean	**2.6133E+03**	2.6885E+03	2.6252E+03	2.6605E+03	2.6347E+03	2.7133E+03	2.6612E+03	2.7506E+03	2.6350E+03
	STD	**5.9660E+01**	3.4777E+01	9.8308E+00	6.3239E+00	1.5019E+01	4.9769E+01	1.8448E+01	5.2013E+01	1.0086E+01
F46	Best	2.5000E+03	2.7716E+03	**2.7268E+03**	2.7928E+03	2.7660E+03	2.6841E+03	2.7849E+03	2.5000E+03	2.5000E+03
	Worst	2.8092E+03	2.9570E+03	**2.7959E+03**	2.8359E+03	2.7966E+03	2.9812E+03	2.8844E+03	3.0906E+03	2.8247E+03
	Mean	2.7739E+03	2.8387E+03	**2.7675E+03**	2.8174E+03	2.7840E+03	2.8661E+03	2.8226E+03	2.8727E+03	2.7851E+03
	STD	5.2575E+01	3.6083E+01	**1.7976E+01**	9.7396E+00	8.8582E+00	5.6766E+01	2.4696E+01	9.1783E+01	5.5270E+01
F47	Best	**2.6002E+03**	2.9309E+03	2.9272E+03	2.9449E+03	2.9266E+03	2.6030E+03	2.8826E+03	2.9995E+03	2.9264E+03
	Worst	**2.9806E+03**	3.4103E+03	3.0030E+03	3.0628E+03	2.9494E+03	3.4386E+03	3.0815E+03	3.2074E+03	3.0214E+03
	Mean	**2.9225E+03**	3.0874E+03	2.9408E+03	2.9951E+03	2.9356E+03	3.2037E+03	2.9852E+03	3.0529E+03	2.9440E+03
	STD	**8.9244E+01**	1.5314E+02	1.6343E+01	2.5200E+01	1.0845E+01	1.5156E+02	5.1328E+01	4.7265E+01	2.0903E+01
F48	Best	**2.6000E+03**	2.9106E+03	2.6017E+03	3.0031E+03	2.6011E+03	2.8169E+03	2.8312E+03	2.8000E+03	2.8000E+03
	Worst	**3.4469E+03**	4.2858E+03	3.5599E+03	3.8060E+03	3.4721E+03	3.9795E+03	4.2815E+03	4.1824E+03	3.6953E+03
	Mean	**2.8864E+03**	3.5170E+03	3.1444E+03	3.4725E+03	3.1031E+03	3.4286E+03	3.4665E+03	3.9384E+03	3.1861E+03
	STD	**1.9924E+02**	4.2678E+02	2.0195E+02	2.5753E+02	2.5678E+02	3.6440E+02	3.5397E+02	2.4755E+02	2.6585E+02

(Continues)

TABLE 7 (Continued)

No.		GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F49	Best	**3.0612E+03**	3.0729E+03	3.0604E+03	3.0664E+03	3.0596E+03	3.1039E+03	3.0671E+03	3.1155E+03	3.0602E+03
	Worst	**3.1225E+03**	3.2695E+03	3.1219E+03	3.0865E+03	3.1138E+03	3.2724E+03	3.2828E+03	3.4901E+03	3.1143E+03
	Mean	**3.0651E+03**	3.1449E+03	3.0801E+03	3.0767E+03	3.0664E+03	3.1661E+03	3.1472E+03	3.1763E+03	3.0699E+03
	STD	**1.0981E+01**	4.8955E+01	2.0089E+01	5.4465E+00	1.3362E+01	4.8720E+01	4.8178E+01	7.7835E+01	1.3416E+01
F50	Best	**3.0000E+03**	3.1653E+03	3.1701E+03	3.1939E+03	3.1581E+03	3.0000E+03	3.0282E+03	3.1877E+03	3.1581E+03
	Worst	**3.1875E+03**	3.5042E+03	3.2387E+03	3.3201E+03	3.1876E+03	3.3445E+03	3.2486E+03	3.2087E+03	3.3710E+03
	Mean	**3.1750E+03**	3.2492E+03	3.1993E+03	3.2363E+03	3.1817E+03	3.1883E+03	3.2077E+03	3.1982E+03	3.2421E+03
	STD	**4.7578E+01**	7.0163E+01	1.4271E+01	2.3818E+01	1.2210E+01	6.0068E+01	3.9678E+01	4.9328E+00	6.5196E+01
F51	Best	**3.1453E+03**	3.2436E+03	3.1542E+03	3.1870E+03	3.1651E+03	3.1728E+03	3.1818E+03	3.3145E+03	3.1517E+03
	Worst	**3.2484E+03**	3.6724E+03	3.4666E+03	3.4169E+03	3.4572E+03	3.5514E+03	3.7038E+03	3.8365E+03	3.4199E+03
	Mean	**3.1857E+03**	3.3945E+03	3.2472E+03	3.2749E+03	3.2893E+03	3.3546E+03	3.3403E+03	3.6195E+03	3.2386E+03
	STD	**2.7915E+01**	1.0051E+02	8.6985E+01	4.4268E+01	1.0095E+02	1.0977E+02	1.4503E+02	1.2203E+02	8.0159E+01
F52	Best	**3.2591E+03**	6.4262E+03	3.3284E+03	4.9323E+04	3.3828E+03	3.8504E+03	4.9357E+03	3.6514E+03	3.5699E+03
	Worst	**8.4655E+03**	7.6566E+06	1.0042E+06	2.0791E+06	8.4455E+05	2.6406E+07	2.1189E+06	1.2562E+06	3.9759E+05
	Mean	**4.1048E+03**	1.4795E+06	4.8519E+04	4.2092E+05	7.9609E+04	2.0140E+06	4.6977E+05	8.9517E+04	4.6786E+04
	STD	**1.2665E+03**	2.2684E+06	1.8127E+05	4.3817E+05	2.1475E+05	5.7538E+06	5.7150E+05	2.2891E+05	8.2842E+04

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

F20 managed to find a far better solution than all optimizers. Overall, GTO performed well in the benchmark functions (F14–F23), and in almost all cases, it is capable of obtaining high-quality solutions compared with other optimizers, thus generating better results.

On the basis of the results from the benchmark (F24–F52) CEC2017 shown in Table 7 and Figure 12, GTO, in general, has been able to generate excellent and significant performance in 24 of the 29 benchmark functions found in this subset. It also had better performed than other optimization algorithms. Upon further examination, one can conclude that GTO has generated better solutions in all hybrid and composition benchmark functions than other optimizers, and thus outperforming others; however, in contrast to the Shifted and Rotated benchmark functions, it is clear it has performed better only in five out of nine of these functions than other optimizers. Figure 12 demonstrates the convergence diagrams for the CEC2017 benchmark, showing fast convergence and high performance and more efforts by the GTO effort. To obtain better solutions and escape local optimization entrapment in all stages of optimization, these evaluations have made it easy for us to understand that GTO has a very high and good capability to explore and exploit phases. In general, GTO proved to be a robust and high-performance algorithm because, as all the evaluations have shown, it has had an acceptable performance compared with other optimization algorithms.

4.5 | Running time analysis

This subsection examines the performance of GTO runtime with nine other optimization algorithms using 52 standard benchmark functions. The average runtime in 30 independent implementations for each benchmark function was calculated to conduct the runtime test for each optimizer algorithm, and the results are summarized in Table 8. According to the results in Table 8, it is clear that the GTO runtime to solve problems with a low ratio, of course, is greater and more acceptable than other optimization algorithms because, in GTO, both exploration and exploitation operations are performed in each iteration on the entire population. It requires more processing and prolongs the runtime. However, GTO has obtained less runtime to solve some benchmark functions than SHO, PSO, and GSA algorithms. In general, even though GTO runtime is longer than some optimization algorithms, it is clear that it has excellent advantages over other optimization algorithms, considering the better capabilities and performance it has shown in solving various problems. So even longer GTO runtime is of great value for use in a variety of issues.

4.6 | Significance of superiority analysis

Wilcoxon rank-sum statistical test with 5% accuracy was used to evaluate and discover essential differences between the proposed model and other optimization techniques.[76] Tables 9–14 illustrate the p-values from the Wilcoxon rank-sum statistical test with an accuracy of 5%. The '+' and '−' signs in Tables 9–14 indicate a positive and negative significant difference between the algorithms. Moreover, the '=' sign in Tables 9–14 states that no significant difference between the algorithms or the difference cannot be determined using the Wilcoxon rank-sum test. It should also first be examined whether the optimizers' results are unequal or not for multiple comparisons. If unequal, post hoc analysis should be performed to elucidate which of the algorithms differs. It is why the nonparametric Friedman's test method[82] is used.

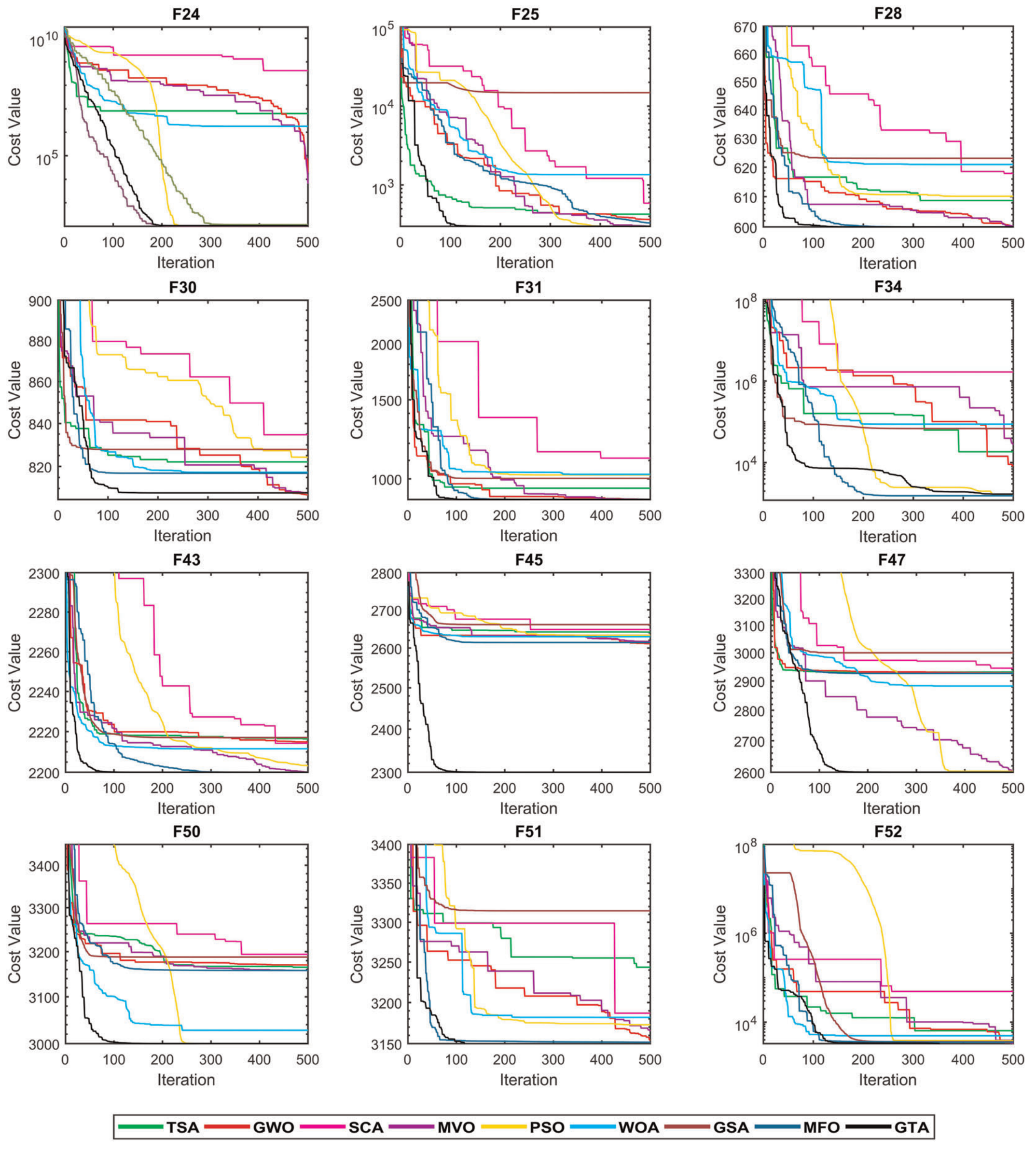

FIGURE 12 Convergence curves of various types of functions for different number of iterations. GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm [Color figure can be viewed at wileyonlinelibrary.com]

The results of this test are summarized in Tables 16–21. In this table, the average ranking of the optimization algorithms' results based on benchmark functions is provided in 6 series of evaluations.

According to the p-values in Table 9, statistically significant differences can be seen in almost all results. According to the p-values in Table 10, GTO has better solutions in almost all

TABLE 8 Comparison of average running time results (seconds) over 30 runs

No.	GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F1	0.2522	0.1126	0.1257	0.1279	0.2532	0.4791	0.0886	0.8066	0.1269
F2	0.2479	0.1225	0.1335	0.1302	0.2062	0.5438	0.1111	0.7949	0.1304
F3	0.8129	0.4778	0.4923	0.4914	0.6117	1.2792	0.5002	1.2706	0.4956
F4	0.2239	0.1083	0.1288	0.1171	0.2154	0.5650	0.0868	0.9281	0.1154
F5	0.2490	0.1349	0.1391	0.1353	0.2353	0.5808	0.1050	0.8116	0.1351
F6	0.2116	0.1216	0.1218	0.1200	0.2160	0.5753	0.0827	0.7799	0.1150
F7	0.3472	0.1808	0.2123	0.1882	0.2906	0.5882	0.1563	0.8550	0.1895
F8	0.2749	0.1369	0.1471	0.1459	0.1736	0.5709	0.1073	0.8055	0.1427
F9	0.2787	0.1229	0.1284	0.1274	0.2358	0.5479	0.0889	0.7898	0.1261
F10	0.2586	0.1294	0.1439	0.1502	0.2551	0.5864	0.0962	0.7997	0.1410
F11	0.3397	0.1404	0.1506	0.1551	0.2711	0.7612	0.1098	0.8197	0.1559
F12	0.6852	0.3332	0.3481	0.3570	0.4480	1.0099	0.3203	1.0135	0.3517
F13	0.7076	0.3319	0.3456	0.3502	0.4595	0.9970	0.3286	1.0109	0.3491
F14	1.3056	0.6637	0.6649	0.7001	0.9096	1.7131	0.7044	0.9289	0.6932
F15	0.2028	0.0720	0.0673	0.0830	0.1730	0.6384	0.0667	0.3603	0.0865
F16	0.1723	0.0479	0.0482	0.0630	0.0931	0.4319	0.0512	0.3075	0.0693
F17	0.1597	0.0414	0.0417	0.0597	0.0910	0.4197	0.0444	0.3037	0.0630
F18	0.1357	0.0399	0.0401	0.0574	0.0869	0.4277	0.0434	0.2998	0.0613
F19	0.2280	0.0943	0.0938	0.1289	0.1450	0.5446	0.1024	0.3762	0.1193
F20	0.2594	0.1008	0.1020	0.1247	0.1504	0.5383	0.1084	0.4261	0.1236
F21	0.3893	0.1738	0.1709	0.1822	0.2245	0.6627	0.1769	0.5769	0.1896
F22	0.4355	0.2245	0.2179	0.2392	0.2840	0.7584	0.2304	0.5340	0.2429
F23	0.5809	0.3684	0.2906	0.3009	0.3546	0.8733	0.3234	0.6067	0.3131
F24	0.2390	0.0893	0.1022	0.1083	0.1640	0.5696	0.0829	0.5098	0.1097
F25	0.2322	0.0876	0.0944	0.1040	0.1485	0.6318	0.0803	0.4713	0.1060
F26	0.2303	0.0853	0.0946	0.1039	0.1558	0.6815	0.0798	0.4704	0.1102
F27	0.2443	0.0919	0.1009	0.1109	0.1620	0.9098	0.0869	0.4787	0.1130
F28	0.2798	0.1133	0.1261	0.1316	0.1824	0.8433	0.1131	0.5013	0.1414
F29	0.2611	0.0941	0.1054	0.1118	0.1618	0.6034	0.1010	0.4839	0.1181
F30	0.2476	0.0928	0.1030	0.1119	0.1603	0.6080	0.0882	0.4785	0.1181
F31	0.2501	0.0945	0.1045	0.1121	0.1613	0.5836	0.1011	0.4792	0.1159
F32	0.2691	0.0975	0.1084	0.1164	0.1654	0.5573	0.0941	0.4851	0.1203
F33	0.2530	0.0896	0.0990	0.1083	0.1465	0.7033	0.0844	0.4789	0.1138
F34	0.2548	0.0916	0.1012	0.1098	0.1556	0.6443	0.0868	0.4768	0.1128

(Continues)

TABLE 8 (Continued)

No.	GTO	TSA	GWO	SCA	MVO	PSO	WOA	GSA	MFO
F35	0.2551	0.0922	0.1022	0.1093	0.1560	0.7267	0.0871	0.4826	0.1199
F36	0.2647	0.0982	0.1094	0.1137	0.1604	0.6125	0.0920	0.4868	0.1182
F37	0.2582	0.0886	0.0991	0.1054	0.1570	0.6042	0.0839	0.4755	0.1104
F38	0.2471	0.0922	0.1067	0.1101	0.1636	0.6436	0.0874	0.4785	0.1174
F39	0.2896	0.1109	0.1222	0.1319	0.1812	0.6622	0.1081	0.4994	0.1363
F40	0.2569	0.0935	0.1036	0.1115	0.1573	0.6295	0.0880	0.4819	0.1211
F41	0.4466	0.2086	0.2254	0.2424	0.2766	0.8117	0.2118	0.5973	0.2411
F42	0.2877	0.1133	0.1251	0.1377	0.1868	0.5900	0.1103	0.6792	0.1417
F43	0.3002	0.1155	0.1299	0.1404	0.1872	0.6646	0.1109	0.4998	0.1477
F44	0.3026	0.1302	0.1449	0.1491	0.2051	0.6738	0.1239	0.5169	0.1541
F45	0.3202	0.1305	0.1441	0.1549	0.2058	0.6838	0.1286	0.5948	0.1583
F46	0.4118	0.1354	0.1502	0.1591	0.2082	0.7103	0.1335	0.5225	0.1626
F47	0.6292	0.1240	0.1352	0.1526	0.2014	0.7202	0.1232	0.5244	0.1512
F48	0.7058	0.1428	0.1551	0.1667	0.3133	0.7127	0.1410	0.5310	0.1691
F49	0.7161	0.1487	0.1610	0.1739	0.3009	0.7327	0.1478	0.5343	0.1763
F50	0.6389	0.1397	0.1525	0.1611	0.2099	0.7625	0.1365	0.5300	0.1658
F51	0.3278	0.1355	0.1482	0.1638	0.2098	0.6633	0.1325	0.5225	0.1654
F52	0.5031	0.2310	0.2533	0.2655	0.3001	0.8735	0.2350	0.6208	0.2642

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

cases. According to the *p*-values in Table 11, GTO is seen to have performed significantly better than other optimization algorithms. The statistical results in Table 12 also confirm that GTO is a significant difference between the results obtained in GTO and other optimization algorithms in almost all cases. On the other hand, the *p*-values in Tables 13 and 14 confirm that GTO, in most cases, has significant performance compared with other optimization algorithms. Finally, according to Table 15, GTO in benchmark functions (F1–F13) in all dimensions has a significant advantage over almost all algorithms. However, in functions (F14–F23), GTO is seen to have outperformed all optimization algorithms. On the other hand, in the functions (F23–F52), GTO performed well in almost all functions and differed significantly from all optimization algorithms, as the results suggested.

Tables 16–21 illustrate Friedman's test results. Examining these results, it is clear that GTO ranks first in all series of evaluations in terms of ranking, so it is reaffirmed that GTO can produce high-quality solutions and is also statistically superior to all algorithms comparison. Finally, in all the evaluations, GTO proved to play a constructive role in the future as a robust algorithm.

TABLE 9 *p*-Values of the Wilcoxon rank-sum test with 5% significance for F1–F13 with 30 dimensions (*p*-values ≥0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO		Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*
F1	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+
F2	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F3	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+
F4	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F5	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	5.0723E-10	+	3.0199E-11	+	9.9186E-11	+	3.0199E-11	+
F6	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	9.8329E-08	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F7	3.0199E-11	+	4.5043E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	8.9934E-11	+	3.0199E-11	+	3.0199E-11	+
F8	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F9	1.2118E-12	+	1.1537E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.6080E-01	=	1.2108E-12	+	1.2118E-12	+
F10	1.2118E-12	+	1.0671E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2954E-08	+	1.2118E-12	+	1.2118E-12	+
F11	3.4507E-07	+	5.5843E-03	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	3.3371E-01	=	1.2118E-12	+	1.2118E-12	+
F12	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	5.5611E-04	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F13	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	8.0727E-01	=	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 10 *p*-Values of the Wilcoxon rank-sum test with 5% significance for F1–F13 with 100 dimensions (*p*-values ≥0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO		Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*
F1	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F2	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F3	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F4	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F5	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F6	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F7	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	1.5465E−09	+	3.0199E−11	+	3.0199E−11	+
F8	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.4742E−10	+	3.0199E−11	+	3.0199E−11	+
F9	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	3.3371E−01	**=**	1.2118E−12	**+**	1.2118E−12	**+**
F10	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	2.8541E−07	+	1.2118E−12	+	1.2118E−12	+
F11	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	NaN	=	1.2118E−12	+	1.2118E−12	+
F12	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F13	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 11 p-Values of the Wilcoxon rank-sum test with 5% significance for F1–F13 with 500 dimensions (p-values ≥ 0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO		Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***
F1	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F2	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F3	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F4	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F5	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F6	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F7	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	5.0723E−10	+	3.0199E−11	+	3.0199E−11	+
F8	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F9	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	NaN	**=**	1.2118E−12	**+**	1.2118E−12	**+**
F10	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	2.7516E−11	+	1.2118E−12	+	1.2118E−12	+
F11	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	NaN	=	1.2118E−12	+	1.2118E−12	+
F12	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F13	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 12 *p*-Values of the Wilcoxon rank-sum test with 5% significance for F1–F13 with 1000 dimensions (*p*-values ≥0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO		Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	*p*-values	R	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*
F1	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F2	3.0199E−11	+	3.0199E−11	+	1.2118E−12	+	3.0199E−11	+	5.2190E−12	+	3.0199E−11	+	3.0199E−11	+	1.2118E−12	+
F3	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+
F4	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F5	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F6	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F7	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.6459E−08	+	3.0199E−11	+	3.0199E−11	+
F8	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.3384E−11	+	3.0199E−11	+	3.0199E−11	+
F9	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	1.2118E−12	**+**	NaN	=	1.2118E−12	**+**	1.2118E−12	**+**
F10	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2599E−08	+	1.2118E−12	+	1.2118E−12	+
F11	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	3.3371E−01	+	1.2118E−12	+	1.2118E−12	+
F12	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F13	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 13 *p*-Values of the Wilcoxon rank-sum test with 5% significance for F14–F23 problems (*p*-values ≥0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO		Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***	***p*-values**	***R***
F14	1.2108E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	6.0793E−10	+	1.2118E−12	+	4.5736E−12	+	1.2656E−05	+
F15	8.2074E−09	+	1.3841E−08	+	4.8297E−09	+	4.8297E−09	+	4.9425E−08	+	2.3162E−08	+	5.2637E−11	+	3.3687E−09	+
F16	1.7203E−12	+	1.7203E−12	+	1.7203E−12	+	1.7203E−12	+	NAN	=	1.7203E−12	+	NaN	=	NaN	=
F17	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	NaN	=	1.2118E−12	+	NaN	=	NaN	=
F18	1.7546E−11	+	1.7546E−11	+	1.7546E−11	+	1.7546E−11	+	5.4258E−01	=	1.7546E−11	+	2.8432E−11	+	3.2643E−03	+
F19	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.2118E−12	+	1.1002E−02	+	1.2118E−E−12	+	1.2118E−12	+	1.2118E−12	+
F20	5.9250E−04	+	5.9250E−04	+	1.4059E−11	+	5.9250E−04	+	4.2227E−01	+	2.3333E−03	+	7.9933E−01	=	7.3279E−03	+
F21	1.3369E−11	+	1.3369E−11	+	1.3369E−11	+	1.3369E−11	+	2.0611E−08	+	1.3369E−11	+	3.0888E−09	+	7.0284E−05	+
F22	5.1436E−12	+	5.1436E−12	+	5.1436E−12	+	5.1436E−12	+	3.8501E−06	+	5.1436E−12	+	1.9080E−08	+	2.9894E−04	+
F23	1.4488E−11	+	1.4488E−11	+	1.4488E−11	+	1.4488E−11	+	4.3452E−03	+	1.4488E−11	+	9.1144E−09	+	2.6270E−01	=

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 14 *p*-Values of the Wilcoxon rank-sum test with 5% significance for F4–F52 problems (*p*-values ≥0.05 are shown in boldface)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO	Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*
F24	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	4.5043E−11	4.2039E−01	=	3.0199E−11	+	3.0199E−11	+	4.1178E−06	+
F25	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	7.3891E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F26	1.4046E−07	+	9.1929E−06	+	9.1929E−06	+	7.9575E−04	8.9538E−03	+	1.9088E−08	+	5.8737E−04	-	2.4940E−08	+
F27	4.9508E−11	+	3.1825E−01	=	3.1825E−01	+	1.3821E−02	1.4575E−10	+	2.3607E−10	+	4.9447E−11	+	4.9719E−04	+
F28	3.0199E−11	+	2.3243E−02	+	2.3243E−02	+	5.4620E−06	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	1.2597E−01	=
F29	3.0199E−11	+	1.0869E−01	=	1.0869E−01	=	3.6439E−02	1.0105E−08	+	4.0772E−11	+	8.0727E−01	=	1.5638E−02	+
F30	3.8180E−10	+	3.8709E−01	=	3.8709E−01	=	7.8446E−01	4.6836E−08	+	2.5711E−07	+	4.1973E−10	+	2.5581E−02	+
F31	1.4617E−10	+	7.2434E−02	=	7.2434E−02	=	5.5536E−02	5.4840E−11	+	3.6829E−11	+	4.0696E−11	+	1.9947E−05	+
F32	8.1465E−05	+	3.1830E−01	=	3.1830E−01	+	4.2039E−01	1.8567E−09	+	1.3594E−07	+	1.6285E−02	+	2.4157E−02	+
F33	3.6897E−11	+	1.6132E−10	+	1.6132E−10	+	6.5183E−09	2.3715E−10	+	3.0199E−11	+	3.0199E−11	+	8.6634E−05	+
F34	4.5043E−11	+	1.6980E−08	+	1.6980E−08	+	3.0199E−11	1.2235E−01	=	3.0199E−11	+	3.0199E−11	+	1.1747E−04	+
F35	3.6897E−11	+	1.2057E−10	+	1.2057E−10	+	7.0430E−07	1.4733E−07	+	7.3891E−11	+	4.5043E−11	+	2.0152E−08	+
F36	1.3111E−08	+	1.1737E−09	+	1.1737E−09	+	5.4620E−06	1.8682E−05	+	8.1527E−11	+	3.0199E−11	+	1.8567E−09	+
F37	3.3384E−11	+	3.0199E−11	+	3.0199E−11	+	4.4205E−06	2.2273E−09	+	4.0772E−11	+	3.0199E−11	+	3.0199E−11	+
F38	3.3520E−08	+	9.3341E−02	=	9.3341E−02	=	5.8737E−04	5.5611E−04	+	2.4913E−06	+	1.9568E−10	+	1.1738E−E−03	+
F39	3.1967E−09	+	8.5641E−04	+	8.5641E−04	+	2.0023E−06	1.8682E−05	+	8.9934E−11	+	8.8910E−10	+	5.8737E−04	+
F40	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	4.0772E−11	+	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+
F41	3.0199E−11	+	1.4643E−10	+	1.4643E−10	+	9.2603E−09	1.0666E−07	+	3.0199E−11	+	3.0199E−11	+	3.3384E−11	+
F42	1.7769E−10	+	1.4067E−04	+	1.4067E−04	+	1.0188E−05	4.5043E−11	+	1.3289E−10	+	3.0199E−11	+	7.2208E−06	+

TABLE 14 (Continued)

	Proposed method versus TSA		Proposed method versus GWO		Proposed method versus SCA		Proposed method versus MVO	Proposed method versus PSO		Proposed method versus WOA		Proposed method versus GSA		Proposed method versus MFO	
No.	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*	*p*-values	*R*
F43	3.0199E−11	+	3.0199E−11	+	3.0199E−11	+	7.3891E−11	3.6897E−11	+	3.0199E−11	+	3.0199E−11	+	4.5043E−11	+
F44	7.3891E−11	+	4.6371E−03	+	4.6371E−03	+	2.2257E−01	5.4941E−11	+	1.6947E−09	+	6.4142E−01	=	6.4142E−01	=
F45	3.0199E−11	+	6.4142E−01	=	6.4142E−01	=	1.1228E−02	6.0658E−11	+	1.9568E−10	+	3.0199E−11	+	1.1058E−04	+
F46	1.8567E−09	+	9.0307E−04	-	9.0307E−04	+	7.5059E−01	1.3111E−08	+	5.0723E−10	+	6.7220E−10	+	1.6798E−03	+
F47	3.3520E−08	+	6.7350E−01	=	6.7350E−01	=	9.6263E−02	4.6159E−10	+	2.0058E−04	+	3.0199E−11	+	9.1171E−01	=
F48	1.0702E−09	+	5.6073E−05	+	5.6073E−05	+	1.5178E−03	2.0283E−07	+	6.0104E−08	+	3.1589E−10	+	7.5991E−07	+
F49	8.9719E−11	+	5.2603E−04	+	5.2603E−04	+	2.7716E−01	4.9630E−11	+	5.4806E−11	+	4.0671E−11	+	2.0661E−02	+
F50	4.6159E−10	+	4.6159E−10	+	4.6159E−10	+	4.7445E−06	1.2023E−08	+	5.9673E−09	+	3.0199E−11	+	6.0459E−07	+
F51	3.3384E−11	+	5.3221E−03	+	5.3221E−03	+	7.0430E−07	1.8500E−08	+	5.9673E−09	+	3.0199E−11	+	5.0842E−03	+
F52	6.6915E−11	+	1.8724E−07	+	1.8724E−07	+	2.4374E−09	2.1532E−10	+	5.4907E−11	+	6.1177E−10	+	1.2864E−09	+

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 15 Statistical results of WSRT obtained by GTO

Function type	GTO versus TSA (+/=/−)	GTO versus GWO (+/=/−)	GTO versus SCA (+/=/−)	GTO versus MVO (+/=/−)	GTO versus PSO (+/=/−)	GTO versus WOA (+/=/−)	GTO versus GSA (+/=/−)	GTO versus MFO (+/=/−)
Function F1–F13 (D30)	13/0/0	13/0/0	13/0/0	13/0/0	12/1/0	11/2/0	13/0/0	13/0/0
Function F1–F13 (D100)	13/0/0	13/0/0	13/0/0	13/0/0	13/0/0	11/2/0	13/0/0	13/0/0
Function F1–F13 (D500)	13/0/0	13/0/0	13/0/0	13/0/0	13/0/0	11/2/0	13/0/0	13/0/0
Function F1–F13 (D100)	13/0/0	13/0/0	13/0/0	13/0/0	13/0/0	12/1/0	13/0/0	13/0/0
Function F14–F23	10/0/0	10/0/0	10/0/0	10/0/0	7/3/0	10/0/0	7/3/0	7/3/0
Function F23–F52	29/0/0	20/8/1	23/6/0	21/7/1	27/2/0	29/0/0	26/2/1	26/3/0
Total	91/0/0	82/8/1	85/6/0	83/7/1	85/6/0	84/7/0	85/5/1	85/6/0

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm; WSRT, wilcoxon static rank test.

TABLE 16 Results of Friedman test of iterative version on (F1–F13) with 30 dimensions

	Evaluation of F1–F13 with 30 dimensions								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	1.5859	5.9487	3.9705	8.3410	6.5513	5.8462	4.2141	6.5308	8.6410
Rank	**1**	**6**	**3**	**9**	**8**	**5**	**4**	**7**	**10**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 17 Results of Friedman test of iterative version on (F1–F13) with 100 dimensions

	Evaluation of F1–F13 with 100 dimensions								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	1.4718	5.5205	3.7333	8.4103	6.9974	5.8846	3.5987	7.3641	8.9513
Rank	**1**	**5**	**4**	**9**	**7**	**6**	**3**	**8**	**10**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 18 Results of Friedman test of iterative version on (F1–F13) with 500 dimensions

	Evaluation of F1–F13 with 500 dimensions								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	1.4333	5.7615	3.8333	8.1949	7.5821	5.9769	3.1859	6.8795	9.0821
Rank	**1**	**5**	**4**	**9**	**8**	**6**	**3**	**7**	**10**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 19 Results of Friedman test of iterative version on (F1–F13) with 1000 dimensions

	Evaluation on F1–F13 with 1000 dimensions								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	1.4423	5.8615	3.9744	8.2269	7.6744	5.9436	3.1103	6.6974	9.1115
Rank	**1**	**5**	**4**	**9**	**8**	**6**	**3**	**7**	**10**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

5 | ENGINEERING OPTIMIZATION PROBLEM

One of the important research areas is the use of *P*-metaheuristics to solve engineering problems. For this, in this section, the GTO performance in solving engineering problems was tested. For this test, seven low- and high-variable common engineering problems in CLEC 2011 Real World Optimization Problems[83] were used. Also, results from GTO performance were compared with

TABLE 20 Results of Friedman test of iterative version on (F14–F23)

	Evaluation of F14–F23								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	1.9200	7.0667	5.5300	8.1233	5.5767	3.7233	6.0367	4.5133	4.0700
Rank	**1**	**8**	**5**	**9**	**6**	**2**	**7**	**4**	**3**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

TABLE 21 Results of Friedman test of iterative version on (F24–F52)

	Evaluation of F24–F52								
	GTO	**TSA**	**GWO**	**SCA**	**MVO**	**PSO**	**WOA**	**GSA**	**MFO**
AVG	2.0567	6.7689	3.9067	6.3078	3.6056	5.4289	6.3978	6.4700	4.3489
Rank	**1**	**9**	**3**	**6**	**2**	**5**	**7**	**8**	**4**

Abbreviations: GSA, gravitational search algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; SCA, sine–cosine algorithm; TSA, tunicate swarm algorithm; WOA, whale optimization algorithm.

GWO,[3] MFO,[19] FFA,[2] TSA,[74] PSO,[28] and EO optimizers.[84] This evaluation is based on 30 independent runs using 30 populations and a maximum of 500 iterations, and finally, the best solution obtained in each of the optimization algorithms was used for comparison.

5.1 | Parameter estimation for Frequency-Modulated (FM) sound waves

FM sound wave synthesis is one of the most critical factors in modern music systems and plays an important role. This issue has six dimensions to optimize the FM synthesizer parameter. At $X = \{a_1, \omega_1, a_2, \omega_2, a_3, \omega_3\}A$ vector is given to the following equation for optimization as a sound wave. This problem is a highly complex one and a multimodal issue, having strong epistasis. This problem has the lowest value $f(\vec{X}_{sol}) = 0$. This problem is mathematically modeled as follows:

$$y(t) = a_1 \cdot sin(\omega_1 \cdot t \cdot \theta + a_2 \cdot sin(\omega_2 \cdot t \cdot \theta + a_3 \cdot sin(\omega_3 \cdot t \cdot \theta))),$$
$$y_0(t) = (1.0) \cdot sin((5.0) \cdot t \cdot \theta - (1.5) \cdot sin((4.8) \cdot t \cdot \theta + (2.0) \cdot sin((4.9) \cdot t \cdot \theta))).$$

In the above equation, $\theta = 2\pi/100$ and the parameters are defined in the range $[-6.4, 6.35]$. The cost function is calculated using the sum of the square errors between the estimated wave and the target wave as follows:

$$f(\vec{X}) = \sum_{t=0}^{100} (y(t) - y_0(t))^2.$$

According to Table 22, there is almost a similar performance between GTO and EO algorithms, with both finding high-quality solutions. Compared with other optimizers, GTO has performed very well.

TABLE 22 Comparison of results for parameter estimation for frequency-modulated (FM) sound waves

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
$x(1)$	0.6141	−0.5886	−0.6654	0.3415	−0.5627	−1.0000	−1.0000
$x(2)$	0.0432	5.0145	−0.1684	4.7881	0.0525	−5.0000	−5.0000
$x(3)$	−4.3251	−3.2779	1.5173	1.4309	−3.4797	−1.5000	1.5000
$x(4)$	4.7923	−4.9324	−0.1287	0.1158	4.8930	−4.8000	4.8000
$x(5)$	0.8339	−0.8562	−4.1335	0.0975	1.1491	−2.0000	2.0000
x(6)	0.1278	−0.1476	−4.8997	0.5480	−4.8345	4.9000	4.9000
Maximum cost	11.8969	13.1807	8.4725	25.1052	17.4291	8.4450E−12	2.2811E−27

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

5.2 | Circular antenna array design problem

The circular-shaped antenna has diverse radar and commercial satellite, mobile, and sonar communication systems.[85–87] This problem has high complexity with 12 dimensions.

The array factor for the circular array is written as follows:

$$AF(\varphi) = \sum_{n=1}^{N} I_n exp\left[jkr\left(cos\left(\varphi - \varphi_{ang}^{n}\right) - cos\left(\varphi_0 - \varphi_{ang}^{n}\right)\right) + \beta_n\right],$$

where

$$\varphi_{ang}^{n} = 2\pi(n-1)/N.$$

Table 23 illustrates the GTO performance results and other optimization algorithms in solving the Circular Antenna Array Design problem. According to the results, one can easily conclude that GTO can find high-quality solutions to this problem and has an outstanding performance compared with other algorithms.

5.3 | Spread spectrum radar polyphase code design probem

In designing radar systems involving pulse compression, one must pay attention to the way waveform is selected. Many radar pulse modulation methods make pulse compression possible. Polyphase codes are very focused attention because of their unique features, digital processing techniques, and easy implementation. In Reference [88], a new polyphase pulse compression code synthesis method is provided. This problem is modeled as a min-max nonlinear nonconvex optimization problem in a continuous optimization space with multiple local optimizations. In this case, the goal is to minimize the biggest among the socialized autocorrelation function samples. It is an NP-hard issue and has 20 constraints. It can be expressed as follows:

$$global\ min_{x\in X} f(x) max\{\varphi_1(x), \ldots, \varphi_{2m}(x)\},$$
$$X = \{x_1, \ldots, x_n\} \in R^n\{0 \le x_j \le 2\pi, j = 1, \ldots, n\},$$

where $m = 2n - 1$ and

TABLE 23 Comparison of results for parameter estimation for circular antenna array design problem

Algorithms	MFO	PSO	GWO	TSA	EO	FFA	GTO
$x(1)$	0.9545	0.8036	0.9866	0.6173	1.0000	1.0000	0.7733
x(2)	0.3995	0.5723	0.4619	0.2384	0.8062	0.6024	0.4872
$x(3)$	0.3198	0.2002	0.3347	0.2417	0.2000	0.2000	0.2708
x(4)	0.2511	0.2189	0.2036	0.2000	0.2068	0.3067	0.2000
$x(5)$	0.2018	0.2001	0.2643	0.2602	0.2000	0.2000	0.3088
$x(6)$	0.8685	0.4562	0.8556	0.2275	0.7701	0.7403	0.3453
x(7)	−26.5547	165.1796	−27.8905	180.0000	162.0306	164.3265	−28.7507
$x(8)$	35.4189	180.0000	38.0731	−180.0000	−166.5521	−175.2702	21.3763
$x(9)$	−75.3217	166.0494	−79.5042	−180.0000	179.6123	−180.0000	−98.3224
$x(10)$	−44.5045	−179.7188	−37.4055	−180.0000	−179.9335	180.0000	26.6935
$x(11)$	88.7929	180.0000	79.0364	180.0000	179.9995	−164.5573	89.9415
$x(12)$	−13.1863	175.4279	−12.8653	180.0000	165.0296	−180.0000	−21.0545
Minimum cost	−17.5798	−12.1064	−17.7263	−10.3666	−12.9313	−12.3261	−19.6726

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

$$\varphi_{2i-1}(x) = \sum_{j=i}^{n} cos\left(\sum_{k=\left|2i-j-1\right|+1}^{j} x_k\right), \quad i = 1, \ldots, n,$$

$$\varphi_{2i}(x) = 0.5 + \sum_{j=i+1}^{n} cos\left(\sum_{k=\left|2i-j\right|+1}^{j} x_k\right), \quad i = 1, \ldots, n-1,$$

$$\varphi_{m+i}(x) = -\varphi_i(x), \quad i = 1, \ldots, m.$$

According to Table 24 on findings from experiments performed by the GTO algorithm and other comparable optimizers, it is easily determined that GTO has performed well in this regard, outperforming other optimizers. However, as the dimensions of high-quality solutions increase, it still has reasonable-quality solutions.

5.4 | Cassini 2: Spacecraft trajectory optimization problem

One of the excellent engineering problems that can be solved using global optimization algorithms is how space missions are designed. Multiple Gravity Assist (MGA) problem is a mathematically optimized problem that includes nonlinear limit and finite-dimensions. MGA is used to find the best possible path for spaceship space voyages. On the other hand, MGA also has certain constraints. These constraints are necessary to find the best path; they can also be obtained using the MGA with deep space maneuver (MGA-1DSM) problem. Finally, using this technique, large-scale optimization problems can be solved, the details of which are fully described in References [89–92]. In the Cassini 2 problem, finding the best possible path to

TABLE 24 Comparison of results for parameter estimation for spread spectrum radar polyphase code design problem

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
$x(1)$	0.0044	4.3971	5.4869	1.2869	6.2667	4.3585	6.1488
$x(2)$	4.2016	1.4516	5.3875	5.8586	6.2107	0.7205	5.0841
$x(3)$	1.7748	4.6356	4.2862	3.2758	2.7031	0.8324	1.6206
$x(4)$	6.2832	4.2592	2.7940	2.6828	3.6306	6.0732	4.2628
$x(5)$	1.4021	6.2832	1.5939	2.2665	2.1111	2.0552	5.0733
$x(6)$	1.7472	4.4308	4.7279	0.3632	6.2527	0.2552	5.2813
$x(7)$	1.8514	2.2753	5.5036	2.1706	1.2884	2.5698	3.6056
$x(8)$	3.2907	2.9177	3.3613	3.7991	3.3188	2.2662	5.1049
$x(9)$	4.0260	3.7852	2.2454	2.8526	4.1096	3.1314	5.1965
$x(10)$	2.4005	2.9126	5.4152	5.8588	4.1900	2.8781	5.4175
$x(11)$	0.0000	0.4020	4.6036	0.4441	4.5901	1.5814	2.9723
$x(12)$	1.5084	2.6156	5.1030	1.4573	4.7653	5.2234	2.2919
$x(13)$	1.2992	4.5284	6.1617	1.2557	2.3749	4.1046	2.5131
$x(14)$	0.9298	3.0150	0.5646	1.8607	2.5506	5.3812	2.4686
$x(15)$	5.6946	6.0450	0.4183	6.1467	0.2602	4.0543	2.6674
$x(16)$	1.3546	4.0678	3.9228	0.8792	1.1331	3.3622	1.5515
$x(17)$	2.6873	3.0968	4.6189	0.5678	1.1350	4.7883	4.2706
$x(18)$	3.5593	5.1608	2.6261	2.4740	3.2753	5.9641	5.7299
$x(19)$	3.2745	5.2118	2.9798	2.3281	2.0097	5.1956	5.3923
$x(20)$	5.0690	3.3131	5.9047	3.5174	4.5150	0.0395	5.4838
Minimum cost	1.1455	1.1367	1.0128	1.5923	1.4710	0.9992	0.6971

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

Saturn's space voyage uses deep space maneuvers. Considering many patterns, we can say that this issue has much complexity, including 22 constraints.

The results from GTO and other comparable optimizers are shown in Table 25. According to Table 25, it is concluded that GTO, compared with other optimizers, has been able to find an excellent path for Cassini 2 problem. Also, the solution found is significantly better than other optimizers.

5.5 | Messenger: spacecraft trajectory optimization problem

Messenger is also a space voyage design problem for Mercury, where the MGA-1DSM problem is used to travel to Mercury. Given the planets' order in this problem's space path, this issue is complex and has 26 constraints. GTO and other optimization algorithms are compared using

TABLE 25 Comparison of results for Cassini 2: spacecraft trajectory optimization problem

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
Tt0	−209.4633	−203.9965	−39.2299	−432.3912	−728.9201	−572.5230	−704.6948
Vinf	3.2830	3.0740	4.7766	3.0000	4.9911	3.0057	3.0000
u	0.4244	0.4622	0.8265	0.0032	0.3588	0.0002	0.4875
v	0.7853	0.7687	0.2854	0.1203	0.2695	0.7075	0.4047
T1	131.3982	158.6309	366.9611	247.3835	137.8282	368.8591	166.8063
T2	461.8716	336.5469	111.8384	453.4750	449.4077	113.2429	394.8529
T3	211.4500	254.5485	177.6345	100.8880	132.7894	288.4974	298.7698
T4	508.1599	573.5396	517.0413	709.2399	691.1092	525.3567	584.0526
T5	1891.0147	2199.9056	2199.2514	2069.9806	2088.2445	2190.2062	1989.4309
eta1	0.2226	0.0108	0.3645	0.4596	0.0100	0.3527	0.0262
eta2	0.5635	0.6326	0.0918	0.0796	0.0100	0.0100	0.0103
eta3	0.0831	0.3883	0.4794	0.0157	0.0100	0.0100	0.0435
eta4	0.0709	0.1366	0.0101	0.3100	0.1989	0.0100	0.1007
eta5	0.0100	0.0107	0.1984	0.0258	0.5660	0.6405	0.0100
r_p1	2.4774	2.3331	1.0503	3.7745	1.9316	1.3821	1.4122
r_p2	3.0812	5.9848	1.2747	1.8825	1.4553	1.4523	4.5920
r_p3	1.1500	1.1500	1.1500	6.1972	2.3022	1.1893	1.1500
r_p4	71.4332	175.6207	4.4314	289.3773	68.2538	286.7064	290.9606
b_incl1	1.2980	0.5502	2.4412	−1.9077	−1.7969	1.4596	−1.3009
b_incl2	−0.7445	0.1282	−0.4835	2.1423	1.0122	−1.8030	1.6104
b_incl3	−1.5539	−2.4487	−1.6798	1.4694	1.7192	−1.6927	−1.8006
b_incl4	1.4787	1.7738	−1.4784	−1.2725	−1.5228	0.8913	−1.3151
Minimum cost	19.4199	21.7884	19.4901	24.5091	20.7313	17.2389	14.6652

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MVO, multiverse optimizer; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

Messenger: Spacecraft Trajectory l2Optimization Problem is illustrated in Table 26. GTO has been able to find a better solution than other optimizers. GTO's performance in solving space voyage problems indicates that GTO can solve such problems.

5.6 | Lennard–Jones (LJ) potential problem

LJ potential problem is used to optimize potential energy to minimize molecular potential energy by considering pure LJ cluster.[93,94] The LJ Potential problem is a multimodal optimization problem[93] with 30 constraints.

$$\vec{p}_i = \{\vec{x}_i, \vec{y}_i, \vec{z}_i\}, \quad i = 1, \dots, N,$$

which is given as follows:

$$V_N(p) = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(r_{ij}^{-12} - 2 \cdot r_{ij}^{-6}\right),$$

where $r_{ij} = ||\vec{p}_i - \vec{p}_i||_2$ with gradient

$$\nabla_j V_N(p) = -12 \sum_{i=1, i \neq j}^{N} \left(r_{ij}^{-14} - r_{ij}^{-8}\right)\left(\vec{p}_j - \vec{p}_i\right), \quad j = 1, \dots, N.$$

The first variable due to the second atom, that is, $x_1 \in [0, 4]$, t, then the second and third variables are such that$x_2 \in [0, 4]$ a and $x_3 \in [0, \pi]$. The coordinates x_i for any other atom is taken to be bound in the range:

$$\left[-4 - \frac{1}{4}\left\lfloor \frac{i-4}{3} \right\rfloor, 4 + \frac{1}{4}\left\lfloor \frac{i-4}{3} \right\rfloor\right].$$

The GTO experiment results and other comparable optimization algorithms in solving the LJ Potential Problem are demonstrated in Table 27.

Table 27 about the LJ Potential Problem test results shows that GTO performed better than other optimizers and managed to provide a much better solution. It has also performed well as constraints on engineering problems have increased.

5.7 | Static economic load dispatch (ELD) problem (instance 4)

The static ELD problem is used to minimizing the fuel cost of production units in a particular period. This problem's constraints are based on the generator's operating constraints, considering the constraints created in the ramp rate and prohibiting some functional areas, which have 40 constraints. Two different models are used to use this problem, including smooth cost functions and nonsmooth cost functions. These two models are as follows:

Objective function: The objective production cost function can be considered as follows:

$$\text{Minimize:} F = \sum_{i=1}^{N_G} f_i(P_i).$$

The cost function can be described for a unit with a valve point loading effect as follows:

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i sin\left(f_i\left(P_i^{min} - P_i\right)\right)\right|.$$

There are several limitations to this, including power balance constraints to consider the energy balance and ramp rate limits and prohibited operating zones.

Power balance constraints or demand constraints: These constraints are based on balancing the total system output and the total system load (P_D) and losses (P_L).

These constraints are based on balancing the total system output and the total system load (P_D) and losses (P_L).

TABLE 26 Comparison of results for Messenger: Spacecraft Trajectory Optimization Problem.

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
t0	2110.2178	2028.0783	2054.0056	2041.8393	2140.2196	2119.5171	2121.2328
Vinf	2.5000	2.9441	3.0905	2.7982	3.0454	4.0500	2.8345
u	0.4146	0.2958	0.2655	0.2669	0.4382	0.7054	0.5514
v	0.6156	0.5843	0.3372	0.8695	0.1656	0.1104	0.4439
T1	287.1243	303.5172	254.6830	263.0881	220.9636	244.3515	181.0357
T2	308.5598	263.2428	272.2233	254.2745	118.4991	234.7506	318.0092
T3	270.1088	243.7431	247.5046	263.5861	328.6136	221.0144	354.1881
T4	263.8982	257.8017	255.3651	263.9089	253.2550	265.2100	181.2484
T5	263.9142	265.1121	267.7502	263.9660	269.9542	264.0798	348.8881
T6	265.4221	266.0375	265.5928	264.8469	262.2830	264.2948	174.2908
eta1	0.4636	0.4248	0.4110	0.3621	0.4329	0.2957	0.4517
eta2	0.4730	0.4114	0.2368	0.4103	0.2402	0.2757	0.4682
eta3	0.5260	0.4655	0.3955	0.4005	0.6469	0.0100	0.7889
eta4	0.0100	0.0342	0.3971	0.5022	0.0765	0.3001	0.2114
eta5	0.0100	0.3659	0.3356	0.0367	0.2173	0.0303	0.6735
eta6	0.4166	0.2607	0.3852	0.0547	0.0161	0.1470	0.0846
r_p1	4.1688	5.5503	6.0000	1.1003	2.2844	6.0000	1.9351
r_p2	1.8143	1.4124	2.4637	1.2682	1.1013	3.1474	3.0574
r_p3	1.0500	2.7356	2.7016	6.0000	2.5748	4.4835	3.4400
r_p4	1.2249	2.4546	6.0000	4.6373	6.0000	6.0000	5.7437
r_p5	5.9336	3.1903	3.2996	1.0500	2.3220	1.9974	2.3688
b_incl1	0.2979	−0.6263	−0.6711	−0.4830	0.1810	−3.1414	2.7598
b_incl2	−1.3690	−0.8602	−1.0240	−0.9280	−0.9396	−1.0629	−1.4527
b_incl3	−1.3990	−1.5479	−0.7454	−1.3936	−3.1416	−0.3684	−3.0640
b_incl4	−0.1553	−0.3599	−0.7031	−0.8976	2.7587	−0.6907	1.2169
b_incl5	−3.0797	−3.0978	1.6515	−0.9712	1.8902	−2.0546	3.1407
Minimum cost	16.9754	19.0315	19.4928	20.8464	17.9505	16.1245	15.5848

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

$$\sum_{i=1}^{N_G} P_i = P_{\mathrm{D}} + P_{\mathrm{L}},$$

where P_{L} is obtained using B-coefficients, given by

$$P_{\mathrm{L}} = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_i + B_{00}.$$

TABLE 27 Comparison of results for the Lennard–Jones potential problem

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
$x(1)$	0.2671	0.5101	0.0885	0.3952	1.6833	0.5063	0.3898
$x(2)$	1.3870	0.6014	0.0564	0.8701	0.0000	0.3234	0.0533
$x(3)$	0.0000	0.3334	0.0001	0.2346	3.1416	0.0993	0.0149
$x(4)$	0.2431	1.1261	−0.4250	0.0311	2.1714	−0.4830	0.2374
$x(5)$	0.6003	−0.1796	0.7549	0.1771	0.3154	0.2170	−0.0356
$x(6)$	0.6206	0.3573	0.4617	0.8615	3.9527	0.1251	−0.9689
$x(7)$	−0.0579	−0.1758	0.5549	−0.4712	4.2500	−1.4984	0.2327
$x(8)$	0.5313	0.3317	0.5691	0.4195	−0.7042	−0.9648	0.9752
$x(9)$	−0.3676	−0.3018	0.6796	0.0113	−4.2500	−0.4689	0.3120
$x(10)$	0.1998	−0.2444	−0.0760	0.8097	4.5000	−0.7647	−0.0475
$x(11)$	−0.2608	−0.5978	0.8217	−0.0967	0.1022	−0.3281	−0.7009
$x(12)$	0.1920	1.1275	1.3947	−0.9175	−3.7141	−0.6517	0.4753
$x(13)$	0.1327	0.1736	0.7013	0.1488	−4.7500	0.0279	−0.4348
$x(14)$	−0.3662	−0.3807	−0.4230	0.6235	−4.7500	−0.6178	0.2358
$x(15)$	−0.7768	0.2576	0.5965	−0.7126	4.7500	−1.1716	0.5067
$x(16)$	0.0037	−0.3448	0.5578	4.4230	1.1704	−1.6942	0.3967
$x(17)$	−0.8250	0.3149	−0.7315	1.6414	0.3347	−0.0508	−0.8329
$x(18)$	−2.8792	0.7309	−0.3505	0.1900	3.9295	−0.8346	−0.4146
$x(19)$	0.3441	0.6694	−0.8490	0.4160	1.6469	−1.3933	−0.3016
$x(20)$	−0.3913	−0.9487	−0.1402	−0.0585	0.0724	−0.1601	0.6182
$x(21)$	1.1478	0.9023	0.2260	−0.0029	4.7661	0.1095	−0.4357
$x(22)$	−0.7464	0.1325	−0.1549	−0.1764	1.5774	−0.0008	1.1382
$x(23)$	−0.0224	0.2311	−0.8594	1.6307	5.5000	0.2862	−0.1329
$x(24)$	0.0111	−1.2411	0.3347	0.1136	−5.5000	−0.7550	−0.5768
$x(25)$	−0.4349	0.5326	−0.4152	0.1417	1.6534	−0.0934	−0.4794
$x(26)$	−0.8681	0.0108	−0.5623	2.5093	−0.5413	1.0809	−0.3347
$x(27)$	0.6086	1.1170	−0.5804	−0.2428	3.9793	−0.1651	−0.3088
$x(28)$	−0.5140	0.4693	−0.1642	−4.3317	0.7903	0.0836	0.6724
$x(29)$	0.0372	0.2896	−0.0697	−3.5969	5.1388	−0.5345	0.7786
$x(30)$	0.9538	−2.1906	0.9489	−0.8126	−6.0000	−0.1812	−0.5759
Minimum cost	−19.9700	−21.9253	−27.3717	−14.2024	−11.1041	−23.4774	−28.2927

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

TABLE 28 Comparison of results for static economic load dispatch problem

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
$x(1)$	65.7732	110.7118	103.0205	108.5997	86.7764	57.1636	111.8975
$x(2)$	104.7878	42.2252	36.0000	89.7401	109.3903	91.9088	100.4746
$x(3)$	63.6692	105.2938	120.0000	110.8107	98.5011	95.7470	64.3511
$x(4)$	172.5876	162.8263	189.6338	157.1027	189.3158	181.0211	145.3649
$x(5)$	77.1357	92.2553	97.0000	49.1501	76.4745	96.5571	50.4449
$x(6)$	99.2621	68.0081	136.5854	94.5158	86.0896	109.7787	138.5457
$x(7)$	183.2318	121.1933	273.9911	256.8686	298.9501	208.6967	260.0106
$x(8)$	287.4259	139.7436	274.2183	158.8165	173.9513	189.2741	230.5568
$x(9)$	287.7518	279.9977	285.4365	200.3664	205.2633	297.9077	247.9155
x(10)	296.1459	288.2853	299.6217	254.1104	219.6204	283.1402	285.6880
$x(11)$	304.0601	303.1599	371.6609	374.9980	314.6719	374.9649	94.0000
$x(12)$	320.7162	349.3907	317.7769	333.6486	113.9803	226.6591	337.9839
$x(13)$	482.7255	482.9042	311.9762	493.6140	155.4001	315.8057	497.1965
$x(14)$	459.5395	499.8803	161.0828	474.1602	488.5325	491.8038	443.7384
$x(15)$	314.7693	487.0160	500.0000	486.8390	500.0000	397.6386	500.0000
$x(16)$	355.7806	499.9725	500.0000	464.3867	491.4372	439.2792	460.5043
$x(17)$	487.0186	419.7674	500.0000	274.4959	421.1742	475.9742	316.5877
$x(18)$	459.9431	500.0000	413.1645	437.8435	486.2448	346.1074	336.7837
$x(19)$	541.0980	271.4420	242.0234	452.2642	488.1976	475.8074	539.5702
$x(20)$	336.0434	421.5196	416.0744	550.0000	525.6506	429.0016	420.1015
$x(21)$	482.8277	438.2721	550.0000	549.9985	549.4358	528.7221	544.1446

TABLE 28 (Continued)

Algorithms	MFO	PSO	GWO	TSA	FFA	EO	GTO
$x(22)$	525.4078	518.0395	372.5198	536.9445	447.9415	549.9375	493.7023
$x(23)$	326.4664	454.4803	549.5955	549.9456	549.9983	432.4329	542.9135
$x(24)$	530.0683	526.5453	548.7954	550.0000	509.0542	529.5707	546.2014
$x(25)$	508.2652	503.4424	550.0000	491.4257	549.9992	360.7464	482.2555
$x(26)$	489.2674	511.7457	529.8968	455.9687	536.6741	519.5425	481.6343
$x(27)$	10.0000	13.6759	58.2096	10.0193	73.1212	39.3881	25.2666
$x(28)$	53.3558	22.6828	51.1016	63.9740	17.9213	43.9776	10.1979
$x(29)$	68.5106	28.2811	25.0228	21.6121	44.8808	64.4903	10.0081
$x(30)$	63.5712	66.8016	91.4735	49.6835	72.5417	49.3813	97.0000
$x(31)$	164.5171	164.6338	60.0007	178.2766	147.4712	176.1681	172.7217
$x(32)$	181.5380	178.5046	189.9991	71.5426	123.4563	188.9978	189.1844
$x(33)$	114.3790	174.2031	60.0000	189.8273	148.6756	160.2995	187.9121
$x(34)$	156.6048	129.2586	196.8030	195.1742	187.6350	186.4852	196.4992
$x(35)$	186.4688	193.9308	184.9826	186.4474	90.0000	180.8683	119.2518
$x(36)$	166.1395	101.9305	200.0000	90.7939	141.1374	117.0903	196.7932
$x(37)$	91.7811	81.6841	55.3783	35.7710	108.1165	109.8832	102.1149
$x(38)$	70.8606	94.2705	25.0000	110.0000	77.5612	75.8633	90.2210
$x(39)$	110.0000	102.8126	106.4758	33.7037	81.5039	52.2144	25.6793
$x(40)$	500.5054	549.2117	545.4791	306.5603	513.2528	549.7036	404.5824
Minimum cost	132535.6506	131817.4757	133014.4698	134808.4967	132076.5271	132681.9214	130651.7695

Abbreviations: EO, equilibrium optimizer; FFA, Farmland Fertility Algorithm; GTO, Gorilla Troops Optimizer; GWO, Gray Wolf Optimization; MFO, moth–flame optimization; PSO, particle swarm optimization; TSA, tunicate swarm algorithm.

Generator constraints: The upper and lower bounds of each generating unit using a pair of inequality constraints are as follows:

$$P_i^{min} \leq P_i \leq P_i^{max}.$$

Ramp rate limits: The existence of units' limitations is due to ramp rate constraints, which are as follows.

Constraints in units are due to ramp rate constraints, which are as follows.

If power generation increases, $P_i - P_i^{t-1} \leq UR_i$.

If power generation decreases, $P_i^{t-1} - P_i \leq DR_i$.

Limitations related to generator performance are as follows:

Constraints related to generator performance are as follows:

$$max(P_i^{min}, UR_i - P_i) \leq P_i \leq min(P_i^{max}, P_i^{t-1} - DR_i).$$

Prohibited operating zones: Prohibition of work activity in some areas to save is described below:

Prohibition of work activity in some areas to save is as follows:

$$P_i \leq \check{P}^{pz} \quad \text{and} \quad P_i \geq \hat{P}^{pz}.$$

The GTO algorithm and other comparable optimization algorithms in solving the static ELD problem are shown in Table 28.

According to the results in Table 28 about testing the static ELD problem using GTO and other optimizers under comparison, it is seen that GTO is still able to provide a better solution than other optimizers, as it has even been able to maintain its search features and show much better performance as constraints have increased. Table 28 indicates that trailing GTO, MFO, FFA, and EO have performed competitively and near. According to GTO experiments in solving engineering problems, with different dimensions and much complexity, it is determined that GTO has an excellent ability to solve various problems, even as dimensions and constraints have increased. It can also be regarded as an excellent option to solve various optimization problems even if dimensions and constraints increase.

6 | CONCLUSION AND FEATURE WORKS

This article provided a new metaheuristic algorithm called GTO, inspired by the Gorilla group and their social way of life in nature. The GTO algorithm makes use of a different procedure to change the exploration and exploitation phases. Also, because various mechanisms are used in this algorithm, it has shown an excellent performance that can play a robust metaheuristic algorithm to solve various problems. Because the results from the various standard functions used for the GTO test indicate an excellent performance, it is required to have proper exploration and exploitation operations to generate excellent results in some of the standard functions under experiment. The proposed algorithm is tested on 52 benchmark function standards: standard, diverse and tested, and seven engineering problems provided at CEC-2011.

On the other hand, the GTO algorithm has been compared with nine other powerful metaheuristic algorithms to appraise its performance. This paper's statistical results suggest that the GTO algorithm has a better solution with better convergence than its competitors. For a fair comparison, Friedman's test and Wilcoxon rank-sum test were used. On the basis of the experimental results, it is concluded that the GTO algorithm applies to real-world case studies with unknown search spaces. This algorithm can also be applied to solve multi-objective optimization problems. In the meantime, GTO can be appraised in the future and used to solve recombination optimization problems and diverse problems with different anchors because metaheuristic algorithms are used in a wide range of problems.

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APPENDIX A

See Tables A1–A4

TABLE A1 Details of unimodal benchmark functions

No.	Type	Function	Dimensions	Range	F_{min}
F1	US	$f(x) = \sum_{i=1}^{d} x_i^2$	30,100,500,1000	$[-100,100]^d$	0
F2	UM	$f(x) = \sum_{i=1}^{d} \left\|x_i\right\| + \prod_{i=1}^{d} \left\|x_i\right\|$	30,100,500,1000	$[-10,10]^d$	0
F3	UM	$f(x) = \sum_{i=1}^{d} \left(\sum_{j=1}^{i} x_j\right)^2$	30,100,500,1000	$[-100,100]^d$	0
F4	US	$f(x) = max_i\{\|x_i\|, 1 \leq i \leq d\}$	30,100,500,1000	$[-100,100]^d$	0
F5	UM	$f(x) = \sum_{i=1}^{d-1} \left[100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right]$	30,100,500,1000	$[-30,30]^d$	0
F6	US	$f(x) = \sum_{i=1}^{d} \left(\left\|x_i + 0.5\right\|\right)^2$	30,100,500,1000	$[-100,100]^d$	0
F7	US	$f(x) = \sum_{i=1}^{d} ix_i^4 + random[0,1)$	30,100,500,1000	$[-128,128]^d$	0

Abbreviations: UM, multimodal; US, unimodal.

TABLE A2 Details of multimodal benchmark functions

No.	Type	Function	Dimensions	Range	F_{min}
F8	MS	$f(x) = -\sum_{i=1}^{d}\left(x_i sin\left(\sqrt{\lvert x_i \rvert}\right)\right)$	30,100,500,1000	$[-500,500]^d$	$-418.9829 \times n$
F9	MS	$f(x) = 10d + \sum_{i=1}^{d}\left[x_i^d - 10cos\left(2\pi x_i\right)\right]$	30,100,500,1000	$[-5.12,5.12]^d$	0
F10	MS	$f(x) = -20exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - exp\left(\frac{1}{d}\sum_{i=1}^{d} cos\, 2\pi x_i\right) + 20 + e$	30,100,500,1000	$[-32,32]^d$	0
F11	MS	$f(x) = \frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30,100,500,1000	$[-600,600]^d$	0
F12	MS	$f(x) = \frac{\pi}{d}\left\{10sin\left(\pi y_1\right) + \sum_{i=1}^{d-1}\left(y_i - 1\right)^2\left[1 + 10sin^2\left(\pi y_{i+1}\right)\right] + \left(y_d - 1\right)^2\right\} + \sum_{i=1}^{d} U\left(x_i, 10,100,4\right)$ $y_i = 1 + \frac{x_i + 1}{4}$ $U\left(x_i, a, k, m\right) = \begin{cases} k\left(x_i - a\right)^m x_i > a, \\ 0 - a < x_i < a, \\ k\left(-x_i - a\right)^m x_i < -a \end{cases}$	30,100,500,1000	$[-50,50]^d$	0
F13	MS	$f(x) = 0.1\left\{sin^2\left(3\pi x_1\right) + \sum_{i=1}^{d}\left(x_i - 1\right)^2\left[1 + sin^2\left(3\pi x_i + 1\right)\right] + \left(x_d - 1\right)^2\left[1 + sin^2\left(2\pi x_d\right)\right]\right\}$ $+ \sum_{i=1}^{d} U\left(x_i, 5,100,4\right)$	30,100,500,1000	$[-50,50]^d$	0

Abbreviation: MS, multimodal scalable.

TABLE A3 Details of fixed-dimension multimodal benchmark functions

No.	Type	Function	Dimensions	Range	F_{min}
F14	FM	$f(x) = \left[\frac{1}{500} + \sum_{i=1}^{25} \frac{1}{i + \sum_{j=1}^{2}\left(x_j - a_{j,i}\right)^6}\right]^{-1}$	2	$[-65,65]^d$	1
F15	FM	$f(x) = \sum_{i=1}^{d}\left[a_i - \frac{x_1\left(b_i^2 + b_i x_2\right)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	$[-5,5]^d$	0.00030
F16	FM	$f(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	$[-5,5]^d$	−1.0316
F17	FM	$f(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	2	$[-5,5]^d$	0.398
F18	FM	$f\left(x\right) = [1 + \left(x_1 + x_2 + 1\right)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)]\times$ $[30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	$[-2,2]^d$	3
F19	FM	$f(x) = -\sum_{i=1}^{4} a_i exp\left(-\sum_{j=1}^{3} b_{ij}\left(x_j - p_{ij}\right)^2\right)$	3	$[1,3]^d$	−3.86
F20	FM	$f(x) = -\sum_{i=1}^{4} a_i exp\left(-\sum_{j=1}^{6} b_{ij}\left(x_j - p_{ij}\right)^2\right)$	6	$[0,1]^d$	−3.32
F21	FM	$f(x) = -\sum_{i=1}^{5}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.1532
F22	FM	$f(x) = -\sum_{i=1}^{7}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.4028
F23	FM	$f(x) = -\sum_{i=1}^{10}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.5363

Abbreviation: FM: fixed dimensions multimodal.

TABLE A4 CEC2017 benchmark tests

No.	Function	Name of the function	Class	Optimum
F24	C01	Shifted and Rotated Bent Cigar Function	Unimodal	100
F25	C03	Shifted and Rotated Zakharov Function	Unimodal	300
F26	C04	Shifted and Rotated Rosenbrock's Function	Multimodal	400
F27	C05	Shifted and Rotated Rastrigin's Function	Multimodal	500
F28	C06	Shifted and Rotated Expanded Schaffer's F6 Function	Multimodal	600
F29	C07	Shifted and Rotated Lunacek Bi-Rastrigin Function	Multimodal	700
F30	C08	Shifted and Rotated Noncontinuous Rastrigin's Function	Multimodal	800
F31	C09	Shifted and Rotated Lévy Function	Multimodal	900
F32	C10	Shifted and Rotated Schwefel's Function	Multimodal	1000
F33	C11	Hybrid Function 1 ($N = 3$)	Hybrid	1100
F34	C12	Hybrid Function 2 ($N = 3$)	Hybrid	1200
F35	C13	Hybrid Function 3 ($N = 3$)	Hybrid	1300
F36	C14	Hybrid Function 4 ($N = 4$)	Hybrid	1400
F37	C15	Hybrid Function 5 ($N = 4$)	Hybrid	1500
F38	C16	Hybrid Function 6 ($N = 4$)	Hybrid	1600
F39	C17	Hybrid Function 7 ($N = 5$)	Hybrid	1700
F40	C18	Hybrid Function 8 ($N = 5$)	Hybrid	1800
F41	C19	Hybrid Function 9 ($N = 5$)	Hybrid	1900
F42	C20	Hybrid Function 10 ($N = 6$)	Hybrid	2000
F43	C21	Composition Function 1 ($N = 3$)	Composition	2100
F44	C22	Composition Function 2 ($N = 3$)	Composition	2200
F45	C23	Composition Function 3 ($N = 4$)	Composition	2300
F46	C24	Composition Function 4 ($N = 4$)	Composition	2400
F47	C25	Composition Function 5 ($N = 5$)	Composition	2500
F48	C26	Composition Function 6 ($N = 5$)	Composition	2600
F49	C27	Composition Function 7 ($N = 6$)	Composition	2700
F50	C28	Composition Function 8 ($N = 6$)	Composition	2800
F51	C29	Composition Function 9 ($N = 3$)	Composition	2900
F52	C30	Composition Function 10 ($N = 3$)	Composition	3000