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Mountain Gazelle Optimizer: A new Nature-inspired Metaheuristic Algorithm for Global Optimization Problems

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ABSTRACT

The Mountain Gazelle Optimizer (MGO), a novel meta-heuristic algorithm inspired by the social life and hierarchy of wild mountain gazelles, is suggested in this paper. In this algorithm, gazelles' hierarchical and social life is formulated mathematically and used to develop an optimization algorithm. The MGO algorithm is evaluated and tested using Fifty-two standard benchmark functions and seven different engineering problems. It is compared with nine other powerful meta-heuristic algorithms to validate the result. The significant differences between the comparative algorithms are demonstrated using Wilcoxon's rank-sum and Friedman's tests. Numerous experiments have shown that the MGO performs better than the comparable algorithms on utmost benchmark functions. In addition, according to the tests performed, the MGO maintains its search capabilities and shows good performance even when increasing the dimensions of optimization problems. The source codes of the MGO algorithm are publicly available at https://www.mathworks.com/matlabcentral/fileexchange/118680-mountain-gazelle-optimizer.

1. Introduction

Many problems in the real world have wide dimensions due to their limitations and various variables, which are classified as NP-hard problems. Different optimization algorithms have been developed to address such challenging issues, including exact and approximate ones. Approximation algorithms have been presented as a novel technique for handling high-dimensional and multi-state complex problems due to the unavailability of accurate optimization methods [1–4]. Heuristic and meta-heuristic algorithms are the two types of approximate algorithms. Because of its local confinement and application of specific optimization problems, heuristic algorithms attracted less attention. Meta-heuristic algorithms have lately been widely employed to address the majority of complicated real-world optimization problems, both multiplexing and nonlinear. Meta-heuristic algorithms provide acceptable solutions in a reasonable time but do not guarantee finding the best optimal solution for a given optimization problem [[5–7]. As a result, investigations over the last two decades reveal numerous efforts to tackle NP-hard problems using meta-heuristic algorithms based on an approximation approach and the pattern of natural events and animal and human social behavior. There are algorithms based on a stochastic and approximate process that can search the solution space to find the correct answer at a good time for optimization problems. These algorithms have solutions for exiting local optimal points. Still, unlike heuristic algorithms, they are not dependent on the type of problem and can be applied to various issues. This is why researchers often refer to them as black-box optimizers. However, a significant challenge in meta-heuristic algorithms is to create a dynamic balance between the two critical factors of exploration and exploitation strategies. Exploration refers to the extensive search in the response space, and exploitation means the productivity of the experiences gained in the search process and focusing on the more promising areas in the response space.

There are numerous nature-inspired meta-heuristics in the literature. Some of the most well-regarded meta-heuristics are briefly presented in this paragraph. Genetic Algorithm (GA) is inspired by Darwinian evolution. This algorithm with two essential combinations and mutation

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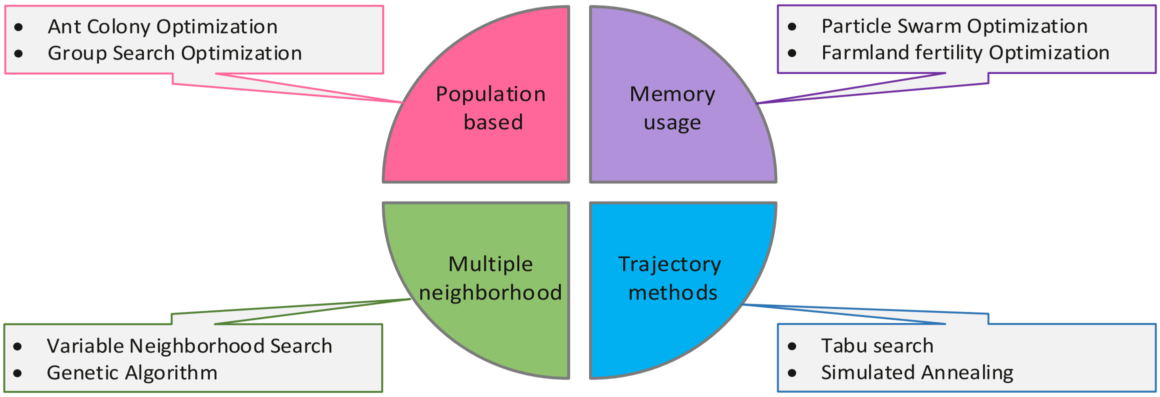

Fig. 1. Meta-hiseristic Callasification.

operators has been used in most optimization problems and is considered one of the most successful algorithms [8]. Karaboga et al. introduced the Artificial Bee Colony (ABC) algorithm in 2005, based on bee group behavior [9]. Worker bees, precursor bees, and search bees are all simulated using the ABC algorithm, which offers mathematical formulae for each step. It had flaws like every meta-heuristic algorithm, and new versions were released afterward.

In meta-heuristic algorithms, the technique of searching and generating optimal solutions for an optimization problem is founded on two crucial concepts: exploration and exploitation [10]. As a result, every successful meta-heuristic algorithm balances exploration and exploitation. Meta-heuristic algorithms use exploration to generate new solutions at the generation phase and reduce exploration as the optimization process advances. By decreasing the exploration process, the exploitation gradually increases. Most of the proposed meta-heuristics are inspired by the search behavior of animals and their prey hunting in nature. So, in this paper, inspired by the lifestyle and behavior of Gazelle, a new meta-heuristic algorithm is presented.

The following is the structure of this paper: The related works are reviewed in Section (2), and the MGO algorithm is described in detail in Section (3). The MGO algorithm's performance is discussed in Section (4). Conclusions and future work are also discussed in Section (5).

2. Related Works

Meta-heuristic algorithms form a random algorithm for finding the optimal solution. The two main problems of meta-heuristic algorithms are getting stuck in local optimal points and premature convergence. To tackle these issues, meta-heuristic algorithms have been developed. Meta-heuristic algorithms are approximation optimization algorithms that provide solutions for exiting from optimum local problems and may be applied to many issues. Several forms of meta-heuristic algorithms have been developed and presented in recent decades. Multiple criteria may be used to classify meta-heuristic algorithms. This classification is shown in Fig. 1.

➢ Population-based: During the search process, algorithms based on one solution update that answer, while population-based algorithms evaluate a population of solutions.
➢ Memory-based: Some meta-heuristic algorithms lack memory, meaning that these algorithms do not use the information obtained during the search (for example, simulated annealing). However, some meta-heuristic algorithms, such as Tabu search, use memory. This memory stores information obtained during the investigation.
➢ Route-based: The route method follows only a single route in the neighborhood chart. Some path-based ways move to worse solutions under certain conditions to avoid the optimal local trap for optimization operations.
➢ Multi-neighborhood: Some meta-heuristic algorithms use more than a few neighborhood structures to generate new solutions. This meta-heuristic algorithm uses N number of neighborhoods to initiate local search operations to avoid local optimization. Then, they use mechanisms to approach the global optimum in the problem space.

Various meta-heuristic algorithms have been proposed using nature-inspired. Some of which are mentioned below. In [11], a nature-based meta-heuristic algorithm inspired by the Golden Eagle hunting process is introduced to solve global optimization problems called the Goldpn Eagle Optimizer (GEO). The behavior of golden eagles in each case during prey's flight is influenced by the tendency to attack and travel by sea. Golden eagles keep the best target in their mind and sometimes make other eagles aware of the place of the target. A mathematical equation is proposed to simulate attack and travel vectors to calculate exploration and exploitation to solve optimization problems. It evaluated 33 benchmark functions from various categories, including unimodal, multimodal, and mixed engineering problems. For composite benchmark functions, the CEC 2017 exam was employed.

In [12], a meta-heuristic algorithm is proposed to optimize the problems of global algorithms inspired by natural selection theory. The proposed method depends on the competition between other meta-heuristic algorithms that allow the production of a substance, the offspring of which can create parental characteristics because they are unique and competitive. Therefore, this improves the convergence of solutions towards an optimal solution and avoids the limitations of other methods that aim to balance exploitation and exploration. According to these algorithms, three types of proposed methods have been developed. In the first type, one of the six algorithms used to update the flow is determined based on a predetermined order and the probability of fitness function performance for each solution. While the second type updates each solution by replacing six algorithms and then using existing algorithms, the current alternative is to update the solutions. The third type is the extension of the second version, which corrects all solutions using only one of six algorithms. Using the CEC 2014 and CEC 2017 benchmark functions, three different tests are run to evaluate the suggested performance. The comparative results supported the proposed method's efficiency compared to other approaches for various performance measures.

A Sine Cosine Algorithm (SCA) is presented in [13] for solving optimization problems with several randomized candidate solutions. In addition, a mathematical model based on sinus and cosine functions in sinusoidal and cosinusoidal (up and down) space draws closer to the ideal answer. Red Colobuses Monkey (RCM), a meta-heuristic algorithm inspired by the behavior of red colobus monkeys, may be utilized to solve optimization issues [14]. In addition, a novel meta-heuristic approach called Arithmetic Optimization Algorithm (AOA) is suggested in [15], which uses the distribution behavior of the significant arithmetic operators in mathematics, such as addition, multiplication,

Fig. 2. Mountain gazelle herd.

subtraction, and divisibility. This algorithm's performance is evaluated in twenty-nine benchmarks and various real-world engineering design difficulties to illustrate its use.

The Novel Caledonian Crow Learning Algorithm (NCCLA) is inspired by efficient social, antisocial, and reinforcing processes. New Caledonian crows used to acquire tool-building activities from pandanus trees to gather food [16]. Rain Optimization Algorithm (ROA) [17] is a new meta-heuristic inspired by showers, which moves to the minimum points after reaching the ground. This algorithm can find global extremum as well as local extremum. The authors have compared it with other available optimization algorithms such as PSO and bat algorithm with twenty-six benchmarks in three dimensions and a drilling optimization problem. The simulations show better performance and less computational time in finding the global minimum. ROA can also find at least one location and be used confidently in optimization problems.

In [18], a population-based optimization algorithm, called the Aquila Optimizer, is proposed, inspired by Aquila's natural behaviours during the baiting process. A series of experiments have been performed to prove the ability of the new optimizer to find optimal solutions to various optimization problems. Other emerging meta-heuristics in the literature are: Group Counseling Optimizer (GCO) [19], Social Spider Optimization (SSO) [20], Bird Mating Optimizer (BMO) [21], Gorilla Troops Optimizer (GTO)[28], Biogeography-Based Optimization (BBO) [22], Glowworm Swarm Optimization (GSO) [23], African Vultures Optimization Algorithm (AVOA) [24], Gravitational Search Algorithm (GSA) [25], Cat Swarm Optimization (CSO) [26], Clonal Selection Algorithm (CSA) [27], League Championship Algorithm (LCA)) [28], Intelligent Water Drops (IWD) algorithm [29], and Differential Evolution (DE) [30].

The large number of meta-heuristic algorithms presented today can raise the main reason for the need for this number of optimization algorithms. The No Free Lunch (NFL) theorem [31] solves this theory. Based on this notion, it has been rationally demonstrated that providing an algorithm for addressing all optimization problems is impossible. In other words, an optimization algorithm's success in addressing specific issues does not ensure that it will succeed in tackling problems of a different type. NFL theory allows researchers to develop new optimization algorithms to solve or improve various issues.

This paper presents a new meta-heuristic algorithm inspired by the group life and hierarchy of mountain gazelles in the wild. In this algorithm, gazelles' hierarchical and group life is formulated mathematically in Section (3).

3. Mountain Gazelle Optimizer (MGO)

The primary motivation for the MGO algorithm is explained in this section, followed by a detailed description of the proposed algorithm and mathematical model.

3.1. Inspiration

Mountain gazelle is a species of Gazelle. This animal is native to the Arabian Peninsula and the surrounding areas, and its distribution in these areas is large, but its density is very low. Its habitat is closely related to the Robinia tree species' habitat. As the temperature rose in the late Holocene, the species ceded parts of its territory to Gazella bennettii, which is well developed for living in hot weather. The mountain gazelle is intensely territorial. A great distance separates their territory from each other. They form three groups: mother-offspring herds, young male herds, and single males' territory [32]. The battle between the gazelles takes place regularly as the males reach adulthood. The struggle of the neighboring males over the environment is more dramatic and has less violence than the battle over the possession of females. Immature males use their horns more infighting than adult males or landowners [33]. The mountain gazelle constantly migrates in search of food over more than 120 km distances. The animal has a very high running speed and can run several hundred meters at 80 kilometers per hour. The mountain gazelle runs very fast [34]. Fig. 2 shows a herd of mountain gazelles.

3.2. Mathematical Model

In this subsection, an optimization algorithm based on social behaviors and the life of mountain gazelles is presented. The basic concepts of social and group life of mountain gazelles have been used to create a mathematical model for the MGO algorithm. The MGO optimization algorithm performs optimization operations using four main factors in the life of mountain gazelles: bachelor male herds, maternity herds, solitary, territorial males, and migration to search for food.

In the MGO algorithm, each gazelle (X_i) can become a member of one

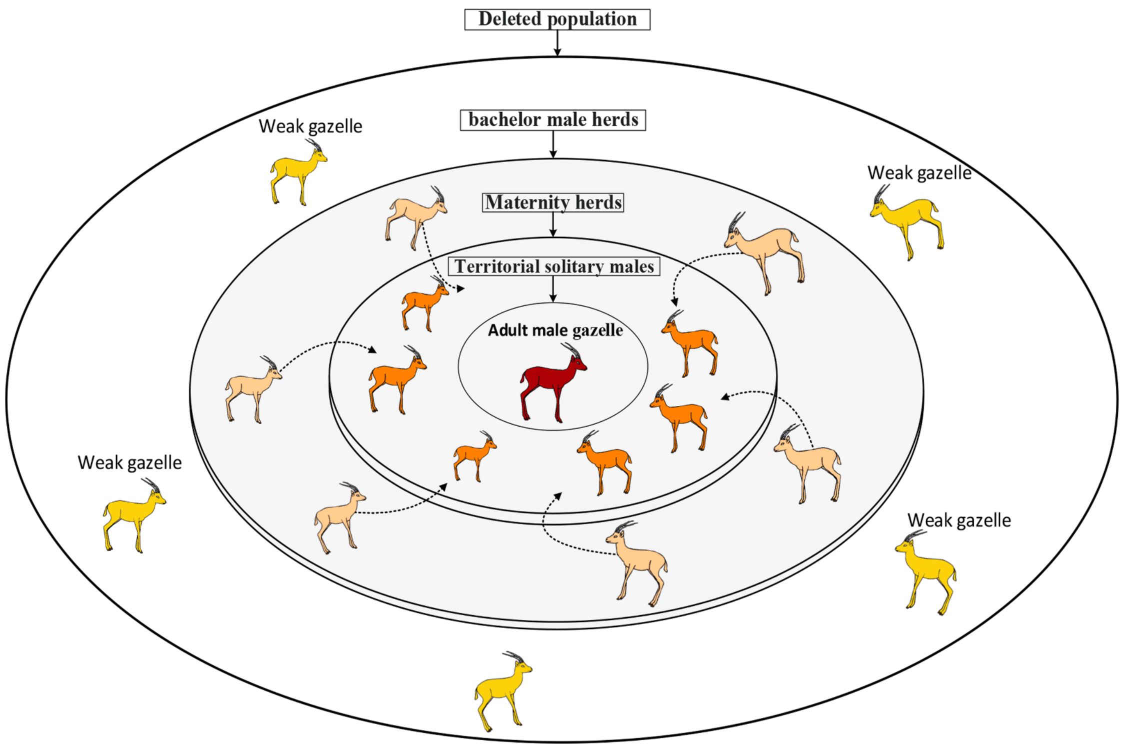

Fig. 3. MGO optimization procedure.

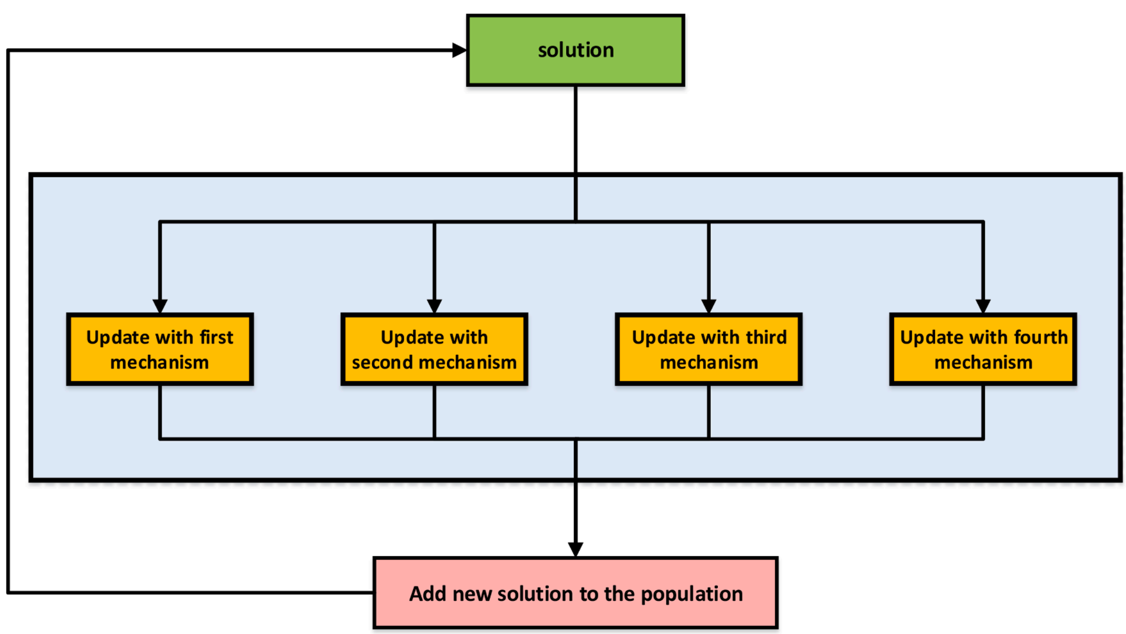

Fig. 4. MGO solution update procedure.

of the herds of maternity herds, bachelor male herds, or solitary, territorial males during the optimization operation. A new gazelle can be born from one of these three herds. MGO's best global solution is adult male gazelle in the herd territory. Because the gazelles in the male bachelor herds are young and not yet robust enough to procreate or take control of the female Gazelle, one-third of the search population in the overall population is estimated to have the lowest cost compared to other options for mathematical modeling.

Also, other solutions available to the whole population are considered gazelles in maternity herds. Strong gazelles with quality solutions are preserved at the end of each repetition. Other solutions that are added to the whole population and have a much lower cost are considered old and sick gazelles and are removed from the entire population. In the following, the mechanisms in MGO to perform optimization operations are formulated and expressed mathematically. Also, Fig. 3 shows an overview of the optimization process based on the agents in the MGO.

On the other hand, according to the nature of the proposed algorithm, exploitation and exploration phases are performed in parallel using four mechanisms, as shown in Fig. 4. As shown in Fig. 4,

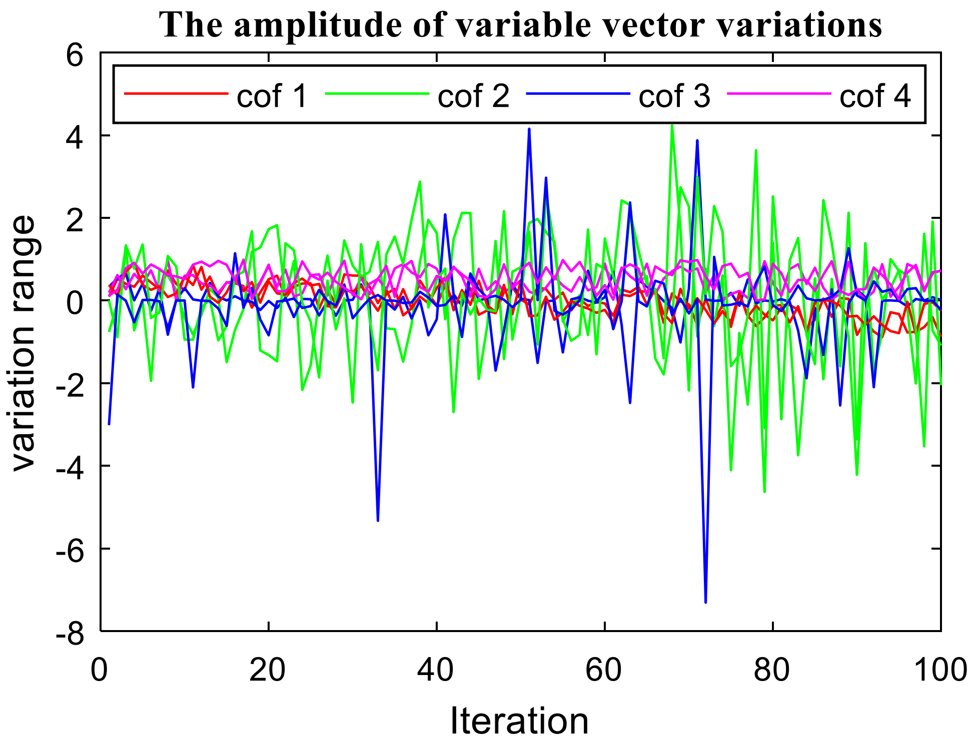

Fig. 5. Amplitude of Cof vector changes.

exploitation and exploration phases are performed in parallel.That is, it is possible for a solution to move towards the best solution and also perform the exploration operation according to the four mechanisms of the proposed model.

3.2.1. Territorial Solitary Males

When male mountain gazelles reach adulthood and become strong enough, they create a solitary territory and are highly territorial, and great distances separate the territories. The battle between adult male gazelles takes place over the territory or possession of the female. The young males try to occupy the territory or the female; on the other hand, the adult males try to protect their environment. Eq. (1) has been used to model the adult male territory.

$$TSM = male_{gazelle} - |(ri_1 \times BH - ri_2 \times X(t)) \times F| \times Cof_r \tag{1}$$

In Eq. (1), $male_{gazelle}$ is the position vector of the best global solution (adult male). The parameters ri_1 and ri_2 are random integers 1 or 2. BH is the young male herd coefficient vector, calculated using Eq. (2). F is also computed using Eq. (3). Cof_r is also a randomly selected coefficient vector updated in each iteration and used to increase the search capability, calculated using Eq. (4).

$$BH = X_{ra} \times \lfloor r_1 \rfloor + M_{pr} \times \lceil r_2 \rceil, \; ra = \left\{ \left\lceil \frac{N}{3} \right\rceil \ldots N \right\} \tag{2}$$

In Eq. (2), X_{ra} is a random solution (young male) in the interval of *ra*. M_{pr} is the average number of search agents $\lceil \frac{N}{3} \rceil$ which were randomly selected. Also, N is the total number of gazelles, while r_1 and $r_2$are random values between 0 and 1.

$$F = N_1(D) \times exp\left(2 - Iter \times \left(\frac{2}{MaxIter}\right)\right) \tag{3}$$

In Eq. (3), in the dimensions of the issue, N_1 is a random number from the standard distribution. The Exponential function is also known as *exp, MaxIter* is the total number of iterations, and *Iter* is the current number of iterations.

$$Cof_i = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)), \end{cases} \tag{4}$$

In Eq. (4), *a* is calculated using Eq. (5). also, r_3, r_4, and *rand* are random numbers in the range of 0 and 1. N_2, N_3 and N_4 are random numbers in the normal range and the dimensions of the problem. In the problem's dimensions, r_4 is likewise a random number in the field of 0 and 1. Finally, *cos* represents the Cosine function.

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter}\right) \tag{5}$$

Finally, in Eq. (5), *MaxIter* represents the total iterations, and *Iter* represents the current number of iterations. The amplitude of the *Cof* vector variation is shown in Fig. 5.

3.2.2. Maternity Herds

Maternity herds play an essential role in the life cycle of mountain gazelles, as these types of packs give birth to solid male gazelles. Male gazelles can also play a role in the delivery of gazelles and young males trying to possess females. This behavior is formulated using Eq. (6).

$$MH = (BH + Cof_{1,r}) + (ri_3 \times male_{gazelle} - ri_4 \times X_{rand}) \times Cof_{1,r} \tag{6}$$

In Eq. (6), *BH* is the vector of the impact factor of young males, which is calculated using Eq. (2). $Cof_{2,r}$ and $Cof_{3,r}$ are randomly selected coefficient vectors that are calculated independently using Eq. (4). ri_3 and ri_4 are integer and random numbers 1 or 2. $male_{gazelle}$ is the best (adult male) global solution in the current repetition. Finally, X_{rand} is the vector position of a gazelle that is randomly selected from the entire population.

3.2.3. Bachelor Male Herds

As male gazelles mature, they tend to create territory and take possession of female gazelles. At this time, the young male gazelles enter

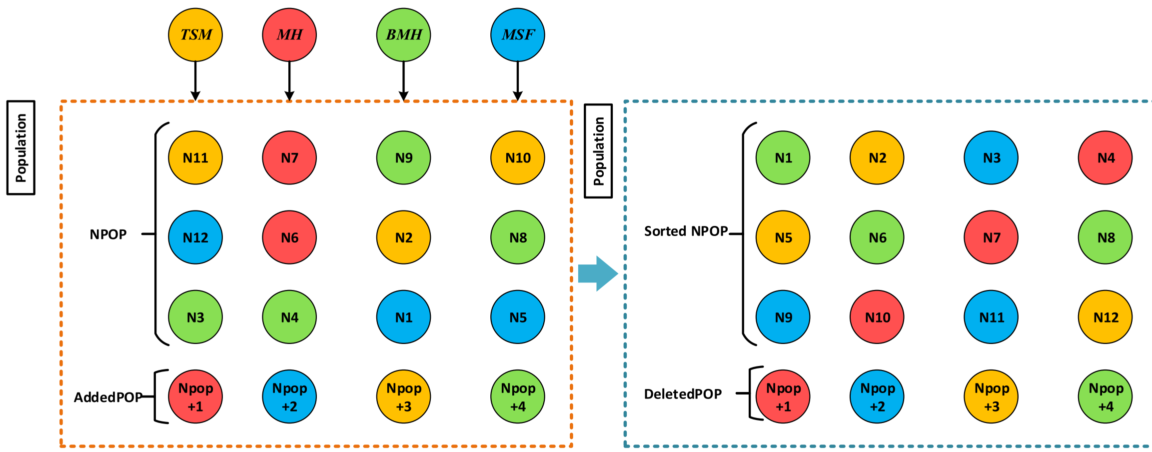

Fig. 6. Population update procedure.

Algorithm 1
Pseudo-code of MGO.

% MGO setting
Inputs: The population size N and maximum number of iterations T
Outputs: Gazelle's location and fitness potential
% initialization
Create a random population using $\boldsymbol{X_i}(i = 1, 2, ..., \boldsymbol{N})$
Calculate Gazelle's fitness levels.
While (stopping condition is not met) **do**
for (each Gazelle ($\boldsymbol{X_i}$)) **do**
%Alone male realm
Calculate *TSM* using Eq. (1)
% Mother and child herd
Calculate *MH* using Eq. (6)
% Young male herd
Calculate *BMH* using Eq. (7)
% Migration to search for food
Calculate *MSF* using Eq. (9)
Calculate the fitness values of *TSM, MH, BMH, and MSF,* Then add them to the habitat
end for
Sort the entire population in ascending order
Update $best_{Gazelle}$
Save the N Best Gazelles in the Max number of population
end while
Return $X_{BestGazelle}$, *best Fitness*

the battle with the male gazelles over the domain and control of the female gazelles, which much violence can accompany. Eq. (7) is used to formulate this behavior of gazelles mathematically.

$$BMH = (X(t) - D) + \left(ri_5 \times male_{gazelle} - ri_6 \times BH\right) \times Cof_r \tag{7}$$

In Eq. (7), $X(t)$ is the position of the gazelle vector in the current iteration. D is calculated using Eq. (8). ri_5 and ri_6 are integers 1 or 2 that are chosen randomly. $male_{gazelle}$ is the position of the male gazelle vector (the best solution). Also, BH is the impact factor of the young male herd, which is calculated using Eq. (2). Cof_r is a randomly selected coefficient vector, calculated and used using Eq. (4).

$$D = \left(|X(t)| + |male_{gazelle}|\right) \times (2 \times r_6 - 1) \tag{8}$$

In Eq. 8, $X(t)$ and $male_{gazelle}$ are the positions of the gazelle vectors in the current iteration, respectively, and the position of the vector is the best solution (adult male). r_6 is also a random number between 0 and 1.

3.2.4. Migration to Search for Food

Mountain gazelles constantly look for food sources and travel long distances to obtain food and migrate. On the other hand, mountain gazelles have high running speed and good jumping power. Eq. (9) has been used to formulate this behavior of gazelles mathematically.

$$MSF = (ub - lb) \times r_7 + lb \tag{9}$$

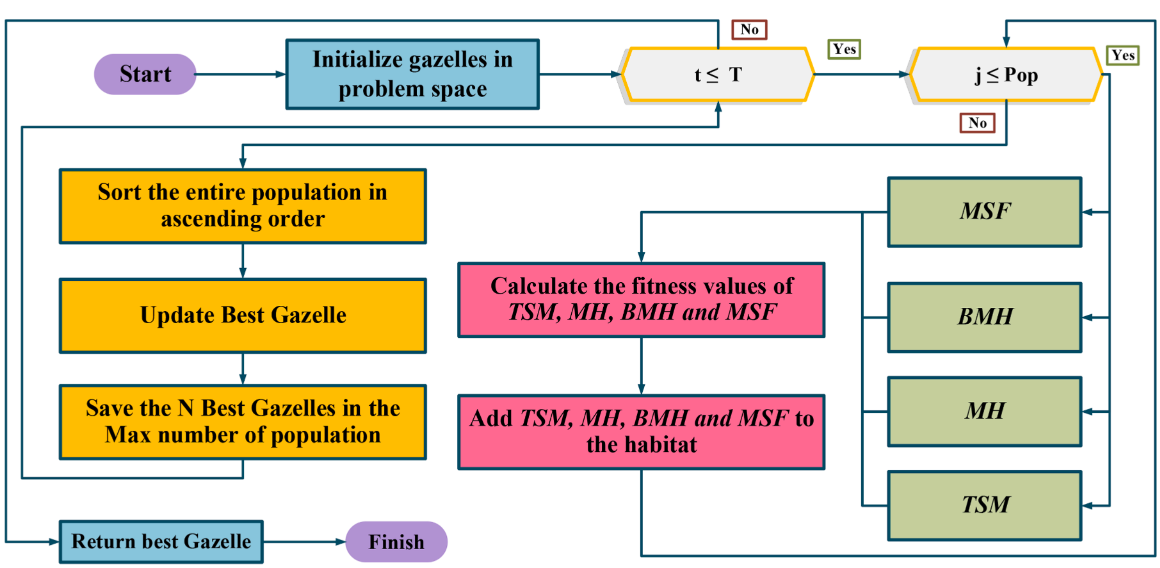

Fig. 7. Flowchart of MGO.

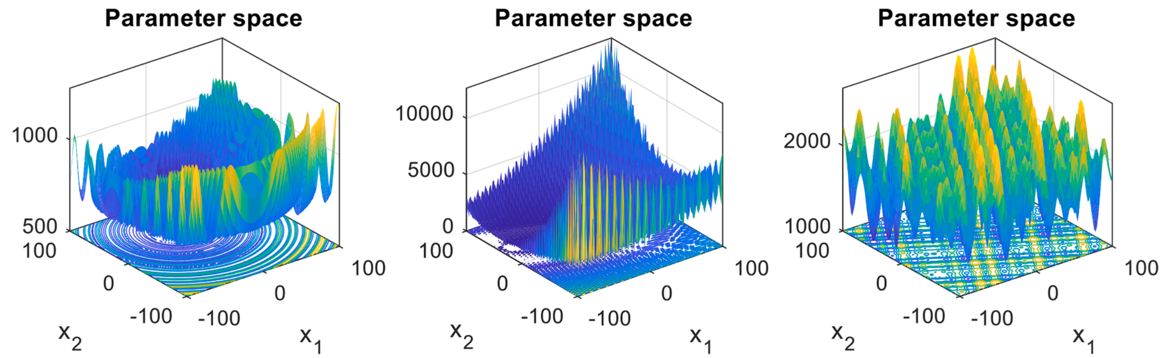

Fig. 8. The benchmark functions C6, C7, and C10 are shown in parameter space.

In Eq. (9), *ub* and *lb* are the problem's upper and lower limits, respectively. Finally, r_7 is an integer between 0 and 1 chosen at random.

The four TSM, MH, BMH, and MSF mechanisms are applied to all gazelles to produce new generations of gazelles. A new era is added to the total population, and each generation is equal to one replication. Moreover, all gazelles are arranged in ascending order at the end of each era. The best gazelles, which have high quality and promising solutions and cost less, are preserved in the total population. Other gazelles, considered old or weak ones, are removed from the whole population. The best Gazelle is also viewed as the adult male gazelle that owns the territory. The above procedure is shown in Fig. 6.

The flowchart and pseudo-code of the MGO algorithm are also shown in Algorithm (1) and Fig. 7.

3.3. Computational Complexity of the MGO Algorithm

It is influenced by three primary factors: initialization, fitness assessment, and Gazelle update. The computational cost of the initialization operation is equivalent to O due to the existence of N Gazelles (N). Furthermore, the computational complexity of the mechanism for producing and updating new solutions, which is conducted on all search agents in the optimization space, is equal to $O\ (T \times N \times D \times 4)$. Where D is the issue dimension., and T is the maximum number of iterations. Finally, the computational complexity of the MGO algorithm is equal to $O\ (T \times N \times 4) \times O\ (f(P))$ when the cost function is evaluated.

3.4. Exploration/Exploration and Convergence

In the MGO algorithm, four different mechanisms are used to optimize each search factor and iteration. Each of the mechanisms utilized has its characteristics, and each of the current tools improves MGO's performance in each of the intensification and variety components. Also, each of these mechanisms uses coefficient vectors with different steps to cause various movements for search agents. In each iteration of the MGO optimization process, four more operations are done on each of the search agents. The result of these operations is a set of the population that several search agents move to solutions. Hopefully, they move, and some solutions search for the problem space, making the exploration and exploitation phases parallel in all optimization stages and avoiding falling into the optimal local trap. At all stages of search engine optimization, they are moving towards promising solutions. Finally, the population update process in the MGO algorithm also ensures that search agents with higher quality solutions are considered and ultimately ensures that all search agents are gathered in one optimal spot.

4. Result and Discussion

The performance of MGO in solving optimization problems is thoroughly assessed in this section.

4.1. Benchmark Set and Compared Algorithms

The performance of the MGO algorithm has been evaluated using a variety of common benchmark functions (unimodal (UM), composition (CM), and multimodal (MM)), each of which may represent a different set of MGO capabilities. As specified, each of the benchmark functions may illustrate various MGO capabilities. The UM benchmark functions (F1-F7) demonstrate optimization algorithms' exploitative capabilities (intensification) with just one global optimum point. Standard MM functions (F8-F23) are utilized to define optimization algorithms' exploration (diversification). Tables 28-30 in the Appendix A section show the mathematical formulae and attributes of the UM and MM functions. Other benchmark functions, such as the benchmark function (F24– F52) in the CEC 2017 competition, have also been employed for additional analyses of the third group. These functions cover shifted MM instances, and the hybrid composite is rotated (see Fig. 8). Because obtaining high-quality solutions in this series of functions requires a good balance in the exploitation and exploration phases and an excellent ability to search in different problem spaces and escape from local optimal points, these functions are used to investigate optimization algorithms as much as possible. Table 31 in the Appendix A section contains details on the CEC benchmark functions. A comparison has been made with WOA [35], MVO [36], SCA [13], MFO [37], GSA [25], PSO [22], TSA[45], FFA [10], and GWO [38] optimization algorithms to evaluate the quality of the results obtained from MGO. The best solution, the worst solution, the standard deviation (STD), and the average findings are used to make this comparison (AVG). The WOA, MVO, SCA, MFO, TSA, GWO, and FFA algorithms were the most recently optimized algorithms in the comparisons. PSO and GSA algorithms, on the other hand, have been chosen as the most often utilized algorithms for solving multiple optimization issues. The Wilcoxon statistical test [39] with a significance threshold of 5% and Friedman's test [40] were employed to discover significant differences in the results produced by MGO compared to other similar optimization techniques.

MGO algorithm was tested and assessed using Matlab R2017a (9.2.0.538062) with Windows 7 Enterprise 64-bit operating system, Intel Core i7-4510U 2.6 GHz CPU, and 8.00 GB RAM, as well as other optimization techniques. All of the tests that were used to assess the MGO algorithm included 30 populations with a maximum of 500 replications. The findings were compared using the acquired results based on 30 independent results. The settings supplied in the WOA [35], MVO [36], SCA [13], MFO [37], GSA [25], PSO [22], TSA [41], FFA [10], and GWO [38] were used to establish the parameters of matching optimization methods. MGO is a parameter-free method, so there are no parameters to specify. The parameter settings for the optimization strategies are shown in Table 1.

4.2. Qualitative results of MGO

In this sub-section, six typical unimodal and multimodal functions

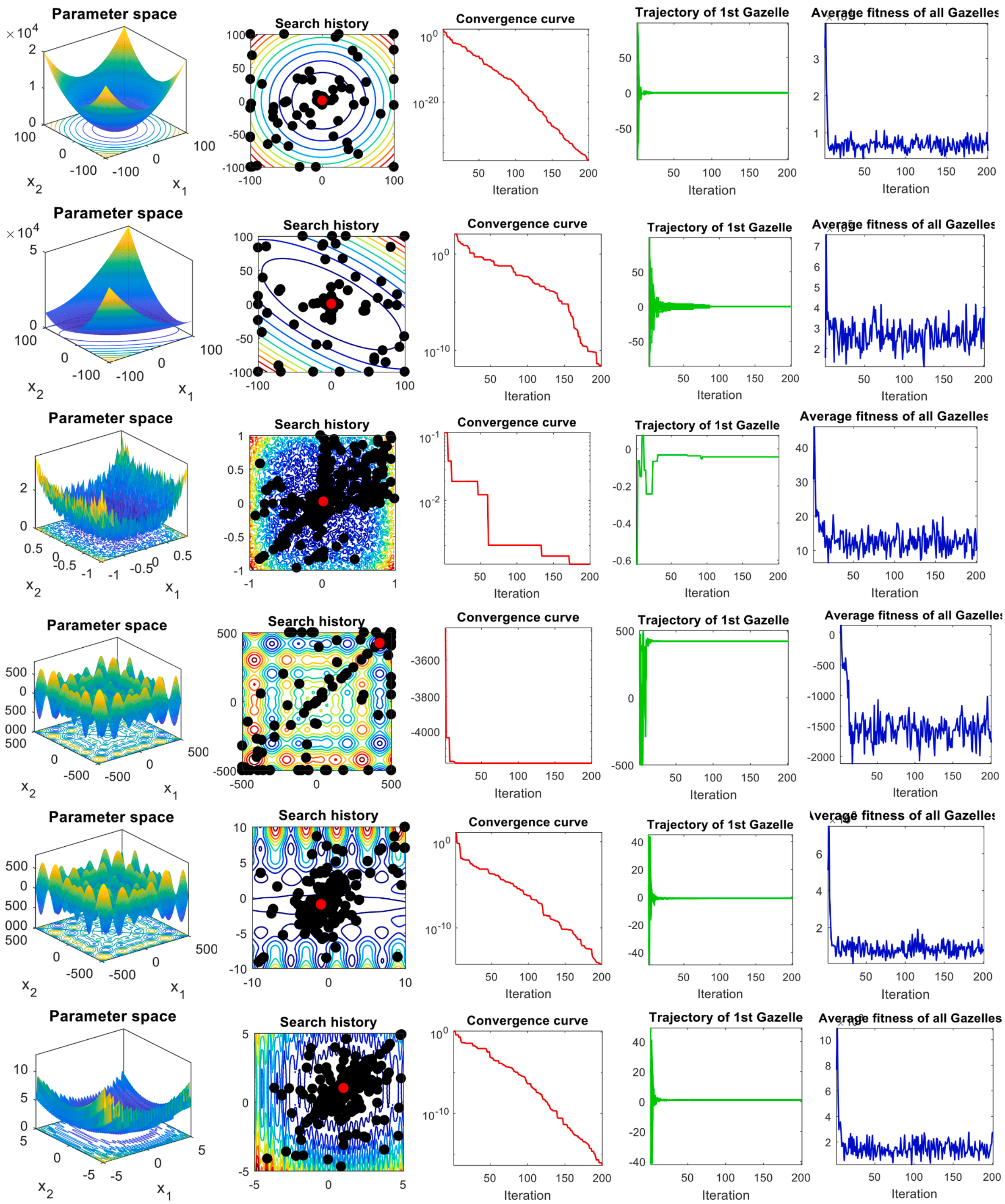

Fig. 9. F1, F3, F7, F8, F12, and F13 function qualitative findings.

have been used to evaluate MGO quality outcomes. This assessment considered four key factors: search history, average population fitness, convergence behavior, and the initial Gazelle trajectory. The locations of search agents in the issue space are shown in search history diagrams. Also, the convergence behavior diagram shows the cost of the best solution (adult male gazelle) during the optimization process. The population's average fitness chart, on the other hand, depicts the changes in the cost of all search parameters throughout the optimization process. The first Gazelle's trajectory graphic also shows the adjustments made to the first Gazelle. According to the search history diagrams in Fig. 9, MGO has consistently addressed diverse issues, examining almost the whole problem space before performing search optimization operations in promising regions. This behavior best shows MGO's capacity to balance the exploitation and exploration stages. The convergence diagrams in Fig. 9, which relate to the cost of the best solution (adult male gazelle) during the optimization operation, show that the MGO has good convergence capabilities. Convergence diagrams also offer a rapid and continuous decreasing pattern. Finally, it can be concluded that MGO has a good performance in the resonance component.

The average fitness of the population diagrams is shown in Fig. 9. A closer look at the average fitness chart of the population reveals that the MGO quickly improves the position of all search agents and then performs optimization operations alongside good points. On the other hand, the amplitude of the changes decreases with increasing repetitions.

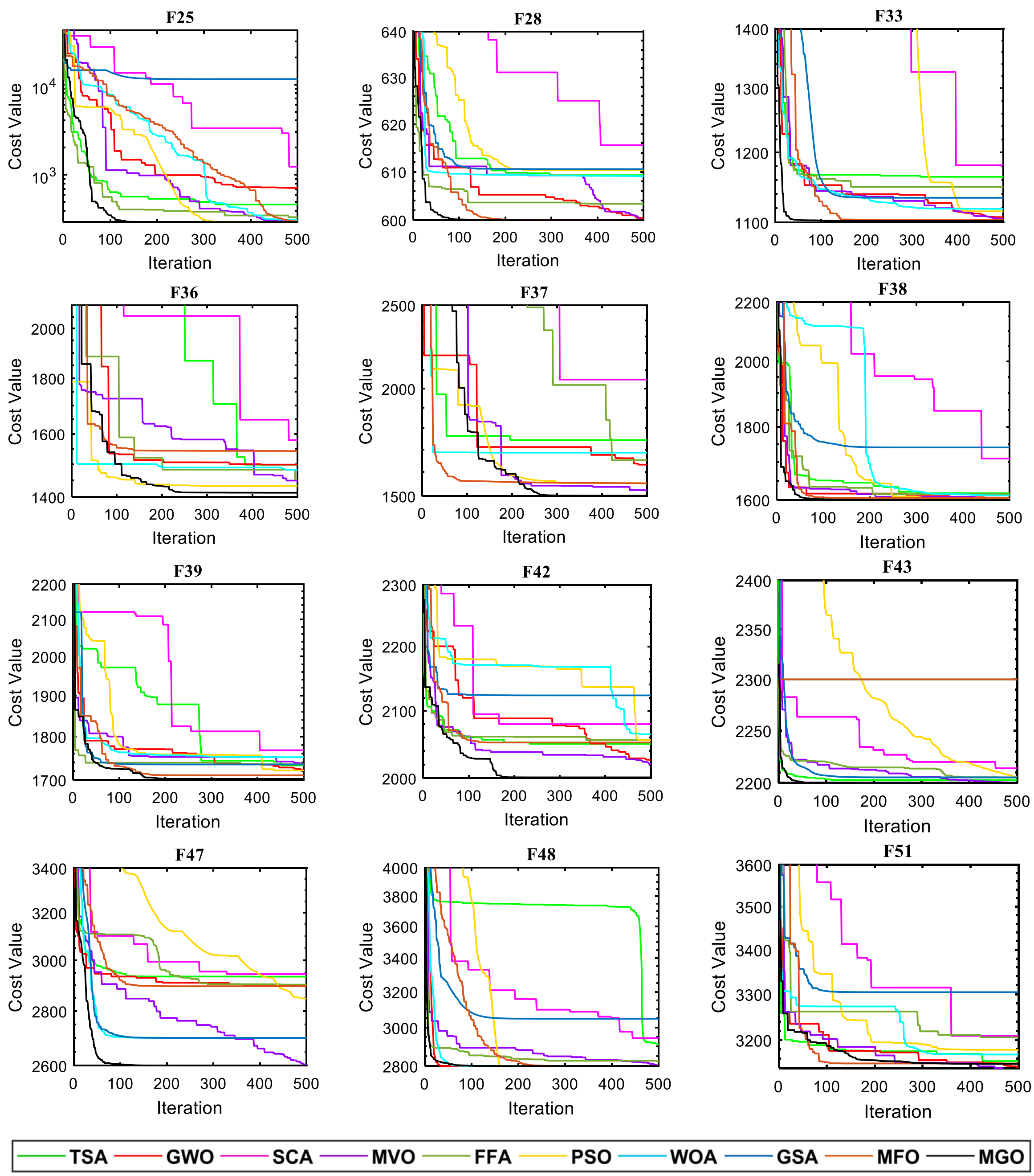

Fig. 10. Curves of convergence for various kinds of functions for varying amounts of iterations.

However, this change can still be seen as short-range oscillations due to the MGO trying to produce various solutions or escape from optimal local points. Finally, it can be concluded that MGO has good performance in diversity components and can maintain diversity well in all optimization stages.

The trajectory diagrams of the first Gazelle show the behavior of the first Gazelle, which is the best solution (adult male) according to the characteristics of the MGO algorithm. Looking closely at these diagrams, it can be concluded that the first Gazelle had sudden movements in the first repetitions and then had very few fluctuations. However, this behavior is due to the conduct of MGO in performing optimization operations. Because in MGO, the first Gazelle is always the best solution and is replaced with other solutions during the optimization operation. However, according to [42], such behaviors can cause convergence at one point. On the other hand, other gazelles can make sudden movements during the optimization operation and navigate the entire optimization space, which results in the first search factor being of good quality.

4.3. Quantitative Results and Discussion

The performance of MGO was tested and assessed in this subsection, and the results achieved by MGO were compared to those obtained by other optimization techniques. The 52 benchmark functions were employed to undertake tests and evaluations, with scalable F1-F13 functions used for scalability testing. F1-F13 functions had 30, 100, 500, and 1000, respectively. This experiment can demonstrate how the MGO responds to large-scale challenges and the quality of the outcomes. On the other hand, it becomes obvious if MGO will sustain its search capabilities in the face of major problems. The functions F14-F52 were then utilized for further assessments. All studies were conducted utilizing the findings of 30 separate performances over 500 iterations and

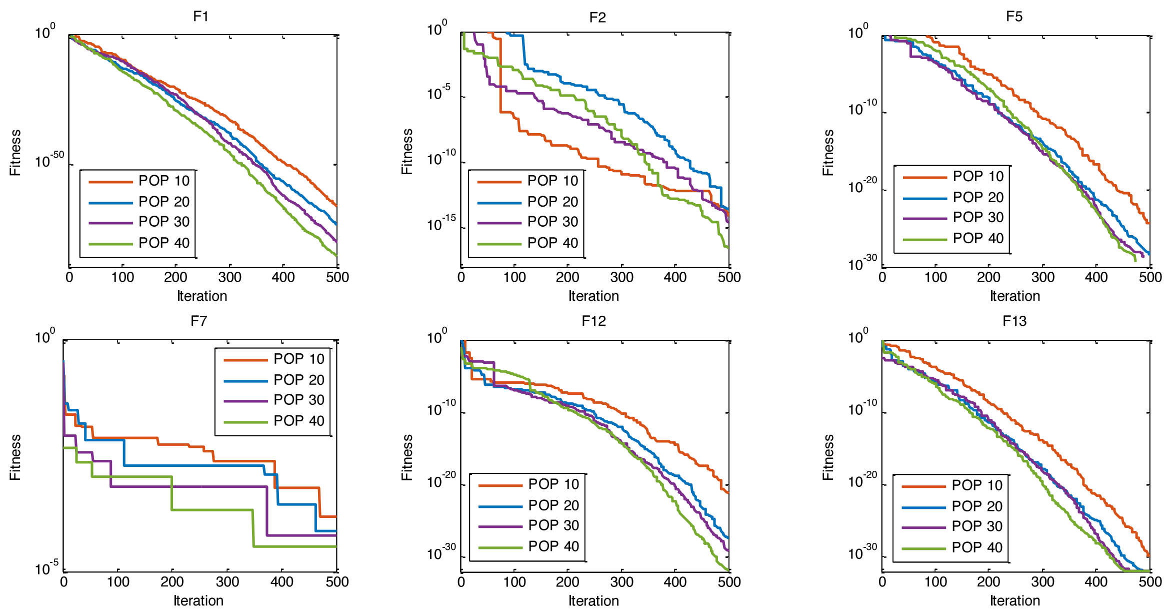

Fig. 11. Curves of convergence for various kinds of population.

four mean error criteria: STD, AVG, Worst, and Best. The scalability test results for the F1-F13 functions, the MGO algorithm, and other related algorithms are shown in Tables (2-5).Tables 6-7 also displays the results of MGO and other optimizers in solving various F14-F52 benchmark functions.

MGO outperformed other optimization algorithms in all sizes and most benchmark functions, as shown in Tables 2-5, which compare results from MGO and different optimization algorithms in the benchmark functions F1-F13 with dimensions of 30, 100, 500, and 1000. Moreover, only the WOA algorithm has performed better in functions F1 and F2. On the other hand, the results Tables 2-5 show the good and significant performance of MGO in solving problems with different dimensions. It has also been able to significantly improve its performance and maintain its search capabilities by increasing the size of the issue. On the other hand, compared to other optimizers, it has produced perfect and significant solutions, while different comparable optimization algorithms lose their performance if the dimensions increase significantly. The outstanding performance of MGO in scalability testing may show a perfect balance in the exploration and exploitation phases and highlight the powerful mechanisms that enable the exploration and exploitation components to provide the essential MGO capabilities.

Inspecting the findings in Table 6, MGO continues to perform well and much better than other optimization algorithms in providing high-quality solutions. MGO has executed closely and competitively with various optimizers in the F16-F19 functions. Moreover, only the F20 function performs worse than the GSA algorithm. MGO has outperformed other optimized algorithms to deliver high-quality solutions in virtually all circumstances. It has also shown outstanding and noteworthy performance.

The results of the F24-F52 CEC2017 benchmark are shown in Table 7. MGO algorithm has exhibited a considerable and good performance when compared to other optimization algorithms, according to the results. Compared to different optimization algorithms, it has demonstrated relatively poor performance in only 6 out of 29 functions. In 23 functions, it has performed better and significantly and has obtained high-quality solutions. MGO performed worse in only one Shifted and Rotated function. However, it performed poorly in the three Hybrid engineering problems compared to the other optimization algorithms.

MGO performed poorly in two Composition functions when compared to other optimizer methods. MGO has shown a speedy and consistent convergence trend in virtually all circumstances, according to Fig. 10, which is connected to the CEC2017 benchmark convergence charts. It can also be concluded that MGO strives to diversify solutions and escape local optimization points throughout the optimization process. For this reason, it can be supposed that MGO also has good capabilities in solving challenging problems. During all the evaluations of MGO, it has been determined that it has a very high and good ability in both components of intensification and diversity. Furthermore, all of the assessments have demonstrated that MGO works well and much better than other optimized algorithms in most circumstances, allowing it to be readily inferred that it is a robust and high-performance algorithm. In the following, experiments have been conducted to evaluate the effect of population and maximum iteration on MGO.

According to the results shown in Table 8, as expected, performance improvement in the MGO algorithm has been seen if the number of iterations is increased. But the remarkable thing is that even in the low number of iterations, MGO still had a good ability to obtain quality solutions. Of course, by increasing the number of iterations, the performance of the algorithm increases dramatically.The number of population has had a significant effect on the performance of MGO and it has been found that if the population increases, the performance of MGO also increases, but MGO has shown well that it has been able to achieve very good results even with a small population. This good performance in finding quality results with small population numbers shows the very good performance of MGO in solving optimization problems.

According to the convergence graphs shown in Fig. 11, it can be concluded that MGO has performed well with the increase in population, but a decreasing and continuous pattern has been seen in all the graphs. This decreasing pattern is easily visible even in the population number of ten and it has shown that even with a small population number, it still tries to find quality solutions and tries not to fall into the local optimal trap.

4.4. Analysis of Run Time

Evaluations are carried out in this subsection to determine the MGO's execution time. Nine comparative optimization techniques and F1-F13 benchmark functions with 1000 dimensions and four Best, Worst, Mean, and STD criteria based on seconds are used in this assessment. In addition, all tests were run with 500 iterations and 30 populations in 30 separate runs. Table 9 displays the findings. MGO has a middle-of-the-road performance. The runtime of MGO for solving

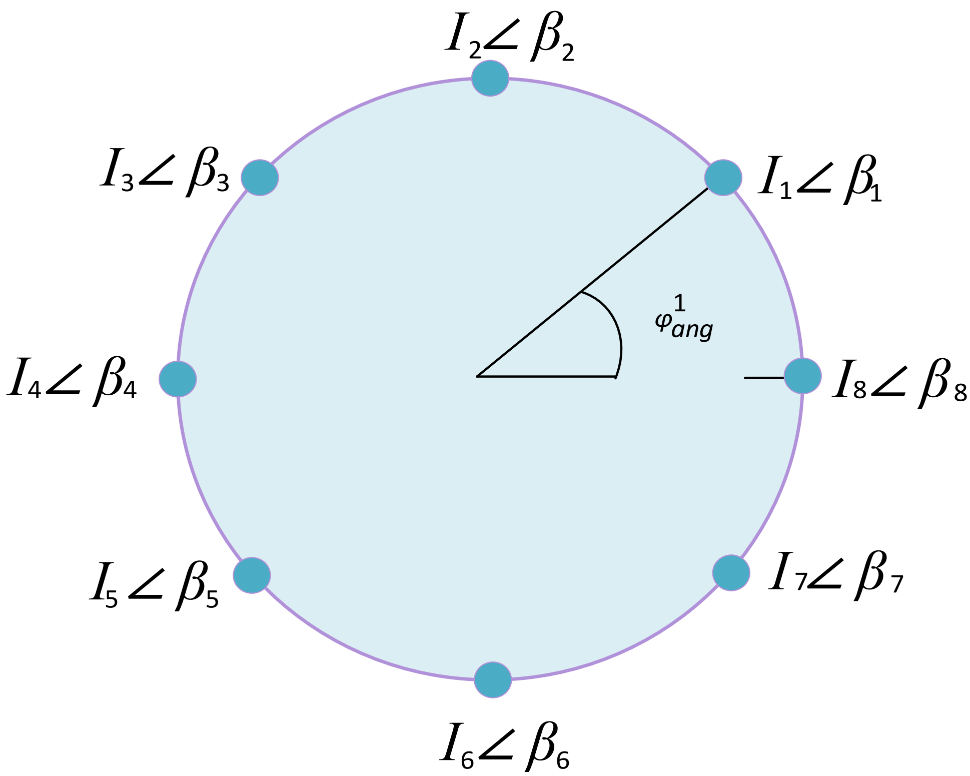

Fig. 12. Geometry of Circular antenna array.

problems is faster than that of other optimization techniques. Using four different methods on all search criteria might be the primary cause of increased execution time. It necessitates more processing and extends the execution duration. MGO takes less time to solve particular benchmark functions than other optimization methods. In general, although MGO's execution time is higher than specific optimization algorithms, the high execution time may be overlooked owing to MGO's exceptional performance in solving problems.

4.5. Significance of Superiority Analysis

In this subsection, further evaluations and significant differences in the results produced by the MGO algorithm compared to other optimized algorithms were discovered using the Wilcoxon rank-sum statistical test with a 5% accuracy. The Wilcoxon rank-sum test p-values with a 5% cautious degree are shown in Tables (10-15). The '+' and '-' marks in Table (2) indicate a significant positive or negative difference between the algorithms. Furthermore, the equal sign in Table (2) shows no significant difference between the methods or that the difference cannot be detected using the Wilcoxon rank-sum test. To conduct numerous comparisons, first, run an assessment to see whether the results from the optimizers are identical. The non-parametric Friedman's test technique was utilized to identify which of the examined algorithms is substantially different in the event of inequality. Tables (16-21) displays the outcomes of this experiment. In addition, this table shows the ranking based on the results of optimization methods based on benchmark functions in six different evaluation series.

According to the p-values in the Tables (10-15), statistically significant differences may be detected in almost every result. MGO algorithm has produced considerably better and more effective solutions than other optimization algorithms, given the p-values. Furthermore, it has outperformed other optimization techniques by a large margin. In Tables (10-13), the MGO algorithm has shown better and significant performance in almost all cases, which indicates that the MGO algorithm has an excellent performance in terms of scalability. According to Table (14), the MGO algorithm has also performed well, and only in some cases has it executed competitively and closely with some optimization algorithms. Finally, according to the results of Table 15, the MGO algorithm has shown excellent and significant performance and, in most functions, has demonstrated outstanding and considerable performance compared to other comparable optimization algorithms. In general, according to the statistical test, it is still shown that the MGO algorithm has a significant advantage over different optimization algorithms in obtaining high-quality solutions.

The Friedman test results are shown in Tables (16-21). In this test, the MGO algorithm is ranked first in all evaluations. Moreover, it turns out that MGO has a good and significant performance compared to other algorithms due to the good results it has been able to obtain in experiments. Finally, MGO is a powerful and efficient algorithm that can solve problems in all different dimensions and complexities and be used in the future as an optimization algorithm in many issues and play a constructive role.

4.6. Engineering Optimization Problem

P-meta-heuristics is a kind of algorithm that may be used to solve various issues, including engineering difficulties. Because addressing engineering issues is important in this research, the suggested method assesses MGO's performance in solving seven engineering problems of varying computational complexity. MGO performance has also been compared to that of MFO [37], PSO [22], GWO [38], AVOA [24], TSA [41], FFA [10], and GTO [43]. This evaluation is based on 30 different implementations with 30 different populations over a maximum of 500 iterations, with the best solution from each optimization algorithm chosen for comparison.

4.6.1. Frequency-Modulated (FM) Sound Waves Parameter Estimation

One of the most critical aspects of current music systems is FM sound wave synthesis. This challenge comprises six dimensions for optimizing the FM synthesizer parameter: a high-complexity, multimodal, and

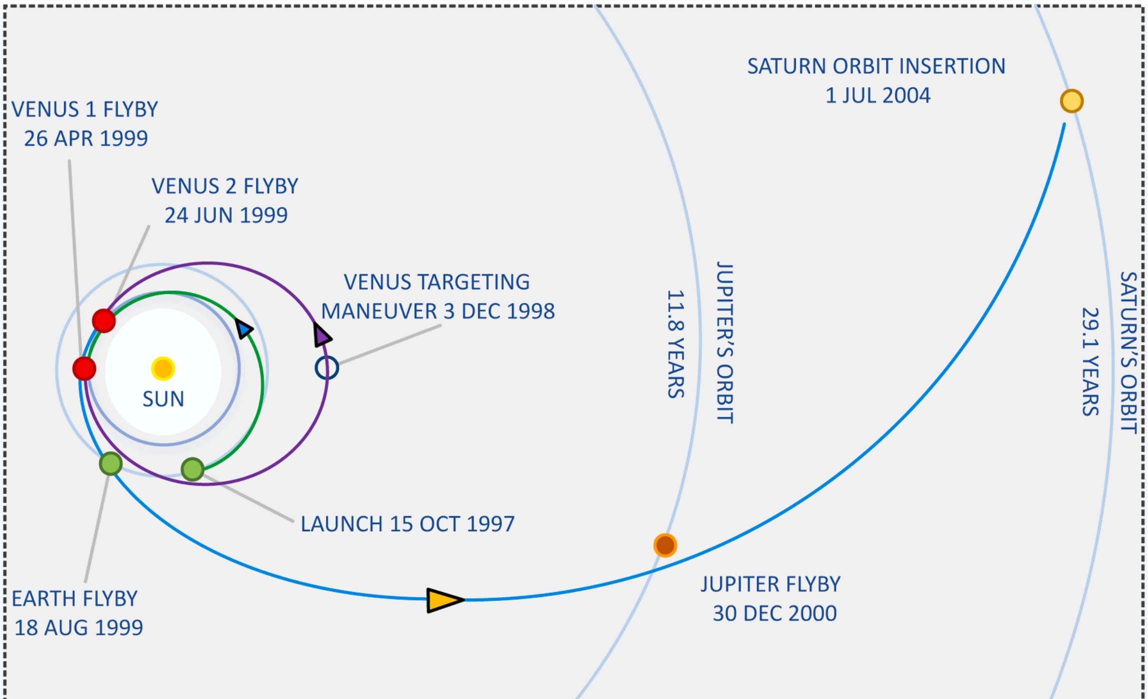

Fig. 13. Cassini: Spacecraft Trajectory.

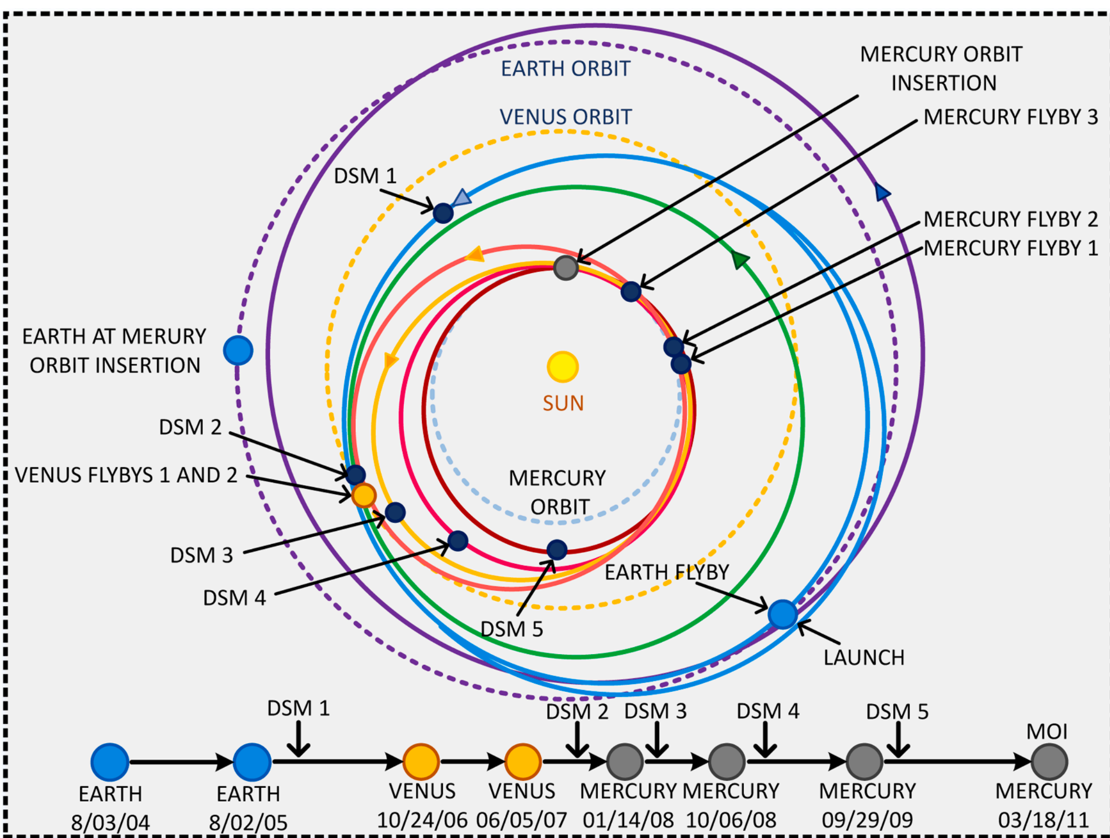

Fig. 14. Messenger: Spacecraft Trajectory.

epistasis problem. The lowest value for this issue is $f(\overrightarrow{X}_{sol}) = 0$. $X = \{a_1, \omega_1, a_2, \omega_2, a_3, \omega_3\}$. It's a sound wave delivered as a vector to the following equation for optimization. The following is a mathematical representation of the problem:

$$\mathbf{y(t)} = \mathbf{a_1.sin}(\omega_1.\mathbf{t}.\theta + \mathbf{a_2.sin}(\omega_2.\mathbf{t}.\theta + \mathbf{a_3.sin}(\omega_3.\mathbf{t}.\theta)))$$

$$y_0(\mathbf{t}) = (\mathbf{1.0}).\mathbf{sin}((\mathbf{5.0}).\mathbf{t}.\theta - (\mathbf{1.5}).\mathbf{sin}((\mathbf{4.8}).\mathbf{t}.\theta + (\mathbf{2.0}).\mathbf{sin}((\mathbf{4.9}).\mathbf{t}.\theta)))$$

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

$$f\left(\overrightarrow{X}\right) = \sum_{t=0}^{100} (y(t) - y_0(t))^2$$

According to the results of solving the FM Sound Waves problem in Table 22, MGO could obtain the best solution. The GTO and AVOA algorithms performed well and provided high-quality solutions compared to other optimization methods.

4.6.2. Circular Antenna Array Design Problem

It is utilized in various applications, including radar design, commercial satellite, sonar communication systems, and mobile communication systems [44–46]. This challenge has a high level of difficulty with 12 dimensions. The circular array's array factor can be seen in Fig. 12 and is expressed 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,

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

The findings of MGO and other optimization algorithms dealing with the Circular Antenna Array Design problem are shown in Table 23. MGO algorithm outperformed different similar optimization algorithms and produced a high-quality solution. The second and third best performance is related to AVOA and GTO algorithms, which have also obtained high-quality solutions.

4.6.3. Spread Spectrum Radar Polly phase Code Design problem

The waveform is crucial in radar systems that employ pulse compression. In radar pulse modulation, there are various ways for pulse compression. Polyphase codes are one of these ways, and it's known for their simplicity of use, unique features, and digital processing procedures. The authors in [47] describe a novel polyphase pulse compression code generation technique, a min-max nonlinear non-convex optimization problem with many local optimizations in a continuous optimization space. The main goal of this problem is to lower the module of the socialized auto-correlation function's greatest among the samples to the minimum achievable value. This problem is also characterized as an NP-hard problem since it has 20 limitations. It may be stated in the following:

$$global\min_{x \in X} f(x) max\{\varphi_1(x), \ldots, \varphi_{2m}(x)\}$$

$$X = \{x_1, \ldots, x_n\} \in R^n\left\{0 \le x_j \le 2\pi, j = 1, \ldots, n\right\}$$

where $m = 2n - 1$ and

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

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

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

The results of the MGO experiment and other related optimization techniques for solving the Spread Spectrum Radar Polly phase Code design issue are shown in Table (24). The findings reveal that MGO performs well and has a strong capacity to solve this issue, as demonstrated by finding an ideal optimum solution. Also, GTO and AVOA algorithms have shown that they can have excellent and acceptable performance in solving this problem.

4.6.4. Cassini 2: Problem of Spacecraft Trajectory Optimization

Designing space missions is one of the most critical and challenging issues that can be solved using optimal global algorithms. The Multiple Gravity Assist (MGA) is a nonlinear, finite-dimensional mathematical optimization problem. MGA is a method for determining the most significant potential space travel path; however, it has drawbacks. The

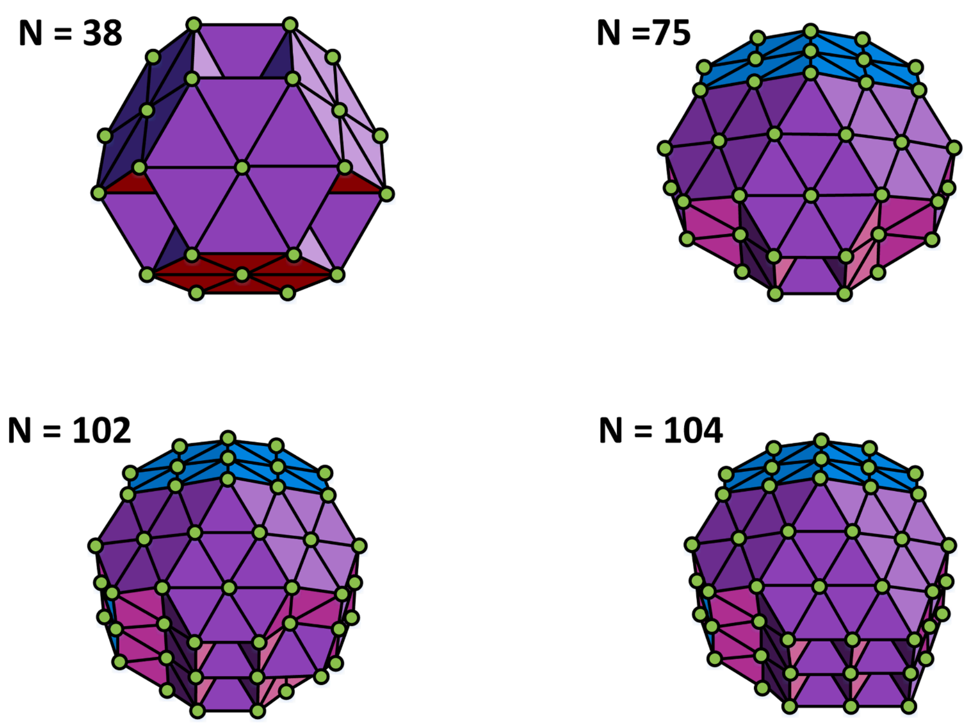

Fig. 15. Lennard-Jones Potential Problem.

MGS with Deep Space Maneuver (MGA-1DSM) challenge may be used to demonstrate the method's limits. In [48–51] provides further information on this topic. Cassini 2 is to identify the most efficient path to Saturn utilizing deep space maneuvers. It is a complicated subject with 22 restrictions shown in Fig. 13.

Table 25 shows the results obtained from MGO and other comparable optimization algorithms. According to the results obtained from the optimization algorithms, the best performance is still related to the MGO algorithm and has received a much more optimal path than other comparable algorithms. On the other hand, the direction obtained from MGO has an excellent and significant cost compared to different optimization algorithms.

4.6.5. Messenger: A Problem of Spacecraft Trajectory Optimization

Messenger is a space travel design challenge that intends to reach Mercury using the MGA-1DSM problem. Its situation is complicated by the sequence in which the spaceship must visit the planets during this mission, and it involves 26 constraints. Table (26) uses the MGO algorithm and other optimization strategies to solve the Messenger issue. The Messenger: Spacecraft Trajectory Optimization Problem is shown in Fig. 14.

According to the results, both of which have achieved optimal and high-quality paths, close and competitive performance can be seen between MGO and GTO algorithms. The AVOA algorithm has also accomplished the path at an acceptable cost.

4.6.6. Lennard-Jones Potential Problem

To optimize potential energy, and according to the pure Lennard-Jones (LJ) cluster [52,53], the Lennard-Jones potential problem is used to minimize the molecular potential energy. The Lennard-Jones Potential problem, with 30 constraints, is a multi-modal optimization problem [52]. In Fig. 15, the Lennard-Jones Potential Problem is shown.

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

Which is given as follows:

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

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

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

The first variable, $x_1 \in [0,\quad 4]$, t, is due to the second atom, during the second and third variables, $x_2 \in [0,\quad 4]$ a and $x_3 \in [0, \pi]$ are attributable to the third atom. Any other atom's x_i coordinates are assumed to be within the range:

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

According to the results shown in Table 27, which were obtained from MGO experiments and other comparable optimization algorithms, it can be concluded that MGO has demonstrated the best performance in solving this problem and has obtained acceptable results. On the other hand, competitive performance and proximity can be seen between GTO and AVOA algorithms, and both algorithms have been able to get proper solutions.

4.6.7. The Problem of Static Economic Load Dispatch (ELD) (Instance 4)

The static ELD problem lowers industrial unit fuel costs over a set period. This problem contains 40 flaws and is very difficult to solve. This issue is solved using two alternative models: smooth cost functions and non-smooth costs. The following are the two models.

Fitness Function: It is possible to think about it in terms of manufacturing costs likes follows:

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

For the unit with valve point loading effect, the cost function is as follows:

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

It has several drawbacks, including power balancing restrictions that must be taken into account and ramp rate limits and banned operating zones.

Power Balance Constraints, also known as Demand Constraints, are based on balancing total system output, total system load (P_D), and losses (P_L). Under these constraints, the overall system output, total system load (P_D), and losses (P_L) are all balanced.

$P_L$is calculated using B- coefficients, which are provided by:

$$P_L = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_i + B_{00}$$

Generator Constraints: The upper and lower limits of each generating unit may be calculated using a pair of inequality constraints:

$$P_i^{min} \le P_i \le P_i^{max}$$

Ramp Rate Constraints: Unit restrictions occur as a result of ramp rate constraints, which are as follows:

If the amount of energy produced grows, $P_i - P_i^{t-1} \le UR_i$

If the amount of energy produced drops, $P_i^{t-1} - P_i \le DR_i$

The following are some generator performance limitations: $\max(P_i^{min}, UR_i - P_i) \le P_i \le \min(P_i^{max}, P_i^{t-1} - DR_i)$

Prohibited Operating Zones: Work activity in specific places is prohibited from saving money, as indicated below:

$$P_i \le \breve{P}^{pz} \ and \ P_i \ \ge \hat{P}^{pz}$$

Table 28 shows the results of solving the Static Economic Load Dispatch Problem by MGO and other algorithms.

According to the findings in Table (28), the MGO algorithm continues to provide the best results and has been able to provide outstanding and acceptable solutions. In addition, MGO's answers are superior to similar algorithms in tackling this problem. MGO has been able to preserve its search functionality and provide decent results despite the vast magnitude of this problem. Then the two algorithms, GTO and AVOA, obtained excellent and acceptable solutions compared to other optimization algorithms. During experiments performed by MGO to solve engineering problems that used problems with different dimensions and constraints and high complexity, MGO showed that it could solve engineering problems with different sizes and conditions with good performance. In the future, it can be evaluated and used in solving many problems in various optimization spaces.

5. Conclusion and future works

MGO algorithm, a novel meta-heuristic algorithm based on mountain deer social and group life in nature, is suggested in this paper. In this algorithm, four different mechanisms were used to perform optimization. These four other mechanisms have created a perfect balance in all optimization stages' exploration and exploitation components. MGO has excelled in addressing global optimization issues, according to several tests and assessments using 52 benchmark functions and seven different engineering challenges with diverse dimensions and high complexity. It may be used to solve various problems as a robust algorithm. Because of the positive results generated by the MGO algorithm in a variety of benchmark functions, getting good marks in each of the tested functions requires special abilities and capabilities in the components of diversity and intensification. It indicates that MGO does an excellent job of balancing the exploration and exploitation phases. MGO's findings were compared to those of nine other sophisticated meta-heuristic algorithms that employed the Friedman's and Wilcoxon rank-sum statistical tests to find significant differences. According to the results of MGO statistical tests, it has shown that it has an excellent advantage over other meta-heuristic algorithms and has been able to obtain much better solutions. The free parameter feature of MGO means that there is no need to set a fixed parameter before the optimization operation. Finally, since MGO employs many finite vectors, it has an excellent ability to explore all optimization spaces and a remarkable ability to escape from local optimum spots. Based on the experiments and experiences gained, it can be concluded that MGO in the future can be a good option in solving real-world problems with unknown search spaces. Multi-objective optimization issues may also be solved using the MGO, which can be tweaked and tested. Because meta-heuristic algorithms can help solve various challenges, future work may be evaluated and utilized to address hybrid optimization problems or complicated problems in artificial intelligence and machine learning using multicode encodings.

Author declaration

None.

CRediT authorship contribution statement

Benyamin Abdollahzadeh: Conceptualization, Software, Writing – original draft, Visualization. **Farhad Soleimanian Gharehchopogh:** Conceptualization, Data curation, Writing – original draft, Visualization, Formal analysis. **Nima Khodadadi:** Writing – original draft, Visualization, Investigation. **Seyedali Mirjalili:** Resources, Writing – original draft, Supervision, Project administration, Visualization.

Declaration of Competing Interest

There is no conflict of interest in this paper

Appendix A

Table A1.

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	UN	$f(x) = \sum_{i=1}^{d} \lvert x_i\rvert + \prod_{i=1}^{d} \lvert x_i\rvert$	30,100,500,1000	$[-10, 10]^d$	0
F3	UN	$f(x) = \sum_{i=1}^{d} (\sum_{j=1}^{i} x_j)^2$	30,100,500,1000	$[-100, 100]^d$	0
F4	US	$f(x) = max_i\{\lvert x_i\rvert, \quad 1 \le i \le d\}$	30,100,500,1000	$[-100, 100]^d$	0
F5	UN	$f(x) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30,100,500,1000	$[-30, 30]^d$	0
F6	US	$f(x) = \sum_{i=1}^{d} (\lvert x_i + 0.5\rvert)^2$	30,100,500,1000	$[-100, 100]^d$	0
F7	US	$f(x) = \sum_{i=1}^{d} i x_i^4 + random[0, 1)$	30,100,500,1000	$[-128, 128]^d$	0

Table 1
Parameter Settings for Comparison and Evaluation of Optimization Algorithms.

Algorithm	Parameter	Value
WOA	Spiral factor b	1
	Convergence constant a	[2,0]
PSO	Inertia factor	0.3
	vMax	6
	c_1	2
	c_2	2
GSA	α	20
	G_0	100
	Power of R	1
TSA	Parameter P_{min}	1
	Parameter P_{max}	4
FFA	K Value	2
	α	0.6
	β	0.4
	W	1
	Q	0.7
MVO	existence probability	[0.2 1]
	traveling distance rate	[0.6 1]
MFO	Spiral factor b	1
	Convergence constant a	[-2 -1]
SCA	A	2
GWO	Convergence constant a	[2 0]

Table 2
(F1-F13) Benchmark Function Results using 30 Dimensions.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F1	Best	2.4152E-81	7.1071E-09	1.4640E-16	7.7275E-24	5.3715E-01	2.7058E-02	1.9674E-29	1.0066E-81	6.5465E-07	5.7305E-01
	Worst	4.9485E-71	7.3614E-05	1.0676E-15	1.6706E-19	2.0002E+04	8.9604E+01	3.3396E-27	5.4085E-73	1.2085E-05	2.8434E+00
	Mean	4.7455E-72	4.4590E-06	4.0447E-16	9.3536E-21	1.6722E+03	1.7454E+01	6.8080E-28	3.8939E-74	3.9445E-06	1.2517E+00
	STD	1.3401E-71	1.4568E-05	2.2730E-16	3.2280E-20	4.6100E+03	2.3343E+01	7.9910E-28	1.3542E-73	3.1824E-06	4.1780E-01
F2	Best	1.6760E-46	5.6941E-06	5.7860E-08	1.1117E-14	1.7467E-01	9.6448E-05	1.5227E-17	9.6450E-58	1.8255E-06	5.0494E-01
	Worst	6.0784E-41	2.0504E-02	3.1070E+00	7.2302E-13	8.0223E+01	5.8977E-02	4.2659E-16	2.3261E-49	1.4826E-05	1.0239E+02
	Mean	3.9067E-42	3.3272E-03	1.8731E-01	1.1458E-13	3.5329E+01	1.4802E-02	9.5812E-17	2.3359E-50	6.8882E-06	1.0213E+01
	STD	1.1893E-41	5.4084E-03	6.0181E-01	1.6055E-13	1.8821E+01	1.7178E-02	8.4204E-17	6.0166E-50	3.6106E-06	2.8546E+01
F3	Best	3.5309E-14	1.8171E+01	4.9511E+02	5.9385E-10	2.3463E+03	1.4440E+03	2.1261E-08	2.2319E+04	3.1508E+03	8.4037E+01
	Worst	1.6370E-07	3.4851E+03	2.0471E+03	1.3015E-03	4.7370E+04	2.5293E+04	7.2409E-04	7.0498E+04	6.7763E+03	3.7398E+02
	Mean	6.8224E-09	5.8934E+02	1.1138E+03	1.9943E-04	2.0003E+04	9.0222E+03	3.8779E-05	4.3494E+04	4.9002E+03	2.0693E+02
	STD	2.9791E-08	9.9009E+02	3.9077E+02	3.6661E-04	1.0242E+04	6.0200E+03	1.3653E-04	1.3319E+04	1.1138E+03	7.6385E+01
F4	Best	5.2537E-30	2.6406E-01	3.9881E+00	1.5725E-02	4.7078E+01	1.7656E+01	9.9694E-08	2.3909E+00	1.1880E+01	1.1059E+00
	Worst	4.1424E-22	2.1015E+00	1.1410E+01	1.3694E+00	8.5407E+01	6.1247E+01	3.8036E-06	9.0194E+01	2.5533E+01	4.1370E+00
	Mean	1.5909E-23	5.3311E-01	7.9578E+00	3.1348E-01	6.9113E+01	3.5695E+01	8.8249E-07	4.4856E+01	1.8298E+01	2.0408E+00
	STD	7.5435E-23	3.8014E-01	1.7893E+00	3.0687E-01	8.4094E+00	1.1289E+01	8.4504E-07	2.6838E+01	3.8689E+00	7.8877E-01
F5	Best	0.0000E+00	1.9874E+01	2.3122E+01	2.6085E+01	1.3794E+02	1.5513E+02	2.5959E+01	2.7205E+01	1.6638E+01	3.7189E+01
	Worst	2.5559E-22	1.0846E+02	1.9138E+02	2.8922E+01	8.0123E+07	2.0577E+06	2.9449E+01	2.8765E+01	2.9955E+02	2.4630E+03
	Mean	1.1953E-23	4.6616E+01	6.3799E+01	2.8446E+01	2.6939E+06	1.0601E+05	2.7213E+01	2.8065E+01	1.2592E+02	3.7516E+02
	STD	4.9592E-23	3.0547E+01	4.5367E+01	8.3086E-01	1.4624E+07	3.8526E+05	8.0820E-01	4.8863E-01	6.3939E+01	5.9447E+02
F6	Best	4.8095E-13	6.7447E-09	1.8296E-16	2.8291E+00	7.4584E-01	4.2022E+00	6.5857E-05	7.7615E-02	5.4281E-07	5.1020E-01
	Worst	3.5099E-08	4.1088E-05	1.0872E+01	5.5397E+00	1.9801E+04	4.2205E+01	1.7633E+00	8.5468E-01	6.7351E-05	1.9736E+00
	Mean	4.5398E-09	2.9114E-06	5.9661E-01	3.9889E+00	2.6696E+03	1.2605E+01	7.6141E-01	3.8596E-01	5.0135E-06	1.1790E+00
	STD	7.6544E-09	7.6033E-06	2.2896E+00	6.2105E-01	5.1945E+03	1.1056E+01	4.4836E-01	2.1045E-01	1.1970E-05	3.7290E-01
F7	Best	3.2450E-05	4.0726E-02	3.3649E-02	2.4796E-03	4.0524E-02	7.1255E-03	5.1293E-04	1.6863E-04	3.1382E-02	1.0751E-02
	Worst	1.5342E-03	1.5602E-01	2.9115E-01	2.5621E-02	5.9234E+01	3.0415E-01	6.0647E-03	1.1151E-02	1.0813E-01	7.7963E-02
	Mean	5.5958E-04	9.5056E-02	1.1077E-01	1.0078E-02	5.4184E+00	8.8694E-02	1.9080E-03	3.2327E-03	6.4023E-02	3.4209E-02
	STD	3.8895E-04	2.9977E-02	5.0936E-02	6.0591E-03	1.2719E+01	7.6005E-02	1.1384E-03	3.0381E-03	1.5924E-02	1.4936E-02
F8	Best	-1.2569E+04	-3.315E+03	-3.156E+03	-7.380E+03	-1.0353E+04	-4.7752E+03	-8.582E+03	-1.256E+04	-9.840E+03	-8.911E+03
	Worst	-1.2569E+04	-1.949E+03	-1.526E+03	-5.079E+03	-6.3081E+03	-3.1472E+03	-3.358E+03	-7.105E+03	-4.733E+03	-6.624E+03
	Mean	-1.2569E+04	-2.590E+03	-2.393E+03	-6.030E+03	-8.5561E+03	-3.7063E+03	-5.935E+03	-1.031E+04	-7.629E+03	-7.948E+03
	STD	3.9992E-08	2.810E+02	3.4829E+02	5.9028E+02	1.0475E+03	3.4448E+02	1.0224E+03	2.0460E+03	1.1994E+03	5.6501E+02
F9	Best	0.0000E+00	1.9899E+01	1.5919E+01	1.1310E+02	1.0158E+02	1.4559E-02	5.6843E-14	0.0000E+00	4.2904E+01	6.6090E+01
	Worst	0.0000E+00	7.2632E+01	5.7708E+01	2.7872E+02	2.6097E+02	9.6781E+01	1.0188E+01	5.6843E-14	1.7201E+02	1.4589E+02
	Mean	0.0000E+00	3.8671E+01	3.2535E+01	1.8033E+02	1.5809E+02	2.7840E+01	2.2537E+00	3.7896E-15	9.3689E+01	1.1183E+02
	STD	0.0000E+00	1.3480E+01	9.9123E+00	4.2043E+01	3.8283E+01	2.7712E+01	2.8569E+00	1.4422E-14	3.4334E+01	2.3540E+01
F10	Best	8.8818E-16	3.7741E-06	8.0795E-09	3.1593E-12	1.4912E+00	3.5294E-02	7.5495E-14	8.8818E-16	1.6993E-04	8.7818E-01
	Worst	4.4409E-15	2.4083E+00	1.6413E+00	3.5226E+00	1.9964E+01	2.0354E+01	1.3234E-13	7.9936E-15	1.5143E-03	2.9371E+00
	Mean	1.7171E-15	3.1302E-01	1.3790E-01	1.8345E+00	1.5907E+01	1.1826E+01	9.5390E-14	4.2040E-15	6.0692E-04	1.8561E+00
	STD	1.5283E-15	7.3029E-01	4.2566E-01	1.6358E+00	6.8527E+00	9.5505E+00	1.5712E-14	2.2726E-15	3.0001E-04	5.8341E-01
F11	Best	0.0000E+00	6.3190E+01	2.2360E+01	0.0000E+00	6.3238E-01	1.2797E-01	0.0000E+00	0.0000E+00	3.0562E-06	7.3648E-01
	Worst	0.0000E+00	1.0377E+02	4.2909E+01	1.0857E-01	9.1184E+01	5.7094E+00	2.3349E-02	1.6580E-01	1.0176E-01	9.7392E-01
	Mean	0.0000E+00	8.3190E+01	3.1955E+01	1.5135E-02	3.9966E+01	1.0750E+00	3.5774E-03	1.0704E-02	1.1305E-02	8.6684E-01
	STD	0.0000E+00	1.0729E+01	5.3367E+00	1.9647E-02	4.5341E+01	9.3963E-01	7.0521E-03	4.0759E-02	1.9653E-02	5.7448E-02
F12	Best	1.5705E-32	9.3714E-11	6.5080E-02	2.9169E+00	6.5723E-01	7.3770E-01	6.7002E-03	5.8552E-03	6.1775E-04	6.7457E-02
	Worst	2.1956E-25	1.5674E+00	5.2553E+00	1.5580E+01	3.4177E+02	8.7693E+06	1.3202E-01	7.3611E-02	2.6340E+00	5.6630E+00
	Mean	1.6966E-26	2.4928E-01	2.3228E+00	7.6995E+00	2.1472E+01	3.2342E+05	4.5589E-02	2.3319E-02	4.6779E-01	1.9878E+00
	STD	4.5383E-26	3.7051E-01	1.3461E+00	3.6513E+00	6.1917E+01	1.6036E+06	2.5588E-02	1.7448E-02	6.8369E-01	1.4369E+00
F13	Best	1.3498E-32	2.9246E-11	6.0010E-02	1.7729E+00	2.9276E+00	2.5746E+00	6.4257E-02	1.1454E-01	1.3832E-03	8.3176E-02
	Worst	6.4034E-32	1.1006E-02	3.4322E+01	5.2452E+00	4.1582E+03	1.0331E+07	1.2207E+00	1.0087E+00	3.2092E+00	5.0993E-01
	Mean	1.8141E-32	2.5662E-03	1.2798E+01	3.0071E+00	1.7993E+02	4.1952E+05	6.8902E-01	5.6260E-01	2.0984E-01	1.9037E-01
	STD	9.9543E-33	4.7275E-03	7.5992E+00	7.3464E-01	7.5646E+02	1.9048E+06	2.7249E-01	2.2373E-01	5.8276E-01	9.3862E-02

Table 3
(F1-F13) Benchmark Function Results using 100 Dimensions.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F1	Best	5.8529E-72	5.0972E-01	3.1277E+03	1.5635E-11	3.6205E+04	4.7498E+02	9.6518E-14	2.5045E-82	4.5580E+05	1.0534E+02
	Worst	5.0778E-59	4.6534E+00	6.9286E+03	1.3357E-09	9.3713E+04	5.5824E+04	4.4092E-12	5.3289E-72	5.2877E+05	2.7368E+02
	Mean	2.8822E-60	1.4251E+00	4.6697E+03	3.1839E-10	6.0415E+04	1.1876E+04	1.2923E-12	2.4446E-73	5.0061E+05	1.5928E+02
	STD	1.0124E-59	9.7808E-01	8.4974E+02	3.3467E-10	1.3893E+04	1.1718E+04	1.1471E-12	9.7724E-73	1.9883E+04	3.2094E+01
F2	Best	1.8226E-39	1.4002E+00	1.1426E+01	2.3004E-08	1.7440E+02	1.3935E+00	2.4139E-08	3.7722E-57	1.4851E+65	3.0770E+02
	Worst	1.1415E-34	6.9190E+00	3.4517E+01	6.9252E-07	3.6354E+02	2.9217E+01	7.7857E-08	6.9052E-49	1.2616E+122	1.2455E+23
	Mean	1.0590E-35	3.3344E+00	2.0029E+01	2.6335E-07	2.4387E+02	9.5487E+00	4.4631E-08	4.3558E-50	4.2223E+120	7.2862E+21
	STD	2.3627E-35	1.4074E+00	4.6785E+00	1.7809E-07	4.3150E+01	6.3595E+00	1.4567E-08	1.3250E-49	2.3031E+121	2.7862E+22
F3	Best	1.3729E-09	7.1514E+03	1.0504E+04	3.2888E+03	1.5359E+05	1.2427E+05	3.3039E+01	4.9758E+05	4.7703E+06	5.3468E+04
	Worst	1.6621E+00	5.9518E+04	3.5025E+04	3.6861E+04	3.4039E+05	3.5558E+05	3.4873E+03	1.6008E+06	6.5316E+06	8.5535E+04
	Mean	1.0307E-01	2.0883E+04	1.9187E+04	1.0919E+04	2.3713E+05	2.4226E+05	7.5728E+02	9.9236E+05	5.4477E+06	6.6821E+04
	STD	3.8330E-01	1.3515E+04	6.0771E+03	6.1124E+03	5.4976E+04	5.3951E+04	7.7203E+02	3.2132E+05	4.4087E+05	7.7974E+03
F4	Best	4.1801E-28	5.4860E+00	1.5172E+01	2.8257E+01	8.9022E+01	8.4115E+01	5.7190E-02	6.6881E+00	9.8511E+01	4.7904E+01
	Worst	5.5156E-20	8.1293E+00	2.5144E+01	7.9158E+01	9.6955E+01	9.3892E+01	4.9102E+00	9.6307E+01	9.9581E+01	7.1172E+01
	Mean	3.3318E-21	6.7348E+00	2.0171E+01	5.0877E+01	9.3474E+01	9.0079E+01	1.0922E+00	7.5603E+01	9.9244E+01	5.9441E+01
	STD	1.1114E-20	6.9549E-01	2.4395E+00	1.1543E+01	2.2602E+00	2.3093E+00	1.1321E+00	2.3049E+01	2.6853E-01	6.1593E+00
F5	Best	1.9281E-28	2.1878E+02	3.1257E+04	9.6146E+01	5.8578E+07	3.7830E+07	9.6040E+01	9.7795E+01	1.8387E+09	3.0550E+03
	Worst	2.4356E-24	8.4957E+02	2.9965E+05	9.8657E+01	3.3527E+08	2.9584E+08	9.8545E+01	9.8434E+01	2.8488E+09	4.3841E+04
	Mean	1.2127E-25	4.3733E+02	1.1327E+05	9.8175E+01	1.5375E+08	1.3578E+08	9.8056E+01	9.8227E+01	2.2646E+09	1.3585E+04
	STD	4.4925E-25	1.2317E+02	6.5403E+04	7.1600E-01	6.7996E+07	7.0654E+07	6.3990E-01	1.6508E-01	2.3030E+08	1.3963E+04
F6	Best	7.9256E-08	3.7238E-01	2.8631E+03	1.2298E+01	2.8829E+04	6.3287E+02	7.8132E+00	2.0091E+00	4.5624E+05	1.2544E+02
	Worst	1.3496E-03	3.1286E+00	6.5628E+03	1.6203E+01	8.7859E+04	2.8446E+04	1.1989E+01	6.3335E+00	5.6417E+05	2.1787E+02
	Mean	1.9521E-04	1.2662E+00	4.7993E+03	1.4417E+01	5.9290E+04	9.5845E+03	1.0289E+01	4.3111E+00	5.1440E+05	1.6392E+02
	STD	3.1368E-04	6.9627E-01	9.3909E+02	1.1057E+00	1.5092E+04	6.4189E+03	1.0520E+00	1.1199E+00	2.4658E+04	2.6503E+01
F7	Best	1.0821E-04	2.7694E+00	1.9486E+00	1.5783E-02	6.9985E+01	1.3179E+01	3.0128E-03	2.4806E-04	1.2095E+04	3.5463E-01
	Worst	1.7247E-03	1.8461E+01	9.8040E+00	1.0481E-01	5.2624E+02	3.5088E+02	1.5339E-02	1.8370E-02	1.7770E+04	1.0061E+00
	Mean	6.5441E-04	5.8645E+00	4.9189E+00	5.6483E-02	2.7669E+02	1.6789E+02	7.5129E-03	4.3495E-03	1.5251E+04	6.9319E-01
	STD	4.2507E-04	3.5868E+00	1.9363E+00	2.4656E-02	1.2509E+02	1.0193E+02	3.2298E-03	3.9707E-03	1.6515E+03	1.6317E-01
F8	Best	-4.189E+04	-6.084E+03	-6.9866E+03	-1.569E+04	-2.619E+04	-7.664E+03	-1.917E+04	-4.159E+04	-5.4857E+04	-2.5278E+04
	Worst	-4.189E+04	-3.999E+03	-3.4879E+03	-1.067E+04	-1.884E+04	-6.143E+03	-6.294E+03	-2.382E+04	-1.8396E+04	-1.9794E+04
	Mean	-4.189E+04	-4.847E+03	-4.5146E+03	-1.312E+04	-2.238E+04	-6.819E+03	-1.512E+04	-3.349E+04	-3.0640E+04	-2.2735E+04
	STD	5.4299E-04	5.5520E+02	7.3772E+02	1.1182E+03	2.0269E+03	3.8295E+02	3.1202E+03	6.0441E+03	8.8362E+03	1.4684E+03
F9	Best	0.0000E+00	1.1118E+02	1.5534E+02	7.3411E+02	6.6759E+02	5.2206E+01	3.5016E-11	0.0000E+00	6.2374E+03	5.2724E+02
	Worst	0.0000E+00	2.3001E+02	2.4689E+02	1.2744E+03	9.5444E+02	5.0201E+02	2.2957E+01	0.0000E+00	6.9272E+03	8.8131E+02
	Mean	0.0000E+00	1.5880E+02	1.9563E+02	9.7420E+02	8.6029E+02	2.6987E+02	8.5684E+00	0.0000E+00	6.6947E+03	6.9110E+02
	STD	0.0000E+00	2.4475E+01	2.5284E+01	1.2350E+02	6.1278E+01	1.0898E+02	6.5612E+00	0.0000E+00	2.0926E+02	9.0014E+01
F10	Best	8.8818E-16	2.2839E+00	3.8067E+00	7.1851E-07	1.9493E+01	4.9789E+00	6.1412E-08	8.8818E-16	1.9258E+01	3.9841E+00
	Worst	4.4409E-15	5.1474E+00	6.2393E+00	3.1463E+00	1.9974E+01	2.0720E+01	3.1089E-07	1.5099E-14	1.9756E+01	2.0326E+01
	Mean	1.9540E-15	3.4326E+00	5.0672E+00	3.0233E-01	1.9842E+01	1.8243E+01	1.3675E-07	4.5593E-15	1.9604E+01	7.9352E+00
	STD	1.6559E-15	7.7478E-01	6.9629E-01	9.2352E-01	1.6443E-01	5.0078E+00	5.3144E-08	3.2964E-15	1.2458E-01	5.6499E+00
F11	Best	0.0000E+00	2.9293E+02	5.9527E+02	2.0147E-11	2.2444E+02	2.3339E+01	1.7153E-13	0.0000E+00	4.0661E+03	1.8900E+00
	Worst	0.0000E+00	3.7786E+02	7.4258E+02	4.2098E-02	8.3913E+02	3.4168E+02	3.6164E-02	1.1102E-16	5.0563E+03	3.3922E+00
	Mean	0.0000E+00	3.3580E+02	6.8845E+02	1.1828E-02	5.5831E+02	1.1877E+02	3.8445E-03	3.7007E-18	4.6372E+03	2.4772E+00
	STD	0.0000E+00	2.2170E+01	3.6036E+01	1.6145E-02	1.5079E+02	7.6957E+01	9.2827E-03	2.0270E-17	2.1372E+02	3.1390E-01
F12	Best	4.5392E-28	7.2916E-02	6.0595E+00	3.3528E+00	4.7901E+07	4.9973E+07	1.7662E-01	2.4693E-02	4.4071E+09	1.4185E+01
	Worst	1.8790E-22	2.8015E+00	2.1729E+01	4.6347E+01	6.0626E+08	7.1436E+08	4.8648E-01	2.0449E-01	9.7134E+09	4.1530E+01
	Mean	1.4673E-23	1.0396E+00	1.1716E+01	1.7059E+01	2.5857E+08	3.2004E+08	3.0666E-01	5.2352E-02	7.4853E+09	2.3225E+01
	STD	3.7348E-23	6.8852E-01	3.4729E+00	9.6078E+00	1.7744E+08	1.9156E+08	8.6161E-02	3.4117E-02	1.5125E+09	6.3074E+00
F13	Best	7.1430E-32	1.0559E+01	1.9434E+02	1.1006E+01	1.4454E+08	1.9532E+08	5.6829E+00	1.2953E+00	9.0528E+09	1.3519E+02
	Worst	1.5033E-27	8.8300E+01	1.9144E+04	1.7048E+01	1.5172E+09	1.0185E+09	7.6699E+00	4.6951E+00	1.3680E+10	2.4025E+02
	Mean	9.3420E-29	4.4825E+01	3.4484E+03	1.3561E+01	6.1104E+08	5.6630E+08	6.7951E+00	2.8644E+00	1.1079E+10	1.7124E+02
	STD	2.8261E-28	2.0855E+01	3.8602E+03	1.5566E+00	3.5193E+08	2.3050E+08	4.6528E-01	9.5732E-01	1.3539E+09	2.3069E+01

Table 4
(F1-F13) Benchmark Function Results using 500 Dimensions.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F1	Best	6.3261E-65	2.2908E+02	5.2419E+04	6.9210E-03	1.0928E+06	5.0536E+04	7.7191E-04	4.7976E-80	4.5580E+05	1.0163E+05
	Worst	7.8225E-57	6.6223E+02	6.8127E+04	1.2910E-01	1.2297E+06	3.7849E+05	3.2104E-03	2.7389E-65	5.2877E+05	1.4205E+05
	Mean	8.3894E-58	4.0788E+02	5.8740E+04	3.6225E-02	1.1592E+06	1.9835E+05	1.4811E-03	9.4540E-67	5.0061E+05	1.1689E+05
	STD	1.9479E-57	9.3153E+01	3.5957E+03	2.6343E-02	3.1816E+04	8.5129E+04	5.0969E-04	4.9969E-66	1.9883E+04	9.3645E+03
F2	Best	4.0752E-37	1.3061E+02	2.9969E+02	4.0002E-03	1.3207E+74	2.1231E+01	6.7216E-03	2.6341E-55	1.4851E+65	3.8167E+159
	Worst	6.6739E-31	2.0196E+02	1.5560E+268	1.9817E-02	7.2167E+135	2.1415E+02	1.3900E-02	3.1156E-46	1.2616E+122	3.8492E+206
	Mean	3.7635E-32	1.6522E+02	5.1868E+266	7.7784E-03	2.4056E+134	1.0630E+02	1.0344E-02	1.7157E-47	4.2223E+120	1.2900E+205
	STD	1.3419E-31	1.7363E+01	Inf	3.8143E-03	1.3176E+135	4.2858E+01	1.6725E-03	6.5873E-47	2.3031E+121	Inf
F3	Best	1.0212E-03	2.2182E+05	4.2099E+05	9.3730E+05	3.3720E+06	4.4122E+06	1.3060E+05	1.3926E+07	4.7703E+06	1.7981E+06
	Worst	1.2988E+03	1.4161E+06	3.7125E+06	1.7299E+06	6.8600E+06	1.1246E+07	4.0507E+05	1.0166E+08	6.5316E+06	2.4718E+06
	Mean	9.5107E+01	5.6552E+05	1.3968E+06	1.3278E+06	5.0562E+06	6.8101E+06	3.1529E+05	3.3931E+07	5.4477E+06	2.0839E+06
	STD	3.0161E+02	2.7686E+05	8.1823E+05	1.8136E+05	9.1791E+05	1.4406E+06	6.7307E+04	1.8132E+07	4.4087E+05	1.8658E+05
F4	Best	2.5475E-24	1.0858E+01	2.5070E+01	9.8908E+01	9.8241E+01	9.7991E+01	5.4793E+01	2.7324E+01	9.8511E+01	9.1461E+01
	Worst	3.3913E-20	1.4880E+01	3.4061E+01	9.9586E+01	9.9449E+01	9.9462E+01	8.4488E+01	9.8858E+01	9.9581E+01	9.6625E+01
	Mean	4.6534E-21	1.3217E+01	2.9055E+01	9.9253E+01	9.8906E+01	9.9008E+01	6.5990E+01	8.5460E+01	9.9244E+01	9.4267E+01
	STD	8.4085E-21	9.9456E-01	2.0098E+00	1.8858E-01	3.7820E-01	3.1750E-01	8.1390E+00	1.6125E+01	2.6853E-01	1.3388E+00
F5	Best	1.1116E-26	2.1847E+04	7.3517E+06	2.3611E+03	4.5341E+09	4.9360E+08	4.9724E+02	4.9557E+02	1.8387E+09	1.3205E+08
	Worst	4.4281E-22	4.6978E+04	1.2410E+07	1.7312E+06	5.5391E+09	2.7620E+09	4.9875E+02	4.9730E+02	2.8488E+09	2.6902E+08
	Mean	3.2347E-23	3.4912E+04	9.4342E+06	1.9593E+05	4.9933E+09	1.9981E+09	4.9810E+02	4.9642E+02	2.2646E+09	1.7830E+08
	STD	8.4085E-23	6.9396E+03	1.4793E+06	3.5949E+05	2.6183E+08	4.6166E+08	2.9732E-01	3.7244E-01	2.3030E+08	2.7638E+07
F6	Best	2.2284E-05	2.6194E+02	5.1000E+04	9.8558E+01	1.1072E+06	8.5302E+04	8.6320E+01	1.6182E+01	4.5624E+05	9.8099E+04
	Worst	9.6604E-02	9.1820E+02	6.7344E+04	1.0577E+02	1.2299E+06	3.5746E+05	9.6150E+01	4.8570E+01	5.6417E+05	1.3722E+05
	Mean	1.3185E-02	4.1107E+02	5.8801E+04	1.0266E+02	1.1653E+06	2.0266E+05	9.1262E+01	3.2585E+01	5.1440E+05	1.1893E+05
	STD	2.5846E-02	1.5448E+02	3.6939E+03	1.4747E+00	2.9111E+04	6.1633E+04	2.4610E+00	7.8545E+00	2.4658E+04	9.2724E+03
F7	Best	7.5304E-05	1.9533E+03	8.1479E+02	1.2726E+00	3.5576E+04	5.8366E+03	2.6550E-02	1.5991E-04	1.2095E+04	7.7210E+02
	Worst	1.8466E-03	2.9580E+03	1.7545E+03	5.8448E+00	4.2683E+04	2.1264E+04	9.0418E-02	1.8554E-02	1.7770E+04	1.4608E+03
	Mean	6.9155E-04	2.3677E+03	1.1334E+03	2.6560E+00	3.8898E+04	1.4940E+04	4.5467E-02	3.3969E-03	1.5251E+04	1.1303E+03
	STD	4.7589E-04	2.8259E+02	1.9372E+02	1.1723E+00	1.8672E+03	3.7393E+03	1.4710E-02	4.1157E-03	1.6515E+03	1.6160E+02
F8	Best	-2.0949E+05	-1.3732E+04	-1.5523E+04	-3.4746E+04	-6.9959E+04	-2.0210E+04	-6.6865E+04	-2.0942E+05	-5.4857E+04	-7.8160E+04
	Worst	-2.0949E+05	-7.7850E+03	-7.1541E+03	-2.6308E+04	-5.0834E+04	-1.2542E+04	-4.2859E+04	-1.1369E+05	-1.8396E+04	-6.8270E+04
	Mean	-2.0949E+05	-1.0804E+04	-1.0461E+04	-3.1077E+04	-6.0741E+04	-1.5929E+04	-5.7424E+04	-1.7290E+05	-3.0640E+04	-7.3166E+04
	STD	2.7521E-02	1.7772E+03	2.0442E+03	2.1058E+03	4.2271E+03	1.6465E+03	4.4577E+03	3.0340E+04	8.8362E+03	3.0001E+03
F9	Best	0.0000E+00	2.1294E+03	2.5978E+03	4.5347E+03	6.7657E+03	5.9049E+02	3.3874E+01	0.0000E+00	6.2374E+03	6.1484E+03
	Worst	0.0000E+00	2.8336E+03	3.0387E+03	7.2966E+03	7.2140E+03	2.4824E+03	1.3955E+02	0.0000E+00	6.9272E+03	6.7935E+03
	Mean	0.0000E+00	2.4039E+03	2.8182E+03	5.8398E+03	6.9845E+03	1.1621E+03	7.9953E+01	0.0000E+00	6.6947E+03	6.3803E+03
	STD	0.0000E+00	1.7236E+02	1.1117E+02	7.3164E+02	1.3346E+02	4.3925E+02	2.6862E+01	0.0000E+00	2.0926E+02	1.5932E+02
F10	Best	8.8818E-16	6.8260E+00	9.9982E+00	4.1370E-03	1.9994E+01	1.0167E+01	1.1904E-03	8.8818E-16	1.9258E+01	2.0613E+01
	Worst	4.4409E-15	8.4758E+00	1.1133E+01	2.2710E-02	2.0476E+01	2.0815E+01	2.4714E-03	7.9936E-15	1.9756E+01	2.0935E+01
	Mean	1.3619E-15	7.7063E+00	1.0692E+01	1.1628E-02	2.0246E+01	1.8697E+01	1.8241E-03	4.9146E-15	1.9604E+01	2.0839E+01
	STD	1.2283E-15	4.3292E-01	2.9110E-01	4.7999E-03	1.5964E-01	3.9077E+00	3.3203E-04	2.2340E-15	1.2458E-01	6.3252E-02
F11	Best	0.0000E+00	1.6763E+03	8.3185E+03	9.6225E-04	9.8292E+03	4.6183E+02	8.8495E-05	0.0000E+00	4.0661E+03	8.5451E+02
	Worst	0.0000E+00	1.8663E+03	9.0469E+03	2.5693E-01	1.0947E+04	3.5856E+03	1.1526E-01	0.0000E+00	5.0563E+03	1.2341E+03
	Mean	0.0000E+00	1.7885E+03	8.6801E+03	6.0434E-02	1.0361E+04	1.8036E+03	2.6425E-02	0.0000E+00	4.6372E+03	1.0523E+03
	STD	0.0000E+00	4.9130E+01	1.7415E+02	9.2346E-02	2.7764E+02	6.6056E+02	4.5178E-02	0.0000E+00	2.1372E+02	7.9442E+01
F12	Best	4.2975E-27	2.8703E+00	9.6241E+01	3.0322E+05	1.0301E+10	3.2155E+09	7.0112E-01	4.2115E-02	4.4071E+09	1.0984E+08
	Worst	2.6890E-21	4.6435E+00	7.1362E+04	8.2395E+06	1.2946E+10	7.8987E+09	8.5431E-01	1.5917E-01	9.7134E+09	2.5886E+08
	Mean	1.0060E-22	3.8666E+00	1.9636E+04	3.2865E+06	1.1864E+10	5.9188E+09	7.5130E-01	8.7540E-02	7.4853E+09	1.7264E+08
	STD	4.8930E-22	4.6638E-01	1.8786E+04	2.4189E+06	6.9532E+08	1.2891E+09	3.5259E-02	3.0456E-02	1.5125E+09	4.0038E+07
F13	Best	4.8797E-30	6.0221E+02	1.6566E+06	4.0267E+04	1.9564E+10	6.1227E+09	4.8284E+01	8.6828E+00	9.0528E+09	2.9433E+08
	Worst	4.3930E-25	9.0046E+02	7.2966E+06	5.3998E+06	2.4494E+10	1.3148E+10	5.3352E+01	3.0111E+01	1.3680E+10	7.7453E+08
	Mean	1.8353E-26	7.4543E+02	4.3705E+06	1.7871E+06	2.2026E+10	1.0034E+10	5.0984E+01	1.8348E+01	1.1079E+10	4.9812E+08
	STD	7.9783E-26	8.5221E+01	1.3187E+06	1.3305E+06	1.3704E+09	1.8349E+09	1.3647E+00	5.9669E+00	1.3539E+09	9.5930E+07

Table 5
(F1-F13) Benchmark Function Results using 1000 Dimensions.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F1	Best	2.0680E-65	2.4923E+03	1.2720E+05	1.7715E+00	2.6080E+06	3.0789E+05	1.3339E-01	1.0072E-78	1.3509E+06	7.2396E+05
	Worst	3.3469E-54	5.9108E+03	1.5000E+05	1.6830E+01	2.7792E+06	7.4978E+05	3.3643E-01	1.0730E-67	1.4979E+06	8.5895E+05
	Mean	2.0920E-55	3.5190E+03	1.3799E+05	4.3320E+00	2.7168E+06	4.9164E+05	2.2308E-01	4.4279E-69	1.4317E+06	8.0989E+05
	STD	7.1240E-55	6.6606E+02	5.3065E+03	2.9531E+00	4.1868E+04	1.2319E+05	4.5294E-02	1.9766E-68	4.0711E+04	3.1810E+04
F2	Best	4.3762E-36	8.0454E+02	1.9516E+266	9.8519E-03	Inf	Inf	2.2151E-01	2.0535E-56	Inf	7.0930E+215
	Worst	7.0749E-31	Inf	5.6922E+291	8.9788E-02	Inf	Inf	2.0058E+00	5.1841E-47	Inf	2.2639E+272
	Mean	3.1598E-32	Inf	1.9014E+290	2.8078E-02	Inf	Inf	6.9958E-01	2.3171E-48	Inf	8.0095E+270
	STD	1.2894E-31	NaN	Inf	2.1605E-02	NaN	NaN	3.9691E-01	9.6498E-48	NaN	Inf
F3	Best	8.2558E-03	7.4284E+05	2.6534E+06	4.5231E+06	1.2690E+07	1.8222E+07	9.6662E+05	4.1802E+07	1.6382E+07	6.6505E+06
	Worst	1.8423E+04	8.7022E+06	2.1171E+07	7.8146E+06	2.6151E+07	3.6295E+07	2.1060E+06	2.3135E+08	2.6079E+07	9.6169E+06
	Mean	2.0856E+03	2.6108E+06	7.7226E+06	6.1985E+06	1.8961E+07	2.7081E+07	1.5166E+06	1.2026E+08	2.0717E+07	8.1288E+06
	STD	4.8253E+03	1.7905E+06	4.4687E+06	8.0401E+05	3.4132E+06	4.4599E+06	2.8441E+05	4.3893E+07	2.4506E+06	8.0662E+05
F4	Best	7.6613E-26	1.4682E+01	3.0987E+01	9.9239E+01	9.9144E+01	9.9200E+01	7.0307E+01	4.2291E+01	9.9218E+01	9.6398E+01
	Worst	1.1359E-18	1.7249E+01	3.7993E+01	9.9781E+01	9.9734E+01	9.9779E+01	8.4285E+01	9.9053E+01	9.9832E+01	9.8742E+01
	Mean	5.2719E-20	1.5704E+01	3.4128E+01	9.9611E+01	9.9500E+01	9.9607E+01	7.8009E+01	7.7184E+01	9.9639E+01	9.7786E+01
	STD	2.0792E-19	6.2236E-01	1.6606E+00	1.2699E-01	1.7429E-01	1.1451E-01	3.1060E+00	1.6856E+01	1.5055E-01	6.6258E-01
F5	Best	6.9113E-26	2.4047E+05	1.9878E+07	1.4254E+07	1.2059E+10	2.7526E+09	1.0132E+03	9.9202E+02	6.7426E+09	2.0053E+09
	Worst	6.6826E-22	4.3051E+05	3.7209E+07	8.5954E+07	1.3095E+10	5.3842E+09	1.0950E+03	9.9582E+02	9.5269E+09	2.7342E+09
	Mean	7.6341E-23	3.3618E+05	2.6960E+07	4.2602E+07	1.2497E+10	3.9254E+09	1.0505E+03	9.9394E+02	8.6544E+09	2.3627E+09
	STD	1.5242E-22	4.4091E+04	3.2504E+06	2.1736E+07	2.6211E+08	7.5000E+08	1.8698E+01	7.7509E-01	5.2350E+08	1.5947E+08
F6	Best	1.2772E-06	2.4440E+03	1.2659E+05	2.2852E+02	2.6512E+06	9.7601E+04	1.9697E+02	2.9351E+01	1.3680E+06	7.5289E+05
	Worst	1.7625E-01	4.7158E+03	1.4652E+05	2.4044E+02	2.8088E+06	8.2782E+05	2.0822E+02	9.8588E+01	1.5422E+06	8.5764E+05
	Mean	2.1746E-02	3.4883E+03	1.3699E+05	2.3441E+02	2.7317E+06	4.9232E+05	2.0271E+02	6.9553E+01	1.4435E+06	7.9923E+05
	STD	4.4438E-02	5.0329E+02	4.6622E+03	3.4657E+00	3.6319E+04	1.7072E+05	2.6725E+00	1.6634E+01	4.8208E+04	2.9390E+04
F7	Best	1.8704E-04	1.5771E+04	5.8848E+03	8.4857E+01	1.8611E+05	3.2415E+04	9.1998E-02	7.8090E-05	9.4633E+04	2.3592E+04
	Worst	2.8759E-03	2.8577E+04	8.9060E+03	1.8967E+03	2.0787E+05	9.9798E+04	2.2645E-01	2.3527E-02	1.2990E+05	3.4579E+04
	Mean	1.0528E-03	2.1410E+04	6.8702E+03	4.7945E+02	1.9669E+05	6.9602E+04	1.4544E-01	5.6916E-03	1.1460E+05	2.9221E+04
	STD	6.8893E-04	3.0007E+03	6.9180E+02	3.7389E+02	6.2727E+03	1.7272E+04	2.9815E-02	5.4080E-03	8.6855E+03	2.2630E+03
F8	Best	-4.1898E+05	-1.9784E+04	-2.1085E+04	-4.9776E+04	-1.0342E+05	-2.9342E+04	-1.0660E+05	-4.1887E+05	-6.7354E+04	-1.1974E+05
	Worst	-4.1898E+05	-1.1276E+04	-9.9474E+03	-3.7320E+04	-7.9627E+04	-1.8153E+04	-2.0322E+04	-2.6668E+05	-2.3845E+04	-9.7907E+04
	Mean	-4.1898E+05	-1.4824E+04	-1.3945E+04	-4.3876E+04	-9.0167E+04	-2.1650E+04	-8.8662E+04	-3.5417E+05	-4.2419E+04	-1.0918E+05
	STD	4.0104E-01	2.0745E+03	2.2934E+03	3.0835E+03	6.2161E+03	1.9878E+03	1.4472E+04	5.5359E+04	1.1817E+04	5.6703E+03
F9	Best	0.0000E+00	5.8035E+03	6.4310E+03	6.8731E+03	1.5193E+04	9.2203E+02	1.1830E+02	0.0000E+00	1.3724E+04	1.4098E+04
	Worst	0.0000E+00	7.0748E+03	7.0831E+03	1.2705E+04	1.5822E+04	3.7715E+03	3.4788E+02	0.0000E+00	1.4672E+04	1.5044E+04
	Mean	0.0000E+00	6.4039E+03	6.7756E+03	9.8365E+03	1.5532E+04	1.9397E+03	1.9570E+02	0.0000E+00	1.4274E+04	1.4605E+04
	STD	0.0000E+00	2.5631E+02	1.4967E+02	1.8284E+03	1.9577E+02	6.9141E+02	5.5243E+01	0.0000E+00	2.3060E+02	2.3378E+02
F10	Best	8.8818E-16	7.7746E+00	1.0860E+01	3.5987E-02	2.0065E+01	1.0822E+01	1.3240E-02	8.8818E-16	2.0102E+01	2.0931E+01
	Worst	4.4409E-15	9.3308E+00	1.1833E+01	2.7831E-01	2.0633E+01	2.0856E+01	2.3145E-02	7.9936E-15	2.0301E+01	2.1019E+01
	Mean	1.3619E-15	8.5188E+00	1.1275E+01	1.2166E-01	2.0316E+01	1.9710E+01	1.8187E-02	4.6777E-15	2.0197E+01	2.0985E+01
	STD	1.2283E-15	3.2110E-01	1.9611E-01	6.1009E-02	1.9269E-01	2.8918E+00	2.5674E-03	2.2726E-15	5.7361E-02	2.0253E-02
F11	Best	0.0000E+00	3.4845E+03	2.0315E+04	7.4751E-02	2.3614E+04	9.7793E+02	1.0370E-02	0.0000E+00	1.2017E+04	6.5853E+03
	Worst	0.0000E+00	3.7033E+03	2.1221E+04	9.5504E-01	2.5456E+04	8.8798E+03	2.4435E-01	0.0000E+00	1.3647E+04	7.6313E+03
	Mean	0.0000E+00	3.5917E+03	2.0742E+04	3.8629E-01	2.4582E+04	3.7438E+03	6.8872E-02	0.0000E+00	1.2860E+04	7.1311E+03
	STD	0.0000E+00	6.0923E+01	2.7004E+02	2.2087E-01	4.8494E+02	1.7371E+03	9.0906E-02	0.0000E+00	4.5527E+02	2.9888E+02
F12	Best	7.0959E-28	4.2959E+00	5.6555E+04	2.4105E+08	2.7960E+10	9.7881E+09	9.0168E-01	5.5826E-02	2.5960E+10	3.5470E+09
	Worst	3.5238E-22	9.0145E+00	8.1569E+05	1.3163E+09	3.1559E+10	1.9367E+10	2.1673E+00	2.7771E-01	3.8470E+10	5.5320E+09
	Mean	2.2783E-23	6.3190E+00	2.9714E+05	5.9871E+08	3.0191E+10	1.3591E+10	1.2770E+00	1.3829E-01	3.3048E+10	4.4060E+09
	STD	6.6733E-23	1.0388E+00	2.0158E+05	2.5059E+08	9.0152E+08	2.1880E+09	3.0966E-01	6.4458E-02	4.1214E+09	4.6267E+08
F13	Best	1.5909E-29	1.6508E+03	1.2433E+07	1.1723E+08	5.2729E+10	1.4415E+10	1.0926E+02	1.4087E+01	4.0597E+10	7.3175E+09
	Worst	5.0494E-25	3.1058E+03	2.5841E+07	1.6103E+09	5.8660E+10	2.8438E+10	1.4816E+02	6.0528E+01	6.6612E+10	1.0621E+10
	Mean	5.3591E-26	2.2124E+03	1.8272E+07	4.8674E+08	5.5904E+10	2.1498E+10	1.2031E+02	3.9919E+01	4.8090E+10	8.9808E+09
	STD	1.1590E-25	3.8699E+02	3.4363E+06	3.3811E+08	1.5762E+09	3.4312E+09	9.1929E+00	1.1505E+01	5.7130E+09	7.0061E+08

Table 6
(F14-F23) Benchmark Function Results.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F14	Best	9.9800E-01	9.9800E-01	9.9800E-01	9.9800E-01	9.9800E-01	9.9801E-01	9.9800E-01	9.9800E-01	9.9800E-01	9.9800E-01
	Worst	9.9800E-01	1.9926E+00	1.4693E+01	1.8304E+01	1.0763E+01	2.9821E+00	1.2671E+01	1.0763E+01	2.9821E+00	9.9800E-01
	Mean	9.9800E-01	1.3294E+00	4.7670E+00	8.2647E+00	2.3131E+00	1.6605E+00	5.5578E+00	3.6767E+00	1.1965E+00	9.9800E-01
	STD	1.8440E-16	4.7662E-01	3.6101E+00	5.5592E+00	2.1912E+00	9.5050E-01	4.8029E+00	3.8380E+00	5.4668E-01	4.6533E-11
F15	Best	3.0749E-04	3.0749E-04	8.6873E-04	3.0798E-04	5.4871E-04	4.3308E-04	3.0749E-04	3.2726E-04	3.3411E-04	4.2655E-04
	Worst	1.2232E-03	2.0363E-02	1.1849E-02	1.1079E-01	2.2519E-03	1.5900E-03	2.0363E-02	3.1048E-03	1.2232E-03	6.2148E-02
	Mean	3.7059E-04	1.2877E-03	4.3344E-03	1.3354E-02	1.0384E-03	1.0220E-03	6.4202E-03	7.5542E-04	6.1376E-04	9.2000E-03
	STD	2.3182E-04	3.6337E-03	2.6346E-03	2.2542E-02	4.3440E-04	3.8162E-04	9.2866E-03	5.5302E-04	1.6192E-04	1.7999E-02
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	-1.0316E+00
	Worst	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0000E+00	-1.0316E+00	-1.0315E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00
	Mean	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0285E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00	-1.0316E+00
	STD	4.7908E-16	6.3877E-16	5.8312E-16	9.6510E-03	6.7752E-16	5.2775E-05	1.2116E-05	1.3420E-09	6.7122E-16	3.5769E-07
F17	Best	3.9789E-01	3.9789E-01	3.9789E-01	3.9789E-01	3.9789E-01	3.9800E-01	3.9789E-01	3.9789E-01	3.9789E-01	3.9789E-01
	Worst	3.9789E-01	3.9789E-01	3.9789E-01	3.9812E-01	3.9789E-01	4.0693E-01	3.9799E-01	3.9793E-01	3.9793E-01	3.9789E-01
	Mean	3.9789E-01	3.9789E-01	3.9789E-01	3.9795E-01	3.9789E-01	4.0004E-01	3.9789E-01	3.9789E-01	3.9789E-01	3.9789E-01
	STD	0.0000E+00	0.0000E+00	0.0000E+00	6.3946E-05	0.0000E+00	2.2510E-03	1.8540E-05	8.5861E-06	8.6681E-06	8.0284E-07
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	3.0000E+00
	Worst	3.0000E+00	3.0000E+00	3.0000E+00	8.4001E+01	3.0000E+00	3.0006E+00	8.4000E+01	3.0004E+00	3.0000E+01	3.0001E+00
	Mean	3.0000E+00	3.0000E+00	3.0000E+00	3.4500E+01	3.0000E+00	3.0001E+00	5.7001E+00	3.0001E+00	3.9000E+00	3.0000E+00
	STD	1.4092E-15	2.0550E-15	4.7794E-15	3.6900E+01	1.8477E-15	1.7182E-04	1.4789E+01	9.8605E-05	4.9295E+00	2.2595E-05
F19	Best	-3.8628E+00	-3.8628E+00	-3.8628E+00	-3.8628E+00	-3.8628E+00	-3.8627E+00	-3.8628E+00	-3.8628E+00	-3.8628E+00	-3.8628E+00
	Worst	-3.8628E+00	-3.8549E+00	-3.8628E+00	-3.8624E+00	-3.8628E+00	-3.8454E+00	-3.8549E+00	-3.8421E+00	-3.8627E+00	-3.8628E+00
	Mean	-3.8628E+00	-3.8620E+00	-3.8628E+00	-3.8626E+00	-3.8628E+00	-3.8547E+00	-3.8608E+00	-3.8584E+00	-3.8628E+00	-3.8628E+00
	STD	2.2584E-15	2.4049E-03	2.4945E-15	1.2065E-04	2.7101E-15	3.6909E-03	3.0870E-03	5.2961E-03	1.4056E-05	4.0765E-06
F20	Best	-3.3220E+00	-3.3220E+00	-3.3220E+00	-3.3212E+00	-3.3220E+00	-3.1646E+00	-3.3220E+00	-3.3216E+00	-3.3220E+00	-3.3220E+00
	Worst	-3.2031E+00	-2.9564E+00	-3.3220E+00	-2.4311E+00	-3.1376E+00	-1.8171E+00	-3.0209E+00	-1.8403E+00	-3.2031E+00	-3.1922E+00
	Mean	-3.2586E+00	-3.2389E+00	-3.3220E+00	-3.2249E+00	-3.2324E+00	-2.9564E+00	-3.2585E+00	-3.1589E+00	-3.3030E+00	-3.2490E+00
	STD	6.0328E-02	1.0146E-01	1.6555E-15	1.7970E-01	5.6221E-02	2.5788E-01	8.7928E-02	3.0066E-01	4.1101E-02	6.0638E-02
F21	Best	-10.1532	-10.1532	-10.1532	-10.0732	-10.1532	-6.5614	-10.1530	-10.1508	-10.1532	-10.1531
	Worst	-10.1532	-2.6305	-2.6829	-2.6052	-2.6305	-0.4973	-2.6826	-2.6267	-4.0130	-2.6304
	Mean	-10.1532	-6.7321	-5.2432	-5.8999	-5.8820	-2.5243	-9.3148	-8.4315	-9.1166	-7.4582
	STD	0.0000	3.5630	3.5442	3.2028	3.2300	2.1547	2.2134	2.6678	1.8449	3.0290
F22	Best	-10.4029	-10.4029	-10.4029	-10.3248	-10.4029	-5.8196	-10.4029	-10.4027	-10.4029	-10.4029
	Worst	-10.4029	-2.7519	-2.7659	-1.8234	-2.7519	-0.5239	-10.3977	-2.7629	-2.7519	-2.7659
	Mean	-10.4029	-6.7370	-10.1484	-7.6860	-7.4010	-3.0259	-10.4009	-6.8074	-9.7349	-8.1483
	STD	0.0000	3.5639	1.3943	3.2861	3.3433	1.7178	0.0013	3.2506	1.9389	3.0920
F23	Best	-10.5364	-10.5364	-10.5364	-10.5156	-10.5364	-6.6124	-10.5361	-10.5321	-10.5364	-10.5363
	Worst	-10.5364	-2.4217	-2.4217	-2.4108	-2.4217	-0.9442	-2.8065	-1.8577	-3.4444	-2.4217
	Mean	-10.5364	-7.2984	-9.9954	-6.5736	-8.0934	-4.1131	-10.2769	-6.9161	-9.8276	-8.4157
	STD	0.0000	3.7994	2.0588	3.8282	3.5508	1.3341	1.4109	3.3276	1.8432	3.1301

Table 7
(F23-F52)Benchmark Function Results.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F24	Best	1.4134E+02	1.1327E+02	1.0574E+02	1.5769E+07	2.2188E+02	3.9604E+08	3.2700E+04	8.8350E+04	9.3500E+06	6.4572E+03
	Worst	4.4871E+03	2.3175E+09	1.0264E+04	1.1987E+10	9.3389E+08	2.1170E+09	5.1689E+08	2.3168E+06	1.4186E+10	5.3765E+04
	Mean	1.0910E+03	2.0157E+08	2.7182E+03	4.0637E+09	9.3390E+07	1.2029E+09	5.8382E+07	7.9463E+05	3.3815E+09	2.1379E+04
	STD	1.0199E+03	5.5560E+08	3.0115E+03	3.0855E+09	2.8495E+08	4.9644E+08	1.2760E+08	6.2029E+05	3.1215E+09	1.1254E+04
F25	Best	3.0000E+02	3.0000E+02	1.1504E+04	4.6900E+02	3.0482E+02	1.2284E+03	7.1354E+02	3.1872E+02	3.3939E+02	3.0004E+02
	Worst	3.0000E+02	1.0587E+04	3.9908E+04	3.1109E+04	2.6315E+04	9.8352E+03	1.1893E+04	1.4056E+03	3.0707E+04	3.0038E+02
	Mean	3.0000E+02	1.7935E+03	2.5784E+04	1.2313E+04	7.1830E+03	4.0663E+03	3.8257E+03	5.7726E+02	1.2138E+04	3.0017E+02
	STD	5.2153E-08	2.5444E+03	6.9933E+03	7.6877E+03	7.5300E+03	1.8833E+03	3.3821E+03	2.4665E+02	9.0517E+03	1.0458E-01
F26	Best	4.0002E+02	4.0000E+02	4.0001E+02	4.0681E+02	4.0000E+02	4.4771E+02	4.0118E+02	4.0051E+02	4.1124E+02	4.0002E+02
	Worst	4.1604E+02	2.4024E+03	4.3810E+02	2.4323E+03	5.1850E+02	5.8302E+02	5.1547E+02	5.3084E+02	2.8940E+03	4.3811E+02
	Mean	4.0107E+02	5.7101E+02	4.1303E+02	9.6809E+02	4.3327E+02	4.8128E+02	4.3611E+02	4.4240E+02	1.0377E+03	4.1566E+02
	STD	3.1287E+00	4.3103E+02	1.8052E+01	6.3846E+02	2.9835E+01	3.3468E+01	1.9524E+01	3.3618E+01	7.4626E+02	1.8670E+01
F27	Best	5.0399E+02	5.2686E+02	5.3980E+02	5.3717E+02	5.1094E+02	5.3176E+02	5.0298E+02	5.1255E+02	5.2741E+02	5.0699E+02
	Worst	5.3556E+02	5.8490E+02	5.8159E+02	6.1957E+02	5.5612E+02	5.7356E+02	5.3184E+02	5.7734E+02	5.9756E+02	5.4809E+02
	Mean	5.1443E+02	5.5155E+02	5.5966E+02	5.6342E+02	5.2741E+02	5.5624E+02	5.1637E+02	5.4868E+02	5.6719E+02	5.2021E+02
	STD	6.0042E+00	1.5575E+01	1.1684E+01	2.0133E+01	1.3550E+01	9.5245E+00	8.3349E+00	1.8070E+01	1.9620E+01	1.0599E+01
F28	Best	6.0000E+02	6.1031E+02	6.1057E+02	6.0930E+02	6.0000E+02	6.1559E+02	6.0024E+02	6.0910E+02	6.0335E+02	6.0011E+02
	Worst	6.0843E+02	6.4867E+02	6.5257E+02	6.8088E+02	6.1316E+02	6.3568E+02	6.0499E+02	6.6124E+02	6.7960E+02	6.2756E+02
	Mean	6.0067E+02	6.2409E+02	6.3265E+02	6.3390E+02	6.0273E+02	6.2504E+02	6.0171E+02	6.3615E+02	6.3290E+02	6.0334E+02
	STD	1.6830E+00	7.6830E+00	1.1947E+01	1.6007E+01	3.9155E+00	4.3677E+00	1.1316E+00	1.4055E+01	1.5939E+01	5.5732E+00
F29	Best	7.0744E+02	7.2919E+02	7.1868E+02	7.6315E+02	7.1721E+02	7.7278E+02	7.1758E+02	7.6015E+02	7.5396E+02	7.1383E+02
	Worst	7.4478E+02	8.4579E+02	7.6069E+02	8.8120E+02	7.6244E+02	8.2702E+02	7.8874E+02	9.2145E+02	8.7821E+02	7.6683E+02
	Mean	7.2574E+02	7.8147E+02	7.3256E+02	8.1880E+02	7.3814E+02	7.9715E+02	7.3801E+02	8.0706E+02	8.1569E+02	7.2938E+02
	STD	8.2081E+00	2.7090E+01	1.0150E+01	3.2697E+01	1.3272E+01	1.3446E+01	1.7083E+01	3.9629E+01	3.1698E+01	1.2999E+01
F30	Best	8.0398E+02	8.2786E+02	8.3184E+02	8.3133E+02	8.1357E+02	8.3840E+02	8.0500E+02	8.1810E+02	8.2885E+02	8.0697E+02
	Worst	8.2669E+02	8.7868E+02	8.8855E+02	8.9390E+02	8.6385E+02	8.6466E+02	8.3089E+02	9.0455E+02	9.0427E+02	8.4578E+02
	Mean	8.1565E+02	8.5061E+02	8.4912E+02	8.6205E+02	8.3506E+02	8.5466E+02	8.1729E+02	8.5699E+02	8.5802E+02	8.1980E+02
	STD	6.9328E+00	1.2803E+01	1.2737E+01	1.8192E+01	1.3688E+01	7.1314E+00	6.6650E+00	2.2884E+01	1.8402E+01	9.5628E+00
F31	Best	9.0000E+02	1.1651E+03	9.6549E+02	9.4190E+02	9.0000E+02	1.0526E+03	9.0003E+02	1.0780E+03	1.0393E+03	9.0000E+02
	Worst	9.0376E+02	2.4301E+03	1.9603E+03	4.4039E+03	1.8271E+03	1.5622E+03	1.3546E+03	3.8897E+03	4.3919E+03	1.0995E+03
	Mean	9.0057E+02	1.5945E+03	1.4845E+03	2.0079E+03	1.0680E+03	1.2753E+03	9.7127E+02	2.0819E+03	1.9525E+03	9.2161E+02
	STD	1.0329E+00	3.2140E+02	2.4958E+02	8.2972E+02	2.6016E+02	1.3392E+02	9.6964E+01	7.4692E+02	8.3653E+02	3.9861E+01
F32	Best	1.1407E+03	1.5624E+03	1.3526E+03	1.3459E+03	1.5865E+03	2.0066E+03	1.1349E+03	1.5009E+03	1.4814E+03	1.0489E+03
	Worst	2.2984E+03	3.0255E+03	2.6527E+03	2.4124E+03	2.9805E+03	2.7831E+03	2.5160E+03	2.4498E+03	2.5485E+03	2.2818E+03
	Mean	1.7409E+03	2.4402E+03	2.0186E+03	1.9968E+03	1.9929E+03	2.4379E+03	1.5903E+03	1.9867E+03	2.0508E+03	1.7032E+03
	STD	3.2895E+02	3.9879E+02	3.4775E+02	2.8143E+02	3.5821E+02	1.8545E+02	3.1809E+02	2.8656E+02	2.6550E+02	2.6345E+02
F33	Best	1.1021E+03	1.1153E+03	1.1343E+03	1.1643E+03	1.1035E+03	1.1812E+03	1.1071E+03	1.1187E+03	1.1497E+03	1.1049E+03
	Worst	1.1260E+03	1.2143E+03	2.0468E+03	6.1473E+03	1.2463E+03	1.5374E+03	1.5496E+03	1.1958E+03	6.9725E+03	1.1636E+03
	Mean	1.1094E+03	1.1525E+03	1.3830E+03	1.8874E+03	1.1406E+03	1.3048E+03	1.1343E+03	1.1523E+03	2.3152E+03	1.1257E+03
	STD	6.3235E+00	2.6797E+01	1.7260E+02	1.1781E+03	3.5014E+01	8.7094E+01	7.9404E+01	2.1240E+01	1.8371E+03	1.4166E+01
F34	Best	2.3105E+03	1.6327E+03	2.0425E+04	3.4328E+04	5.1307E+03	2.9398E+06	2.3780E+04	3.7580E+04	5.7947E+04	6.9135E+03
	Worst	3.8886E+04	4.4933E+04	3.6037E+06	3.2026E+08	7.7872E+06	5.4701E+07	1.3107E+07	3.1453E+07	1.0038E+08	1.0582E+07
	Mean	1.1711E+04	1.2397E+04	1.2148E+06	5.8034E+07	1.0758E+06	1.4763E+07	2.7942E+06	5.4090E+06	3.1120E+07	1.6125E+06
	STD	9.3494E+03	1.0652E+04	8.6290E+05	9.8675E+07	1.6396E+06	1.2546E+07	3.9506E+06	7.7543E+06	3.7816E+07	2.3150E+06
F35	Best	1.3244E+03	1.4277E+03	2.7685E+03	3.4822E+03	1.4973E+03	8.9023E+03	1.9202E+03	2.1484E+03	2.5365E+03	1.4960E+03
	Worst	2.0158E+04	2.0690E+04	1.1895E+04	4.1402E+04	2.1567E+04	1.0576E+06	8.9399E+04	6.1109E+04	6.9917E+04	2.0684E+04
	Mean	4.3569E+03	4.9944E+03	6.6598E+03	1.5159E+04	7.5856E+03	2.8752E+05	1.4739E+04	1.6443E+04	1.8642E+04	8.2572E+03
	STD	4.7227E+03	4.1980E+03	2.1597E+03	9.6433E+03	4.7317E+03	2.6711E+05	1.7354E+04	1.1933E+04	1.5062E+04	6.9654E+03
F36	Best	1.4128E+03	1.4336E+03	2.3373E+03	1.4991E+03	1.5433E+03	1.5794E+03	1.4994E+03	1.4834E+03	1.4529E+03	1.4469E+03
	Worst	1.5778E+03	1.2872E+04	1.3210E+04	7.7476E+03	3.9770E+04	6.5790E+03	7.7273E+03	7.4021E+03	8.1446E+03	3.3127E+04
	Mean	1.4535E+03	3.0949E+03	7.2434E+03	4.3705E+03	5.1541E+03	2.9676E+03	3.1183E+03	2.3235E+03	5.0542E+03	4.8056E+03
	STD	3.5753E+01	2.7078E+03	2.4286E+03	2.8312E+03	6.9354E+03	1.5280E+03	2.0720E+03	1.4947E+03	2.8495E+03	6.4955E+03
F37	Best	1.5022E+03	1.5526E+03	2.7571E+04	1.7430E+03	1.5525E+03	2.0494E+03	1.6320E+03	1.6851E+03	1.6519E+03	1.5237E+03
	Worst	1.5732E+03	8.2983E+04	7.4814E+04	8.4129E+04	2.8106E+04	3.3863E+04	1.0303E+04	1.3221E+04	8.5464E+04	1.4083E+04
	Mean	1.5255E+03	1.6858E+04	4.6740E+04	2.0015E+04	4.7305E+03	4.8431E+03	3.4325E+03	5.4525E+03	3.0802E+04	2.3177E+03
	STD	1.6881E+01	2.1101E+04	1.1688E+04	2.5973E+04	5.1275E+03	5.7534E+03	2.4110E+03	3.7458E+03	3.4995E+04	2.4169E+03
F38	Best	1.6003E+03	1.6013E+03	1.7410E+03	1.6172E+03	1.6054E+03	1.7102E+03	1.6055E+03	1.6114E+03	1.6148E+03	1.6024E+03
	Worst	1.7303E+03	2.1682E+03	2.3791E+03	2.6618E+03	1.9442E+03	1.9559E+03	1.8839E+03	1.9806E+03	2.3681E+03	1.9710E+03
	Mean	1.6427E+03	1.8779E+03	2.0406E+03	1.8514E+03	1.7733E+03	1.7709E+03	1.7013E+03	1.7588E+03	1.8729E+03	1.7269E+03
	STD	4.4048E+01	1.5565E+02	1.9544E+02	2.0153E+02	1.0877E+02	6.4793E+01	8.4265E+01	1.0149E+02	1.6133E+02	1.0539E+02
F39	Best	1.7024E+03	1.7213E+03	1.7350E+03	1.7328E+03	1.7105E+03	1.7678E+03	1.7229E+03	1.7517E+03	1.7353E+03	1.7347E+03
	Worst	1.8515E+03	1.9051E+03	2.1968E+03	2.0056E+03	1.9275E+03	1.9923E+03	1.8007E+03	2.0145E+03	2.1345E+03	1.9849E+03
	Mean	1.7430E+03	1.7718E+03	1.8911E+03	1.8626E+03	1.7906E+03	1.8251E+03	1.7543E+03	1.8569E+03	1.8703E+03	1.8040E+03
	STD	4.2273E+01	3.8275E+01	1.3756E+02	6.5789E+01	5.2468E+01	5.1642E+01	1.9432E+01	7.7101E+01	9.7406E+01	6.2897E+01
F40	Best	3.1511E+04	1.9268E+03	4.1036E+03	5.2658E+03	3.0888E+03	1.8686E+04	5.4493E+03	2.0280E+03	7.8251E+03	3.4141E+03
	Worst	8.8499E+04	4.9099E+04	2.1622E+06	1.8862E+07	5.5990E+04	1.1561E+06	4.5252E+04	4.8185E+04	1.8882E+07	8.6216E+04
	Mean	6.3343E+04	1.6149E+04	8.4243E+04	1.2909E+06	1.9079E+04	3.1674E+05	1.5622E+04	1.6188E+04	2.5485E+06	3.1907E+04
	STD	1.4556E+04	1.2269E+04	3.9250E+05	4.7759E+06	1.4674E+04	2.8897E+05	9.3495E+03	1.0618E+04	6.5086E+06	2.6322E+04
F41	Best	1.9155E+03	1.9064E+03	1.7370E+04	1.9457E+03	1.9382E+03	3.1322E+03	1.9403E+03	1.9451E+03	1.9751E+03	1.9160E+03
	Worst	1.2737E+04	9.0689E+03	2.5907E+06	1.4278E+06	1.5959E+04	3.5002E+04	6.6331E+04	1.1506E+04	1.4158E+06	8.4944E+03
	Mean	3.9895E+03	3.6811E+03	5.5904E+05	4.4986E+05	5.8220E+03	9.8062E+03	9.0189E+03	3.5162E+03	1.6686E+05	2.4697E+03
	STD	2.3297E+03	1.8202E+03	5.5924E+05	5.9131E+05	4.3082E+03	7.5029E+03	1.5093E+04	1.9612E+03	3.3052E+05	1.2921E+03
F42	Best	2.0013E+03	2.0557E+03	2.1235E+03	2.0503E+03	2.0523E+03	2.0798E+03	2.0265E+03	2.0645E+03	2.0560E+03	2.0208E+03
	Worst	2.1183E+03	2.2415E+03	2.5750E+03	2.5358E+03	2.2840E+03	2.1633E+03	2.2705E+03	2.3075E+03	2.4198E+03	2.3527E+03

(*continued on next page*)

Table 7 (*continued*)

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
	Mean	2.0258E+03	2.1406E+03	2.3690E+03	2.1855E+03	2.1074E+03	2.1114E+03	2.0897E+03	2.1512E+03	2.2028E+03	2.0906E+03
	STD	2.5979E+01	5.0940E+01	1.0270E+02	1.0361E+02	4.9547E+01	2.1718E+01	6.7048E+01	6.2148E+01	9.9354E+01	7.3082E+01
F43	Best	2.2000E+03	2.2053E+03	2.2052E+03	2.2026E+03	2.3000E+03	2.2138E+03	2.3000E+03	2.3000E+03	2.2051E+03	2.2000E+03
	Worst	2.2000E+03	2.4015E+03	2.3623E+03	2.4134E+03	2.3000E+03	2.3644E+03	2.3000E+03	2.3000E+03	2.3904E+03	2.3449E+03
	Mean	2.2000E+03	2.2920E+03	2.3140E+03	2.3333E+03	2.3000E+03	2.2618E+03	2.3000E+03	2.3000E+03	2.3424E+03	2.2928E+03
	STD	1.3865E-11	5.9189E+01	3.5836E+01	5.5841E+01	0.0000E+00	5.2709E+01	0.0000E+00	0.0000E+00	3.9193E+01	5.2595E+01
F44	Best	2.3000E+03	2.3279E+03	2.3000E+03	2.3085E+03	2.2157E+03	2.3722E+03	2.2067E+03	2.2197E+03	2.3137E+03	2.2009E+03
	Worst	2.3326E+03	4.4757E+03	4.0698E+03	4.2714E+03	2.2896E+03	3.8718E+03	2.2347E+03	2.2872E+03	3.8799E+03	2.3300E+03
	Mean	2.3059E+03	2.8998E+03	3.0476E+03	2.7808E+03	2.2318E+03	2.4991E+03	2.2204E+03	2.2519E+03	2.8221E+03	2.3028E+03
	STD	8.5094E+00	5.8930E+02	6.9071E+02	5.2229E+02	1.4776E+01	2.6394E+02	7.4909E+00	1.6225E+01	4.3989E+02	1.9820E+01
F45	Best	2.6107E+03	2.6395E+03	2.6736E+03	2.6451E+03	2.6650E+03	2.6454E+03	2.4108E+03	2.6676E+03	2.6392E+03	2.6092E+03
	Worst	2.6311E+03	2.8286E+03	2.9693E+03	2.7603E+03	2.7065E+03	2.6739E+03	2.7087E+03	2.8974E+03	2.7487E+03	2.6476E+03
	Mean	2.6211E+03	2.7153E+03	2.7574E+03	2.6864E+03	2.6892E+03	2.6616E+03	2.6623E+03	2.7215E+03	2.6878E+03	2.6360E+03
	STD	5.0263E+00	4.6172E+01	6.8685E+01	2.9281E+01	1.0736E+01	8.2613E+00	5.0137E+01	4.5901E+01	3.0159E+01	9.9033E+00
F46	Best	2.7649E+03	2.5888E+03	2.5000E+03	2.7935E+03	2.8085E+03	2.6213E+03	2.6000E+03	2.5019E+03	2.7849E+03	2.7598E+03
	Worst	2.7903E+03	2.9681E+03	2.9474E+03	2.9429E+03	2.8374E+03	2.8415E+03	2.8246E+03	2.8881E+03	2.9930E+03	2.7984E+03
	Mean	2.7768E+03	2.8522E+03	2.8317E+03	2.8525E+03	2.8191E+03	2.8120E+03	2.7432E+03	2.6719E+03	2.8467E+03	2.7772E+03
	STD	6.6587E+00	7.8549E+01	9.1597E+01	3.7601E+01	6.9626E+00	4.1358E+01	1.0315E+02	1.3364E+02	4.4667E+01	1.1282E+01
F47	Best	2.6005E+03	2.8488E+03	2.7000E+03	2.9343E+03	2.8963E+03	2.9442E+03	2.8988E+03	2.7000E+03	2.9025E+03	2.6019E+03
	Worst	2.9754E+03	3.4257E+03	3.2353E+03	3.7552E+03	3.0425E+03	3.1591E+03	3.0051E+03	3.1238E+03	3.4651E+03	2.9760E+03
	Mean	2.9288E+03	3.1624E+03	3.0140E+03	3.1803E+03	2.9484E+03	3.0089E+03	2.9498E+03	2.9536E+03	3.1041E+03	2.8674E+03
	STD	6.3916E+01	1.5237E+02	1.3193E+02	2.2250E+02	3.9537E+01	4.9660E+01	2.2222E+01	6.3118E+01	1.5199E+02	1.3538E+02
F48	Best	2.8000E+03	2.6000E+03	3.0486E+03	2.9123E+03	2.8000E+03	2.9438E+03	2.8000E+03	2.8000E+03	2.8232E+03	2.8009E+03
	Worst	3.4308E+03	4.0572E+03	4.1824E+03	4.4093E+03	3.6912E+03	3.7758E+03	3.6584E+03	3.7708E+03	4.3506E+03	3.3472E+03
	Mean	3.0223E+03	3.5799E+03	3.9508E+03	3.6728E+03	3.2660E+03	3.4219E+03	3.1732E+03	3.0536E+03	3.5864E+03	3.0677E+03
	STD	1.8540E+02	4.2764E+02	2.5442E+02	3.7879E+02	2.5363E+02	2.8801E+02	3.1941E+02	3.3996E+02	4.2568E+02	1.7735E+02
F49	Best	3.0603E+03	3.1134E+03	3.1092E+03	3.0709E+03	3.1246E+03	3.0706E+03	3.1042E+03	3.1491E+03	3.0752E+03	3.0601E+03
	Worst	3.1208E+03	3.5112E+03	3.5648E+03	3.5562E+03	3.2471E+03	3.0865E+03	3.3297E+03	3.4353E+03	3.3352E+03	3.1086E+03
	Mean	3.0614E+03	3.1821E+03	3.2259E+03	3.1562E+03	3.1535E+03	3.0775E+03	3.2004E+03	3.2439E+03	3.1297E+03	3.0861E+03
	STD	1.3984E+01	8.9531E+01	1.4230E+02	9.1013E+01	2.3136E+01	4.7070E+00	6.8903E+01	7.3275E+01	4.9030E+01	1.1906E+01
F50	Best	3.0000E+03	3.1581E+03	3.0000E+03	3.0229E+03	3.1000E+03	3.1899E+03	3.1045E+03	2.9280E+03	3.0461E+03	3.0012E+03
	Worst	3.3026E+03	3.1875E+03	3.2123E+03	3.5836E+03	3.4925E+03	3.2604E+03	3.4565E+03	3.4686E+03	3.4479E+03	3.1876E+03
	Mean	3.1750E+03	3.1865E+03	3.1884E+03	3.3022E+03	3.2358E+03	3.2312E+03	3.2187E+03	3.2228E+03	3.2982E+03	3.1784E+03
	STD	6.3333E+01	5.3795E+00	3.9673E+01	1.1934E+02	9.9632E+01	1.5692E+01	6.6219E+01	7.7964E+01	9.1548E+01	3.4641E+01
F51	Best	3.1491E+03	3.1786E+03	3.3045E+03	3.1549E+03	3.1500E+03	3.2091E+03	3.1427E+03	3.1690E+03	3.2057E+03	3.1360E+03
	Worst	3.2684E+03	3.6758E+03	3.8568E+03	3.7175E+03	3.3841E+03	3.3851E+03	3.4040E+03	3.3784E+03	3.5863E+03	3.4739E+03
	Mean	3.1998E+03	3.3614E+03	3.5972E+03	3.3823E+03	3.2227E+03	3.2898E+03	3.2009E+03	3.2611E+03	3.3903E+03	3.2675E+03
	STD	3.5307E+01	1.1859E+02	1.2244E+02	1.4124E+02	5.9060E+01	4.5700E+01	6.5359E+01	6.2939E+01	8.5280E+01	1.0051E+02
F52	Best	3.4355E+03	3.7292E+03	4.7885E+03	7.2743E+03	4.8905E+03	4.1471E+04	3.7236E+03	5.6332E+03	5.3467E+03	4.1200E+03
	Worst	1.1106E+05	7.1467E+06	1.1387E+07	6.7961E+06	8.0467E+05	2.7219E+06	6.7840E+05	4.4790E+06	6.9973E+06	1.6878E+06
	Mean	1.6103E+04	9.4929E+05	7.1556E+05	1.3317E+06	1.4722E+05	4.3631E+05	7.5294E+04	9.4832E+05	1.5916E+06	9.4067E+04
	STD	2.1488E+04	1.9545E+06	2.5078E+06	2.1024E+06	2.3252E+05	5.3012E+05	2.0445E+05	1.1580E+06	2.0700E+06	3.2829E+05

Table 8
(F1-F13)Benchmark Function Results 'for to evaluate the effect of population size and maximum iteration on the proposed model'.

function	metric	Population				Iteration			
		10	20	30	40	100	200	300	400
F1	Mean	9.8782E-54	6.0503E-65	2.9892E-73	3.2569E-79	1.9235E-13	2.3538E-28	9.9596E-43	1.6378E-57
	STD	5.4016E-53	2.7268E-64	7.4658E-73	1.6239E-78	9.5572E-13	8.6956E-28	4.4819E-42	5.5173E-57
F2	Mean	1.7832E-34	7.8305E-38	2.8241E-42	3.8533E-46	1.4209E-08	2.8833E-17	7.0335E-26	5.2730E-34
	STD	5.9247E-34	3.0748E-37	8.7458E-42	1.0980E-45	2.5515E-08	5.6098E-17	1.2263E-25	1.1468E-33
F3	Mean	1.6616E-03	1.4099E-05	1.4359E-07	9.1493E-10	1.3423E-01	2.6392E-02	1.9829E-05	1.3238E-04
	STD	7.0581E-03	6.2860E-05	6.1354E-07	3.7867E-09	3.8735E-01	1.0986E-01	5.2743E-05	7.2329E-04
F4	Mean	3.8285E-18	5.6629E-22	2.7366E-24	1.4667E-26	6.9036E-06	9.0676E-11	1.7420E-15	2.3352E-19
	STD	9.8780E-18	2.2688E-21	8.2692E-24	4.2593E-26	2.3308E-05	2.9074E-10	6.9805E-15	5.7322E-19
F5	Mean	4.3497E-19	8.3019E-22	2.6340E-22	5.1651E-22	7.0243E-05	1.7760E-11	6.8039E-17	1.4418E-16
	STD	1.6368E-18	4.3300E-21	1.4424E-21	2.2213E-21	1.7557E-04	3.1190E-11	1.6611E-16	7.6693E-16
F6	Mean	1.1408E-04	6.9806E-07	3.0442E-09	6.0442E-11	1.8290E-03	4.0854E-05	2.6177E-06	2.7351E-07
	STD	2.0261E-04	2.1364E-06	5.7835E-09	2.7730E-10	2.8898E-03	1.0226E-04	9.9781E-06	6.2918E-07
F7	Mean	8.6204E-04	7.3934E-04	5.3095E-04	3.8622E-04	1.9472E-03	8.8464E-04	6.7070E-04	6.2199E-04
	STD	7.7421E-04	9.0955E-04	4.4930E-04	3.4108E-04	2.1853E-03	7.0815E-04	4.6737E-04	5.0767E-04
F8	Mean	-1.2569E+04	-1.2569E+04	-1.2569E+04	-1.2569E+04	-1.2569E+04	-1.2569E+04	-1.2569E+04	-1.2569E+04
	STD	1.3417E-03	4.8899E-05	4.1807E-08	1.0645E-08	8.5315E-03	2.1437E-04	5.3813E-05	6.4787E-07
F9	Mean	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00	9.4739E-15	0.0000E+00	0.0000E+00	0.0000E+00
	STD	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00	3.6819E-14	0.0000E+00	0.0000E+00	0.0000E+00
F10	Mean	2.1908E-15	2.4277E-15	1.2434E-15	1.2434E-15	3.0454E-08	4.2040E-15	1.5987E-15	1.8356E-15
	STD	1.7413E-15	1.7906E-15	1.0840E-15	1.0840E-15	5.7000E-08	2.2726E-15	1.4454E-15	1.5979E-15
F11	Mean	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00	6.1295E-14	0.0000E+00	0.0000E+00	0.0000E+00
	STD	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00	2.5788E-13	0.0000E+00	0.0000E+00	0.0000E+00
F12	Mean	9.5850E-18	3.5828E-22	1.4499E-25	2.0453E-28	9.2993E-08	1.8300E-12	1.7015E-17	1.1012E-20
	STD	1.6755E-17	1.2010E-21	3.3624E-25	8.6561E-28	2.3195E-07	4.5365E-12	3.3876E-17	5.8919E-20
F13	Mean	3.6626E-24	2.0829E-30	2.3852E-32	1.3621E-32	4.6956E-08	1.4954E-14	7.4836E-21	1.3414E-27
	STD	1.7090E-23	4.8700E-30	1.8597E-32	3.7610E-34	1.4122E-07	4.3673E-14	3.1921E-20	2.6349E-27

Table 9
Comparison of average running time (seconds) for larger-scale situations with 1000 variables across 30 runs.

No.		MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
F1	Best	2.5976E+00	1.1503E+00	1.4437E+01	2.0669E+00	1.6925E+00	2.0666E+00	2.7536E+00	2.2421E+00	1.5230E+00	3.9248E+00
	Worst	2.8011E+00	1.3447E+00	3.7665E+01	2.1623E+00	2.9206E+00	2.7989E+00	2.8895E+00	2.8633E+00	1.5836E+00	4.2926E+00
	Mean	2.6142E+00	1.1806E+00	1.7607E+01	2.0885E+00	1.8669E+00	2.1380E+00	2.7849E+00	2.3330E+00	1.5359E+00	3.9850E+00
	STD	3.6091E-02	4.3496E-02	5.9252E+00	1.8446E-02	3.1976E-01	1.2942E-01	2.7455E-02	1.1140E-01	1.1742E-02	6.8595E-02
F2	Best	2.7075E+00	1.2533E+00	6.4605E+01	2.1109E+00	1.7418E+00	2.1393E+00	2.8166E+00	2.2884E+00	1.7229E+00	1.6840E+00
	Worst	2.7277E+00	1.3069E+00	1.1760E+02	3.6335E+00	1.7766E+00	2.1732E+00	2.8707E+00	2.4283E+00	2.3791E+00	1.7317E+00
	Mean	2.7155E+00	1.2719E+00	7.7461E+01	2.2903E+00	1.7545E+00	2.1506E+00	2.8421E+00	2.3732E+00	1.8116E+00	1.7102E+00
	STD	4.7273E-03	1.2909E-02	1.5588E+01	4.0214E-01	8.3165E-03	8.5164E-03	1.4084E-02	3.4205E-02	1.8504E-01	1.1290E-02
F3	Best	5.6078E+01	2.6370E+01	4.2611E+01	2.7001E+01	2.6967E+01	2.9771E+01	3.0399E+01	3.0919E+01	4.3625E+01	2.8563E+01
	Worst	8.2429E+01	5.0516E+01	9.0914E+01	5.1033E+01	3.0402E+01	4.5524E+01	4.6711E+01	4.6826E+01	6.6184E+01	5.1912E+01
	Mean	5.9664E+01	3.3624E+01	5.0589E+01	3.4728E+01	2.7217E+01	3.6846E+01	3.7291E+01	3.7673E+01	4.7661E+01	3.5887E+01
	STD	7.3321E+00	6.9053E+00	1.1391E+01	8.3643E+00	6.4377E-01	7.4357E+00	7.6663E+00	7.6180E+00	7.3067E+00	7.8385E+00
F4	Best	2.5886E+00	1.0555E+00	1.8730E+01	2.0565E+00	1.6881E+00	2.0871E+00	2.7419E+00	2.2207E+00	2.4770E+00	3.8964E+00
	Worst	2.6933E+00	1.2810E+00	4.7148E+01	2.0979E+00	1.7265E+00	3.2035E+00	2.8287E+00	2.3646E+00	2.6333E+00	3.9810E+00
	Mean	2.6009E+00	1.1794E+00	2.9989E+01	2.0709E+00	1.7024E+00	2.6353E+00	2.7618E+00	2.2971E+00	2.5560E+00	3.9357E+00
	STD	1.8014E-02	5.9663E-02	8.5686E+00	9.2414E-03	9.3741E-03	4.6555E-01	1.7578E-02	3.4297E-02	4.2327E-02	1.9928E-02
F5	Best	2.7589E+00	1.2809E+00	1.4533E+01	2.1251E+00	1.7624E+00	3.0416E+00	2.8207E+00	2.3239E+00	2.6479E+00	4.0093E+00
	Worst	5.5110E+00	1.3333E+00	3.2582E+01	2.9264E+00	1.8057E+00	3.1851E+00	2.9105E+00	2.5924E+00	2.8302E+00	4.0417E+00
	Mean	3.9045E+00	1.2984E+00	1.9305E+01	2.2085E+00	1.7767E+00	3.0991E+00	2.8507E+00	2.3980E+00	2.7136E+00	4.0224E+00
	STD	1.0186E+00	1.2027E-02	5.6669E+00	1.9856E-01	9.8326E-03	3.2678E-02	1.9468E-02	6.1876E-02	4.4676E-02	8.9793E-03
F6	Best	2.6022E+00	1.2598E+00	1.4440E+01	2.0617E+00	1.6943E+00	2.9249E+00	2.7567E+00	2.2156E+00	2.4868E+00	3.9294E+00
	Worst	2.6197E+00	1.4386E+00	2.4960E+01	3.0188E+00	1.7431E+00	3.1089E+00	2.8543E+00	2.3973E+00	2.5941E+00	4.0869E+00
	Mean	2.6123E+00	1.2810E+00	1.6249E+01	2.1103E+00	1.7119E+00	2.9878E+00	2.7841E+00	2.3054E+00	2.5379E+00	3.9709E+00
	STD	4.2791E-03	3.8499E-02	2.4915E+00	1.7290E-01	1.1193E-02	4.3296E-02	1.9405E-02	3.5265E-02	2.7580E-02	2.7704E-02
F7	Best	7.5344E+00	3.2345E+00	1.6434E+01	4.2458E+00	3.8915E+00	5.9933E+00	5.2138E+00	4.6700E+00	5.1658E+00	6.1294E+00
	Worst	1.0251E+01	3.2906E+00	2.3050E+01	4.3698E+00	4.2093E+00	6.1495E+00	5.2990E+00	4.8258E+00	1.0453E+01	9.1170E+00
	Mean	7.9800E+00	3.2707E+00	1.7583E+01	4.3128E+00	3.9703E+00	6.0471E+00	5.2598E+00	4.7644E+00	6.9848E+00	6.4247E+00
	STD	8.8311E-01	1.1410E-02	2.2176E+00	1.8668E-02	4.8629E-02	3.5962E-02	2.0525E-02	4.0953E-02	1.2625E+00	6.6943E-01
F8	Best	5.5140E+00	1.7508E+00	1.4775E+01	2.4896E+00	2.1023E+00	3.8269E+00	3.2207E+00	2.6327E+00	2.3999E+00	2.1107E+00
	Worst	6.5812E+00	1.9635E+00	1.8706E+01	2.5346E+00	3.2907E+00	4.0231E+00	3.2960E+00	2.8723E+00	2.4958E+00	2.2722E+00
	Mean	6.1916E+00	1.8986E+00	1.5098E+01	2.5066E+00	2.3115E+00	3.8748E+00	3.2544E+00	2.7577E+00	2.4478E+00	2.1631E+00
	STD	1.9099E-01	7.3017E-02	7.8266E-01	1.1875E-02	3.7747E-01	4.6213E-02	1.8049E-02	5.3076E-02	2.4577E-02	3.4856E-02
F9	Best	5.3386E+00	1.6797E+00	1.4601E+01	2.3604E+00	2.0430E+00	2.3065E+00	2.9632E+00	2.3914E+00	2.2313E+00	4.3137E+00
	Worst	5.7428E+00	1.8163E+00	2.1035E+01	2.5747E+00	2.1974E+00	3.5434E+00	3.3513E+00	2.5828E+00	2.3806E+00	5.0652E+00
	Mean	5.4808E+00	1.7073E+00	1.6403E+01	2.3973E+00	2.0654E+00	2.9967E+00	3.0000E+00	2.5112E+00	2.2509E+00	4.3807E+00
	STD	1.0894E-01	2.3666E-02	2.5457E+00	3.8868E-02	2.9506E-02	5.4109E-01	6.9698E-02	5.0716E-02	2.6326E-02	1.3554E-01
F10	Best	5.4742E+00	1.7480E+00	1.4611E+01	2.3398E+00	2.0912E+00	2.3829E+00	3.0026E+00	2.4993E+00	2.3398E+00	4.4011E+00
	Worst	5.8405E+00	2.6226E+00	3.2181E+01	2.4174E+00	2.1540E+00	2.5758E+00	3.0615E+00	2.7216E+00	2.4020E+00	4.4445E+00
	Mean	5.5725E+00	1.9310E+00	1.7091E+01	2.3648E+00	2.1142E+00	2.5131E+00	3.0264E+00	2.5662E+00	2.3568E+00	4.4203E+00
	STD	8.5205E-02	3.0762E-01	4.0150E+00	1.9632E-02	1.5893E-02	6.3992E-02	1.1535E-02	4.6857E-02	1.4054E-02	1.2089E-02
F11	Best	3.3136E+00	2.0382E+00	1.4838E+01	2.4658E+00	2.2644E+00	2.5448E+00	3.1732E+00	2.6277E+00	2.7085E+00	4.5560E+00
	Worst	6.2582E+00	3.3226E+00	2.4592E+01	2.5164E+00	2.3437E+00	2.6914E+00	3.4038E+00	5.5884E+00	2.9769E+00	1.1437E+01
	Mean	3.8589E+00	2.2194E+00	1.9931E+01	2.4889E+00	2.2823E+00	2.6528E+00	3.2050E+00	2.8905E+00	2.7528E+00	5.2750E+00
	STD	1.0801E+00	2.9013E-01	2.9935E+00	1.2970E-02	1.9927E-02	2.8274E-02	4.2179E-02	5.9193E-01	4.6668E-02	1.7330E+00
F12	Best	8.7098E+00	4.4093E+00	2.0006E+01	5.2376E+00	4.8691E+00	5.5623E+00	6.1947E+00	5.6631E+00	6.7754E+00	7.0526E+00
	Worst	8.8317E+00	4.6291E+00	1.7225E+01	7.6733E+00	4.9391E+00	5.6806E+00	6.8696E+00	1.1902E+01	6.8765E+00	1.6957E+01
	Mean	8.7471E+00	4.5409E+00	5.2685E-01	5.4132E+00	4.9007E+00	5.5963E+00	6.3076E+00	8.2005E+00	6.8133E+00	9.0954E+00
	STD	2.6683E-02	5.1248E-02	2.0006E+01	5.3411E-01	2.0095E-02	2.2548E-02	1.3861E-01	1.6509E+00	2.2885E-02	2.8093E+00
F13	Best	8.6972E+00	4.5887E+00	1.7077E+01	5.2493E+00	4.8583E+00	5.5648E+00	6.1562E+00	7.1825E+00	6.7239E+00	7.0249E+00
	Worst	9.2093E+00	6.3586E+00	1.8263E+01	5.3340E+00	5.0213E+00	5.6313E+00	9.1202E+00	1.3429E+01	1.0371E+01	1.7553E+01
	Mean	8.7438E+00	4.6732E+00	1.7220E+01	5.2874E+00	4.8995E+00	5.5960E+00	6.9506E+00	1.0289E+01	6.9540E+00	1.0571E+01
	STD	9.4281E-02	3.1902E-01	2.2404E-01	2.0724E-02	3.4475E-02	1.5463E-02	1.2313E+00	1.8518E+00	7.3544E-01	2.9206E+00

Table 10

Wilcoxon rank-sum test p-values with 5% significance for F1–F13 with 30 dimensions (p-values less than 0.05 are boldfaced).

	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	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	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	7.7272E-02	=	3.0199E-11	+	3.0199E-11	+
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	+	3.0199E-11	+
F3	3.0199E-11	+	3.0199E-11	+	1.9568E-10	+	3.0199E-11	+	3.0199E-11	+	5.4941E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
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	+	3.0199E-11	+
F5	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+	2.7218E-11	+
F6	6.0658E-11	+	1.1077E-06	+	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	+	1.3111E-08	+	6.7362E-06	+	3.0199E-11	+	3.0199E-11	+
F8	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+	3.0180E-11	+
F9	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.1747E-12	+	1.6074E-01	+	1.2118E-12	+	1.2118E-12	+
F10	7.5741E-12	+	7.5741E-12	+	7.5741E-12	+	7.5741E-12	+	7.5741E-12	+	7.1677E-12	+	2.2157E-05	+	7.5741E-12	+	7.5741E-12	+
F11	1.2118E-12	+	1.2118E-12	+	1.9457E-09	+	1.2118E-12	+	1.2118E-12	+	5.5843E-03	+	1.6080E-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	+	3.0199E-11	+
F13	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+	1.9545E-11	+

Table 11

Wilcoxon rank-sum test p-values with 5% significance for F1–F13 with 100 dimensions (p-values less than 0.05 are boldfaced).

No	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	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	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	-	3.0199E-11	+	3.0199E-11	+
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	+	3.0199E-11	+
F3	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
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	+	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	+	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	+	3.0199E-11	+
F7	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	6.2828E-06	+	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	+	3.0199E-11	+
F9	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	NaN	=	1.2118E-12	+	1.2118E-12	+
F10	1.0149E-11	+	1.0149E-11	+	1.0149E-11	+	1.0149E-11	+	1.0149E-11	+	1.0149E-11	+	4.4959E-04	+	1.0149E-11	+	1.0149E-11	+
F11	1.2118E-12	+	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	+	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	+	3.0199E-11	+

Table 12
Wilcoxon rank-sum test p-values with 5% significance for F1–F13 with 500 dimensions (p-values less than 0.05 are boldfaced).

No	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	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	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	-	3.0199E-11	+	3.0199E-11	+
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	+	3.0199E-11	+
F3	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
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	+	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	+	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	+	3.0199E-11	+
F7	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.8307E-05	+	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	+	3.0199E-11	+
F9	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	NaN	=	1.2118E-12	+	1.2118E-12	+
F10	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	1.8162E-08	+	4.0806E-12	+	4.0806E-12	+
F11	1.2118E-12	+	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	+	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	+	3.0199E-11	+

Table 13
Wilcoxon rank-sum test p-values with 5% significance for F1–F13 with 1000 dimensions (p-values less than 0.05 are boldfaced).

No	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	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	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	-	3.0199E-11	+	3.0199E-11	+
F2	3.1602E-12	+	3.0199E-11	+	3.0199E-11	+	1.2118E-12	+	1.2118E-12	+	3.0199E-11	+	3.0199E-11	-	1.2118E-12	+	3.0199E-11	+
F3	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
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	+	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	+	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	+	3.0199E-11	+
F7	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	5.9706E-05	+	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	+	3.0199E-11	+
F9	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	NaN	=	1.2118E-12	+	1.2118E-12	+
F10	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	4.0806E-12	+	6.9836E-08	+	4.0806E-12	+	4.0806E-12	+
F11	1.2118E-12	+	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	+	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	+	3.0199E-11	+

Table 14
Wilcoxon rank-sum test p-values with 5% significance for F14–F23 issues (p-values less than 0.05 are boldfaced).

No	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	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	1.3872E-04	+	3.1767E-10	+	9.2707E-12	+	2.8041E-02	+	9.2707E-12	+	9.2450E-12	+	9.2707E-12	+	5.3120E-01	=	9.2707E-12	+
F15	6.0104E-08	+	4.5043E-11	+	8.4848E-09	+	1.6903E-09	+	1.1737E-09	+	1.6980E-08	+	4.5726E-09	+	7.1186E-09	+	8.1014E-10	+
F16	3.0502E-02	+	3.5903E-04	+	1.4488E-11	+	2.3638E-05	+	1.4488E-11	+	1.4488E-11	+	1.4488E-11	+	1.2630E-04	+	1.4488E-11	+
F17	NaN	=	NaN	=	1.2118E-12	+	NaN	=	1.2118E-12	+	1.2118E-12	+	1.2118E-12	+	6.6096E-05	+	1.2118E-12	+
F18	1.8886E-02	+	3.5659E-09	+	2.8520E-11	+	3.3355E-01	=	2.8520E-11	+	2.8520E-11	+	2.8520E-11	+	1.6790E-02	+	2.8520E-11	+
F19	2.2891E-02	+	9.6506E-06	+	1.4634E-11	+	9.6506E-06	+	1.4634E-11	+	1.4634E-11	+	1.4634E-11	+	1.4785E-02	+	1.4634E-11	+
F20	5.2134E-01	=	3.1655E-02	-	3.7315E-03	+	7.4461E-02	=	1.6200E-11	+	1.5502E-02	+	2.9529E-04	+	8.3778E-01	=	1.1376E-04	+
F21	2.5605E-02	+	2.9113E-08	+	1.0149E-11	+	1.2529E-03	+	1.0149E-11	+	1.0149E-11	+	1.0149E-11	+	1.8397E-08	+	1.0149E-11	+
F22	6.9396E-05	+	8.3984E-06	+	1.7203E-12	+	4.6666E-02	+	1.7203E-12	+	1.7203E-12	+	1.7203E-12	+	9.7733E-07	+	1.7203E-12	+
F23	9.8430E-03	+	5.7522E-08	+	1.3974E-11	+	4.2078E-01	=	1.3974E-11	+	1.3974E-11	+	1.3974E-11	+	4.7778E-07	+	1.3974E-11	+

Table 15
Wilcoxon rank-sum test p-values with 5% significance for F24–F52 issues (p-values less than 0.05 are boldfaced).

No	MGO versus PSO		MGO versus GSA		MGO versus TSA		MGO versus MFO		MGO versus SCA		MGO versus GWO		MGO versus WOA		MGO versus FFA		MGO versus MVO	
	p-values	R	P-values	R	P-values	R	P-values	R	P-values	R	p-values	R	P-values	R	P-values	R	P-values	R
F24	5.3951E-01	=	6.7869E-02	=	3.0199E-11	+	3.8710E-02	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	1.3289E-10	+
F25	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+
F26	4.9128E-01	=	1.2553E-02	+	3.3536E-09	+	4.8152E-02	+	2.8646E-11	+	2.0276E-03	+	5.7872E-04	+	5.3215E-10	+	4.0361E-02	+
F27	5.4840E-11	+	3.0123E-11	+	3.0142E-11	+	1.0559E-03	+	3.6829E-11	+	4.1189E-02	+	2.0307E-09	+	4.4960E-11	+	1.4530E-02	+
F28	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	7.6973E-04	+	3.0199E-11	+	1.7290E-06	+	3.0199E-11	+	3.6897E-11	+	1.1937E-06	+
F29	8.1014E-10	+	1.1882E-02	+	3.6897E-11	+	5.8282E-03	+	3.0199E-11	+	3.1466E-02	+	4.5043E-11	+	3.3384E-11	+	5.5923E-01	=
F30	3.0047E-11	+	3.0010E-11	+	3.0047E-11	+	1.1067E-07	+	3.0047E-11	+	9.5873E-01	=	1.9478E-10	+	3.0047E-11	+	7.4795E-02	=
F31	3.0123E-11	+	4.0671E-11	+	6.0510E-11	+	2.7533E-03	+	3.6806E-11	+	1.9106E-02	+	3.3301E-11	+	3.6806E-11	+	5.2600E-05	+
F32	5.5329E-08	+	5.8282E-03	+	2.8913E-03	+	1.2732E-02	+	2.3715E-10	+	6.1452E-02	=	4.6371E-03	+	6.9125E-04	+	8.3026E-01	=
F33	1.0937E-10	+	3.0199E-11	+	3.0199E-11	+	1.0277E-06	+	3.0199E-11	+	1.1674E-05	+	6.0658E-11	+	3.0199E-11	+	1.1937E-06	+
F34	9.1171E-01	=	4.5043E-11	+	3.6897E-11	+	2.8716E-10	+	3.0199E-11	+	6.6955E-11	+	3.6897E-11	+	3.0199E-11	+	3.1967E-09	+
F35	4.6263E-02	+	6.7650E-05	+	1.5964E-07	+	5.5611E-04	+	4.5043E-11	+	2.3168E-06	=	9.8329E-08	+	7.6950E-08	+	5.8282E-03	+
F36	1.5964E-07	+	3.0199E-11	+	6.0658E-11	+	3.3384E-11	+	3.0199E-11	+	8.1527E-11	+	3.1589E-10	+	2.3715E-10	+	2.5721E-07	+
F37	4.9752E-11	+	3.0199E-11	+	3.0199E-11	+	4.5043E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	5.4617E-09	+
F38	9.8329E-08	+	3.0199E-11	+	1.8567E-09	+	2.1540E-06	+	9.7555E-10	+	4.4272E-03	+	1.0277E-06	+	6.7220E-10	+	1.3250E-04	+
F39	2.1265E-04	+	1.2541E-07	+	4.5726E-09	+	2.1327E-05	+	7.6950E-08	+	1.8575E-03	+	1.5581E-08	+	3.0811E-08	+	2.4913E-06	+
F40	6.6955E-11	+	5.5727E-10	+	1.4932E-04	-	2.8716E-10	+	7.6588E-05	+	4.9752E-11	+	6.0658E-11	+	5.0842E-03	+	1.7479E-05	+
F41	7.6183E-01	=	3.0199E-11	+	5.2650E-05	+	2.0621E-01	=	4.7445E-06	+	7.7312E-01	+	5.1060E-01	=	2.2658E-03	+	1.7836E-04	+
F42	1.2050E-10	+	3.0180E-11	+	1.0930E-10	+	6.7183E-10	+	1.9557E-10	+	1.8724E-07	+	8.9880E-11	+	8.1479E-11	+	4.4424E-07	+
F43	2.6622E-11	+	2.6622E-11	+	2.6622E-11	+	1.0281E-12	+	2.6622E-11	+	1.0281E-12	+	1.0281E-12	+	2.6622E-11	+	2.6622E-11	+
F44	4.0772E-11	+	5.9428E-02	+	9.9186E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	-	3.0199E-11	+	7.3891E-11	+	3.5638E-04	+
F45	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	3.0199E-11	+	5.5727E-10	+	3.0199E-11	+	3.0199E-11	+	4.7869E-02	+
F46	6.0104E-08	+	8.4808E-09	+	3.0199E-11	+	3.0161E-11	+	8.4848E-09	+	2.6965E-02	+	7.7272E-02	=	4.5043E-11	+	8.1875E-01	=
F47	1.1023E-08	+	8.1975E-07	+	7.3803E-10	+	4.0354E-01	+	3.8202E-10	+	5.8282E-03	+	5.0842E-03	+	3.0811E-08	+	1.7666E-03	+
F48	2.6673E-06	+	3.7925E-10	+	1.0957E-08	+	6.8935E-04	+	1.9938E-06	+	1.2195E-02	+	2.5180E-02	+	7.0106E-07	+	3.5104E-02	+
F49	6.0658E-11	+	4.9752E-11	+	2.3715E-10	+	2.9803E-11	+	2.1947E-08	+	3.6897E-11	+	3.0199E-11	+	5.0723E-10	+	4.3685E-02	+
F50	1.3853E-06	+	8.4848E-09	+	5.5727E-10	+	2.7084E-02	+	3.0199E-11	+	1.0277E-06	+	9.5332E-07	+	5.5727E-10	+	8.8411E-07	+
F51	8.4848E-09	+	3.0199E-11	+	1.4733E-07	+	1.0233E-02	+	2.6695E-09	+	1.2967E-02	+	7.1988E-05	+	1.4643E-10	+	2.9205E-02	+
F52	1.1711E-02	+	3.1830E-03	+	1.4733E-07	+	1.3367E-05	+	3.0811E-08	+	4.2039E-02	+	7.5991E-07	+	3.5201E-07	+	3.7782E-02	+

Table 16
Friedman iterative version test results on F1-13 with 30 dimensions.

	Evaluation on F1-13 with 30 dimensions									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	1.3359	5.5513	6.2308	5.6410	8.6795	8.1564	3.5551	3.7500	5.7179	6.3821
Rank	1	4	7	5	10	9	2	3	6	8

Table 17
Friedman iterative version test results on F1-13 with 100 dimensions.

	Evaluation on F1-13 with 100 dimensions									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	1.2641	5.1103	6.8513	4.8256	8.8256	8.2487	3.1103	2.9128	7.6615	6.1897
Rank	1	5	7	4	10	9	3	2	8	6

Table 18
Friedman iterative version test results on F1-13 with 500 dimensions.

	Evaluation on F1-13 with 500 dimensions									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	1.2551	5.0897	6.1410	5.0795	8.9410	7.5282	3.2487	2.6141	8.3462	6.7564
Rank	1	5	6	4	10	8	3	2	9	7

Table 19
Friedman iterative version test results on F1-13 with 1000 dimensions.

	Evaluation on F1-13 with 1000 dimensions									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	1.2628	5.0654	5.9154	5.1513	8.8833	7.5449	3.2667	2.5577	8.4782	6.8744
Rank	1	4	6	5	10	8	3	2	9	7

Table 20
Friedman iterative version test results on F14-23.

	Evaluation on F14-23									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	2.6067	3.8917	4.8233	7.8267	3.9617	8.7533	6.3933	6.8700	3.6467	6.2267
Rank	1	3	5	9	4	10	7	8	2	6

Table 21
Friedman iterative version test results on F24-52.

	Evaluation on F24-52									
	MGO	PSO	GSA	TSA	MFO	SCA	GWO	WOA	FFA	MVO
Avg	2.6222	5.6922	6.8322	7.3667	4.7622	6.6811	4.1989	5.8322	7.4278	3.5844
Rank	1	5	8	9	4	7	3	6	10	2

Table 22
Parameter Estimation for FM Sound Waves Results Comparison.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
x(1)	0.8563	1.0000	-0.4157	0.8360	-0.6488	-0.6639	-1.0000	1.0000
x(2)	4.9215	5.0000	-5.2297	4.9302	-0.1581	2.9114	-5.0000	5.0000
x(3)	-1.1521	-1.5000	4.5497	-1.1490	-1.5158	-2.9857	-1.5000	-1.5000
x(4)	2.4955	4.8000	0.0623	-2.5071	0.1149	-6.4000	-4.8000	4.8000
x(5)	-4.9331	-2.0000	0.2036	4.9417	4.1441	-4.7684	2.0000	-2.0000
x(6)	-2.4247	-4.9000	4.5415	2.4318	-4.8978	-0.1178	-4.9000	-4.9000
Maximum cost	11.2072	1.7264e-27	21.9830	11.4902	8.4161	15.1569	6.0233e-28	4.5625e-28

Table 23
Results Comparison for Parameter Estimation for Circular Antenna Array Design.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
x(1)	0.8062	0.8403	0.6669	0.857	0.9303	0.9739	0.943	0.8508
x(2)	0.5121	0.4023	0.4403	0.4845	0.7117	0.7718	0.7488	0.5133
x(3)	0.2	0.2711	0.2	0.2022	0.2	0.2597	0.2002	0.2
x(4)	0.2139	0.2029	0.2008	0.2498	0.2	0.331	0.2144	0.2
x(5)	0.2002	0.2734	0.2	0.2	0.2433	0.2482	0.2366	0.2
x(6)	0.513	0.5223	0.4797	0.6878	0.4062	0.6731	0.4069	0.5069
x(7)	164.999	-25.4411	167.0892	159.51	157.6035	169.3933	-23.8391	156.5063
x(8)	-179.9525	11.252	-178.2412	-166.6094	-174.5494	179.4584	7.6921	-166.7679
x(9)	-179.9997	-65.6306	-179.9998	143.9936	129.1926	166.6478	-72.3221	103.7584
x(10)	-179.9732	-47.2177	-179.6962	119.5825	-157.0268	179.3466	24.338	174.3789
x(11)	-179.7293	51.7754	-175.991	180	-133.9601	-165.3896	64.1407	-107.9589
x(12)	-180	-8.9441	-179.9999	169.9087	161.911	167.7404	-26.3047	165.751
Minimum cost	-11.8036	-15.3097	-11.8772	-13.0667	-14.4785	-12.0413	-15.8921	-16.3727

Table 24
The Spread Spectrum Radar Polly phase Code Design problem's parameter estimate findings are compared.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
x(1)	3.7643	1.7673	0.0000	5.3459	5.9761	0.9018	4.1379	3.4439
x(2)	3.5857	3.6229	0.9110	4.1544	0.0655	6.2780	2.0215	4.7133
x(3)	0.2371	4.5886	4.0235	5.7449	2.7591	4.7914	2.9017	4.5651
x(4)	5.2065	4.0369	4.1120	3.1858	6.2064	5.1166	0.0519	6.2776
x(5)	1.7656	5.2571	2.8719	5.3388	2.1098	6.2830	2.6415	5.5799
x(6)	3.9157	4.7998	0.0026	0.2790	5.8477	3.6368	0.3615	3.5984
x(7)	4.6432	5.4172	1.7525	3.7722	3.7525	4.1194	4.7690	3.2109
x(8)	4.0449	6.1601	3.0444	5.0511	1.8515	4.0504	2.3738	1.9472
x(9)	2.3303	3.2246	0.0000	4.2102	6.2608	0.9870	4.4372	1.0811
x(10)	5.9729	4.0468	1.3956	3.9716	3.8266	2.8878	5.5257	5.4138
x(11)	2.3618	2.8266	1.1492	6.2734	5.1280	1.9519	3.1163	2.9129
x(12)	2.7628	3.6991	2.6240	3.6302	2.5764	3.7872	2.6681	3.1246
x(13)	3.3923	0.2848	0.0069	3.4847	3.2448	2.4249	6.2832	5.5273
x(14)	6.2832	4.6764	4.6325	4.7661	4.8573	3.7590	6.2143	2.8597
x(15)	4.6238	5.7047	1.3454	3.2942	3.2787	4.4466	4.7862	4.1080
x(16)	5.1883	5.6313	1.1522	4.8486	4.4893	4.4348	5.6195	3.7457
x(17)	4.3321	5.8002	2.0195	1.9980	3.2014	4.8493	6.1916	6.0035
x(18)	4.9264	0.0001	3.0406	0.0267	2.0817	2.3718	5.8634	5.5345
x(19)	3.0213	4.1634	4.3818	0.0169	2.2289	4.4032	4.3176	6.2452
x(20)	0.0000	3.0255	0.3144	1.1922	5.8931	5.6148	2.8766	5.3374
Minimum cost	1.3660	1.1171	1.4018	1.3287	1.2871	1.3418	1.1130	1.0539

Table 25
Cassini 2: Spacecraft Trajectory Optimization Problem results Compared.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
Tt0	-0.698	-0.8944	-0.7081	-0.7639	-0.7189	-0.7485	-0.8771	-0.8297
Vinf	0.003	0.003	0.0036	0.003	0.003	0.003	0.003	0.003
u	0.0005	0.0004	0.0005	0.0005	0.0005	0.0005	0.0007	0.0006
v	0.0004	0.0004	0.0003	0.0002	0.0004	0.0003	0.0003	0.0005
T1	0.1673	0.3771	0.2487	0.226	0.2415	0.174	0.1611	0.2013
T2	0.2272	0.431	0.2247	0.2351	0.2247	0.2246	0.4494	0.4184
T3	0.2474	0.2711	0.1716	0.1496	0.1098	0.1988	0.116	0.071
T4	0.8312	0.5766	0.9049	0.5541	0.5467	0.5627	0.5519	0.5264
T5	2.0265	2.1225	2.2	1.6538	1.6564	1.7592	1.6438	1.4742
eta1	0	0.0004	0.0005	0.0005	0.0005	0.0002	0	0.0003
eta2	0.0001	0.0007	0	0.0003	0.0002	0	0.0007	0.0003
eta3	0.0005	0	0.0003	0.0005	0.0005	0.0005	0.0005	0.0004
eta4	0.0004	0.0001	0.0004	0	0	0	0	0
eta5	0	0	0	0.0009	0.0007	0	0	0.0009
r_p1	0.0017	0.0034	0.005	0.0043	0.0015	0.0011	0.0023	0.0015
r_p2	0.0058	0.0015	0.0011	0.0011	0.0011	0.0026	0.0011	0.0032
r_p3	0.0032	0.0012	0.002	0.0012	0.0012	0.0012	0.0012	0.0012
r_p4	0.1529	0.2622	0.291	0.1232	0.111	0.11	0.1209	0.1276
b_incl1	-0.0031	0.0003	-0.0003	-0.0031	-0.0031	-0.0031	0.0007	-0.0018
b_incl2	0.0001	-0.0019	-0.0005	0.003	-0.0029	0.0006	-0.0028	-0.0025
b_incl3	-0.0007	-0.0017	-0.0026	-0.0016	-0.0017	-0.0014	-0.0017	-0.0014
b_incl4	-0.0014	-0.0013	-0.001	-0.0015	-0.0015	-0.0015	-0.0015	-0.0015
Minimum cost	22.8551	16.2347	23.0305	19.1534	18.664	19.6871	16.6502	11.9238

Table 26
Messenger: Spacecraft Trajectory Optimization Problem outcomes compared.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
t0	2.0714	2.0628	2.0698	2.0552	2.0366	2.1369	2.13	2.0498
Vinf	0.0036	0.0026	0.0029	0.003	0.0025	0.004	0.004	0.004
U	0.0003	0.0006	0.0003	0.0003	0.0003	0.0006	0.0007	0.0007
V	0.0003	0.0001	0.0005	0.0003	0.0008	0.0004	0.0001	0.0005
T1	0.2486	0.2541	0.2544	0.2545	0.2947	0.2261	0.2461	0.2466
T2	0.2643	0.2424	0.2533	0.2533	0.2524	0.2262	0.2309	0.2462
T3	0.2388	0.2544	0.2525	0.2573	0.2446	0.2515	0.2145	0.2639
T4	0.2591	0.2648	0.2633	0.2605	0.2565	0.2336	0.2639	0.2639
T5	0.2641	0.2594	0.2592	0.2639	0.2639	0.2653	0.2661	0.2621
T6	0.2663	0.2655	0.267	0.2658	0.2701	0.2783	0.2637	0.262
eta1	0.0004	0.0004	0.0004	0.0004	0.0005	0.0004	0.0003	0.0004
eta2	0.0004	0.0003	0.0003	0.0004	0.0004	0.0004	0.0002	0.0003
eta3	0.0004	0.0004	0.0004	0.0004	0.0003	0.0004	0.0005	0.0005
eta4	0.0008	0	0.0002	0.0001	0.0003	0.0004	0.0006	0
eta5	0.0003	0.0002	0.0005	0.0002	0	0.0006	0.0002	0.0002
eta6	0.0002	0.0005	0.0001	0.0001	0.0004	0.0005	0.0002	0.0003
r_p1	0.0055	0.0027	0.0026	0.0023	0.0028	0.0029	0.006	0.006
r_p2	0.0024	0.0025	0.0016	0.0022	0.0022	0.0024	0.0025	0.002
r_p3	0.0018	0.0011	0.0014	0.0011	0.0011	0.0059	0.0011	0.0011
r_p4	0.0057	0.0011	0.0024	0.0016	0.0034	0.0019	0.006	0.0011
r_p5	0.006	0.006	0.0059	0.0018	0.0035	0.006	0.0015	0.0011
b_incl1	-0.0025	-0.0031	-0.0014	-0.0028	-0.0002	0.0004	-0.0031	-0.0031
b_incl2	-0.0011	-0.0014	-0.0009	-0.001	-0.001	-0.0013	-0.0007	-0.0014
b_incl3	0.0031	-0.0028	-0.0015	-0.0031	-0.0011	-0.0018	-0.002	-0.0031
b_incl4	-0.0009	-0.0031	0.003	-0.0004	-0.0026	-0.002	-0.0028	0.0031
b_incl5	0.0031	-0.0014	0.0031	-0.0031	0	-0.0031	-0.003	-0.0028
Minimum cost	18.343	17.0065	20.9774	17.9803	19.1548	18.2458	16.1534	16.1514

Table 27
Results for the Lennard-Jones Potential Problem are compared.

Algorithms	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
x(1)	0.2191	0.9744	1.1446	2.4260	0.1845	0.9230	0.5917	0.0013
x(2)	0.1055	0.3207	0.3617	2.3338	0.0975	1.3388	0.8631	0.5844
x(3)	0.6581	0.8799	0.9487	1.4674	0.3418	0.3322	0.4295	0.1561
x(4)	-0.7760	-0.0701	1.3787	1.6137	0.1284	0.3173	0.0965	-0.0525
x(5)	-0.7018	-0.2286	1.0670	1.9784	1.0974	1.4672	-0.0693	1.6972
x(6)	-0.4561	-0.4577	0.3002	1.9434	0.4013	1.1002	0.2062	1.4568
x(7)	0.4993	0.6641	0.9984	1.9138	0.6386	-0.7715	1.2737	0.4977
x(8)	-0.8273	1.2033	0.1599	1.1290	1.5379	1.3928	-0.4823	1.2068
x(9)	0.5104	0.5158	-0.0040	2.6861	1.1769	-0.1041	-0.8185	0.7403
x(10)	-2.1010	-0.1007	1.4305	2.7660	1.6231	-0.1213	-0.0184	0.7987
x(11)	-0.5801	-0.2676	1.2320	0.6730	0.3919	1.9607	0.4376	1.7201
x(12)	-1.1785	0.6894	1.2874	2.4355	1.1275	0.3800	1.0534	-0.0679
x(13)	0.7579	-0.4616	1.9206	3.0433	1.1239	0.0759	0.8125	-0.1466
x(14)	-1.0985	1.1332	0.2283	1.5627	0.9314	1.3196	-0.6975	1.5526
x(15)	-0.4195	0.4489	0.3775	1.2280	1.8233	-1.5619	0.0193	0.0229
x(16)	-0.4761	0.0854	0.1683	3.4532	1.1130	0.0164	0.9311	-0.5206
x(17)	-0.5859	0.6274	2.2346	1.3582	1.1602	0.9781	0.2606	1.1293
x(18)	0.4849	1.1131	0.3727	2.1178	0.3873	0.3215	-0.2827	0.8153
x(19)	-1.4355	0.1801	1.6453	2.8448	0.6647	0.7381	0.9346	0.4592
x(20)	-0.8043	0.4763	2.1713	1.5498	0.5609	0.6101	-0.0132	2.1639
x(21)	-1.8767	0.1416	1.4611	2.8936	1.0496	-0.2801	0.7140	0.7592
x(22)	-0.1007	0.7498	1.9207	2.4707	1.1650	-0.1085	0.0143	-0.5239
x(23)	-1.3567	-0.3169	0.6838	1.5023	0.1879	0.8855	0.4183	2.1468
x(24)	-0.0779	0.1463	1.9229	1.9958	0.2652	-0.6902	-0.6471	0.6930
x(25)	-1.9858	-0.7834	2.3611	1.6718	1.6707	1.2008	1.6901	0.1107
x(26)	-1.5516	0.2244	1.5391	1.0029	1.3795	-0.2737	-0.2232	2.4917
x(27)	-1.4489	0.1195	1.6571	1.7119	1.1435	-0.1405	0.0726	-0.0895
x(28)	0.1127	0.8442	2.1088	1.5862	2.5099	-0.0011	-0.4307	1.1129
x(29)	-0.3475	0.4609	1.6265	1.7066	0.8163	0.0276	0.7371	2.6257
x(30)	-0.2518	-0.5487	0.7193	-1.0395	1.0233	-0.0768	0.1844	0.1772
Minimum cost	-18.7772	-25.0378	-18.7481	-20.0394	-24.6593	-19.2259	-25.1980	-26.1765

Table 28
Results for the Static Economic Load Dispatch Problem are compared.

Algorithms	MFO	PSO	AVOA	TSA	MFO	GWO	FFA	GTO	MGO
x(1)	94.2903	102.1274	72.6791	77.1147	94.2903	94.2778	99.8223	76.5689	100.736
x(2)	79.4035	102.5005	106.7938	85.5407	79.4035	75.2105	114	49.3801	67.1046
x(3)	113.1972	92.1762	103.445	108.8629	113.1972	91.2701	107.2386	107.4273	116.3646
x(4)	170.1823	151.4949	173.5404	165.6477	170.1823	167.5406	156.9572	153.4782	178.5287
x(5)	81.647	70.6534	88.8556	87.4591	81.647	80.8865	94.6954	89.0489	62.5156
x(6)	126.2661	89.9427	129.9574	140	126.2661	94.1372	125.3505	124.1414	131.0379
x(7)	281.2696	240.6249	256.3891	227.1889	281.2696	219.9746	267.4509	281.162	260.9009
x(8)	248.8129	259.3466	255.5501	229.8279	248.8129	237.3954	236.6435	189.0456	260.5773
x(9)	279.0515	259.6409	234.4761	234.5504	279.0515	246.6919	253.4732	278.8324	269.4037
x(10)	215.0868	236.6764	283.2951	237.9718	215.0868	250.7806	300	264.0701	177.0867
x(11)	324.6556	250.7764	318.0449	301.1619	324.6556	314.1112	331.8762	308.4073	343.2345
x(12)	301.3433	348.0769	238.0055	375	301.3433	354.2169	340.5321	252.2118	117.2838
x(13)	466.9403	488.0614	447.882	392.5417	466.9403	434.0577	428.1277	399.265	188.7268
x(14)	468.2182	472.3202	321.7507	417.1299	468.2182	461.6519	300.7466	407.0739	455.4767
x(15)	361.5181	232.9528	451.8964	500	361.5181	394.1532	450.5072	422.2163	417.6972
x(16)	429.679	475.9931	345.8357	125	429.679	374.6033	328.001	476.6762	442.3396
x(17)	475.8367	465.4866	457.8702	432.3106	475.8367	464.0417	374.6196	469.188	433.7663
x(18)	391.9338	376.6092	465.2828	351.2134	391.9338	462.7799	475.7827	378.6943	463.5666
x(19)	402.5017	335.9595	550	486.3591	402.5017	456.4983	497.9614	383.8124	496.9573
x(20)	500.911	534.5057	479.4542	436.5729	500.911	445.4131	509.9127	467.2353	490.4716
x(21)	532.8763	503.6944	473.462	478.2707	532.8763	493.3194	483.2876	550	543.7029
x(22)	502.7068	526.4446	441.2471	508.8514	502.7068	403.1425	485.0987	419.0794	437.7175
x(23)	518.0773	465.2293	491.2898	539.4702	518.0773	523.5939	463.445	528.7867	499.7855
x(24)	487.7732	512.6434	504.3097	479.1017	487.7732	466.2593	280.6015	467.0582	550
x(25)	431.0201	376.5033	416.493	513.9357	431.0201	508.2876	496.0431	467.2857	539.0968
x(26)	404.2119	514.4128	462.5784	465.5287	404.2119	504.9801	550	539.0085	471.7511
x(27)	26.5077	98.1493	61.0809	84.8445	26.5077	111.707	73.6453	90.9391	25.6356
x(28)	129.154	63.4583	75.8473	89.423	129.154	43.1623	94.5359	82.1293	73.4153
x(29)	47.1379	113.9436	55.5562	94.9363	47.1379	43.2527	107.9487	36.9283	61.9317
x(30)	92.8118	63.108	77.1571	89.3219	92.8118	64.2398	61.8497	75.1901	89.6103
x(31)	106.2088	161.7563	115.1086	161.7647	106.2088	158.315	125.0906	185.2795	154.4111
x(32)	127.0781	139.7814	174.3597	129.2665	127.0781	156.787	149.4888	167.9009	190
x(33)	144.9771	119.7129	148.2531	190	144.9771	137.3487	112.6381	180.6087	189.7773
x(34)	171.5724	132.0886	147.2162	175.684	171.5724	143.7188	143.8317	164.4129	189.5788
x(35)	152.1724	176.5228	154.4746	167.8291	152.1724	166.9628	160.1629	152.7015	194.8051
x(36)	188.0025	167.7784	127.2678	176.1559	188.0025	146.9606	166.623	161.7154	194.6649
x(37)	80.9657	92.0751	90.0547	110	80.9657	106.937	83.3756	51.5326	57.836
x(38)	85.856	76.3692	108.4832	66.1369	85.856	74.6172	93.5344	27.3359	67.7963
x(39)	85.6943	99.1696	93.8171	93.1958	85.6943	95.1676	59.4287	95.0836	68.7631
x(40)	372.4512	511.2407	500.9313	474.8362	372.4512	431.5329	515.6687	479.0886	425.9412
Minimum cost	1.39E+05	1.43E+05	1.36E+05	1.41E+05	1.39E+05	1.40E+05	1.43E+05	1.37E+05	1.33E+05

Table 29
Details of multimodal benchmark functions.

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

Table 30
Details of fixed-dimension multimodal benchmark functions.

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

Table 31
CEC2017 benchmark tests.

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

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