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Solve Global Optimization Problems Based On Metaheuristic Algorithms

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ABSTRACT : *Metaheuristic algorithms have evolved with exciting performance to solve complex real-world combinatorial optimization problems. These combinatorial optimization problems span across engineering, medical sciences, and sciences generally. In this paper we have proposed metaheuristic algorithms for solving the global optimization problems. The global optimization problems are one of interested problems in artificial intelligence, medical sciences, engineering and machine learning. We have discussed a number of algorithms such as Whale Optimization Algorithm (WOA), the Bat Algorithm (BA), War Strategy Optimization (WSO), and Ant Lion optimization algorithm (ALO). In our paper we have tested our algorithms on twenty-three benchmark functions. The numerical results show that the War Strategy optimization algorithm (WSO) has the best performance more than the other algorithms to solve global optimization problems, and the Bat Algorithm (BA) has the worst performance to solve the global optimization problems. The experimental results for various global optimization problems prove the superiority of the War strategy optimization algorithm.*

KEYWORDS *metaheuristic algorithms, war Strategy optimization algorithm, whale optimization algorithm, bat algorithm, ant Lion optimization algorithm.*

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I. INTRODUCTION

Optimization is a way of finding the best solution among a given set of options in the objective function which it's goal is minimization or maximization. Optimization problems play an important role in various fields such as engineering design, agricultural services, manufacturing system, economics etc. Type of optimization problems is multi objective optimization, multimodal optimization and combinatorial optimization (Oyelade, 2022).

In combinatorial optimization problems, there is a finite solution set X and a real-valued function $f: X \rightarrow R$ where we seek a solution $x^* \epsilon X$ with $f(x^*) \leq f(x)$, $\forall x \epsilon X$. Crew scheduling, vehicle routing, and VLSI routing are all common instances. It is theoretically conceivable to enumerate all potential solutions and assess each in order to identify the globally optimal answer in a combinatorial optimization (CO) issue. Due to the exponential expansion of most solution spaces, this strategy is often undesired and intractable.

A new type of approximation algorithm has arisen that attempts to combine fundamental heuristic approaches in higher level frameworks targeted at exploring a search space rapidly and effectively. These strategies are now frequently known as metaheuristics (Scriptor, (2006)). The word metaheuristic refers to an iterative search method that steers the process over the search space in the goal of finding the best answer. Ant Colony Optimization (ACO), Evolutionary Computation (EC), including Genetic Algorithms (GA), Iterated Local

Search (ILS), Simulated Annealing (SA), and Tabu Search (TS) are examples of this family of algorithms. Metaheuristic algorithms are best characterized by how they work in the search space:

- Nature-inspired vs. non-nature-inspired.
- Population-based vs. single-point search.
- Dynamic vs. static objective functions.
- One vs. several neighbourhood structures.
- Memory consumption vs. memory-less approaches.

We will discuss a number of algorithms such as Whale Optimization Algorithm (WOA), the Bat Algorithm (BA), War Strategy Optimization (WSO), and Ant Lion optimization algorithm(ALO), we will begin with Whale Optimization algorithm.

II. RELATED WORK

In the last 20 years, a new type of approximation algorithm has arisen that attempts to combine fundamental heuristic approaches in higher level frameworks targeted at exploring a search space rapidly and effectively. These strategies are now frequently known as metaheuristics. Glover coined the word metaheuristic in 1986, and it best describes an iterative search approach that steers the process over the search space in the goal of discovering the ideal answer.

Holland presented the Genetic Algorithm (GA) in 1992, inspired by Darwinian evolutionary notions, as the first and most popular approach for addressing optimization issues. This approach, with two recombination and mutation operators, has been widely employed in most optimization situations and is regarded as one of the successful algorithms, with numerous enhanced and recombination variants previously described "Geem" et al. presented the Harmony Search (HS) algorithm in 2001, which was derived from artist's search processes for the optimal condition of harmony. After the first version of this approach was introduced in numerous optimization situations, it was widely employed due to its simplicity.

Particle swarm optimization (PSO) was developed in 1995 based on the swarming behaviour of animals in nature, such as birds and fish. PSO has since been the centre of interest, spawning an intriguing research field known as swarm intelligence. It has been applied in nearly every optimization field, including computational intelligence and design/planning applications. "Karaboga" introduced the artificial bee colony (ABC) program in 2005, which is based on bee's collective behaviour. The ABC algorithm simulates employed bees, onlooker bees, and scout bees and provides mathematical formulas for each step. This algorithm, like any metaheuristic algorithms, had its weaknesses, with improved versions introduced later. In 2008, Yang introduced an algorithm inspired by the luminosity of fireflies. In this algorithm, the amount of light intensity and attractiveness of each firefly was formulated, in a way that Each firefly's brightness or light is compared to that of other fireflies, with lowlight fireflies going towards brighter fireflies. Of course, fireflies occasionally fly at random, which resulted in an enhanced version of the method.

Yang presented an algorithm inspired by bat behavior in 2010,12, which is based on the acoustic resonance behavior of bats at varied pulse rates and loudness. The gravitational search algorithm is an optimization technique based on gravity and mass interactions (GSA). Search agents are a collection of masses that interact with one another using Newton's laws of gravity and motion. Agents are viewed as objects, and their mass is used to determine their function. Gravity forces draw all of these items to each other, causing all objects to gravitate toward heavier ones uniformly. As a result, the masses communicate with one another directly through gravity. As this stage assures the algorithm's efficiency, heavy masses corresponding to plausible solutions move slower and lighter. Each mass (agent) in GSA is distinguished by four characteristics: location, inertial mass, active gravity mass, and passive gravity mass. The mass's location is related to the solution of the issue, and its gravitational and inertial masses are calculated using an appropriate fitness function. The hunter seeker method, a novel metaheuristic algorithm for optimization issues, was introduced in 2013. Randomly generated solutions serve as the hunter in this method, while the seeker is allocated based on their performance in the objective function. Their performance may be quantified, and this is known as the survival rate. For numerical optimization, the Spider Monkey Optimization (SMO) algorithm is introduced, along with a new model for numerical optimization based on spider monkey feeding behavior modelling.

Spider monkeys are categorized as animals based on their social structure of "fission and fusion". Due to a scarcity of food, these animals migrate from larger groups to smaller groups and vice versa. Food, as well as vice versa “Oveis Abedinia” et al. (2014) introduced a novel metaheuristic method based on Shark Smell Optimization in 2014. (SSO). This algorithm is based on the shark's capacity to seek prey, which is obtained from the shark's sense of smell and movement towards the source of the scent. The suggested optimization approach mathematically models the shark's diverse activities in the search region, i.e. seawater. The Symbiotic Organisms Search (SOS) algorithm is one of the most recent ways for solving optimization issues based on naturally interacting organisms. This algorithm takes into account three stages of mutualism, parasitism, and commensalism in nature, which may help or hurt each other. However, in Reference, the chaos integrated SOS (CSOS) algorithm was created for global optimization. The suggested method incorporates chaotic local search, which improves the search process.

As the most promising search space area centered around the best solution It raises the likelihood of sustaining a better solution and finally improving the solution's quality Furthermore, the suggested approach outperforms others in multidimensional test functions, suggesting that it is effective. CSOS might be regarded a rising star due to its mix of exploration and exploitation. A nonlinear engineering optimization tool for handling complicated nonlinear engineering optimization issues. The Moth–flame optimization (MFO) method is a new exploration model inspired by the traversal orientations of moths. Moths fly at night at a constant angle to the moon because they have a highly good mechanism for moving in a straight line over great distances. However, because this behavior is scientifically modelled for optimization, these fantasy insects are locked in a futile and lethal spiral journey around artificial light. The suggested MFO method assumes that the answer to the issue is a moth, and the problem variables are the positions of the butterflies in the search space. By adjusting their location vector, butterflies may fly in one, two, three, or extremely high dimensions. Gray Wolf Optimization, a novel metaheuristic algorithm based on hierarchical grey wolf behavior, was introduced in 2014. (GWO). Ordinary wolves dubbed omega after the three wolves alpha, beta, and delta in this procedure. In the simulation, the three best answers are alpha, beta, and delta wolves, with the remaining possibilities being regular wolves. In 2017, a metaheuristic algorithm based on the lives of butterflies was presented, with two groups of Artificial Butterfly Optimization (ABO) situated between exploration and exploitation of the search space. However, the creators of this algorithm released two versions of ABO1 and ABO2 with three different flight types. The modified ABC method was presented as a result of a greatly enhanced general approach and a restricted adaptive technique for universal optimization. Based on the substantially enhanced universal technique and restricted adaptive strategy for optimization issues, the updated ABC was dubbed IGALABC. The ABC algorithm's exploration and exploitation capabilities was balanced and improved during this search phase.

There are others, such as the Golden Ball (GB) algorithm, Cuckoo Search (CS), and others. The Simulated Annealing (SA) method, Gravitational Optimization, and Biogeography Based Optimization are all examples of optimization techniques. (Gb SA), Group Counselling Optimizer (GCO), and BBO. Bird Mating Optimizer (BMO), Clonal Selection Algorithm (CSA), Optimization of Social Spiders (IWD) algorithm, Imperialist Competitive Algorithm (ICA), Intelligent Water Drops (SSO), CBO (Colliding Bodies Optimization), LCA (League Championship Algorithm), Differential Evolution (DE), the Charged System Search (CSS) algorithm, the Ray Optimization method (RO), and the Water Evaporation Optimization (WEO) Algorithm, the Glowworm Swarm Optimization (GSO) algorithm, the Dolphin Echolocation Optimization (DEO) algorithm, and the Water Cycle Algorithm (WCA).

III. WHALE OPTIMIZATION ALGORITHM

Whales are awe-inspiring creatures. They are claimed to be the biggest mammals on the planet. An adult whale may grow to be 30 m long and weigh 180 t. There are seven species of killer whales: killer, Minke, Sei, humpback, right, fin back, and blue. Whales are commonly regarded to be predators. Because they must breathe from the ocean's surface, they never sleep. Half of the brain is actually inactive. Whales are intriguing because they are regarded to be highly intelligent and emotional creatures. Whales have spindle cells in their brains that are identical to human spindle cells, according to Hof and Van Der Gucht (S. Mirjalili, (2006)).

In humans, these cells are in charge of judgement, emotions, and social actions. In other words, spindle cells distinguish humans from other organisms. Whales have twice as many of these cells as an adult human, which is the primary reason for their intelligence. It has been demonstrated that whales can think, learn, assess, communicate, and even get emotional in the same way that humans do, but at a far lower level of intelligence. Whales (particularly killer whales) have been discovered to be capable of developing their own vernacular. Another fascinating aspect is whaled social behavior. They either live alone or in small groups. They are, however, typically seen in groups. Some of them (for example, killer whales) can dwell in large groups. Humpback whales are among the largest baleen whales (Mecopteran novaeangliae). A mature humpback whale is around the size of a school bus. Krill and tiny fish herds are their preferred prey. The most intriguing aspect of humpback whales is their unique hunting technique. This foraging habit is referred to as the bubble-net feeding approach (S. Mirjalili, (2006)). Humpback whales prefer to hunt schools of krill or tiny fish at the surface of the water. This foraging is done by blowing characteristic bubbles along a circle or '9'-shaped path. Prior to 2011, this phenomenon was solely examined through surface observations. Goldbogen et al. (Watkins, (1979)) studied this phenomenon with tag sensors.

They recorded 300 tag-derived bubble-net feeding sessions from 9 different humpback whales. They discovered two bubble-related movements and termed them 'upward-spirals' and 'double loops'. Humpback whales dive roughly 12 m deep and then begin to generate bubbles in a spiral configuration around the prey and swim up toward the surface in the former motion. The subsequent technique is divided into three stages: coral loop, lob tail, and capture loop (Watkins, (1979)). Has in-depth info It is worth noting here that bubble-net feeding is a unique activity found solely in humpback whales. The spiral bubble-net feeding manoeuvre is mathematically described in this study in order to undertake optimization (Goldbogen, 2013).

IV. BAT ALGORITHM

We may construct numerous bat-inspired or bat algorithms by idealizing some of the echolocation features of micro bats. We now employ the following approximate or idealized criteria for simplicity:

- All bats utilize echolocation to measure distance, and they also 'know' the difference between food/prey and background obstacles in some mysterious way (Yang, 2010).
- Bats seek for prey by flying randomly with velocity v_i at position x_i with a set frequency f_{min}, changing wavelength, and loudness A_0.
- They may automatically modify the wavelength (or frequency) of their emitted pulses as well as the rate of pulse emission r [0, 1] based on their target's proximity.
- Although the loudness might change in a variety of ways, we assume that it ranges from a high (positive) A_0 to a little constant value A_{min}.

Another evident simplification is the lack of use of ray tracing in calculating time delay and three-dimensional topography. Though this may be a useful feature for computational geometry, we will not utilize it because it is more computationally intensive in multidimensional scenarios. For the sake of simplicity, we employ the following approximations in addition to these simplified assumptions. In general, a frequency f in a range $[f_{min}, f_{max}]$ corresponds to a wavelength range [min, max]. A frequency ranges of [20kHz, 500kHz] corresponds to a wavelength range of 0.7 mm to 17 mm. For the sake of simplicity, we can use any wavelength for a particular situation. In practice, we may modify the range by altering the wavelengths (or frequencies), and the detectable range (or biggest wavelength) should be set to be equivalent to the size of the area of interest, before toning down to lower ranges.

Furthermore, we do not have to utilize the wavelengths themselves; instead, we can modify the frequency while keeping the wavelength constant. This is because and f are connected since f is constant. This later technique will be used in our implementation. For the sake of simplicity, let us suppose f $[0, f_{max}]$. Higher frequencies, we know, have shorter wavelengths and travel a shorter distance. Bats often have ranges of a few meters. The pulse rate can simply be in the range [0, 1], where 0 indicates no pulses at all and 1 indicates the greatest rate of pulse emission.

V. WAR STRATEGY OPTIMIZATION

Ancient kingdoms had a military to defend themselves against incursions by other dynasties (Ayyarao, 2022). The kingdom's army is made up of a variety of troops such as soldiers, chariots, elephants, and so on. During the conflict, each kingdom devises a stratagem known as "Vyuha" in order to assault the opposite army and win the fight, therefore establishing their domination. During a war, a Vyuha is a pattern or arrangement of diverse army soldiers employed to capture the opposing kingdom (Chakravarti, 1944.).

The emperor and commanders of each unit will coordinate their troops in a certain way to guarantee that their army reaches the desired targets and achieves the goal. The mission's aims, challenges, problems, and prospects influenced the development of the fighting plan. War strategy is a constantly changing dynamic process in which armed forces simply cooperate and attack the adversary. As the fight proceeds, this tactic may adjust to changing situations. The king's and commander's positions have a continuing influence on the army soldier's status. The flags on top of the king's and army commander's chariots show their location, which all troops can see.

Soldiers on the team are taught a strategy based on the sounds of a drum or another musical instrument. When one of the military leaders dies, the plan shifts, and every subsequent commander must learn how to rebuild and maintain the war strategy's foundation. The King's goal is to defeat the enemy king/leader, whilst the army soldier's main goal is to assault the rival side and advance in rank. The following are the various steps involved in the military strategy:

RANDOM ATTACK

Attack On the battlefield, army forces are strategically distributed throughout the whole battleground and assault the opposing army. The army head or commander is the strongest of the army members with the most offensive force. The King is the commander-in-chief of numerous army heads.

ATTACK STRATEGY

The major goal of this tactic is to assault the opponent. The King takes command and directs the army men. Army forces discover the opponent's weak points (promising search space) and continue to attack. The King and Commander go in two separate chariots, each with a flag on top. The Soldiers' placements are constantly changed dependent on the locations of the King and the Commander. If a soldier succeeds in increasing his offensive force (fitness value), his rank will rise. As the soldier progresses, he will set a positive example for the others to follow. If the new location is not suited for fighting, the soldier returns to his prior position. Army forces advance in all directions and take enormous moves to modify their location at the start of the fight.

SIGNALING BY DRUMS

The King's strategy changes constantly dependent on the scenario on the battlefield. As a result, a group of troops beat the drums in time. Based on the beat of the drums, the troops will modify their strategy and shift their positions.

DEFENSE STRATEGY

The fundamental goal of this strategy is to defend the King while avoiding defeat in combat. The commander, or Army chief, takes the lead and creates a chain to surround the King with army forces. As a result, each soldier changes his or her position dependent on the locations of the soldiers around him or her, as well as the position of the monarch. During the fight, army forces attempt to examine a vast region of the war field (search space). To mislead the enemy army, the army changes its strategy dynamically from time to time.

REPLACEMENT / RELOCATION OF WEAK SOLDERS

During a conflict, the soldier with the lowest combat skills or a wounded soldier might be treated the same as an enemy soldier. With his bad performance, the Army's overall reputation is jeopardized (algorithm efficiency). Few troops die during the fight, which may have an influence on the war's outcome. The army has two alternatives in this situation. One method is to replace damaged or weak soldiers with new soldiers. The weak soldier might be relocated as a second option. As a result, he will be led (mean position of all the troops) and insulated by all the other soldiers to defend him, so maintaining army morale and increasing the army's chances of winning the military fight.

TRAPS BY OPPOSITION

Depending on its strengths, the opposing army adopts a range of techniques to cause the former army to proceed in the wrong direction or to achieve the incorrect goal (local optima).

VI. ANT LION OPTIMIZER

Antlions (doodlebugs) are members of the “Myrmeleontidae” and “Neuroptera” families (net-winged insects). Antlions have two distinct life stages: larvae and adults. A natural total lifetime of up to three years can be seen in larvae (adulthood lasts just 3–5 weeks). Antlions develop into adults by metamorphosing in a cocoon. They hunt largely as larvae, while the adult stage is for reproduction. Their names are derived from their distinct hunting style and preferred prey.

Antlion larvae digs a cone-shaped trench in the sand by moving in a circular pattern and tossing sand with its huge mouth [(Scharf I S. A., 2008), (D.)]. Depicts multiple cone-shaped pits of varying diameters. After digging the trap, the larval hides under the cone's bottom (as a sit-and-wait predator (Scharf I O. O., 2006)) and waits for insects (ideally ants) to get trapped in the pit (Scharf I O. O., 2006). The pointed edge of the cone allows insects to readily fall to the bottom of the trap. When the antlion discovers there is a prey in the trap, it attempts to capture it. Insects, on the other hand, are not always trapped right away and attempt to escape the trap. In this situation, antlions smartly toss sands towards the pit's edge in order to slip the prey towards the pit's bottom.

When a prey is trapped in the mouth, it is pushed under the dirt and eaten. Antlions toss the remnants outside the pit after devouring the prey and preparing the pit for the next hunt. Another intriguing aspect of antlion behavior is the relationship between trap size and two factors: hunger level and moon shape. Antlions tend to dig larger traps when they get more hungry (Grzimek B, 2004) and/or when the moon is full (Goodenough J, 2009). They have developed and adapted in this manner to increase their chances of survival. It has also been revealed that an antlion does not directly monitor the shape of the moon to determine the size of the trap, but instead uses an internal lunar clock (Goodenough J, 2009). The ALO algorithm was inspired mostly by the foraging behavior of antlion larvae.

VII. RESULTS AND DISCUSSION

By addressing 23 mathematical optimization problems, the numerical efficiency of the methods established in this work was tested. The issues are traditional benchmark functions from the optimization literature [(Yao X, 1999)- (Yang, 2010)]. Tables 1–3 summarize the test problems by presenting the cost function, range of variation of optimization variables, and optimal value f_{min} as reported in the literature. In Tables 1-3, V_no denotes the number of design variables. A population size is 30 and a maximum iteration are 500 were used for all algorithms. Benchmark functions are classified into three types: unimodal, multimodal, and fixed-dimension multimodal.

It is also worth noting that the composite test functions provide challenging test functions by shifting the global optimum to random positions before each run, occasionally locating the global optimum on the search space boundaries, and rotating the functions using the F (x) = f (R* x) formula, where R is an orthogonal rotation matrices calculated using Salmon's method (R., 1996).

A comprehensive set of benchmark functions with a good combination of features is used to assess the versatility of previous metaheuristic algorithms. Whale optimization algorithm (WOA), the Bat Algorithm (BA), War Strategy (WSO), and Ant Lion optimization algorithm(ALO) are evaluated on the 23 benchmark test functions. The complete details of the functions are given in the following Table.

In Table 4, we notice from the result that the performance of the War strategy optimization algorithm is the best results as in F3, F4, F5, F7, F10, F12, F15, and the performance of Bat algorithm is the worst results as in F1, F2, F3, F4, F5, F6, F7, F9, F10, F11, F12, F14, F15, F17, F18.

Table 1. Description of unimodal benchmark functions

Function	V_no	Range	Min
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \Pi_{i=1}^{n} \lvert x_i \rvert$	30	[-10,10]	0
$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	30	[-100,100]	0
$F_4(x) = max_i \{ \lvert x_i \rvert, 1 \leq i \leq n \}$	30	[-100,100]	0
$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30,30]	0
$F_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[-100,100]	0
$F_7(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	30	[-1.28,1.28]	0

Table 2. Description of multimodal benchmark functions.

$F_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	30	[-500,500]	-418.9829×5
$F_9(x) = \sum_{i=1}^{n} [x_i^2 - 10 \cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0
$F_{10}(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i)\right) + 20 + e$	30	[-32,32]	0
$F_{11}(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \Pi_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
$F_{12}(x) = \frac{\pi}{n} \left\{ 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 [1 + 10 \sin^2(\pi y_i + 1)] + (y_n - 1)^2 \right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4} \quad u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	[-50,50]	0

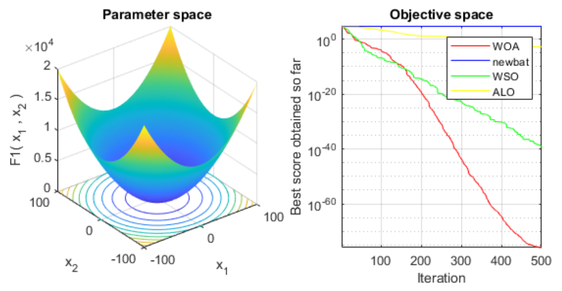
$F_{13}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i-1)^2[1+\sin^2(3\pi x_i+1)] + (x_n-1)^2[1+\sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i,5,100,4)$	30	[-50,50]	0

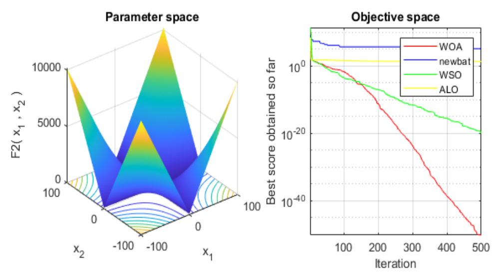
Table 3. Description of fixed-dimension multimodal benchmark functions.

Function	V_no	Range	Min
$F_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6}\right)^{-1}$	2	[-65,65]	1
$F_{15}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1({b_i}^2+b_i x_2)}{{b_i}^2+b_i x_3+x_4}\right]^2$	4	[-5,5]	0.00030
$F_{16}(x) = 4{x_1}^2 - 2.1{x_1}^4 + \frac{1}{3}{x_1}^6 + x_1x_2 - 4{x_2}^2 + 4{x_2}^4$	2	[-5,5]	-1.0316
$F_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2}{x_1}^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1-\frac{1}{8\pi}\right)\cos x_1 + 10$	2	[-5,5]	0.398
$F_{18}(x) = [1+(x_1+x_2+1)^2(19-14x_1+3{x_1}^2-14x_2+6x_1x_2+3{x_2}^2)] \times [30+(2x_1-3x_2)^2 \times (18-32x_1+12{x_1}^2+48x_2-36x_1x_2+27{x_2}^2)]$	2	[-2,2]	3
$F_{19}(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{3} a_{ij}(x_j-p_{ij})^2\right)$	3	[1,3]	-3.86
$F_{20}(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{6} a_{ij}(x_j-p_{ij})^2\right)$	6	[0,1]	-3.32
$F_{21}(x) = -\sum_{i=1}^{5}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.1532
$F_{22}(x) = -\sum_{i=1}^{7}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	4	[0,10]	-10,4028
$F_{23}(x) = -\sum_{i=1}^{10}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.5363

Table 4. Comparison of best values for (WOA), (BA), (WSO), and (ALO) metaheuristic algorithms using the classical benchmark functions.

	WOA	BA	WSO	ALO
F1	3.58E-86	55439.47	8.79E-45	0.001064
F2	3.72E-51	42783.63	1.05E-17	11.5933
F3	23848.74	95894.61	4.07E-43	4724.127
F4	45.3314	65.8034	9.68E-21	24.6339
F5	28.7343	62537721	1.08E-07	703.5497
F6	0.40113	19379.34	0.000837	0.000218
F7	0.020124	102.6218	0.001413	0.24818
F8	-8605.23	-8618.78	-12569.5	-8495.69
F9	0	369.5806	0	99.496
F10	4.44E-15	19.9632	8.88E-16	6.3283
F11	0	353.0485	0	0.050737
F12	0.009186	59443413	1.14E-10	7.6961
F13	0.90155	1.11E+09	3.88E-07	0.36059
F14	0.998	28.3793	0.998	0.998
F15	0.000334	0.040137	0.000307	0.020363
F16	-1.0316	-0.78416	-1.0316	-1.0316
F17	0.39789	0.94468	0.39789	0.39789
F18	3	61.0217	3	3
F19	-3.8627	-3.7146	-3.8628	-3.8628
F20	-3.3056	-1.8083	-3.2031	-3.2026
F21	-10.1502	-0.55013	-10.1532	-2.6829
F22	-2.7637	-0.8319	-10.4029	-3.7243
F23	-9.6555	-1.4289	-10.5364	-3.8354





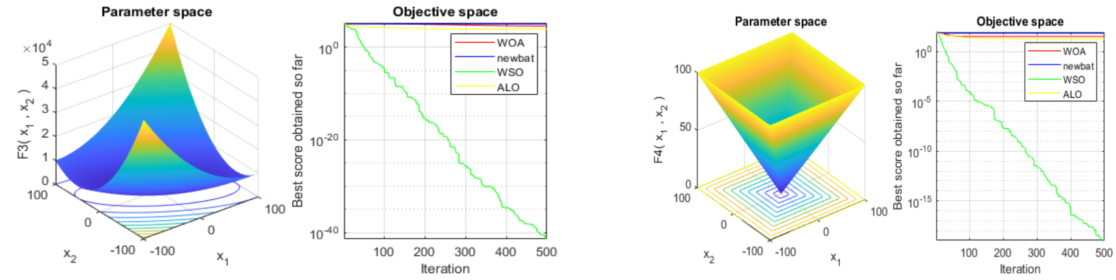
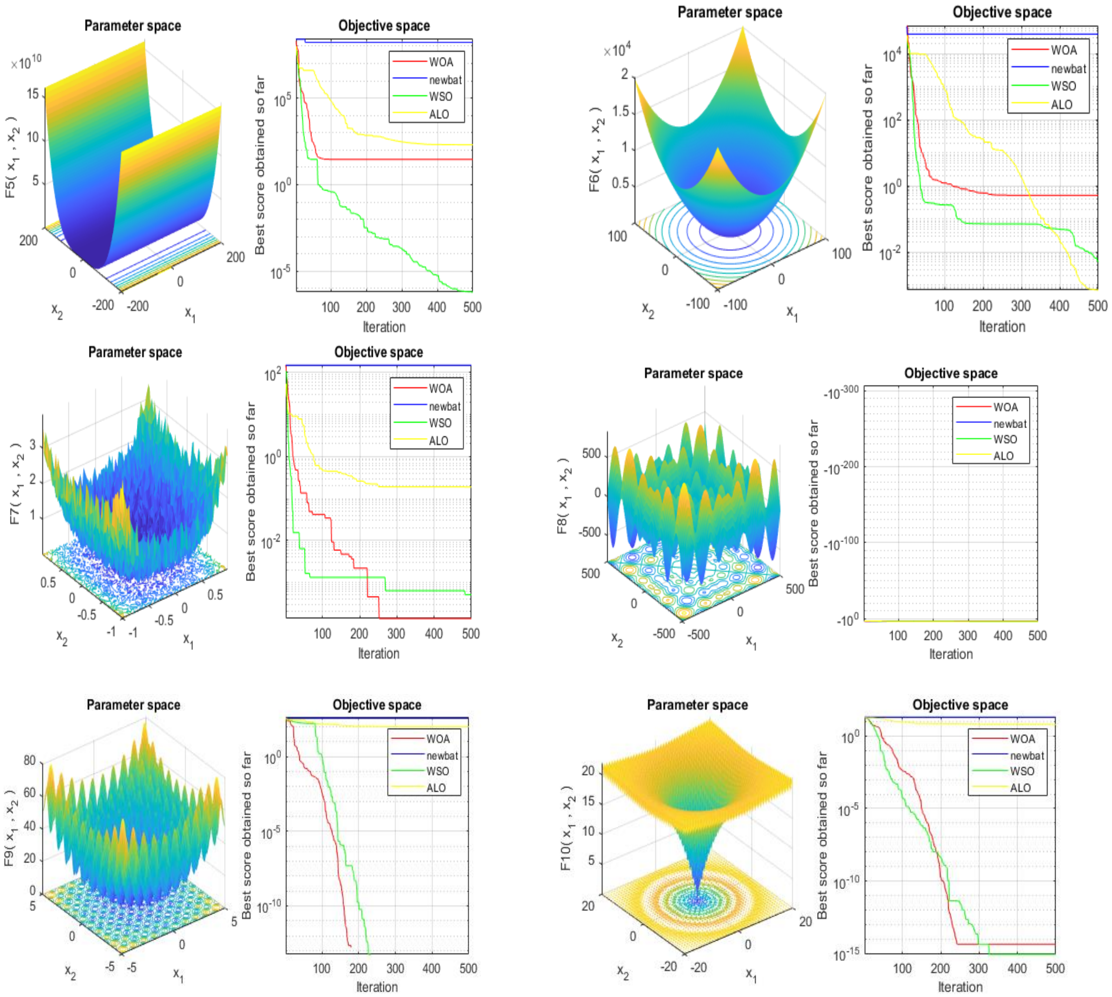


Fig 1: Comparison of best values for (WOA), (BA), (WSO), and (ALO) metaheuristic algorithms using the classical benchmark functions (F1, F2, F3, F4).



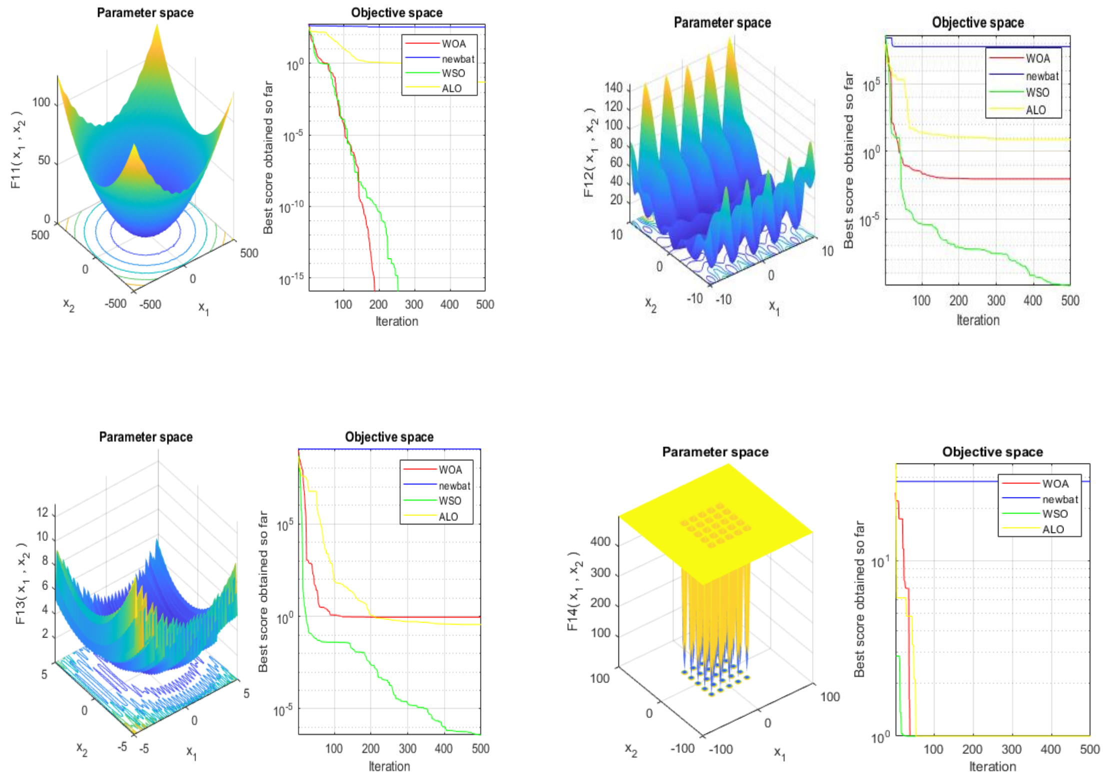
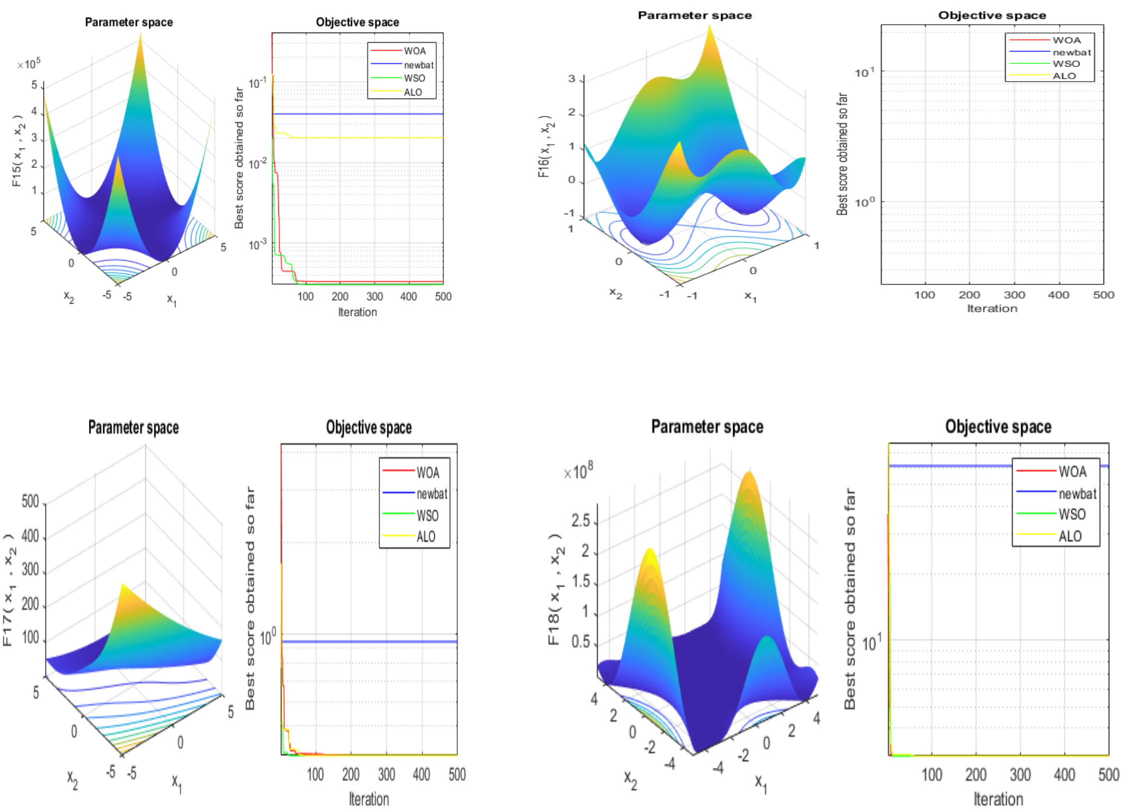


Fig 2: Comparison of best values for (WOA), (BA), (WSO), and (ALO) metaheuristic algorithms using the classical benchmark functions (F5, F6, F7, F8, F9, F10, F11, F12, F13, F14).



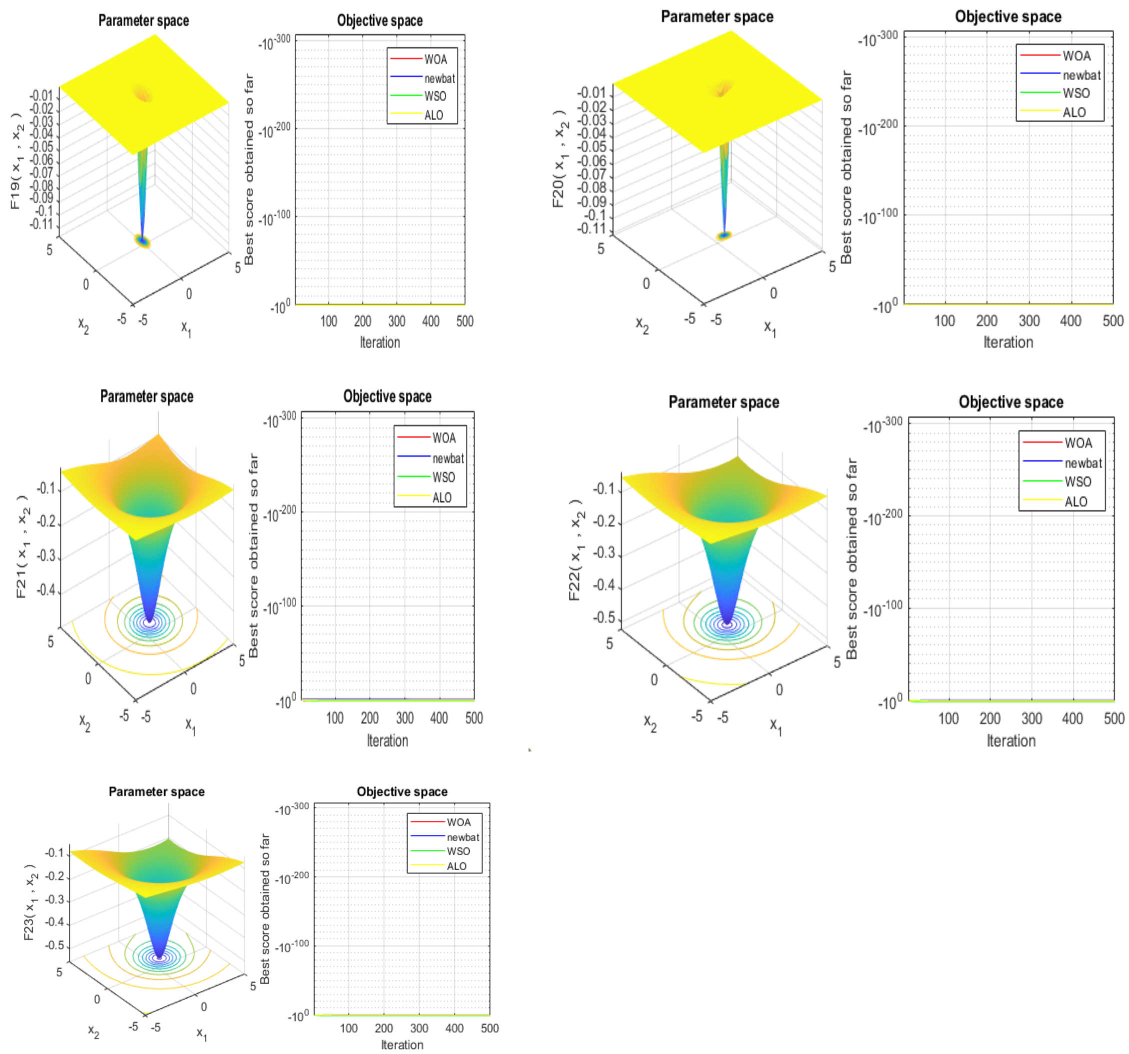


Fig 3: Comparison of best values for (WOA), (BA), (WSO), and (ALO) metaheuristic algorithms using the classical benchmark functions (F15, F16, F17, F18, F19, F20, F21, F22, F23).

VIII. CONCLUSION

We have get an overview of the various metaheuristic strategies for global optimization. We present an overview of four metaheuristic algorithms whale optimization algorithm (WOA), the Bat Algorithm (BA), War Strategy (WSO), and Ant Lion optimization algorithm(ALO). We discuss the mechanism of each algorithms and test its performance on twenty-three benchmark functions and compare its performance. We notice from the result that the performance of the War strategy optimization algorithm is the best results as in F3, F4, F5, F7, F10, F12, F15, and the performance of Bat algorithm is the worst results as in F1, F2, F3, F4, F5, F6, F7, F9, F10, F11, F12, F14, F15, F17, F18.

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