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Implementation of combined new optimal cuckoo algorithm with a gray wolf algorithm to solve unconstrained optimization nonlinear problems

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ABSTRACT

In this article, a combined optimization algorithm was proposed which combines the optimal adaptive Cuckoo algorithm (OACS) which is a Nature-inspired algorithm with a Gray Wolf optimizer algorithm (GWO). Sometimes considering the cuckoo algorithm alone, it may fail to find the local minimum-point and also fails to reach the solution because of the slow speed of its convergence property. Therefore, considering the new proposed adaptive combined algorithm gave a strong improvement for using this to reach the minimum point in solving (12) nonlinear test problems. This is suitable to solve a large number of nonlinear unconstraint optimization test functions with obtaining good and robust numerical results.

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1. INTRODUCTION

Optimization algorithms, in the present day, have become one of the most important algorithms that address life or applied problems as they contain multiple algorithms to solve these issues. Most of the minimum point search algorithms, especially gradient-based search methods, are local search algorithms. The search process usually starts with a guess and continues to improve the quality of solutions in terms of the number of iterations possible. If the functions are univariate, convexity can ensure that the ultimate optimal solution is global. If the functions are multivariate, the search is likely to be disrupted global optimally. Therefore, some variations with randomness should be used as an example of the genetic algorithm, which is a global search algorithm. Another example is simulated annealing, which is also used for global research and ensures that the optimal global solution is reached as computing time approaches infinity. Finding the best global solution is more efficient for these issues. For this was the development of many algorithms known as metaheuristic, which means here meta "beyond" or "higher level" and heuristic means "find" or "discovery by experiment and error" [1]. These metaheuristic methods include:

a) Local search-based algorithms: it works with a single pass solution by repeatedly developing and increasing the fitness function until stopping criteria are reached for more details [2-5].
b) Evolutionary search-based algorithm: the population strategy uses a set of randomly generated solutions, which blend interactively until the acceptable solution is reached until it reaches new and optimal solutions in terms of its fitness function for more details [6-9].

c) Swarm search-based algorithm: the principle of the work of these algorithms is to use the population method in each iteration, as the current solutions are produced using historical information obtained by the generations generated in the previous iterations for more details note [10-16].

The cuckoo search algorithm proposed for the first time by Yang and Deb at (2009) [17] is one of the evolutionary search algorithms used to solve optimization problems in various fields of engineering and science on a large scale. This algorithm is very effective in solving global optimization because it can maintain a balance between local and global random paths using the switch parameter. There are two stages to generating possibilities in traditional methods:

a) The first stage is a randomly generated Levi's flight.
b) The second stage the work of the host birds to give up the cuckoo eggs.

If we compare the behavior of the cuckoo with the flight of Lévy, we notice that it is as random as the flight of Lévy. There are three types of brood parasitism (brood parasitism within the species), nest rearing and cooperative breeding. n most cases, the behavior of the parasite cuckoo is chosen as a nest, where the host bird lays its eggs and lays its eggs, too [18]. There are three steps in the iterative search process including (global Lévy flight random walk, local random walk, and selection operation). The first steps to find the new solutions and are generated by Lévy flights (Levy flights by Mantegna's algorithm) as:

$$\text{Lévy} = \frac{\mathrm{a}}{|b|^{1/\rho}}, \rho \in [1,3] \tag{1}$$

Where a is the normal distribution and b is the standard normal distribution s.t. (c>0 step size for updating new solution):

$$a \sim N(0, \sigma^2) \ \&\ b \sim N(0,1) \tag{2}$$

$$\sigma = \left[\frac{\Gamma(1+\rho)\sin(\frac{\pi\rho}{2})}{\Gamma(\frac{1+\rho}{2})\rho 2^{(\rho-1)/2}}\right]^{\frac{1}{\rho}} \tag{3}$$

$$step_i(k) = c \oplus \text{Lévy}\ (\rho) \tag{4}$$

$$x_i(\mathrm{k}+1) = x_i(\mathrm{k}) + step_i(k) \tag{5}$$

Steps have been drawing local random walk through trips Lévy through the big steps that follow the distribution of Lévy:

$$\text{Lévy} \ \sim \ u \ = \ k^{-\rho} \tag{6}$$

The above is the details of the operation of the local random walk that produces the second new solution generation by cuckoo search algorithm:

$$x_i(\mathrm{k}+1) = x_i(\mathrm{k}) + step_i(k) \oplus \text{randn} \oplus (x_i(\mathrm{k}) - x_{gbest}) \tag{7}$$

Where x_{gbest} is the global best solution among all x_i for i (for i = 1, 2, . . ., N) at time k, that is very effective for global optimization problems since it maintains a balance between local random walk and the global random walk that is controlled by a switching parameter p_c ∈[0,1], [19-21].

The grey wolf optimizer (GWO) as a novel swarm intelligence optimization algorithm was put forward by Seyedali Mirjalili *et. al.* in 2014 [22], this algorithm is a metaheuristic algorithm inspired by nature as it mimics the characteristics (leadership and hunting of gray wolves). Members of the Gray Wolves family can be divided into a somewhat hierarchical, as we note through the study that they prefer to search for prey in a box of 5-12 wolves. To define pyramid levels, we take these assumptions into conventional GWO to simulate their efficacy over gray wolves: the wolf α is at the top level being the leader of the wolf pack (it makes all kinds of decisions like hunting, maintaining discipline, sleeping and waking time for a full package), β wolf is the second-best player in the group has the highest probability of becoming a leader in the group α (at this level are subordinate wolves and help the α leader in decision-making or other activities), δ wolves, dominates wolves from back and the last level (responsible for maintaining safety and integrity in the Wolf Pack) [23], the lowest family member is the ω Gray Wolf. Omega plays the role of a scapegoat. Omega wolves always have to submit to all the other dominant wolves. They are the last wolves allowed to eat them. Mathematical representation of the basic stages of gray wolves in hunting:

a) Prey Searching: this is done through the random distribution of gray wolves in the search area.

b) Encircling of Prey: Gray wolves curl around prey to surround them using mathematical modeling, from (9) and (10). Where the wolf updates its position within the solution area.

$$\vec{A} = 2 * \vec{a} * r_1 - \vec{a} \tag{8}$$

$$\vec{C} = 2 * \vec{r}_2 \tag{9}$$

$$\vec{D} = \left|\vec{C} * \vec{X}_p - \vec{X}(k)\right| \tag{10}$$

$$\vec{X}(k+1) = \vec{X}_p - \vec{A} * \vec{D} \tag{11}$$

$$a = 2 - k\left(\frac{2}{N}\right) \tag{12}$$

Where (k: current iteration; $\vec{A}$ and $\vec{D}$: vector of coefficients; $\vec{X}_p$, the prey vector location; $\vec{X}$: the Gray Wolf position vector; whereas, the values of $\overrightarrow{a}$ are linearly reduced from 2 to 0, respectively; r_1 and r_2 are random vectors in the standard uniform distribution over the period [0,1].

c) Hunting: alternating between members of the wolf family, since the alpha wolf usually performs the hunting process, and the beta and delta wolf may participate in the hunting process in the limited research area and it is not possible to know the best site (prey). The hunting behavior of the wolves can be simulated from the following equations:

$$\vec{D}_\propto = \left|\vec{C}_1 * \vec{X}_\propto - \vec{X}\right|$$
$$\vec{D}_\beta = \left|\vec{C}_2 * \vec{X}_\beta - \vec{X}\right|$$
$$\vec{D}_\delta = \left|\vec{C}_3 * \vec{X}_\delta - \vec{X}\right|$$

As for the prey site for the alpha, beta and delta wolves, it is calculated from:

$$\vec{X}_1 = \vec{X}_\propto - \vec{A}_1 * \vec{D}_\propto \tag{13}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 * \vec{D}_\beta \tag{14}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 * \vec{D}_\delta \tag{15}$$

As for the best site that the wolves can go to (alpha, beta, and delta), it is calculated as an average [22]:

$$\vec{X}(k+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{16}$$

Researchers have continued to develop different classes of these algorithms by relying on parts within the algorithm or by combining them with algorithms that support them to strengthen them, such as [24-30].

2. NEW PROPOSED ALGORITHM

In this article we have proposed a good and efficient modification of the cuckoo algorithm (OACS) mixed with the gray wolves algorithm by updating:

$$Lévy = \frac{a}{1+|b|^{2/\rho}}, \rho \in [1,3] \tag{17}$$

$$step_i(k) = \frac{\text{Lévy }(\rho) - \sigma}{n} \tag{18}$$

$$x_i(k+1) = x_i(k) + step_i(k) \oplus randn \oplus \left(x_i(k) - x_{gbest}\right) \tag{19}$$

where (n= Number of nests (or different solutions)) and (19) is better in terms of numerical results, as we will notice in the next numerical results section. As the composition represents the average difference between the fibrous steps and the calculated variance within (3), when added to the updated step, it speeds us up to the target in the test functions. We used this updated algorithm in place of the traditional cuckoo algorithm associated with the Gray Wolf algorithm which gave convincing improvement ratios. The following Figure 1 represents the flowchart of the optimized updated Cuckoo algorithm with the Gray Wolves algorithm.

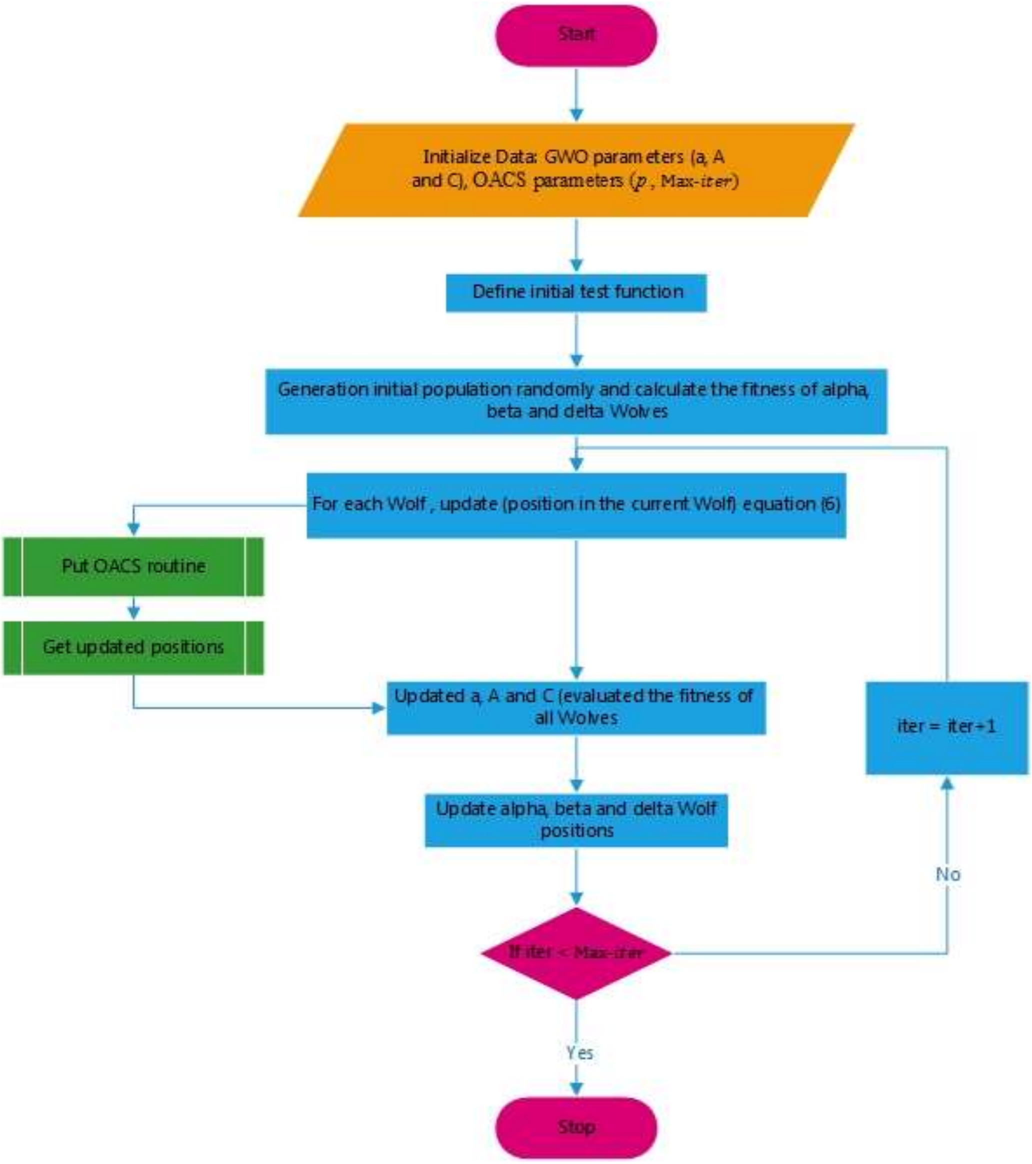


Figure1. Flowchart of the optimal cuckoo algorithm interfering with the gray wolf algorithm

3. NUMERICAL RESULTS

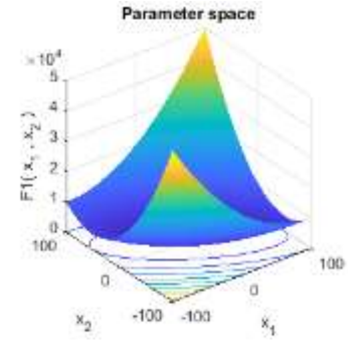
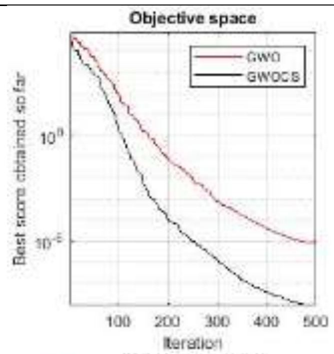
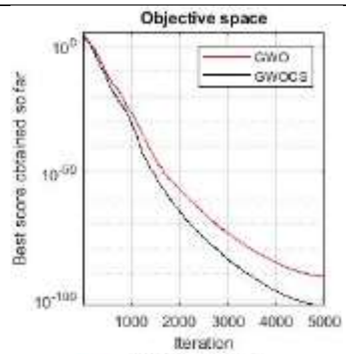
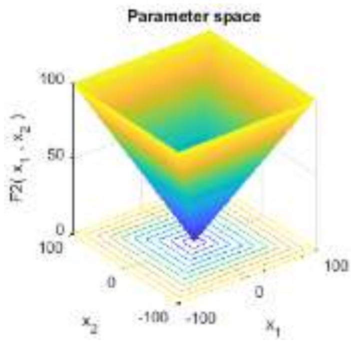
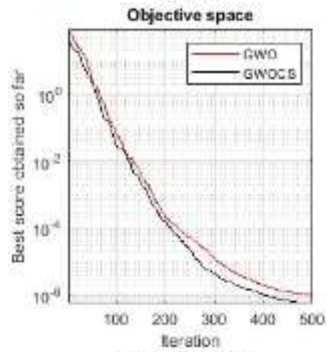
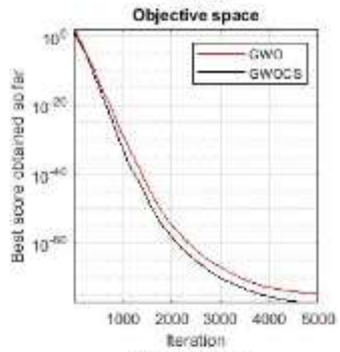
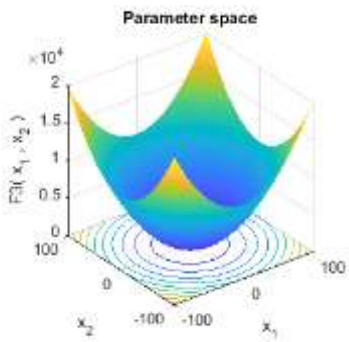
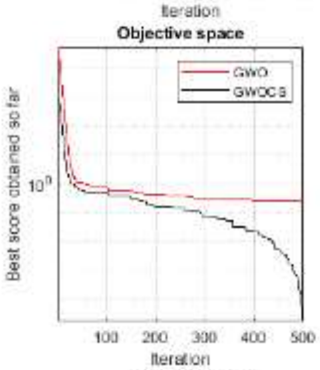
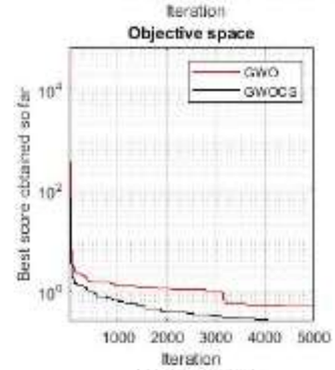
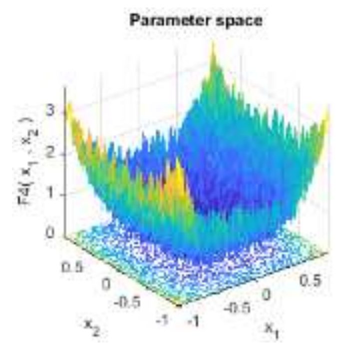
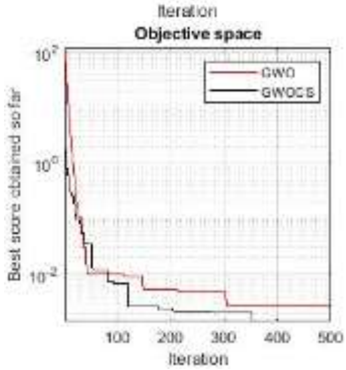
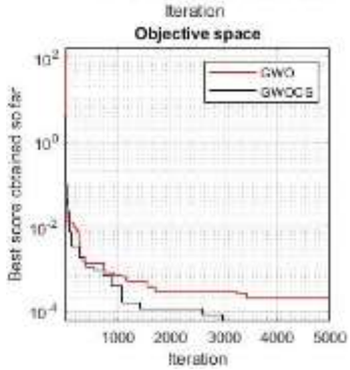
In this section, we used to implement the new proposed algorithm inside a laptop with a processor Intel(R) Core(TM) i5 for the Matlab 2018 software. The new algorithm was made by changing the program provided by Gupta *et al.* [31] where the following Table 1 parameters were used:

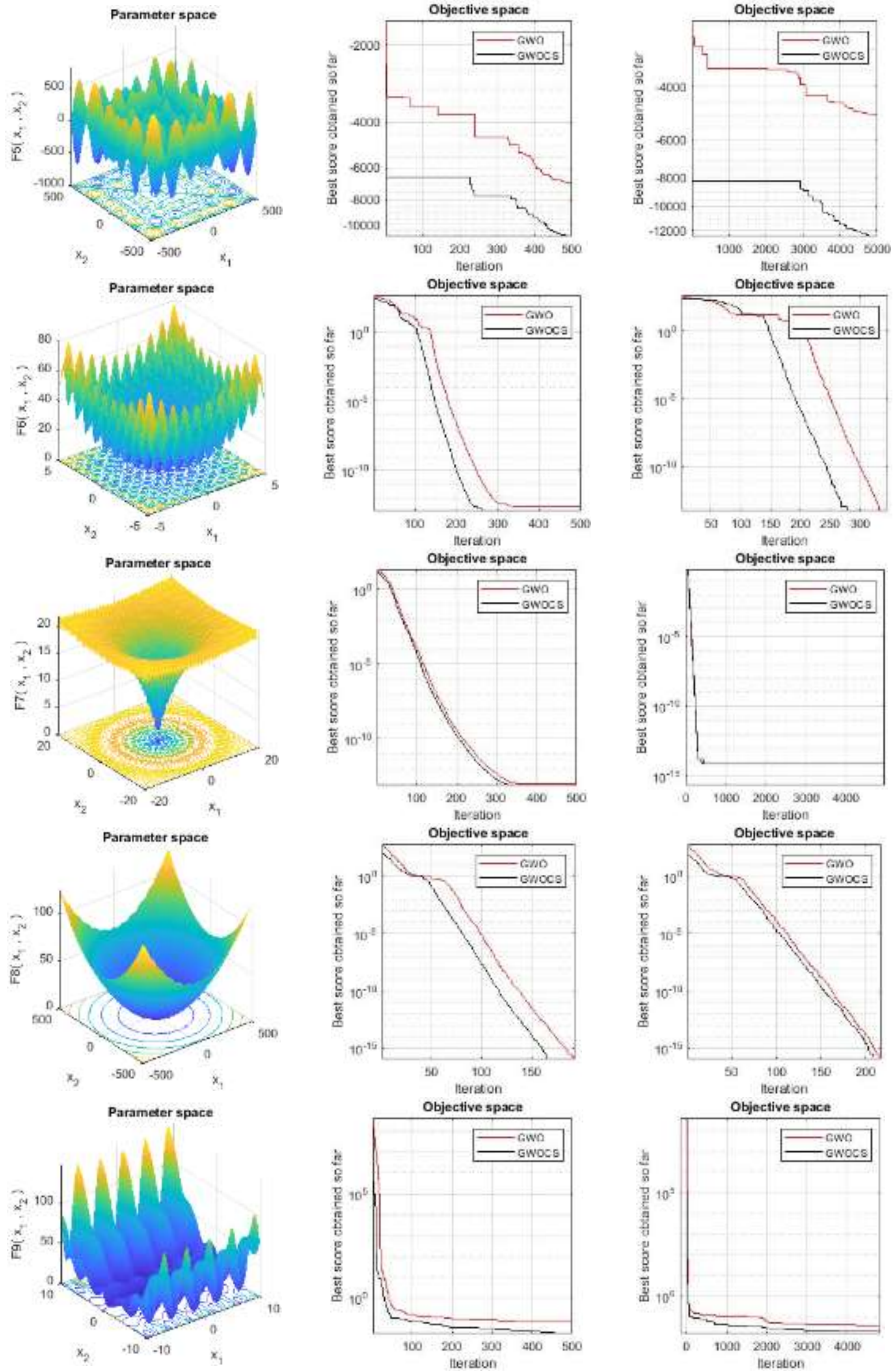
Table1. The amounts of the parameters

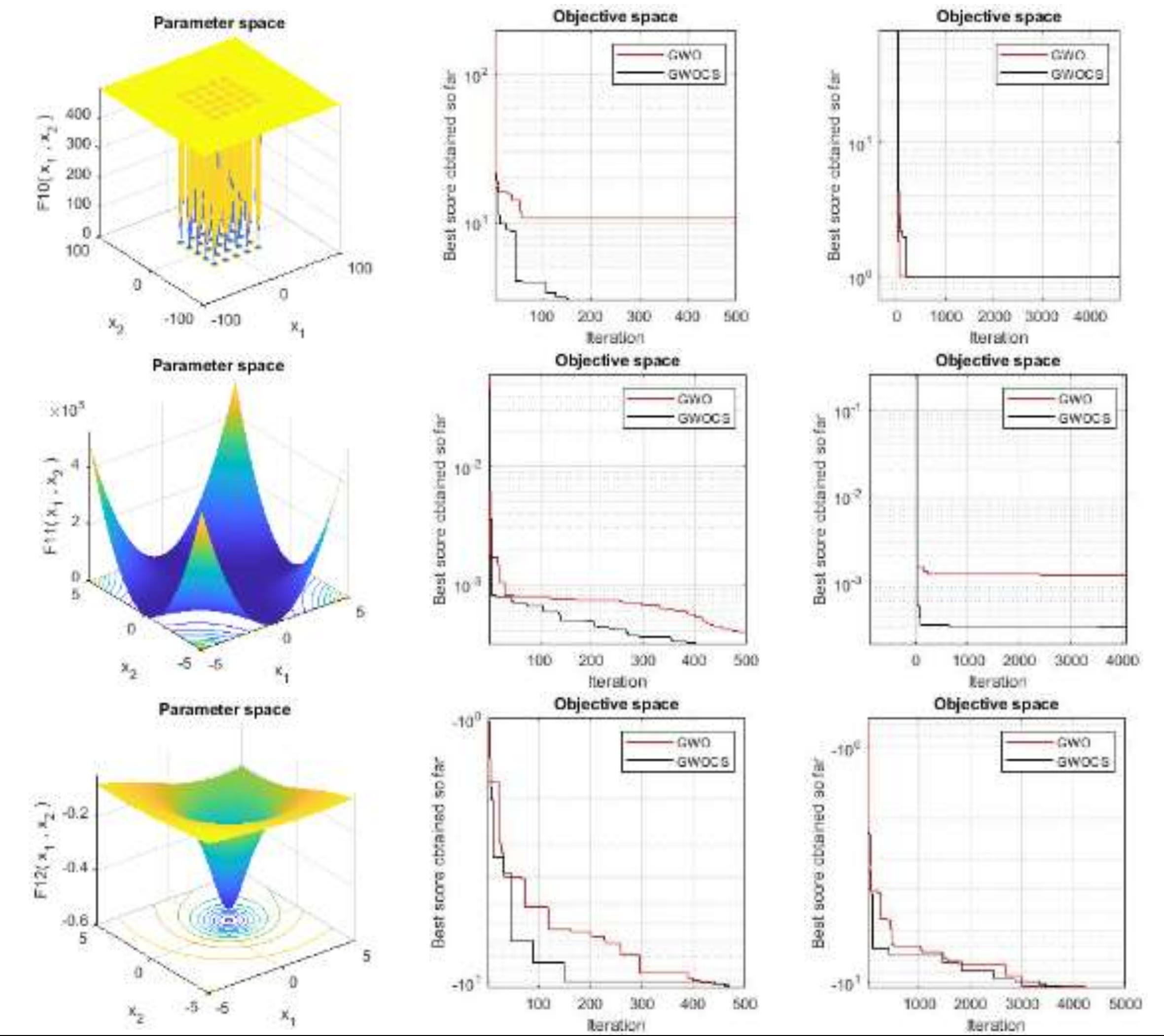
Parameters	Detiales
$niter$ = 500	Number of iterations
n = 30	Number of nests
Max-$iter$ =500	Maximum number of iterations
Max-$iter$ =5000	
$\rho = 3/2$	Levy flights parameter

In the following Table 2, we show the effect of the new optimization of the Cuckoo algorithm interfering with the Gray Wolf algorithm on 12 test functions and compare the effect of this new algorithm with its basic algorithm in terms of the number of higher iterations as in:

Table 2. Results of the performance of (12) test functions compared to the new algorithm (OACS) Vs. (GWO)

Functions	Max-$iter$ =500	Max-$iter$ =5000
		
		
		
		


Parameter space
F5(x1 , x2)
Objective space
GWO
GWOCS
Best score obtained so far
Iteration
Parameter space
F6(x1 , x2)
Objective space
Parameter space
F7(x1 , x2)
Objective space
Parameter space
F8(x1 , x2)
Objective space
Parameter space
F9(x1 , x2)
Objective space



4. CONCLUSION

We notice from Table 2 that the results drawn in a curve to reach the optimum point of the (12) functions that the new algorithm may apply as a result with the wolf algorithm in two test functions only in the case that the maximum number of iterations equal (500), while the rest of the functions the performance of the new algorithm is the best. In the case of the maximum number of iterations (5000), the new algorithm is the best in performing compared to the basic algorithm in most jobs except two functions whose performance is equal.

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