Chaotic approach for improving global optimization in Yellow Saddle Goatfish

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Abstract

Yellow Saddle Goatfish Algorithm (YSGA) is an optimization model inspired by the hunting behavior of yellow saddle goatfish which emulates their collaborative behaviors with chaser fish and blocker fish. To improve the global convergence, chaotic maps have been combined with YSGA in this paper. Chaotic is a nonlinear deterministic system that displays complex, noisy-like, and unpredictable behavior. Due to its non-repetitive nature, an overall search can be carried out at a higher speed. The proposed algorithm is based on the excellence of the chaotic searching using a multi-chaotic approach and the YSGA optimization, which has been applied to 68 benchmark functions. The results of the proposed Multi-Chaotic Yellow Saddle Goatfish algorithm are compared with YSGA and also with nine other states of art meta-heuristic algorithms. The results show that the proposed algorithm improves the performance of the YSGA algorithm.

KEYWORDS
benchmark functions, chaotic maps, meta-heuristic algorithm, Yellow Saddle Goatfish optimization

1 INTRODUCTION

In recent years, researchers have proposed various algorithms to solve optimization problems. Some optimization problems are very complex and require an optimal solution in a reasonable amount of time.1 Moreover, for the problems having more than one local optima, the output may depend on an initial fitness and the solution may trap in local optima. Moreover, in the problems in which the objective function has multiple or sharp peaks, the gradient search may become unstable.2 Due to the drawbacks of traditional methods, the popularity of the meta-heuristic optimization techniques has increased, and researchers are relying on these techniques especially for complex optimization problems.3,4

Meta-heuristic optimizations, which mimic the behavior of natural phenomena, are becoming more prevalent in engineering applications like a structure design problem, product design, process planning, yield-driven design, and so forth.2,5 Meta-heuristic optimizations are very simple, stochastic in nature, do not need any gradient information, and provide the guiding strategies to solve the problems.6,7

Metaheuristic algorithms are generally classified into four classes: Evolutionary algorithms, Swarm-based algorithms, Physics-based algorithms, and Human-based algorithms.5

Evolutionary algorithms are enthused by the concept of evolution in nature. The genetic algorithm is an example of evolutionary algorithms, which is proposed by Holland in 1992.8 Other commonly used evolutionary algorithms are...
Genetic Programming,9 Evolution Strategy,10 Biogeography-Based Optimizer,11 and Sunflower Optimization algorithm (SFO).12

Swarm-based algorithms are inspired by the social behavior of creatures in nature like swarms, herds, flocks. The main feature of this class is the sharing of collective information of all individuals during the optimization process. Particle Swarm Optimization13 is a swarm-based algorithm which is proposed by Kennedy and Eberhart in 1995.13 The other popular swarm-based algorithms are Gray Wolf Optimization (GWO),14 Whale Optimization Algorithm (WOA),5 Butterfly Optimization Algorithm (BOA),15 Cuckoo Search Algorithm,16 Grasshopper optimization algorithm (GOA),17 Ant Lion Optimizer18 and Fitness Dependent Optimizer (FDO): Inspired by the Bee Swarming Reproductive Process.19

Physics-based algorithms are based on physical rules. The physics-based algorithms are Big-Bang Big-Crunch,20 Gravitational Search Algorithm (GSA),21 Artificial Chemical Reaction Optimization Algorithm,22 and Ray Optimization.23

Human-based algorithms are influenced by human behavior. The well-liked human-based algorithms are Seeker Optimization algorithm,24 Teaching Learning-Based Optimization (TLBO),25 Social-Based algorithm,26 Harmony Search (HS),27 and Jaya Algorithm.28

Regardless of nature, all these population-based meta-heuristic algorithms have two characteristics: intensification and diversification.5 Diversification globally explores the search space by randomization to find global optima.29 Intensification investigates the search space, to find the current best solution.16 Keeping a proper balance between these characteristics is the most challenging task due to the stochastic nature of the optimization process.30

The cooperative behavior of several animal groups has attracted the attention of numerous scientific communities.31 Biologists have examined this collaborative phenomenon to produce biological models while engineers have implemented these models as a method for finding the solution for many real-world complex problems.32

One of the most interesting collaborative behavior found in fish is the hunting strategy presented by the Yellow Saddle Goatfish (YSG) (*Parupeneus cyclostomus*)33,34 and has been explored in this paper.

For all the metaheuristic techniques, good performance is achieved by a suitable trade-off between exploration and exploitation phases. All population-based algorithms use these features but with different operators and mechanisms. The search speed and overall performance of meta-heuristic techniques can be dealt with by the Chaos and hence applied to the Yellow Saddle Goatfish Algorithm (YSGA) in this work.

In this paper, a modified Yellow Saddle Goatfish using multi-chaotic maps, named as Multi Chaotic Yellow Saddle Goatfish Algorithm (MCYSGA) that uses 10 chaotic maps has been proposed for avoiding the problem of early convergence which may lead to entrapment in a locally optimal solution. In this work, these 10 chaotic maps, have been combined using a multi-chaotic approach with the YSGA.

2 | CHAOS THEORY

Chaos theory deals with the study of chaotic dynamical systems that are sensitive to initial conditions. The blending properties and Stochastic behavior of chaos have a positive effect on search speed and overall performance of meta-heuristic techniques.35 There are various methods wherein the chaotic maps have been used to solve optimization problems. Chaos has complex, noisy-like, pseudo-random behavior that is generated by non-linear deterministic systems.36 It has several important dynamical characteristics, such as the sensitive dependence on initial conditions, ergodicity, stochastic, infinite unstable periodic motions, and regularity properties.37 Small variances in values at the preliminary solutions will result in great alterations after many iterations. These characteristics of chaos enhance the searchability of a meta-heuristic algorithm.38 Chaos theory has been successfully applied to solve problems in different areas, like optimization problems,39 communications and numerical simulation,40 engineering design,41 sound, and vibration.42 Chaotic maps are used in the optimization algorithm to overcome local optima and to speed up the convergence.43 Different chaotic maps have different properties of their own.

Chaotic maps have improved the performance of various meta-heuristic algorithms. The chaotic HS algorithm has improved the quality of results in optimization problems and global search capability by avoiding the local solutions for the benchmark functions.4 The artificial Bee Colony algorithm has been modified to avoid local optima and to improve the convergence speed by using chaotic maps for solving large scale problems and engineering design optimization.44 A chaotic sequence-based Differential Evolution (DE) approach has been proposed for solving the Dynamic Economic Dispatch Problem with valve-point effect.45 A hybrid of Chaotic Flower Pollination and Gray Wolf Algorithms has been proposed for parameter extraction of bio-impedance models (simplified Hayden and Double-Shell models).46 To improve
### Table 1 Summary of Chaotic Maps

| S. No. | Year | Authors               | No. of Maps | Name of the Maps                                                                 |
|--------|------|-----------------------|-------------|----------------------------------------------------------------------------------|
| 1      | 2010 | Alatas                | 7           | Circle Map, Gauss Map, Logistic Map, Sinus Map, Sinusoidal Map, Tent Map, Henon Map |
| 2      | 2010 | Alatas                | 7           | Circle Map, Gauss Map, Logistic Map, Sinus Map, Sinusoidal Map, Tent Map, Henon Map |
| 3      | 2010 | He et al             | 1           | Logistic Map                                                                    |
| 4      | 2013 | Gandomi et al         | 12          | Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map, Intermittency Map, Liebovitch Map |
| 5      | 2015 | Wang et al            | 12          | Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map, Intermittency Map, Liebovitch Map |
| 6      | 2016 | He et al             | 1           | Logistic Map (* is used with Levy flight which also kind of Chaotic map)          |
| 7      | 2017 | Mirjalili and Gandomi | 10          | Cubic Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map |
| 8      | 2018 | Kohli, and Arora      | 10          | Bernoulli map, Cubic Map, Chebyshev Map, Circle Map, Logistic Map, Sine Map, Sinusoidal Map, Tent Map, Iterative chaotic map with infinite collapses (ICMIC) Map, Piecewise Map |
| 9      | 2018 | Kaur and Arora       | 10          | Cubic Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map |
| 10     | 2019 | Yousri et al          | 10          | Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map |
| 11     | 2019 | Yousri et al          | 10          | Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map |

The performance of the firefly algorithm a new approach has been introduced with chaotic maps. The results of the Firefly algorithm with chaos outperform the firefly algorithm. When chaotic maps are combined with a cuckoo search algorithm to enhance the performance of the algorithm. The results demonstrate the performance of the hybrid approach is comparable as well as superior. To solve the reliability-redundancy allocation problem chaotic map is combined with the Firefly algorithm. The results of this hybrid approach outperform exits solutions. In TLBO chaotic maps and Lévy flight have been used to improve its search efficiency for global numerical optimization problems. The chaotic GWO algorithm has shown better results for solving constrained optimization problems apart from the algorithm itself. To provide a proper balance between the exploration and exploitation phase a chaotic approach has been used in the GSA. To achieve a global optimum solution BOA with chaotic maps has been used to solve the benchmark function and engineering problems. The convergence rate and the performance of Whale Optimization have improved using chaotic maps. To enhance the search capability of the Firefly algorithm a new approach has been introduced with the gauss chaotic map. The results of this hybrid show significant improvement. To control the undesirable behavior of Permanet Magnet Synchronous Motor, Chaotic Whale Optimization variants (CWOA) have been proposed to extract the model parameters accurately and rapidly.

A summary of the chaotic maps used by the researchers is presented in Table 1, which indicates the chaotic maps used in their works.

This has motivated us to apply multiple chaotic maps to the YSG algorithm. This combination has yielded good results and it has improved the performance of the YSG algorithm.

### 3 Chaotic Map

Chaotic comes from the word chaos which means property of a complex system whose behavior is unpredictable, and map means mapping or using chaos behavior in function. There are a wide variety of maps in the field of optimization. In Chaotic YSGA, 10 maps are used and described in Table 2.
YSG ALGORITHM

The YSG algorithm is a meta-heuristic algorithm proposed by Zaldívar et al, in the year 2018, which follows the pack hunting behavior of yellow saddle goatfish. Pack hunting is a behavior of an animal for hunting in a group to capture prey. Many animals have an impressive strategy to capture prey. The YSG uses pack hunting for capturing the prey. Yellow saddle fish hunts in a group in which one fish is chaser fish and the other is blocker fish. The hunting behavior of YSG considers the hunting area as the search space and the number of fish as populations. The algorithm uses two search agents (fish) to find prey: chaser and blocker. The YSG algorithm is divided into five stages, which are discussed below:

4.1 Initial stage

A population of \( n \) goatfish is randomly generated as \( P \left( \{p_1, p_2, \ldots, p_n\} \right) \) and is uniformly distributed within the boundaries \( b^{low} \) and \( b^{high} \) of \( d \) dimensional search space. The initialization is formulated as follow:

\[
P^j = \text{rand} \cdot \left( b^{high}_i - b^{low}_i \right) + b^{low}_i
\]

where \( j = 1, 2, \ldots, n \) (population); \( i = 1, 2, \ldots, d \) (dimension); \( \text{rand} \) is a random distribution between \([0,1]\). Dot represents the elementwise multiplication.

The YSGA works in groups for hunting. Population \( P \) is divided into clusters. K-means algorithm is used for dividing elements into the cluster \( \{c_k, c_k, \ldots, c_k\} \), \( k \) is the number of clusters. Considering the population \( P \) as a dataset, the square error between \( \mu_l \) and a set of data points \( \{p_1, p_2, \ldots, p_y\} \) in cluster \( c_l \). K-means function is denoted as:

\[
e(c_l) = \sum_{p_g \in c_l} ||p_g - \mu_l||^2 \quad g = 1, 2, \ldots, y; l = 1, 2, \ldots, k
\]
\[ E(c) = \sum_{j=1}^{k} e(c_j); \text{ the sum of squared error over all clusters} \tag{3} \]

Here \( y \) is calculated using the K-means algorithm and its value can be different for every cluster \( c_i \).

### 4.2 Chaser fish

Within the group of YSGA there is only one chaser fish \( \Phi_i \in \text{pop} \) who leads the hunts. The chaser fish is selected by fitness values. In each group, a fish that is closer to the solution is selected as chaser fish. This chaser fish tries to find the location of the prey with a random walk. The new position is calculated as:

\[ \Phi_{i+1} = \Phi_i + \alpha \odot \text{levy}(\beta) \tag{4} \]

where \( 0 < \beta \leq 2; \Phi_{i+1} \) is the new position of chaser fish, \( \Phi_i \) is the current position of fish. The step size is defined by \( \alpha \) in this \( \alpha = 1 \). The product \( \odot \) means element-wise multiplication and \( \beta \) is known as Lévy index.

\[ \beta = 1.99 + \frac{0.001 \ t}{t_{\text{max}}/10} \tag{5} \]

Here \( t \) and \( t_{\text{max}} \) are the current generations and maximum iteration,

\[ S = \alpha \odot \text{levy}(\beta) \sim \alpha \left( \frac{u}{|v|^2} \right) (\Phi_i^t - \Phi_{\text{best}}^t) \tag{6} \]

Here, \( S \) and \( \Phi_{\text{best}}^t \) is the random step and the best chaser fish from the cluster. The normal distribution, \( u \) and \( v \) is defined as:

\[ u \sim N(0, \sigma_u^2) \tag{7} \]
\[ u \sim N(0, \sigma_v^2) \tag{8} \]

\( \sigma_u \) and \( \sigma_v \) are denoted as follows, considering \( \Gamma \) as the Gamma function:

\[ \sigma_u = \begin{cases} \Gamma(1 + \beta) \sin \frac{\pi \beta}{2} \Gamma \left( \frac{1+\beta}{2} \right) \beta^{(\beta-1)/2} & , \ \sigma_v = 1 \\ \end{cases} \]

Using the above equations, the new position of chaser fish given in Equation 4 can be rewritten as:

\[ \Phi_{i+1} = \Phi_i + S \tag{9} \]

Thus, a new position of the best chaser fish is calculated as:

\[ \Phi_{\text{best}}^{i+1} = \Phi_{\text{best}}^i + S' \tag{10} \]
\[ S' = \alpha \left( \frac{u}{|v|^{1/\beta}} \right) \tag{11} \]

### 4.3 Blocker fish

After choosing chaser fish, all the remaining fish become the blocker fish. The movement of blocker fish is depicted as a logarithmic spiral. Chaser fish is one fish that is the closest to prey, blocker fish follows the spiral path around chaser...
fish and every blocker fish their path which changed after each iteration.

\[ \phi^{t+1}_g = D_g \cdot e^{b \rho} \cdot \cos(2 \pi \rho) + \Phi_t \]  \hspace{1cm} (12)

where \( \rho \) is a random number between \([a, 1]\), to increase exploitation, as iteration increases the value of a is linearly decreased from \(-1\) to \(-2\). Chaser fish position is defined when \( \rho = -2 \) as range reaches \([-2, 1]\). Shape and the direction of the spiral are determined by the constant \( b \) and the \( b = 1 \). \( D_g \) is the distance between the current position of chaser fish and blocker fish in the cluster \( c_l \).

\[ D_g = | r \cdot \Phi_t - \phi^{t}_g | \] \hspace{1cm} (13)

where \( \{\Phi_t, \phi^{t}_g\} \in c_l \), and \( r \) is a random distribution between \([-1, 1]\).

### 4.4 Exchange of roles

Once chaser and blocker fish are chosen. The chaser fish is one that is closer to the prey. The objective of blocker fish is to avoid the escape of prey. During hunting prey moves in the hunting area if the prey is near to blocker fish, then blocker fish becomes chaser fish and vice versa, This phenomenon is called an exchange of roles. In the algorithm, the element that has the best fitness is chosen as chaser fish.

### 4.5 Change of a zone

After exploiting the whole area by hunting all the prey, the group of fish moves to the other sector for finding new prey. It is depicted as:

\[ p^{t+1}_g = \Phi_{best} + p^{t}_g \] \hspace{1cm} (14)

where \( p^{t+1}_g \) is the new position of fish, \( \Phi_{best} \) is the best solution from all the clusters, \( p^{t}_g \) is the current position of fish (chaser or blocker). If in a cluster value of chaser fish has improved, it is exchanged with the global best. This process avoids the local optima.

### 5 CHAOTIC YSGA

The chaotic YSG algorithm has been proposed by introducing Chaos Theory in the YSG algorithm for better convergence. Chaotic behaviors have similarities to randomness, and these are formed by using deterministic iteration formulas. Chaotic maps are providing a regular chaotic motion in the original feasible space of a problem. Hence, these satisfy the convergence criteria and also these have a global search ability. Chaotic maps help an optimization algorithm in exploring the search space more globally due to its dynamic behavior. So, to further improve the performance of the YSG algorithm, chaotic maps have been used in the chaser fish, where multiple chaotic maps are applied. The chaotic maps have properties such as stable fixed point, periodic oscillation, bifurcations, and ergodicity. The non-repetition behavior of chaos helps to perform an overall search at a higher speed than a random search.

Every group of chaotic YSGA has only one chaser fish \( \Phi_t \in P \) which leads the hunts. Chaser fish is selected by the fitness value. For each group, a fish that is closer to the solution is selected as a chaser fish. The chaser fish tries to find the location of prey computed with a random walk. The randomness of a fish is now modeled by chaotic maps. For the location updation of every chaser fish different chaotic maps are used. The new location of chaser fish is calculated as:

\[ \Phi^{t+1}_i = \Phi^{t}_i + M_i \] \hspace{1cm} (15)

\( \Phi^{t+1}_i \) is the new position of chaser fish, \( \Phi^{t}_i \) is the current position of the fish. \( M_i \) is \( i \)th chaotic map selected from 10 maps listed in Table 2. In the chaotic maps initial value 0.7 is used.
Algorithm for Multi Chaotic YSGA

Input: \( n, k, t_{\text{max}}, M \)
Output: \( \Phi_{\text{best}} \)

initialize Population \( P = \{p_1, p_2, \ldots, p_n\} \), \( \lambda = 10 \)
calculate Fitness Value for each particle
identify the global best \( \Phi_{\text{best}} \)
partition the population \( P \) into \( k \) clusters \( \{c_1, c_2, \ldots, c_k\} \)
identify the chaser \( \Phi_l \) and blocker \( \phi_g \) fish for every cluster
while (\( t < t_{\text{max}} \))
for every cluster \( c_l \)
execute hunting routine for chaser fish with multi chaotic maps using Equation (15)
execute blocking routine for blocker fish using Equation (12)
calculate fitness value for each fish
if \( \phi_g \) has better fitness value than \( \Phi_l \)
exchange role by updating \( \Phi_l \)
endif
if \( \Phi_l \) has better fitness value than \( \Phi_{\text{best}} \)
update \( \Phi_{\text{best}} \)
endif
if fitness \( \Phi_l \) value of has improved
\( q \leftarrow q + 1 \)
endif
if \( q > \lambda \)
execute routine for changing the zone
\( q \leftarrow 0 \)
endif
end for
\( t \leftarrow t + 1 \)
end while

6 EXPERIMENTAL RESULTS AND DISCUSSION

YSGA is combined with chaotic maps\(^3,4,7,60,61\) described in Table 2. Ten chaotic maps (Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map maps) are combined with YSGA to give new algorithms (YSGA-C1 to YSGA-C10).

To evaluate the performance of the proposed optimization algorithm, 68 benchmark functions\(^62\) have been used to find the global optimum. These benchmark functions are divided into five categories: Unimodal fixed dimension functions (F1 to F9), Unimodal variable dimension functions (F10 to F24), Multimodal fixed dimension functions (F25 to F51), and Multimodal variable dimension functions (F52 to F68). Unimodal functions having only one optima solution and multimodal functions having more local solutions and one global solution.

Apart from this, 10 Congress on Evolutionary Computation (CEC-2019) functions\(^19\) have been used for the evaluation of the proposed work. Table 3 describes the parameter setting for various optimization techniques used.

Table 4A compares 10 chaotic versions of YSGA for unimodal fixed dimension functions, Table 4B compares the results for unimodal variable dimension functions, similarly Tables 4C, 4D, and 4E compare the chaotic versions of YSGA for Multimodal fixed dimension functions, Multimodal variable dimension functions, and CEC-2019 functions. In the table for each function average and below it, its standard deviation is mentioned. It has been observed from the tables that chaotic maps applied to YSGA individually dominate the results achieved for YSGA.

Inspired by the results of the chaotic variant, a multi-chaotic concept has been used in this paper that has improved the results further. GOA,\(^17\) Jaya algorithm,\(^28\) GWO algorithm,\(^14\) SFO algorithm,\(^12\) WOA,\(^5\) Ant Lion Optimization (ALO) algorithm,\(^18\) FDO algorithm.\(^19\)
### TABLE 3 Parameter settings for algorithms used

| Algorithm                                          | Parameter settings                                      | Iterations |
|----------------------------------------------------|--------------------------------------------------------|------------|
| Grasshopper Optimization Algorithm (GOA)           | $N = 50$, $C_{max} = 1$, $C_{min} = 0.00004$            | 1000       |
| Jaya algorithm (JAYA)                              | $N = 50$                                                | 1000       |
| Grey Wolf Optimization (GWO)                       | $N = 50$                                                | 1000       |
| Chaotic Gravitational Search Algorithm (CGSA)      | $N = 50$, $\alpha = 20$, $G_0 = 100$, ElitistCheck = 1, $R_{power} = 1$, chValueInitial = 20 | 1000       |
| Sunflower Optimization (SFO)                       | $N = 50$, Pollination rate = 0.1, Mortality rate = 0.01 | 1000       |
| Whale Optimization Algorithm (WOA)                 | $N = 50$                                                | 1000       |
| Ant Lion Optimizer (ALO)                           | $N = 50$                                                | 1000       |
| Fitness Dependent Optimizer (FDO)                  | $N = 50$, weight factor = 0                             | 1000       |
| Improved Chaotic Electromagnetic Field Optimization (ICEFO) | $N = 50$, $R_{rate} = 0.3$, $P_{rate} = 0.2$, $P_{field} = 0.1$, $N_{field} = 0.45$ | 1000       |
| Multi Chaotic Yellow Saddle Goatfish Algorithm (MCYSGA) | $N = 50$, number of cluster $k = 4$, $l = 10$          | 1000       |

Apart from these optimization techniques, two chaotic-based optimization methods; Chaotic Gravitational Search Algorithm (CGSA)\(^{51}\) and Improved Chaotic Electromagnetic Field Optimization (ICEFO)\(^{63}\) have been used for comparing the performance of the proposed multi-chaotic yellow saddle goatfish algorithm. The parameters set for all these algorithms are shown in Table 3. The maximum iterations for these algorithms are 1000 and the search agents/searching elements for each algorithm ($N$) are 50.

Table 5A shows an average accuracy and standard deviation after 30 independent runs of these methods. The values in bold indicate for proposed multi-chaotic YSGA indicate the functions for which either it is better than the other algorithms or it has the same average value as the other algorithms. It has been observed from Table 5A, which compares the average accuracy of unimodal fixed dimension functions, that the proposed algorithm achieves better or the same results for 6 functions. A comparison of results for unimodal variable dimension functions, presented in Table 5B indicates that multi-chaotic YSGA has better or the same performance for nine functions. There are 27 multimodal fixed dimension functions, the performance of 20 functions is the same or better than the other algorithms used in the comparisons, as shown in Table 5C. In the case of multimodal variable dimension functions, which are shown in Table 5D, seven functions have shown better performance, out of which one function (F53) has achieved the global minimum value, which is also with the WOA. Cumulative results of these functions indicate that 42 functions out of these 68 functions have shown better or similar performance in terms of the average value of 30 runs. FDO dominates in six functions, CGSA in five functions, GWO in three functions, and all the others in two functions. Some of these algorithms give the same results (Table 5E).

In the YSG algorithm, chaotic maps are used to update the position values of the search agents. These maps create randomness in the position updating, which helps in the complete exploration of the search space. Improvement in the exploration search ability improves the overall performance of YSGA and helps to avoid local optimal solutions.

Figure 1 represents the plot of $F_1$ and $F_4$ (unimodal fixed dimension functions), $F_{10}$ and $F_{13}$ (unimodal variable dimension functions), $F_{25}$ and $F_{29}$ (multimodal fixed dimension functions), $F_{53}$ and $F_{54}$ (multimodal variable dimension functions). Also, these indicate the exploration of the proposed approach, the search history of one dimension for these functions, and the convergence curve is also shown. It has been observed from the figure that the proposed modifications have effectively explored the search-space and has resulted in more accurate results.

To validate the results of unimodal fixed dimension, unimodal variable dimension, multimodal fixed dimension, multimodal variable dimension, Wilcoxon rank-sum test\(^{64}\) has been used, which is a non-parametric test. The performance of the test is given in Table 6. This test is safer and robust for comparing the optimization performances of the two methods.\(^{55}\) It measures the differences in the performance of two methods for all function and compares the methods based on $p$-values. The significance level for this test is set to 0.05. The comparison is conducted between the Multi-Chaotic Yellow Saddle Goatfish algorithm (MCYSGA) versus nine metaheuristic optimization algorithms. Table 6 shows the outcomes with this test for the pairwise comparisons of MCYSGA and other metaheuristic algorithms in terms of fitness values. At
| Functions | YSGA-C1     | YSGA-C2     | YSGA-C3     | YSGA-C4     | YSGA-C5     | YSGA-C6     | YSGA-C7     | YSGA-C8     | YSGA-C9     | YSGA-C10      | YSGA       |
|-----------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|---------------|------------|
| F1        | 2.788E-07   | 1.326E-07   | 1.790E-07   | 1.203E-07   | 1.557E-02   | 1.313E-07   | 9.447E-08   | 1.625E-07   | 9.832E-08   | 1.558E-02     | 1.000E+16  |
|           | 5.587E-07   | 1.757E-07   | 2.771E-07   | 1.518E-07   | 8.530E-02   | 1.608E-07   | 1.239E-07   | 2.085E-19   | 1.163E-07   | 8.531E-02     | 4.068E+00  |
| F2        | 4.418E-04   | 6.088E-04   | 4.876E-04   | 5.892E-04   | 7.763E-04   | 7.062E-04   | 7.969E-04   | 5.656E-04   | 5.921E-04   | 1.873E+05     | 1.000E+00  |
|           | 4.050E-04   | 3.652E-04   | 4.019E-04   | 5.607E-04   | 4.955E-04   | 4.333E-04   | 7.889E-31   | 1.000E+21   | 1.000E+21   | 1.000E+21     | 1.000E+21  |
| F3        | 5.049E-06   | 7.050E-06   | 6.320E-06   | 1.005E-05   | 1.307E-06   | 3.107E-06   | 7.639E-06   | 6.379E-06   | 1.129E-16   | 1.000E+00     | 1.000E+00  |
|           | 5.626E-06   | 1.162E-05   | 7.939E-06   | 1.331E-05   | 9.798E-06   | 6.137E-06   | 1.384E-07   | 5.435E-06   | 1.281E-05   | 1.000E+00     | 1.000E+00  |
| F4        | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00     | 4.000E+02  |
|           | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00     | 4.000E+02  |
| F5        | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01   | 2.926E-01     | 5.011E-01  |
|           | 9.551E-08   | 3.436E-07   | 3.914E-07   | 1.199E-07   | 2.218E-07   | 2.098E-06   | 2.535E-06   | 2.926E-01   | 2.926E-01   | 2.926E-01     | 5.011E-01  |
| F6        | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01   | 1.911E+01     | 4.761E+08  |
|           | 2.107E-03   | 2.405E-03   | 1.843E-03   | 2.012E-03   | 1.747E-03   | 1.859E-03   | 1.407E-03   | 2.960E-03   | 2.960E-03   | 2.960E-03     | 1.713E-03  |
| F7        | 2.190E-06   | 1.897E-06   | 1.978E-06   | 1.084E-06   | 1.303E-06   | 1.014E-06   | 2.023E-06   | 1.502E-06   | 1.393E-06   | 1.957E-06     | 9.998E+13  |
|           | 2.784E-06   | 2.157E-06   | 2.297E-06   | 2.126E-06   | 1.289E-06   | 2.181E-06   | 7.415E-08   | 2.142E-06   | 2.630E-06   | 2.630E-06     | 0.000E+00  |
| F8        | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00     | 0.000E+00  |
|           | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00   | 0.000E+00     | 0.000E+00  |
| F9        | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03  | -3.791E-03    | 4.080E+08  |
|           | 5.679E-10   | 1.602E-10   | 1.973E-10   | 2.834E-10   | 1.350E-10   | 7.956E-11   | 4.099E-10   | -3.791E-03  | 3.626E-10   | 1.908E-10     | 0.000E+00  |

Note: For each method, mean and standard deviation (below mean) is computed for all the functions.
| Functions | YSGA-C1 | YSGA-C2 | YSGA-C3 | YSGA-C4 | YSGA-C5 | YSGA-C6 | YSGA-C7 | YSGA-C8 | YSGA-C9 | YSGA-C10 | YSGA |
|-----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|-------|
| F10       | 2.223E-175 | 9.977E-174 | 4.269E-176 | 1.593E-179 | 3.109E-177 | 3.175E-175 | 1.789E-174 | 6.340E-172 | 4.002E-178 | 2.369E-175 | 3.000E+05 |
| F11       | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 6.546E-310 | 0.000E+00 | 1.414E-309 | 4.900E-313 | 0.000E+00 | 0.000E+00 | 0.000E+00 |
| F12       | 8.713E-98 | 5.671E-99 | 1.800E-98 | 5.783E-98 | 8.442E-101 | 2.951E-100 | 5.658E-99 | 2.490E-100 | 1.821E-97 | 7.160E-100 | 3.000E+03 |
| F13       | 1.268E+01 | 2.313E+01 | 2.657E+01 | 2.755E+01 | 2.451E+01 | 1.956E+01 | 1.975E+01 | 1.808E+01 | 1.907E+01 | 1.997E+01 | 1.000E+02 |
| F14       | 6.659E-01 | 8.517E-01 | 8.549E-01 | 8.014E-01 | 8.041E-01 | 7.465E-01 | 8.084E-01 | 9.403E-01 | 8.966E-01 | 8.770E-01 | 2.970E+05 |
| F15       | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 | -2.975E+03 |
| F16       | 3.056E-99 | 2.729E-99 | 1.981E-98 | 1.217E-99 | 4.729E-99 | 1.472E-99 | 4.085E-99 | 1.382E-101 | 1.209E-99 | 3.990E-99 | 1.000E+60 |
| F17       | 9.158E-99 | 9.114E-99 | 1.083E-97 | 5.480E-99 | 2.299E-98 | 5.312E-99 | 1.607E-98 | 2.390E-87 | 5.860E-99 | 2.011E-98 | 3.629E-44 |
| F18       | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 |
| F19       | NA      | NA      | NA      | NA      | NA      | NA      | NA      | NA      | NA      | NA      | NA    |
| F20       | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 | 6.667E-01 |
| F21       | 1.920E-06 | 1.187E-06 | 1.855E-06 | 1.908E-06 | 9.593E-07 | 1.725E-06 | 1.833E-06 | 6.667E-01 | 1.703E-06 | 1.138E-06 | 0.000E+00 |
| F22       | 5.482E-10 | 7.832E-14 | 1.422E-15 | 5.450E-13 | 1.241E-15 | 6.091E-16 | 2.119E-10 | 1.048E-11 | 2.302E-14 | 9.672E-15 | 7.085E+08 |
| F23       | 2.993E-09 | 4.290E-13 | 7.751E-15 | 2.949E-12 | 5.767E-15 | 3.229E-15 | 1.160E-09 | 4.262E-07 | 1.250E-13 | 3.034E-14 | 0.000E+00 |
| F24       | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 |

Note: NA indicates that results for this could not be computed.
**TABLE 4C** Comparison of performance using chaotic maps for multimodal fixed dimension functions

| Functions | YSGA-C1   | YSGA-C2   | YSGA-C3   | YSGA-C4   | YSGA-C5   | YSGA-C6   | YSGA-C7   | YSGA-C8   | YSGA-C9   | YSGA-C10  | YSGA     |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| F25       | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 2.001E+04 |
| F26       | -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| -1.956E+02| 1.470E+00 |
| F27       | -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| -1.000E+02| 4.466E-01 |
| F28       | -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| -1.068E+02| 1.616E+00 |
| F29       | -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| -1.032E+00| 3.335E+11 |
| F30       | 3.979E-01 | 3.981E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 3.979E-01 | 2.424E+06 |
| F31       | 4.800E+00 | 3.000E+00 | 3.000E+00 | 3.900E+00 | 3.900E+00 | 3.900E+00 | 3.000E+00 | 3.903E+00 | 3.000E+00 | 4.801E+00 | 1.382E+18 |
| F32       | -3.732E+00| -3.806E+00| -3.732E+00| -3.835E+00| -3.294E+00| -3.573E+00| -3.678E+00| -3.860E+00| -3.533E+00| 0.000E+00 | 5.208E+02 |
| F33       | -1.767E+00| -7.835E-01| -1.062E+00| -9.681E-01| -1.034E+00| -6.811E-01| -1.243E+00| -1.181E+00| -1.709E+00| -1.328E+00| 0.000E+00 |
| F34       | -2.063E+00| -2.004E+00| -2.063E+00| -2.063E+00| -2.063E+00| -2.063E+00| -2.063E+00| -2.063E+00| -2.063E+00| -2.132E+02| 3.529E-18 |
| F35       | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 1.000E+00 | 3.000E+04 |
| F36       | 8.655E-01 | 8.138E-01 | 6.713E-01 | 7.961E-01 | 8.058E-01 | 7.357E-01 | 8.177E-01 | 8.583E-01 | 8.326E-01 | 8.027E-01 | 1.415E+03 |
| F37       | -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36| -3.142E+36|
| F38       | -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| -4.292E+01| 1.122E+04 |
|           | 8.167E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 8.185E-02 | 0.000E+00 |

(Continues)
| Functions | YSGA | YSGA-C10 | YSGA-C9 | YSGA-C8 | YSGA-C7 | YSGA-C6 | YSGA-C5 | YSGA-C4 | YSGA-C3 | YSGA-C2 | YSGA-C1 |
|-----------|------|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| F39       | 4.84E-05 | 5.09E-05 | 8.72E-13 | 1.06E-13 | 7.35E-13 | 6.29E-13 | 2.47E-13 | 4.69E-03 | 6.49E-05 | 4.84E-05 | 4.84E-05 |
| F40       | 9.41E-05 | 8.98E-05 | 8.87E-13 | 7.87E-13 | 8.48E-13 | 8.48E-13 | 6.29E-13 | 2.47E-13 | 4.69E-03 | 6.49E-05 | 4.84E-05 |
| F41       | 1.08E-02 | 1.01E-02 | 1.06E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 | 1.05E-02 |
| F42       | 1.21E-02 | 1.18E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 | 1.15E-02 |
| F43       | 1.17E-02 | 1.03E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 | 1.01E-02 |
| F44       | 1.48E-03 | 1.38E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 | 1.34E-03 |
| F45       | 1.38E-03 | 1.29E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 | 1.25E-03 |
| F46       | 1.05E-03 | 9.85E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 | 9.65E-04 |
| F47       | 1.00E-03 | 9.70E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 |
| F48       | 1.00E-03 | 9.70E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 |
| F49       | 1.00E-03 | 9.70E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 |
| F50       | 1.00E-03 | 9.70E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 | 9.50E-04 |
### TABLE 4E  Comparison of performance using chaotic maps for CEC-19 functions

| Functions | YSGA-C1 | YSGA-C2 | YSGA-C3 | YSGA-C4 | YSGA-C5 | YSGA-C6 | YSGA-C7 | YSGA-C8 | YSGA-C9 | YSGA-C10 | YSGA |
|-----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|-------|
| F69       | 2.116E+06 | 1.975E+06 | 2.826E+06 | 1.948E+06 | 2.057E+06 | 2.856E+06 | 1.900E+06 | 1.665E+06 | 1.875E+06 | 2.239E+06 | 1.047E+11 |
|           | 2.538E+06 | 1.995E+06 | 3.247E+06 | 1.873E+06 | 2.637E+06 | 3.017E+06 | 2.038E+06 | 3.374E+07 | 1.200E+06 | 1.838E+06 | 3.104E-05 |
| F70       | 1.735E+01 | 1.735E+01 | 1.735E+01 | 1.735E+01 | 1.735E+01 | 1.736E+01 | 1.736E+01 | 1.735E+01 | 1.735E+01 | 1.735E+01 | 4.898E+02 |
|           | 1.235E-02 | 3.251E-03 | 3.508E-02 | 6.615E-03 | 2.214E-02 | 5.084E-02 | 4.973E-02 | 1.734E-02 | 3.359E-03 | 2.607E-03 | 1.734E-13 |
| F71       | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.271E+01 |
|           | 7.834E-04 | 8.508E-04 | 7.179E-04 | 6.888E-04 | 8.460E-04 | 2.615E-04 | 7.352E-04 | 1.270E-04 | 9.837E-04 | 3.818E-04 | 0.000E+00 |
| F72       | 1.389E+03 | 1.920E+03 | 1.925E+03 | 1.679E+03 | 1.755E+03 | 1.775E+03 | 1.522E+03 | 2.072E+03 | 1.792E+03 | 2.052E+03 | 3.167E+05 |
|           | 1.100E+03 | 1.512E+03 | 1.391E+03 | 1.609E+03 | 1.433E+03 | 1.565E+03 | 1.128E+03 | 1.841E+03 | 1.456E+03 | 1.197E+03 | 1.776E-10 |
| F73       | 2.080E+00 | 2.180E+00 | 2.065E+00 | 2.041E+00 | 2.283E+00 | 2.281E+00 | 2.126E+00 | 2.123E+00 | 2.006E+00 | 2.175E+00 | 4.416E+01 |
|           | 3.956E-01 | 3.976E-01 | 3.912E-01 | 3.416E-01 | 3.705E-01 | 5.015E-01 | 4.657E-01 | 1.057E+00 | 3.488E-01 | 4.665E-01 | 0.000E+00 |
| F74       | 9.608E+00 | 9.242E+00 | 9.616E+00 | 9.486E+00 | 9.407E+00 | 9.351E+00 | 9.434E+00 | 9.672E+00 | 9.548E+00 | 9.217E+00 | 2.458E+01 |
|           | 9.353E-01 | 1.021E+00 | 6.282E-01 | 8.489E-01 | 8.401E-01 | 8.291E-01 | 7.999E-01 | 1.020E+00 | 7.323E-01 | 8.550E-01 | 0.000E+00 |
| F75       | 4.263E+02 | 3.495E+02 | 3.970E+02 | 3.533E+02 | 3.922E+02 | 3.718E+02 | 3.608E+02 | 3.476E+02 | 3.945E+02 | 4.132E+02 | 3.319E+03 |
|           | 1.775E+02 | 1.126E+02 | 1.658E+02 | 1.374E+02 | 1.165E+02 | 1.160E+02 | 1.394E+02 | 3.195E+02 | 1.466E+02 | 1.038E+02 | 4.625E-13 |
| F76       | 5.174E+00 | 5.200E+00 | 5.248E+00 | 5.183E+00 | 5.212E+00 | 5.256E+00 | 5.221E+00 | 5.196E+00 | 5.116E+00 | 5.321E+00 | 8.831E+00 |
|           | 5.386E-01 | 5.438E-01 | 4.410E-01 | 5.118E-01 | 5.567E-01 | 5.274E-01 | 5.434E-01 | 3.010E+00 | 4.967E-01 | 4.836E-01 | 3.61E-15  |
| F77       | 8.775E+01 | 5.036E+01 | 6.586E+01 | 5.938E+01 | 6.223E+01 | 7.064E+01 | 9.114E+01 | 1.026E+02 | 1.068E+02 | 7.970E+01 | 2.764E+04 |
|           | 1.247E+02 | 9.569E+01 | 1.199E+02 | 1.071E+02 | 1.093E+02 | 1.172E+02 | 1.123E+02 | 2.339E+00 | 1.697E+02 | 1.536E+02 | 7.401E-12 |
| F78       | 2.025E+01 | 2.022E+01 | 2.007E+01 | 2.019E+01 | 2.004E+01 | 2.032E+01 | 2.029E+01 | 2.029E+01 | 2.028E+01 | 2.028E+01 | 2.134E+01 |
|           | 2.278E-01 | 2.149E-01 | 1.066E+00 | 5.374E-01 | 7.881E-01 | 8.835E-02 | 3.064E-01 | 2.035E+01 | 7.624E-02 | 9.571E-02 | 7.227E-15 |
### TABLE 5A Comparison of performance for unimodal fixed dimension functions

| Function | MCYSGA | GOA   | JAYA  | GWO   | CGSA  | SFO   | WOA   | ALO   | FDO   | ICEFO  |
|----------|--------|-------|-------|-------|-------|-------|-------|-------|-------|--------|
| F1       | 1.557E-07 | 1.016E-01 | 0.000E+00 | 1.817E-08 | 3.649E-03 | 4.489E-03 | 1.557E-02 | 1.270E-01 | 1.047E-31 | 7.010E-08 |
|          | 4.186E-07 | 2.635E-01 | 0.000E+00 | 1.979E-08 | 6.264E-03 | 6.389E-03 | 5.346E-05 | 8.530E-02 | 2.889E-01 | 1.085E-31 |
| F2       | 5.607E-04 | 1.320E-13 | 0.000E+00 | 9.885E-08 | 0.000E+00 | 0.000E+00 | 7.104E-05 | 6.363E-14 | 4.470E-31 | 7.706E-10 |
|          | 3.650E-04 | 9.390E-14 | 0.000E+00 | 8.716E-08 | 0.000E+00 | 0.000E+00 | 5.794E-05 | 1.103E-13 | 1.050E-30 |        |
| F3       | 1.384E-08 | 1.384E-08 | 1.384E-08 | 1.384E-08 | 1.270E-02 | 9.285E-03 | 9.629E-08 | 1.384E-08 | 9.677E-30 | 1.569E-10 |
|          | 6.812E-103 | 6.812E-103 | 6.812E-103 | 6.812E-103 | 6.955E-02 | 5.086E-02 | 6.812E-103 | 1.981E-07 | 6.812E-103 | 3.606E-30 |
| F4       | 0.000E+00 | 6.114E-15 | 8.763E-48 | 1.203E-277 | 3.334E-04 | 0.000E+00 | 5.985E-16 | 1.826E-03 | 0.000E+00 | 5.794E-16 |
|          | 0.000E+00 | 5.498E-15 | 1.970E-47 | 0.000E+00 | 1.826E-03 | 0.000E+00 | 3.649E-15 | 1.970E-47 | 0.000E+00 | 8.571E-16 |
| F5       | 2.926E-01 | 2.926E-01 | 2.926E-01 | 2.926E-01 | 3.012E-01 | 3.009E-01 | 2.926E-01 | 2.926E-01 | 2.926E-01 | 2.926E-01 |
|          | 2.794E-07 | 3.004E-08 | 4.800E-06 | 3.248E-08 | 6.260E-03 | 6.721E-03 | 4.639E-06 | 1.810E-05 | 1.701E-13 | 1.109E-15 |
| F6       | 1.911E+01 | 1.911E+01 | 1.911E+01 | 1.911E+01 | 2.628E+01 | 3.890E+01 | 1.911E+01 | 1.911E+01 | 1.911E+01 | 1.911E+01 |
|          | 5.675E-15 | 9.100E-10 | 1.070E-14 | 2.527E-06 | 6.979E+00 | 7.538E+01 | 1.289E-14 | 1.137E-04 | 4.470E-10 | 3.280E-11 |
| F7       | 8.676E-07 | 1.305E-03 | 7.612E-10 | 1.775E-07 | 4.760E-04 | 3.296E-05 | 2.031E-06 | 1.366E-15 | 6.623E-31 | 4.61E-04 |
|          | 9.069E-07 | 1.710E-03 | 9.179E-10 | 2.609E-07 | 1.777E-03 | 1.806E-04 | 2.002E-03 | 3.469E-06 | 3.223E-15 | 8.451E-31 |
| F8       | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 |
|          | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 | 0.000E+00 |
| F9       | -3.790E-03 | -3.791E-03 | -3.791E-03 | -3.791E-03 | -1.842E-03 | -1.300E-03 | -3.791E-03 | -3.791E-03 | -3.791E-03 | -3.791E-03 |
|          | 5.260E-10 | 1.777E-14 | 1.744E-08 | 2.830E-11 | 1.447E-03 | 1.401E-03 | 1.764E-18 | 3.563E-10 | 4.042E-15 | 2.575E-14 |

*Note: For each method, mean and standard deviation (below mean) is computed for all the functions.*
| Function | MCYSGA | GOA | JAYA | GWO | CGSA | SFO | WOA | ALO | FDO |
|----------|--------|-----|------|-----|------|-----|-----|-----|-----|
| F10      | 3.985E-176 | 2.237E-01 | 4.741E+00 | 2.653E-70 | 2.485E-17 | 1.407E+01 | 7.591E-175 | 5.160E-07 | 5.945E-01 |
| F11      | 0.000E+00 | 2.056E-07 | 1.736E-13 | 1.232E-230 | 3.745E-30 | 6.942E-05 | 2.822E-250 | 1.309E-07 | 1.411E-08 |
| F12      | 2.885E-99 | 1.537E+01 | 1.080E+01 | 4.677E-40 | 2.283E-08 | 8.683E-01 | 1.507E-106 | 2.874E-01 | 2.046E-17 |
| F13      | 8.700E-01 | 7.889E-00 | 5.749E+00 | 1.832E-17 | 5.118E-09 | 1.265E+00 | 2.656E-01 | 8.897E+00 | 2.436E-01 |
| F14      | 9.791E-01 | 4.691E+00 | 7.124E+00 | 3.179E-01 | 2.727E-17 | 1.503E+01 | 4.500E+03 | 7.037E-07 | 2.280E-29 |
| F15      | 1.55E+02 | 2.555E-00 | 1.122E-01 | 2.836E-00 | 4.404E-40 | 4.462E-09 | 3.868E+140 | 6.244E-06 | 6.942E-05 |
| F16      | 7.842E-102 | 2.371E-21 | 5.471E+30 | 6.555E-40 | 2.316E-08 | 1.025E+01 | 1.385E-108 | 9.572E+19 | 5.276E-16 |
| F17      | 0.000E+00 | 9.466E-06 | 1.644E-05 | 2.730E-229 | 1.958E-07 | 5.085E-01 | 0.000E+00 | 1.541E-21 | 3.867E-73 |
| F18      | 2.709E+01 | 3.614E-02 | 1.729E-02 | 2.624E+01 | 2.399E+01 | 6.436E+01 | 2.679E+01 | 1.331E+02 | 3.189E+01 |
| F19      | 1.19E+176 | 6.327E+00 | 5.391E-03 | 8.962E-73 | 3.995E-17 | 1.147E-02 | 2.665E-171 | 7.975E-11 | 1.552E-43 |
| F20      | 6.667E-01 | 6.379E-00 | 3.939E+00 | 6.667E-01 | 6.667E-01 | 8.026E-01 | 6.667E-01 | 1.676E+00 | 6.754E-01 |
| F21      | 4.945E-10 | 7.050E-01 | 2.561E-01 | 3.159E-06 | 1.020E-04 | 2.899E-01 | 1.586E-06 | 8.212E-01 | 3.781E-04 |
| F22      | 2.709E+09 | 7.049E-01 | 1.744E-01 | 4.361E-06 | 3.578E-05 | 2.480E-01 | 1.225E-04 | 3.753E-06 | 4.851E-01 |
| F23      | 4.340E-232 | 8.844E-210 | 4.425E-232 | 1.577E-148 | 1.691E-38 | -9.890E-02 | 0.000E+00 | -1.000E+00 | 2.661E-143 |
| F24      | 3.475E+171 | 1.004E-01 | 6.221E-01 | 3.121E-71 | 2.224E-16 | 3.956E-01 | 5.100E-173 | 4.673E-01 | 8.020E-42 |
|          | 0.000E+00 | 1.229E+00 | 2.848E-01 | 5.802E-01 | 1.141E-01 | 4.660E-01 | 0.000E+00 | 5.208E-01 | 3.349E-41 |
### Table 5C Comparison of performance for multimodal fixed dimension functions

| Function | MCYSGA  | GOA     | JAYA    | GWO     | CGSA    | SFO     | WOA     | ALO     | FDO     | ICEFO   |
|----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| F25      | 0.000E+00 | 9.488E-01 | 5.624E-66 | 0.000E+00 | 7.515E-20 | 0.000E+00 | 1.238E-269 | 8.458E-14 | 4.140E-87 | 4.644E-12 |
| F26      | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 | -1.956E+02 |
| F27      | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 | -2.022E+00 |
| F28      | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 | -1.068E+02 |
| F29      | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 | -1.032E+00 |
| F30      | 3.979E-01  | 3.979E-01  | 3.979E-01  | 3.979E-01  | 4.13E-01  | 4.64E-01  | 3.979E-01  | 3.979E-01  | 3.979E-01  | 3.979E-01  |
| F31      | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  | 3.000E+00  |
| F32      | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 | -3.862E+00 |
| F33      | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 | -3.319E+00 |
| F34      | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 | -2.063E+00 |
| F35      | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  | 1.000E+00  |
| F36      | 1.759E+02  | 1.803E+02  | 1.803E+02  | 1.803E+02  | 1.87E+02   | 9.067E-01  | 1.803E+02  | 1.803E+02  | 1.803E+02  | 1.803E+02  |
| F37      | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 | -2.416E+01 |
| F38      | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 | -4.294E+01 |

(Continues)
| Function | MCGSA | GOA | JAYA | ICEFO | ALO | DFO |
|----------|-------|-----|------|------|-----|-----|
| F39      | 4.84E-05 | 4.84E-05 | 4.84E-05 | 4.84E-05 | 4.84E-05 | 4.84E-05 |
| F40      | 2.75E-04 | -5.63E-04 | -2.55E-04 | -3.36E-02 | -8.24E-04 | -5.64E-04 |
| F41      | 3.42E-04 | 4.72E-04 | 5.61E-05 | 3.05E-01 | 3.16E-02 | 3.44E-01 |
| F42      | 6.47E-02 | 6.47E-02 | 6.47E-02 | 6.47E-02 | 6.47E-02 | 6.47E-02 |
| F43      | 1.50E-03 | 1.08E-03 | 1.54E-03 | 8.73E-03 | 2.06E-03 | 9.22E-03 |
| F44      | 3.61E-05 | 3.09E-13 | 2.00E-06 | 2.98E-03 | 3.86E-02 | 9.30E-02 |
| F45      | 2.81E-05 | 2.79E-01 | 6.87E-07 | 1.92E-01 | 1.92E-01 | 1.92E-01 |
| F46      | 6.00E-03 | 1.29E-03 | 3.61E-03 | 1.92E-01 | 1.92E-01 | 1.92E-01 |
| F47      | 1.04E-03 | 1.08E-01 | 3.60E-01 | 9.64E-03 | 4.00E-02 | 6.93E-05 |
| F48      | -9.63E-01 | -1.08E-01 | 1.92E-01 | 9.64E-03 | 4.00E-02 | 6.93E-05 |
| F49      | 2.33E-02 | 6.32E-02 | 1.88E-02 | 9.64E-03 | 4.00E-02 | 6.93E-05 |
| F50      | -1.86E-02 | -1.86E-02 | 1.88E-02 | 9.64E-03 | 4.00E-02 | 6.93E-05 |
| F51      | 4.04E-22 | 1.00E-14 | 8.16E-14 | 4.04E-22 | 1.00E-14 | 8.16E-14 |
| Function | GOA | JAYA | WOA | CSMA | ICEFO |
|----------|-----|------|------|------|-------|
| F52      | 1.177E+02 | 2.264E+02 | 2.133E+02 | 2.342E+02 | 2.147E+00 |
| F53      | 5.397E+01 | 1.168E+01 | 9.685E+00 | 3.322E+01 | 3.144E+01 |
| F54      | 2.724E+00 | 6.582E+00 | 1.492E+00 | 1.000E+00 | 9.280E+00 |
| F55      | 1.305E+00 | 6.916E+00 | 9.569E+00 | 1.700E+00 | 1.700E+00 |
| F56      | 9.262E+00 | 3.119E+00 | 3.530E+00 | 5.219E+00 | 2.474E+00 |
| F57      | 3.349E+00 | 6.916E+00 | 1.492E+00 | 1.000E+00 | 9.280E+00 |
| F58      | 2.580E+00 | 2.109E+00 | 3.982E+00 | 5.072E+00 | 5.609E+00 |
| F59      | 6.409E+00 | 5.648E+00 | 2.789E+00 | 4.296E+00 | 3.308E+00 |
| F60      | 2.580E+00 | 2.109E+00 | 3.982E+00 | 5.072E+00 | 5.609E+00 |
| F61      | 6.010E+00 | 3.979E+00 | 5.494E+00 | 2.789E+00 | 4.296E+00 |
| F62      | 6.409E+00 | 5.648E+00 | 2.789E+00 | 4.296E+00 | 3.308E+00 |
| F63      | 1.232E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F64      | 1.887E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F65      | 1.232E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F66      | 1.887E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F67      | 1.232E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F68      | 1.887E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| F69      | 1.232E+00 | 4.726E+00 | 4.726E+00 | 7.259E+00 | 2.340E+00 |
| Function | MCYSGA | GOA | JAYA | GWO | CGSA | SFO | SPBO | WOA | ALO | FDO | ICEFO |
|----------|--------|-----|------|-----|------|-----|------|-----|-----|-----|-------|
| CEC1     | 1.801E+10 | 4.032E+09 | 1.175E+11 | 3.659E+07 | 3.726E+12 | 8.401E+09 | 4.972E+09 | 2.741E+06 | 3.268E+09 | 1.119E+07 | 3.390E+10 |
| CEC2     | 2.785E+10 | 3.518E+09 | 5.848E+10 | 8.564E+07 | 2.617E+12 | 6.696E+09 | 3.017E+09 | 2.724E+06 | 2.527E+09 | 1.607E+07 | 1.651E+10 |
| CEC3     | 1.736E+01 | 1.738E+01 | 1.747E+01 | 1.734E+01 | 1.323E+04 | 7.430E+02 | 1.734E+01 | 1.734E+01 | 1.734E+01 | 1.734E+01 | 1.735E+01 |
| CEC4     | 4.000E-02 | 5.003E-02 | 3.818E-02 | 1.097E-04 | 4.178E+03 | 4.181E+02 | 7.227E-15 | 6.245E-04 | 1.600E-04 | 7.929E-10 | 4.230E-03 |
| CEC5     | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 | 1.270E+01 |
| CEC6     | 1.744E-07 | 1.521E-04 | 2.219E-04 | 1.857E-06 | 3.613E-15 | 1.015E-03 | 1.795E-11 | 1.809E-03 | 3.613E-15 | 2.262E-12 | 9.250E-09 |
| CEC7     | 2.617E+03 | 4.078E+01 | 1.770E+03 | 4.262E+01 | 7.423E+00 | 2.176E+04 | 9.105E+00 | 1.792E+02 | 2.902E+01 | 2.482E+01 | 6.640E+01 |
| CEC8     | 1.454E+03 | 7.336E+01 | 7.432E+02 | 1.945E+01 | 2.933E+00 | 6.020E+03 | 3.359E+00 | 6.984E+01 | 1.363E+01 | 9.548E+00 | 1.128E+01 |
| CEC9     | 2.117E+00 | 1.321E+00 | 2.195E+00 | 1.370E+00 | 1.004E+00 | 6.544E+00 | 1.007E+00 | 1.642E+00 | 1.181E+00 | 1.080E+00 | 1.583E+00 |
| CEC10    | 4.238E+01 | 1.203E+01 | 1.239E+01 | 2.247E+01 | 7.693E+03 | 9.535E+01 | 6.669E+03 | 3.810E+01 | 1.210E+01 | 2.940E+02 | 1.456E+01 |
| CEC11    | 9.504E+00 | 5.489E+00 | 1.026E+01 | 1.059E+01 | 1.000E+00 | 1.121E+01 | 3.650E+00 | 8.566E+00 | 4.380E+00 | 7.764E+00 | 1.177E+01 |
| CEC12    | 7.237E+01 | 1.344E+00 | 6.533E-01 | 4.663E-01 | 9.870E-06 | 1.034E+00 | 3.149E+01 | 1.056E+00 | 1.549E+00 | 7.210E+01 | 6.835E+01 |
| CEC13    | 3.847E+02 | 3.092E+02 | 6.641E+02 | 2.853E+02 | 1.430E+02 | 1.476E+03 | 2.454E+02 | 4.390E+02 | 3.297E+02 | -2.214E+01 | 9.832E+02 |
| CEC14    | 1.190E+02 | 1.903E+02 | 1.488E+02 | 2.556E+02 | 5.177E+01 | 1.419E+02 | 4.881E+01 | 2.835E+02 | 2.470E+02 | 6.857E+01 | 1.547E+02 |
| CEC15    | 5.242E+00 | 5.275E+00 | 6.300E+00 | 4.585E+00 | 5.089E+00 | 6.358E+00 | 3.329E+00 | 5.689E+00 | 5.060E+00 | 4.007E+00 | 6.267E+00 |
| CEC16    | 4.167E-01 | 8.105E-01 | 2.464E-01 | 8.326E-01 | 4.542E-01 | 3.797E-01 | 4.485E-01 | 4.927E-01 | 5.837E-01 | 5.872E-01 | 4.427E-01 |
| CEC17    | 6.611E+01 | 2.435E+00 | 3.940E+02 | 4.296E+00 | 2.546E+00 | 4.291E+03 | 2.657E+00 | 4.510E+00 | 2.367E+00 | 2.349E+00 | 3.313E+00 |
| CEC18    | 1.140E+02 | 7.031E+02 | 1.140E+02 | 7.493E+01 | 9.342E+02 | 6.037E+02 | 9.228E+02 | 8.578E+01 | 1.258E+02 | 5.361E+03 | 2.803E+01 |
| CEC19    | 2.012E+01 | 2.006E+01 | 2.041E+01 | 2.039E+01 | 1.999E+01 | 2.068E+01 | 3.682E+00 | 2.016E+01 | 1.935E+01 | 1.533E+01 | 2.059E+01 |
| CEC20    | 9.364E-01 | 7.259E-02 | 6.562E-02 | 7.818E-02 | 1.268E-02 | 1.102E-01 | 6.572E+00 | 9.946E-02 | 3.655E+00 | 8.604E+00 | 1.226E+01 |
| FN | Function Name | Plot | Search History | Convergence Curve |
|----|---------------|------|----------------|-------------------|
| F1 | Beale         | ![Beale Plot](image) | ![Search History](image) | ![Convergence Curve](image) |
| F4 | Matyas        | ![Matyas Plot](image) | ![Search History](image) | ![Convergence Curve](image) |
| F10| Sphere        | ![Sphere Plot](image) | ![Search History](image) | ![Convergence Curve](image) |
| F13| Schwefel’ s 2.21 | ![Schwefel’s 2.21 Plot](image) | ![Search History](image) | ![Convergence Curve](image) |
| F25| Egg Crate     | ![Egg Crate Plot](image) | ![Search History](image) | ![Convergence Curve](image) |
| F29| Camel Hump    | ![Camel Hump Plot](image) | ![Search History](image) | ![Convergence Curve](image) |

**FIGURE 1** (Continued)
the significance level of 0.05, if the $p$-value for MCYSGA versus other metaheuristic algorithms is less than 0.005 then MCYGA has significant results. It is observed from the table that the $p$-value in the case of GOA, JAYA algorithm, SFO, ALO, FDO, and ICEFO are much lower than the desired value of 0.05 establishing the statistical significance of the results except GWO, CGSA, WOA, and ALO which have higher $p$ values. Multi Chaotic YSG algorithm performed significantly better than five metaheuristic optimization algorithms.

It has been observed that the chaotic maps have improved the performance of YSGA by solving the problem of premature convergence and local optima stagnation. Small variances in values at the preliminary solutions will result in great alterations after many iterations. Chaotic maps have characteristics such as sensitive dependence on initial conditions, ergodicity, stochastic, infinite unstable periodic motions, and regularity properties. These properties enhance the searchability of a meta-heuristic algorithm. So multiple chaotic maps have improved the performance of the proposed Multi-Chaotic YSG algorithm as compared to the YSG algorithm as well as the other state of the art algorithms.

**7 | CONCLUSION**

In this paper, Chaos theory and the YSG optimization algorithm are combined with proposed a Chaotic YSGA with multiple chaotic maps. Due to the dynamic behavior of chaos, it helps an optimization algorithm in exploring the search space more dynamically and globally. The use of chaotic maps in the YSG algorithm helps avoid the local optima and in improving the global optima. Ten chaotic maps are combined with YSGA which include Chebyshev Map, Circle Map, Gauss Map, Iterative Map, Logistic Map, Piecewise Map, Sine Map, Singer Map, Sinusoidal Map, Tent Map maps. To evaluate the performance of the proposed optimization algorithm, 68 benchmark functions have been used to find global optima. Besides, 10 functions of CEC-19 are also used for evaluating the performance of the proposed modifications in the YSG algorithm. A comparison of individual Chaotic YSGA with YSGA shows that chaotic maps have improved the performance of the algorithm. The application of multiple chaotic maps has further improved performance. From a comparison of Multi Chaotic YSGA with nine other states of the art meta-heuristic optimization algorithms, it has been observed that the proposed approach has been improved the performance of the algorithm for the 42 benchmark functions out of 68 unimodal fixed dimension, unimodal variable dimension, multimodal fixed dimension, and multimodal variable dimension functions. We are further working on the other chaotic maps for analysis.
PEER REVIEW INFORMATION

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

CONFLICT OF INTEREST

The authors have no conflict of interest relevant to this article.

AUTHOR CONTRIBUTIONS

Davinder Kashyap: Conceptualization; data curation; methodology; software. Birmohan Singh: Conceptualization; formal analysis; supervision. Manpreet Kaur: Supervision; validation.

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