JOURNAL OF OPTOELECTRONICS LASER

ISSN: 1005-0086

Volume 41 Issue 8, 2022

A Hybrid Sparrow and Bee Optimization Algorithm Was Applied to an Evolution Metaheuristic Optimization Algorithm

Farah Sami Khoshaba

Department of Information System Engineering, Erbil Technical Engineering, Erbil Polytechnic University, Erbil, Iraq

ABSTRACT

Computer scientists regularly create new process improvement methods as a result of the growing complexity of real-world optimization issues. In nature-inspired optimization methods, the employment of metaheuristic and evolutionary computing techniques is gaining popularity. This paper introduces Sparrow and Bee's optimization as a hybrid proposed method (HPM). This revision of an existing algorithmic metaphor based on Sparrow's actions and Bee in nature is a revision of the hybrid Sparrow and Bee optimization. This algorithm combines several arbitrary and adaptive factors to show the exploitation and exploration of the search region in several optimization explorations. The algorithm's outcomes are shown graphically. Different test phases are used to evaluate the overall performance of the HPM. First, a collection of well-known testing outcomes, such as composite functions, unimodal, and multimodal, is used to investigate the exploitation, search, avoidance of local optima, and convergence of the high-performance computing model (HPM). Additional special metrics such as (the most suitable solution through optimization as well as search history) are used to qualitatively and quantitatively examine and verify the achievement of HPM on turned two-dimensional inspection functions. Additionally, When the effects of analysis functions and achievement metrics are combined, the proposed method can search various While optimization is being successfully carried out, parts of a search space should converge to global optimum and avoid local optima, and make use of encouraging areas of a search range. The HPM algorithm creates an ordinary wing framing with a reasonably low drag despite working with physical challenges like confined and unknown search areas, which explains why the techniques can be extremely effective while working with these challenges.

Keywords: Metaheuristic, Swarm intelligence, Global Optimum, Bee and Sparrow Optimization.

I. INTRODUCTION

Swarm intelligence systems based on population have received widespread acceptance and extensive use for a range of optimization challenges. These are how they are described: An algorithm for Swarm intelligence that is based on population is based on a number of many things that cooperate to solve a problem by exchanging knowledge, offering help, and/or competing against one another, in contrast to popular standard techniques, such as algorithms for hill-climbing[1][2].

The procedures of meta-heuristic optimization are very similar to those that were used in the earlier decades. Furthermore, there are several broad studies as well as a number of remarks on the optimization techniques applied in many fields. The author discusses meta-heuristics, which are frequently used in decision-making[3] [1]. Suppleness, flexibility, the use of a derivation-free tool, and the avoidance of local optima are all factors that contribute to this topic's popularity. See also: Most of the time, they resorted to very straightforward concepts [4].On computers, it is possible to implement some straightforward ideas. Integrity also engenders the possibility of proposing new checks, hybridizations of two or more meta-heuristics, and improvements to recently developed meta-heuristics, among other possibilities. Apart from that, integrity allows for a simple and convenient deduction on the many experts, which can be used to help them with their problems [6].

Extraction and exploration are also important concerns for some swarm intelligence meta-heuristic techniques, and they are a significant source of concern for them. There's many community computational intelligence techniques, have survived in recent years, including ant colony optimization (ACO), particle swarm optimization (PSO)[5], brain storm optimization [1][2] artificial bee colony algorithm(ABC) [6][7], and imperialist competitive algorithm [8].

While this is happening, met-heuristic algorithms aim to find a certain create extra in each optimized issue, where the advantage of every optimal solution is developed primarily till that parameter period is reached [11]. Depending on how a technique can be globally or localized in scope, it is divided into methods for local and global search. Approximate solution search strategies for local corresponding levels are offered to produce a few of the object parts on the set of solutions, however, the real function is maybe the maximum or minimum value [12]. For obtaining the best possible result while each type of Swarm intelligence algorithm is utilized to produce the best results when an optimized function is poorly understood or its organization is excessively complex [13] [14]. The efficiency of a search technique during the ideal time indicates the likelihood of discovering an issue's convergence and extremum solution at the optimum period[9].

Every area of scientific and engineering development faces the standard analytical challenge of getting better at finding the best answers. In reality, optimization techniques can be classified as either stochastic or deterministic. Utilizing preservation strategies to address optimization issues necessitates enormous computational expenditures, which makes them unsuitable for difficult problems such as random optimization [16]. Applying meta-heuristics based on a community of optimization problem answers or iterative development seems to be a more trustworthy method for resolving the optimization issue (either in a swarm or evolutionarily based technologies)[10].

This study introduces the new optimization technique known as sparrow optimization. This approach imitates the methods employed by sparrows to find food sources. Keep in mind that there are two distinct breeds of house sparrows that are breeds: the producer and the scrounger. While the scroungers rely on the producers to provide them with food, the producers actively seek sources of food. The findings also demonstrate that the birds frequently transition between generating and scrounging behavior patterns. Additionally, it may be claimed that sparrows typically employ both the producer and scrounger strategies to find food[18].

This paper proposes a novel optimization with a hybrid swarm intelligence technique in response to the foregoing discussions. As a result of the foregoing arguments, this paper proposes a novel optimization strategy for hybrid swarm intelligence, which is referred to as "Sparrow Bee optimization." (HPM). The key contributions are summarized as follows: (1) a new hybrid system, the HPM is presented inspired by the foraging and anti-predation activities of the sparrow population; (2) instead of using the presented HPM, in both discovery and utilization of the optimization search space are enhanced to some extent; and (3) the presented HPM is actually achieved in problems of practical engineering. Finally, several comparative studies will be carried out in order to assess the efficacy and efficiency of the proposed algorithm in this article. The simulation experiments demonstrated that the proposed HPM is better in terms of search accuracy, premature convergence, consistency and avoiding of local optimal value to other traditional approaches. This article is organized as follows. After the Introduction, Section 2 provides a survey of the broad optimization literature. Section 3 contains a succinct introduction to the Bee Optimization Algorithm. The authors discuss the Sparrow Search optimization techniques in section 4. The approach in detail and section 5 provides the experimental results. The findings are in the final section.

II. SPARROW SEARCH ALGORITHM (SSA)

The motivation behind the SSA is covered in this section. Following that, a thorough description of the mathematical model and the SSA is given

Biological characteristics

The various kinds of sparrows are typically social birds. They are found almost everywhere in the world and like to reside in areas where people live. Additionally, they are omnivore birds that primarily eat weeds or grain seeds. The sparrows are common resident birds, as is widely known. The sparrow is highly intelligent and has a good memory, unlike many other little birds. Keep in mind that there are two distinct breeds of house sparrows that are kept as pets: the producer and the scrounger [11]. While the scroungers use the producers to get food, the producers actively look for food sources. In addition, the information demonstrates that the birds typically employ flexible behavioral methods and alternate between generating and scrounging [12] [13] [14]. Additionally, it may be claimed that sparrows typically employ both the producer and scrounger strategies to find food[11] [15] [16]. Studies have demonstrated that people keep an eye on one another's group behavior. In the meantime, predators in the flock of birds employ the partners with large intakes as competition to improve their own rate of predation by obtaining food [17] [18].

Additionally, when a sparrow picks a certain foraging strategy, its energy stores may be a significant factor. Those with low energy reserves will likely scavenge more than those with sufficient energy reserves[18]. It is important to note that birdPredators are often more likely to assault those on the colony's edge. and are continuously attempting to gain an advantage[19] [20].Researchers also understand that all birds have a genuine interest in everything while also being constantly watchful. As an illustration, One or more of the birds chirp and the entire flock takes off when one of them spots a predator [21] [22]..

Model and algorithm in mathematics

Concurring to the past depiction of the sparrows, able to set up the scientific demonstrate to develop the sparrow look calculation. For effortlessness, we idealized the taking after conduct of the sparrows and defined comparing rules.

(1) The producers provide scrounging zones or directions for all scroungers and have high levels of energy saves. It is reliable for identifying areas with abundant food sources. The assessment of an individual's wellbeing values determines the amount of energy saved.

(2) The sparrow starts tweeting stiffly as soon as it recognizes the predator. If the alert value surpasses the security edge, the producer should send every scavenger to a safe region.
(3) If a sparrow searches for better food sources, it can reach a creator, but the proportions of makers and scavengers remain the same across the population.
(4) The producers would be the birds with the highest levels of energy. A lot of famished Scroungers are more prone to travel to distant locations in quest of food to get energy.
(5) Scavengers seek a producer who can provide the best food in their pursuit of food. Many scavengers could be watching closely the producers while they are waiting for food and competing with them for it in an effort to boost its particular predatory activity.
(6) When in danger, the sparrows at the group's periphery move quickly toward the safe region to take up a better position, whereas the sparrows in the center of the group wander aimlessly to be near one another. To find food in the simulation experiment, we must utilize computer-generated sparrows. The following matrix can be used to show where sparrows are located:

$$\begin{bmatrix} x_{1,1}x_{1,2} \cdots \cdots\ x_{1,d} \\ x_{2,1}x_{2,2} \cdots \cdots\ x_{2,d} \\ \cdots \\ x_{n,1}x_{n,2}\ \cdots \cdots\ x_{n,d} \end{bmatrix} \quad (1)$$

where d appears to be the measurement of the elements that need to be maximized and n is the number of sparrows. At that time, the following vector can be used to convey the overall health value of all sparrows:

$$\begin{bmatrix} f([x_{1,1}x_{1,2} \cdots \cdots\ x_{1,d}]) \\ f([x_{2,1}x_{2,2} \cdots \cdots\ x_{2,d}]) \\ \cdots \\ f([x_{n,1}x_{n,2}\ \cdots \cdots\ x_{n,d}]) \end{bmatrix} \quad (2)$$

where denotes the sparrow's amount, the value of each push in FX refers to the birds regard for their own wellbeing. The makers in the SSA who place a higher premium on wellbeing have priority access to food in the meal plan. Additionally, the creators are concerned with acquiring food and managing the population's expansion. The makers can then look for food in a much wider range of locations than the scavengers can. In accordance with principles (1) and (2), the maker's workspace is renovated as follows during each cycle:

$$X_{ij}^{t+1} = \begin{cases} X_{ij}^{t}.\exp\left(\frac{-i}{\propto.iter_{max}}\right) if R_2\ < ST \\ X_{ij}^{t} + Q.L if R_2\ \geq ST \end{cases} \quad (3)$$

X_{ijt} refers to the value of the jth measurement of the ith sparrow at cycle t, where t denotes the current cycle and j = 1, 2..., d. $Iter_{max}$ might be the algorithm with the most iterations. (0, 1) could be an erroneous number. Separately, R2 (R2 [0, 1]) and ST (ST [0.5, 1.0]) address the security edge and the alert esteem. Q could be an irrational number that follows the rules of distribution. L appears as an matrix of 1,…, d, where the interior value of each component is 1.The manufacturer switches to broad view mode when R2 ST, which denotes that there are no nearby predatorsIf R2 ST, it indicates that the predator has already been spotted by some sparrows, and all sparrows must promptly fly to other secure sites. The scroungers must follow regulations (4) and (5). Some scroungers investigate the manufacturers more frequently, as was already said. They leave right away to seek for food in a new location. as soon as they learn that the maker has found excellent sustenance. If they succeed, they can swiftly obtain the maker's food, after which they proceed to follow the guidelines (5). The position upgrading formula for the scrounger looks like this:

$$X_{ij}^{t+1} = \begin{cases} X_{ij}^{t}.\exp\left(\frac{X_{worst}^{t} - X_{ij}^{t}}{\propto.iter_{max}}\right) if i > n/2 \\ X_{p}^{t+1} + \left|X_{ij}^{t} - X_{p}^{t+1}\right|.A^{+}.L otherwise \end{cases} \quad (4)$$

where XP represents the ideal role played by the maker. X_{worst} denotes the current, notably region in the entire world. When I > n/2 and A+ = AT (AAT)-1, which refers to a lattice of 1 d for which each internal component is arbitrarily assigned 1 or 1, It implies that the scrounger has access to more terrible wellness esteem is more likely to be famished.These aware of danger sparrows should compensate 10% to 20% of the whole population, according to their predictions in the recreation test. These sparrows' starting placements are randomly generated within the population. In accordance with rule (6), the numeric show may be expressed as follows:

$$X_{ij}^{t+1} = \begin{cases} X_{best}^{t} + \beta.\left|X_{ij}^{t} - X_{best}^{t}\right| if f_i > f_g \\ X_{ij}^{t} + K.\left(\frac{\left|X_{ij}^{t} - X_{worst}^{t}\right|}{(f_i - f_w) + \varepsilon}\right) if f_i = f_g \end{cases} \quad (5)$$

where the current global ideal region is X_{best}. With an value of and a variance of 1,, the step measure control parameter, might represent a typical distribution of irregular integers. K [1, 1] may include any number. Here, fi represents the show sparrow's health rating. The current global best and worst wellness values, respectively, are fg and fw. To avoid a zero-division error, is the least consistent.For simplicity, when The sparrow is shown to be at the edge of the gather by fi > fg. Speaking to the middle of the population, X_{best} is safe in its vicinity. The sparrows in the center of the flock, according to fi = fg, appear to be aware of the danger and have gotten closer to the others. K is both the step measure control coefficient and a symbol for the direction the sparrow is moving.

III. BEE OPTIMIZATION ALGORITHMS

Swarm intelligence is recognized in the behavior of insect colonies such as ants and bees, which is defined as collective intelligence. It is through this extremely coordinated operation that insect colonies are able to solve problems that are beyond the capabilities of individual fragments by working together and communicating primitively amongst themselves. In a honey bee colony, for example, this model allows bees to investigate the circumstance in flower group exploration, which allows them to gather valuable information (source of food). As part of this exploration, different bees from the colony will identify and label the specific conditions of food that they have discovered [1].

Bees are dependent on personality depending on the comparably simple behaviors of a single insect in order to survive. In order to express singular insects as intelligent, it is reasonable to assume they are capable of implementing modifications to complex tasks while maintaining a large several traditional insect groups and modifications to their behavioral models. The excellent instance is in charge of keeping the nectar running.

BEE Algorithm

One of the optimization algorithms used to obtain the best answer is the Bee algorithm, which mimics the natural behavior of a community of bees. Figure 1 depicts the pseudo-code of the Bee algorithm in a straightforward manner, while Figure 2 depicts the algorithm's flowchart. Many variables must be configured for the algorithm to work properly, including the following:

- number for the scout Bees is (n)
- A list of the selected sites (m) from among the visit sites (n)
- A list of the top-ranked sites (e) from the list of potential sites (m)
- A list of the quantity of bees attracted from the best place (e) (nep)
- The quantity of bees that were recruited from other (m-e) locations besides the chosen site (nsp).
- It is important to establish the initial size of patches (ngh) that include the location, its halting criteria, and the neighborhood around.
- In the Bees algorithm, there is a population of individuals, recognized as a "Bee," and this procedure is repeated over and over again. Each Bee encodes a potential answer to the problem being encoded in a specific problem space. The area that can be searched for information about the issue is known as the search space, and it contains all explanations for the issue that could be considered.In general, the Bees algorithm is used to search for items inplaces that are too big to be fullysearched (as in combinatorial optimization). Because each task has specific computational benefits, solutions to a problem can be encoded in a variety of ways. One of the most important characteristics of the The strength of the Bees method is its capacity for parallel, multi-point searches of the function space.In this context, the capacity to parallelize the Bees algorithm implementation is not referred to as parallelism; rather, it refers to the ability to represent a large number ofpotential solutions in a single generation of a single population of potential solutions.
- In each production, while some solutions are implemented using the Bees algorithm, a variety of other solutions are also implemented.

Input: n is the scout bee, m are the chosen sites, e is the best of m, nep are the bees recruited for e, nsp are the patch size and stop criteria for bees recruited for m-e and ngh are respectively.
output: ideal answer (s).
1. Begin with arbitrary solutions in a population of n.
2. Calculate the population's fitness.
3. Loop (stopping requirement not satisfied) /Generating fresh population.
4. Selected locations for neighbourhood research m.
5. Recruit bees for the selected sites (more bees for the best e sites) and determine fitness levels.
6. Select the proper bee from every patch of ngh.
7. Permit the remaining bees (n-m) to go on a haphazard exploration and gauge their fitness.
8. Close loop.

Figure 1 The fundamental bee's algorithm pseudocode

Out of these positions, the search for the function area proceeds, and the bees interpret the circumstances in parallel with one another. It differs from other searching techniques, like a search on a single element in the function space, in that it based the search on a single element in the function space as opposed to other searching techniques, like a search on a single element in the function space. Absolute parallelism is the ability to investigate various configurations for each solution in a given time frame.

IV. OVERALL IMPLEMENTATION

The initiation stage and the end stage are also present, in addition to the four significant stages. The startup stage of the bee includes initializing the sparrow parameter as well as the bee parameters specified in the preceding section. The initialization of bee is way better when conveyed haphazardly and equitably, Relevant parameters should be initialized in accordance with different optimization problems. As a conclusion condition, one may use a variety of circumstances, such as the passage of time, achievement of a specific accuracy standard, depletion of available resources for health, etc. The steps in detail are as follows in figure.

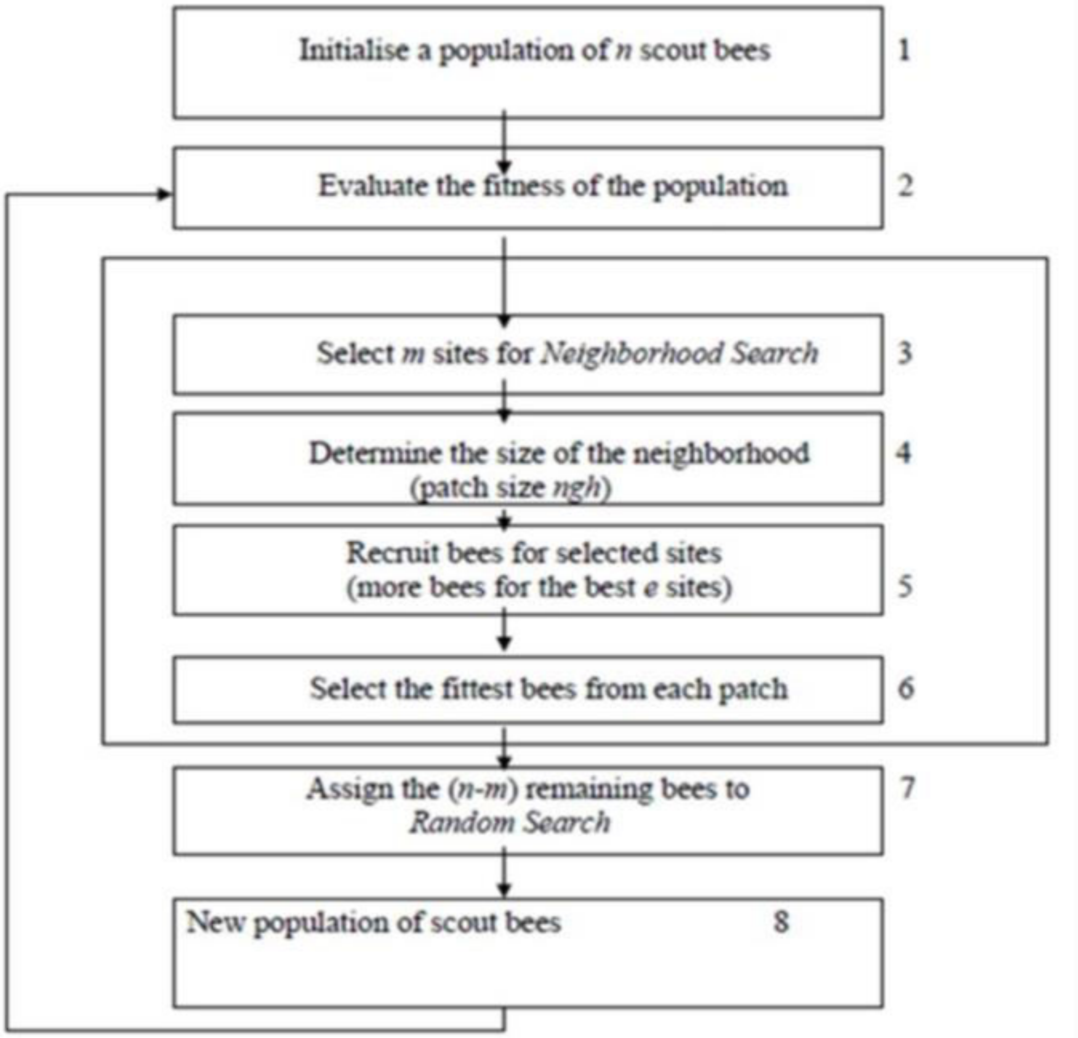

Figure 2 The bees algorithm flowchart

Algorithm 1 The HPM's basic structure.

Input: Maximum iterations, G
the quantity of producers, SD: the proportion of sparrows that notice danger
The alert value is R2, N1: the quantity of sparrows
N2: Scouts present. Bees. Out of n2 visited locations, how many sites were chosen?
Out of the m selected sites, how many are the best ones?
The quantity of Bees hired for the greatest e-sites
The quantity of Bees hired for the other (m-e) chosen sites
ngh: A site's and its surrounding area are included in the initial size of patches (ngh).
Establish the relevant parameters for the population of n1 sparrows and n2 scout bees.
Output:*X*best, *fg*.
1.while (t G), first
2: Determine who is currently the best and worst athlete by ranking the fitness values.
3: R2 = rand (1)
4: PD for **I** = 1.
5: Update the sparrow's location using equation (3);
I = (PD + 1): n1 for 6: end for 7.
8: Update the sparrow's location using equation (4);
9: End of for 10: If I = 1, then n2
11: Selected locations for neighborhood research m.
12: Recruit bees for the selected sites (more bees are needed for the best-performing sites) and

determine fitness levels.
13: From each ngh patch, choose the right bee.
14: Permit the remaining bees (n-m) to swarm randomly and determine how fit they are.
15: End for
16: Discover the brand-new place;
17: Update it if the new location is superior to the previous one;
18: t = t + 1
19 End while and then
20: return Xbest, fg.

The authors utilize virtual sparrows to find food in the simulation experiment. Eq (1) can be used to depict the position of sparrows. Where n1 denotes the number of sparrows to be optimized and d denotes the dimension of the variables to be improved After that, can be used to express the fitness value of all sparrows using eq(2). Where the value of each row in and n is the number of sparrows in FX is the individual's fitness value. Inside the SSA, food producers with greater fitness values are given preference. Furthermore, the producers are in charge of finding food and directing the entire population's movement. As a result, producers have a wider range of options than scavengers when looking for food.

During each iteration, the producer's location is changed according to rules (1) and (2) as eq (3). It suppose that these sparrows, who are aware of the threat, make up 10% to 20% of the whole population in the simulation experiment. These sparrows' beginning placements are produced at random in the population.

Equation according to rule can be used to state the mathematical model (6). Xbest is the current optimum position on Earth, according to (5). The normal distribution of random variables has a mean of 0 and a variation of 1, data serves as the foundation for the step size control parameter. K [1, 1] is a number that was chosen at random. The contemporary sparrow has a fi fitness value. The best and worst fitness numbers currently available are fg and fw, respectively. the lowest constant to prevent zero-division-error. It is assumed that the locations sensed by scout bees in step 2 are suitable. In step 11, the bees who produce the highest fitnesses must be designated as "chosen Bees," and the locations they find during neighborhood exploration are selected once more. The algorithm then regulates neighborhood investigations from the chosen sites in steps 12 and 13, enabling more Bees to investigate the neighborhood on certain of the key e places. Alternately, the advantages of improved fitness are chosen to reduce the likelihood of bees. It displays investigations into a community from a reputable e-site that talks about uplifting cures, such raising more Bees to help them than other chosen Bees. A crucial Bees Algorithm step that happens simultaneously with scouting is this differential recruiting. Only the Bee with the greatest fitness score is picked to create the subsequent Bee population on any patch in step 13.

V. EXPERIMENTAL EVALUATION

The PHM method is evaluated using 23 benchmark functions in this section. The 23 benchmark functions are the common ones that some analysts use [11] [12] as shown in figures 4-6. In spite of the effortlessness, the creators have chosen specific test functions to enable the comparison of results to those of modern meta-heuristics. Tables 1-3 provide these benchmark functions, where Dim alludes to the measurement of the work, Run refers to the sides of the function’s investigation extend, and f_{min} alludes to ideal [13]. These standard capacities are the exchanged, overseen, expanded, and combined factors of the classic capacities that speak to the foremost with the current standard capabilities, complicated [14]. Mention that the CEC 2005 technical report provides detailed descriptions of standardized functions [11]. 30 iterations of the PHM algorithm were run for each performance measure function. Tables 5 and 6 lists the statistical results (standard deviation and average). The PHM algorithm is contrasted with the PSO[5] as an SI-based technique and GSA[12] as a physics-based algorithm in order to validate the results. In addition, three EAs are compared to the PHM algorithm: DE[13], Fast Evolutionary Programing (FEP) and[14], Supernova Optimizer (SO)[10], WOA[15] Whale Optimization Algorithm, and GOA[16] Grey Wolf Optimizer.

In general, citation roles fall into one of four categories: unimodal, multimodal, multimedia, fixed-dimension multimedia, or composite. Since they only have one global rule, functions F1 through F7 are unimodal. We can roughly estimate the optimization potential of the meta-heuristic algorithms under consideration thanks to these functions. Tables 5 and 6 show that PHM is one of the numerous meta-heuristic indicative algorithms that are extremely aggressive. The optimizer appeared out of place, acting on the toughest test issues as the normal active among all helpful actors. Therefore, the current algorithm will guarantee very successful exploitation.

The graphical features include numerous local updates, the total of which dramatically rises as the problem's severity (number of design parameters). Therefore, this kind of research problem is particularly useful if the objective is to determine the exploration potential of the optimization technique. The findings in F8 - F23 (Integrated multimedia functions and multimedia) in Tables 5 and 6 show that PHM also has strong exploration potential. In some test problems, The best or second-best algorithm is always the one in use at the moment. This is expected given the PHM method's integrated search procedure and mechanisms, which push this algorithm in the direction of overall optimization. There are no local optima for the first set of test features. This makes it a good match for convergence speed calculation and algorithm exploitation. For the above test functions, a global limit of more than 500 iterations may be imposed by a sample of 30 search operators.

In certain terms, to get a note, the efficiency of exploration operators must be observed by optimization. On a machine with the following specs, MATLAB is used to implement the simulation tests: 8th generation Core i5 processor running at 1.6 GHz with 8GB of RAM and Windows 10. For the experiments in FOA, the optimum criteria are used: Cr= (10,0) is initially set to 10 and decreases by 0.002 with each iteration. Random variables R1 and R2 are (0,1), while CC was chosen at random during the first iteration before being calculated using equation (3). (0,1).

In order to evaluate the actions of the candidate solutions, 30 search agents can solve the two-dimensional variant of the evaluation metric. Notice that to provide more difficult tests, the optimum of the test functions is transferred to a position other than the root. Figure 7 shows the search history of search agents. This figure demonstrates that the PHM algorithm looks for the search space's promising areas. The sampled sites' very high dispersion around the global optimum demonstrates that, in addition to the discovery, the PHM Utilizing the highest optimistic region of a target region, algorithm.

PHM's results show that, compared to the algorithms listed above, it is more competitive and effective. The efficacy, versatility and accuracy of the presented algorithm were demonstrated by those findings. The results obtained show that, compared to the unimodal results, Finding the multi-model function's best solution value was more successful with the PHM algorithm. This reflects PHM's supremacy in the quest for discovery. Such actions will ensure, according to [17], that a community algorithm ultimately converges to a point in a search space. The results of the convergence are compared by the authors with the results in[16][15]. The PHM, WOA, PSO and GSA dilemmas are correlated and plotted in Figure 7 (A, B, C) for some of the problems and in Figure 7 (GWO, PSO and GSA) for the other problems (D, E, F). It is shown that PHM is sufficiently successful with meta-heuristic techniques of other state-of-the-art. To see the convergence rate of the algorithms, the dilemmas of the PHM, PSO, WOA, and GSA are given in Figure 7. Notice that the greatest average shows the combination of the right approach for each execution with 30 runs.

It is shown by the figure that by optimizing the test functions, the PHM algorithm demonstrates some distinct convergence habits. First of all, the PHM algorithm's convergence tends to be enhanced as iteration rises. It was attributable to the suggested adaptive strategy for PHM that helps in the basic stages of the iterative process to search for successful areas of the search and accumulate very quickly after around half of the cycles, in the ideal direction. The second action is convergence towards the optimum, as can be seen in F2 only in the final iterations. It is shown by the figure, that when the test functions are optimized, the PHM algorithm demonstrates some distinct convergence habits.

The performance ranges of a unimodal fitness function are shown in Figure 7 A to aid in conceptually assessing the computing effectiveness of four algorithms. This suggests that PHM performs well throughout the F1, F3, and F4 test functions, which is unquestionably superior to PSO, GSA, and WOA. The PHM should be given a higher fitness rating in the beginning stages before improving to a good level for the F5 test function after 500 or more repeats. The suggested PHM not only improves the premature convergence but also has an excellent reputation in comparison to other techniques, as seen by the F8 and F12 assessment functions convergence graphs. The precision of the PHM is particularly useful for all comparison techniques, including for the F14 test feature. Additionally, the WOA and PSO both discover greater value from the best value gained, but the GSA receives poor value. The other three methods are simple to locally tune, and the PHM works pretty similarly on the two separate training sets, F15 and F16. The four methods will enclose the F17 test function in local optimum regions for each separate experiment. The GSA performs better than the other three algorithms while trying to solve F19. It is seen that the PHM swiftly converges to the ideal solution for the F15 test function after about 500 iterations. As a result, the PHM's convergence rate is exceptionally high. Additionally, four test functions—F17, F19—are accessible, with the convergence rate of the PHM being higher than that of the PSO, GSA, and GWO. because at the start of the iteration, the PHM immediately converges to a constant value. The simulation results demonstrated that the PHM has a significant amount of power. enhancing the capability for the optimization of fixed-dimension, multimodal, and unimodal test functions. Additionally, it is demonstrated that the PHM faces some competition from other cutting-edge algorithms. Therefore, it is expected that the PHM achieves a particular equilibrium between global discovery and local exploitation. The analysis of the results also reveals that PHM delivered a competitive and efficient result in its attempt to find the best answer that is very comparable to the comparison algorithms for the functions F20, F21, F22, and F23 that pose exceedingly challenging problems from the collection of multimodal extended mimic the actions through hybrid composition functions.

VI. CONCLUSION

The research implemented a new approach hybrid method social behavior can be used to enhance the swarm optimization algorithm. PHM has been presented as an alternative approach to resolve optimization issues. Solutions have been critical in the proposed PHM algorithm based on the location of the best option so far, to improve their websites. The site can be upgraded to allow the solutions to go to or from the target point, guaranteeing that the search space is used and explored. 23 test functions were utilized to gauge the PHM's level of effort and effectiveness from a local and global search standpoint.The outcomes demonstrated that PHM has the capacity to avoid DE, FEP, PSO, GSA, and GWO. Results from the functioning of unimodal test showed dominance when utilizing the PHM method. Later, it was demonstrated that it was possible to find PHM with results for multimodal functions.

REFERENCES

[1] S. W. Kareem, Novel Swarm Intelligence Algorithms For Structure Learning Of Bayesian Networks And A Comparative Evaluation, Graduate School Of Natural And Applied Sciences, Yasar University, 2020.

[2] Y. Shi, „An optimization algorithm based on brainstorming process,“ International Journal of Swarm Intelligence Research, Bd. 2, Nr. 4, pp. 35-62, 2011.

[3] Y. Shi, „Brain storm optimization algorithm Conference on Swarm Intelligence,“ Chongqing pp 303-309, 2011.

[4] A. Kaveh, M. Khayatazad, „A New Meta-Heuristic Method: Ray Optimization”. 112–113:283–94.,2012.,“ Computers & Structures, pp. 283-294, 2010.

[5] K. Ahmed, B. Al-Khateeb and M. Mahmood, „Application of Chaos Discrete Particle Swarm Optimization Algorithm On Pavement Maintenance Scheduling Problem,“ Cluster Computing, , Bd. 22, p. pages4647–4657, 2018.

[6] Shahab Wahhab Kareem and Mehmet Cudi Okur, „Evaluation of Bayesian Network Structure Learning Using Elephant Swarm Water Search Algorithm,“ in Handbook of Research on Advancements of Swarm Intelligence Algorithms for Solving Real-World Problems, Chapter 8, IGI Global, 2020, pp. 139-159.

[7] Kennedy, J. and Eberhart, R., „Particle swarm optimization,“ in IEEE International Conf. on Neural Networks, , Vol. 4, pp. 1942-1948., Perth, 1995.

[8] D. Karaboga, „An idea based on honey bee swarm for numerical optimization,“ Erciyes University, , Kayseri, 2005.

[9] Karaboga, D. and Basturk, B., „A powerful and efficient algorithm for numerical functionoptimization: artificial bee colony (ABC) algorithm,“ Journal of Global Optimization, Bd. 39, Nr. 3, pp. 459-471., 2007.

[10] Esmaeil, A. and Lucas, C., „Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition,“ in IEEE Congress on Evolutionary Computation, Singapore, pp.4661-4667, 2007.

[11] Shahab Kareem, Mehmet C Okur, „Bayesian Network Structure Learning Using Hybrid Bee Optimization and Greedy Search,“ in Çukurova University, Adana, Turkey, 2018.

[12] Shahab Wahhab Kareem, Mehmet Cudi Okur, „Pigeon Inspired Optimization of Bayesian Network Structure Learning and a Comparative Evaluation,“ Journal of Cognitive Science, pp. 535-552, 4 20 2019.

[13] Shahab Wahhab Kareem, Mehmet Cudi Okur, „Structure Learning of Bayesian Networks Using Elephant Swarm Water Search Algorithm,“ International Journal of Swarm Intelligence Research, pp. 19-30, 2 11 2020.

[14] Amin Salih Mohammed, Shahab Wahhab Kareem, Ahmed khazal al azzawi and M. Sivaram, „Time Series Prediction Using SRE- NAR and SRE- ADALINE,“ Jour of Adv Research in Dynamical & Control Systems, 12 10 2018.

[15] Yudong Zhang, Shuihua Wang, and Genlin Ji, „A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications,“ Mathematical Problems in Engineering, Bd. 2015, p. 38, 2015.

[16] Sami H. Ismael, Shahab Wahhab Kareem, Firas H. Almukhtar, „Medical Image Classification Using Different Machine Learning Algorithms,“ AL-Rafidain Journal of Computer Sciences and Mathematics, pp. 135-147, 1 14 2020.

[17] Amjad A. Hudaib & Hussam N. Fakhouri, „Supernova Optimizer: A Novel Natural Inspired Meta-Heuristic,“ Modern Applied Science;, Bd. 12, Nr. 1, pp. 32-50, 2018.

[18] Tian-qi WU, Min YAO, Jian-hua YANG, „Dolphin swarm algorithm,“ Technol Electron Eng, Bd. 17, Nr. 8, pp. 717-729, 2016.

[19] Barnard, C. J., & Sibly, R. M., „Producers and scroungers: A general model and its application to captive flocks of house sparrows,“ Animal Behaviour, Bd. 29, p. 543–550., 1981.

[20] Barta, Z., Liker, A., & Mónus, F., „The effects of predation risk on the use of social foraging tactics,“ Animal Behaviour,, Bd. 68, p. 301–308, 2004.

[21] Coolen, I., Giraldeau, L. A., & Lavoie, M., „Head position as an indicator of producer and scrounger tactics in a ground feeding bird.,“ Animal Behaviour, Bd. 61, p. 895–903, 2001.

[22] Koops, M. A., & Giraldeau, L. A., „Producer-scrounger foraging games in starlings: A test of rate-maximizing and risk sensitive models," Animal Behaviour, Bd. 51, p. 773–783, 1996.
[23] Johnson, C., Grant, J. W. A., & Giraldeau, L.-A., „The effect of handling time on interference among house sparrows foraging at different seed densities," Behaviour,, Bd. 138, p. 597–614., 2001.
[24] Liker, A., & Barta, Z., „The effects of dominance on social foraging tactic use in house sparrows.," Behaviour,, Bd. 139, p. 1061–1076, 2002.
[25] Bautista, L. M., Alonso, J. C., & Alonso, J. A., „Foraging site displacement in common crane flocks," Animal Behaviour, Bd. 56, p. 1237–1243, 1998.
[26] Lendvai, A. Z., Barta, Z., Liker, A., & Bokony, V., „The effect of energy reserves on social foraging: Hungry sparrows scrounge more," Proceedings of the Royal Society of London, Biological Sciences , Bd. 271, p. 2467–2472., 2004.
[27] R. Budgey, „Three dimensional bird flock structure and its implications for birdstrike tolerence in aircraft.," Stara Lesna International Bird Strike Committee., 1998.
[28] Pomeroy, H., & Hepner, F., „Structure of turning in airborne rock dove (Columba livia) flocks.," The Auk, Bd. 109, Nr. 2, p. 256–267, 1992.
[29] W. D. Hamilton, „Geometry for the selfish herd," Journal of Theoretical Biology, Bd. 31, p. 295–311, 1971.
[30] H. R. Pulliam, „On the advantages of flocking," Journal of Theoretical Biology, Bd. 38, p. 419–422., 1973.
[31] Yao X, Liu Y, Lin G. , „Evolutionary programming made faster.," Evolut Comput,IEEE Trans , Bd. 3, p. 82–102., 1999.
[32] S. Mirjalili, „The Ant Lion Optimizer," Advance Engineering Software, p. 80–98, 2015.
[33] Liang J, Suganthan P, Deb K., „Novel composition test functions for numerical global optimization.," in Swarm intelligence symposium, IEEE; 2005. p. 68–75., 2005.
[34] Suganthan PN, Hansen N, Liang JJ, Deb K, Chen YP, Auger A, „Problem definitions and evaluation criteria for the CEC 2005 special session on real parameter optimization," Nanyang Technological University, , Singapore,, 2005.

Table 1 Benchmarks for unimodal functions.

Function		Dim	Range	F_{min}	Function Name
F1	F1(X)=$\sum_{i=1}^{n} x_i^2$	30	[-100,100]	0	Sphere
F2	F2(x)=$\sum_{i=1}^{n} \lvert X_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	[-10,10]	0	Schwefel2.22
F3	F3(x)=$\sum_{i=1}^{n}(\sum_{j=1}^{i} x_j)^2$	30	[-100,100]	0	Schwefel 1.2
F4	F4(x)=$max_i\{\lvert x_i\rvert, 1 \le i \le n\}$	30	[-100,100]	0	Schwefel 1.2

Table 2 Multimodal Basic Functions

Function		Dim	Range	F_{min}	Function Name
F5	F5(x)=$\sum_{i=1}^{n-1}[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2]$	30	[-30,30]	0	Rosenbrock's
F6	F6(x)=$\sum_{i=1}^{n}([x_i + 0.5])^2$	30	[-100,100]	0	Shifted Rosenbrocks Function
F7	F7(x)=$\sum_{i=1}^{n} ix_i^4 + random[0,1)$	30	[-128,128]	0	Quartic

Table 3 Functions for multimodal benchmarking.

Function		Dim	Range	F_{min}	Function Name
F8	F8(x)=$\sum_{i=1}^{n} -x_i\sin(\sqrt{\lvert x_i\rvert})$	30	[-500,500]	-418.9829*5	Schwefe
F9	F9(x)=$\sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0	Shifted Rastrigins
F10	F10(x)=-20exp(-0.2$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$) $-$ exp ($\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)$)+20+e	30	[-32,32]	0	Ackley
F11	F11(x)=$\frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0	Griewangk's

F12	F12(x)=$\frac{\pi}{n}\{10\sin(\pi y_1) + \sum_{i=1}^{n=1}(y_i-1)^2[1+10sin^2(\pi y_{i+1})] + (y_n-1)^2\} + \sum_{i=1}^{n} u(x_i,10,100,4)$ $y_i = 1+\frac{x_i+1}{4}$, $u(x_i,a,k,m) = \begin{cases} k(x_i-a)^m x_i > a \\ 0 \quad -a < x_i < a \\ k(-x_i-a)^m x_i < -a \end{cases}$	30	[-50,50]	0	Schwefels Problem
F13	F13(x)=$0.1\{sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i-1)^2[1+sin^2(3\pi x_i+1)] + (x_n-1)^2[1+sin^2(2\pi x_n+1)]\} + \sum_{i=1}^{n} u(x_i,10,100,4)$	30	[-50,50]	0	Expanded Extended Griewank's

Table 4 lists the benchmark functions for fixed-dimension multimodality.

Function	Formula	Dim	Range	F_{min}	Function Name
F14	F14(x)=$(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6})^{-1}$	2	[-65,65]	1	Hybrid Composition Functions
F15	F15(x)=$\sum_{i=1}^{11}[a_i-\frac{x_i(d_i^2+b_ix_2)}{h_i^2+b_ix_3+x_4}]^2$	4	[-5.5]	0.00030	
F16	F16(x)=$4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$	2	[-5,5]	-1.0316	Camel
F17	F17(x)= $(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6)^2+10\left(1-\frac{1}{8\pi}\right)cosx_1+10$	2	[-5,5]	0.398	Branin
F18	F18(x)=$(1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)x[30+(2x_1-3x_2)^2*(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	2	[-2,2]	3	Goldstein
F19	F19(x)=-$\sum_{i=1}^{4}c_i\exp(-\sum_{j=1}^{3}a_{ij}(x_j-p_{ij})^2)$	3	[1,3]	3.86	Hartmann 3-D
F20	F20(x)=-$\sum_{i=1}^{4}c_i\exp(-\sum_{j=1}^{6}a_{ij}(x_j-p_{ij})^2)$	6	[0,1]	-3.32	Hartmann 6-D
F21	F21(x)= -$\sum_{i=1}^{5}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.1532	Rotated Hybrid Composition
F22	F22(x)= -$\sum_{i=1}^{7}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.4028	Rotated Hybrid Composition Function with High Condition Number Matrix
F23	F23(x)= -$\sum_{i=1}^{10}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.5363	F23: Non-Continuous Rotated Hybrid Composition Function

Table 5 Multimodal benchmark function results

GWO		PSO		GSA		DE		FEP		PHM	
Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std
6.59 E-28	6.34 E-05	1.36E-04	0.000202	2.53 E-16	9.67 E-17	8.2 E-14	5.9 E-14	5.70E-04	0.00013	2.18 E-84	2.28 E-84

7.18 E-17	0.029014	0.042144	0.045421	0.055655	0.194074	1.5 E-09	9.9 E-10	0.0081	0.00077	1.32 E-75	1.8 E-75
3.29 E-06	79.14958	70.12562	22.11924	896.5347	318.9559	6.8 E-11	7.4 E-11	0.016	0.014	4.21 E-05	1.31E-05
5.61 E-07	1.315088	1.086481	0.317039	7.35487	1.741452	0	0	0.3	0.5	0.2	0.84
26.8158	69.90499	96.71832	60.11559	67.54309	62.22534	0	0	5.06	5.87	5.25	0.28
0.816579	0.000126	0.000102	8.28 E-05	2.5 E16	1.74 E-16	0	0	0	0	0.25	0.13
0.002213	0.100286	0.122854	0.044957	0.089441	0.04339	0.00463	0.0012	0.1415	0.3522	0.01	0.01
-6123.1	-4087.44	-4841.29	1152.814	-2821.07	493.0375	-11080.1	574.7	-12554.5	52.6	-543.3	1577.743
0.310521	47.35612	46.70423	11.62938	25.96841	7.470068	69.2	38.8	0.046	0.012	0	0
1.06 E-13	0.077835	0.276015	0.50901	0.062087	0.23628	9.7 E-8	4.2 E-8	0.018	0.002	3.25 E-15	1.25 E-15
0.004485	0.006659	0.009215	0.007724	27.70154	5.040343	0	0	0.016	0.022	0.0225	0.0221
0.053438	0.020734	0.006917	0.026301	1.799617	0.95114	7.9 E-14	8 E-15	9.2 E-6	3.6 E6	0.026371	0.0264
0.654464	0.004474	0.006675	0.008907	8.899084	7.126241	5.1 E-14	4.8 E-14	0.00016	0.000073	0.157	0.017
4.042493	4.252799	3.627168	2.560828	5.859838	3.831299	0.998004	3.3 E-16	1.22	0.56	1.35	1.24
0.000337	0.000625	0.000577	0.000222	0.003673	0.001647	4.5 E-14	0.00033	0.0005	0.00032	0	0.007
-1.03163	-1.03163	-1.03163	6.25 E-16	-1.03163	4.88 E-16	-1.03163	3.1 E-13	-1.03	4.9 E-7	-.0.84	4.44 E-20
0.397889	0.397889	0.397889	0	0.397889	0	0.397889	9.9 E-9	0.398	1.5 E-7	0.39	1.56 E-5
3.000028	3	3	1.33 E-15	3	4.17 E-15	3	2 E-15	3.02	0.1	3	0
-3.86263	-3.86278	-3.86278	2.58 E-15	-3.86278	2.29 E-15	N/A	N/A	-3.86	0.000014	-3.2561	0.002
-3.28654	-3.25056	-3.26634	0.060516	-3.31778	0.023081	N/A	N/A	-3.27	0.059	-3.00	0.05
-10.1514	-9.14015	-6.8651	3.019644	-5.95512	3.737079	-10.1532	2.5E-06	-5.52	1.59	-4.60	3.02
-10.4015	-8.58441	-8.45653	3.087094	-9.68447	2.014088	-10.4029	3.9 E-7	-5.53	2.12	-2.02	3.00
-10.5343	-8.55899	-9.95291	1.782786	-10.5364	2.6 E-15	-10.5364	1.9 E-7	-6.57	3.14	-4.33	2.55

Table 6 Results of multimodal benchmark functions

WOA		PHM		PSO	
Ave	Std	Ave	Std	Ave	Std
1.41 E-30	4.91 E-30	0	0	0	0

1.06 E-21	2.39 E-21	0	0	0	0
5.39 E-07	2.93 E-21	4.25 E-06	0.05E-06	0	0
0.072581	0.39747	0	0	0	0
27.86558	0.763626	28.65	0.013	28.941	0.041
3.116266	0.001149	1.25	0.1463	6.407	0.445
0.001425	0.001149	0	0	7.73E-06	7.79E-06
-5080.76	695.7968	-2953	457.743	-2937.66	362.795
0	0	0	0	0	0
7.4043	9.897572	0	0	8.88E-16	0
0.000289	0.001586	0	0	0	0
0.339676	0.214864	0.0421	0.0751	1.191922	0.250995
1.889015	0.2498594	0.231	0.010	2.869524	0.092223
2.111973	2.498594	1.871	1.826	7.697852	4.132355
0.000572	0.000324	0	0	0.015245	0.021199
-1.0316	4.2 E-7	0	0	-3.75588	0.10269
0.397914	2.7 E-5	0.278	1.95 E-6	-2.42127	0.415247
3	4.22 E-15	3	0	-2.5158	0.942216
-3.85616	0.002706	-2.861	0.0527	-2.60698	0.893182
-2.98105	0.376653	-0.145	0.4124	N/A	N/A
-7.04918	3.629551	-6. 654	3.002	N/A	N/A
-8.18178	3.829202	-6.584	3.0254	N/A	N/A
-9.34238	2.414737	-6.4814	3.238	N/A	N/A

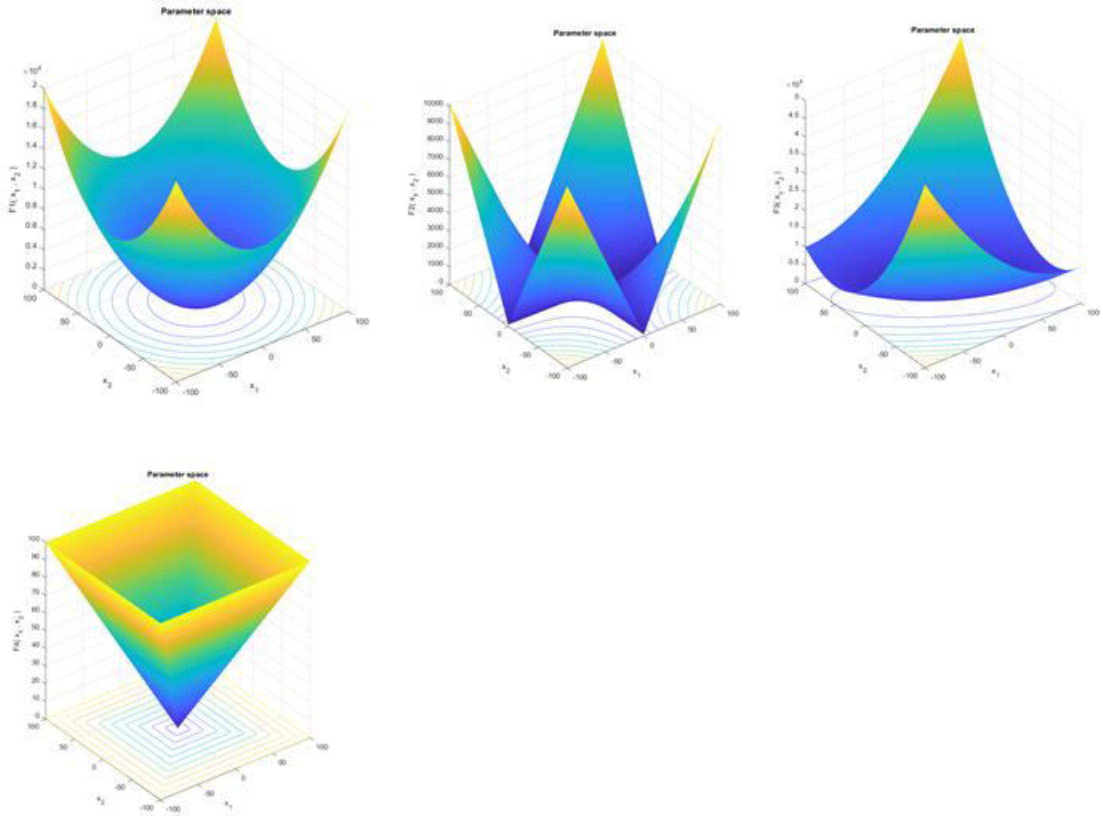

Figure 4 Unimodal functions

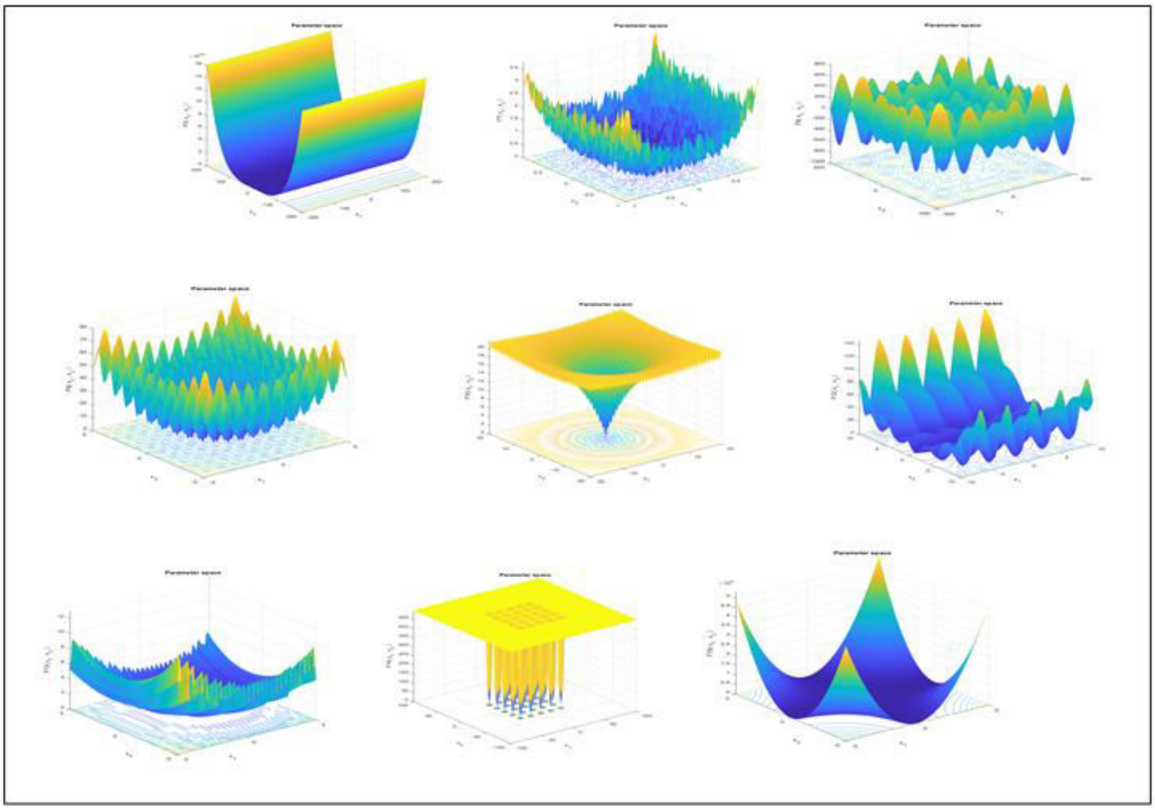

Figure 5 Multimodal Function

JOURNAL OF OPTOELECTRONICS LASER ISSN: 1005-0086

Volume 41 Issue 8, 2022

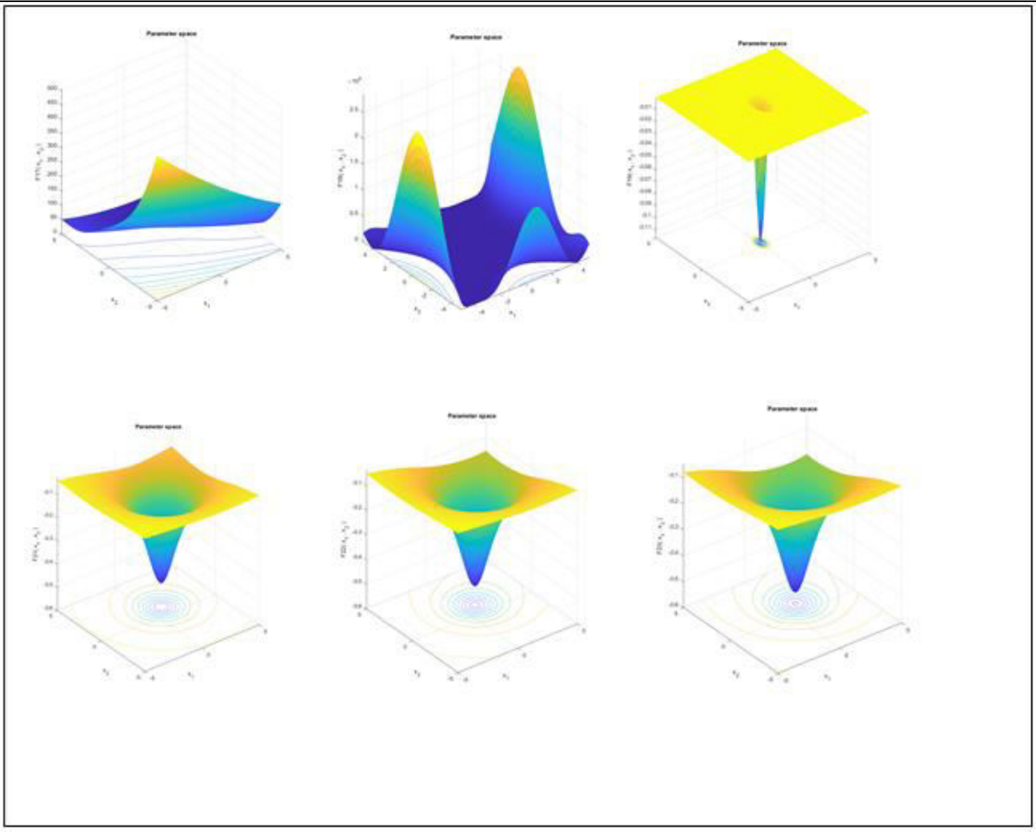

Figure 6 multimodal functions with fixed dimensions.

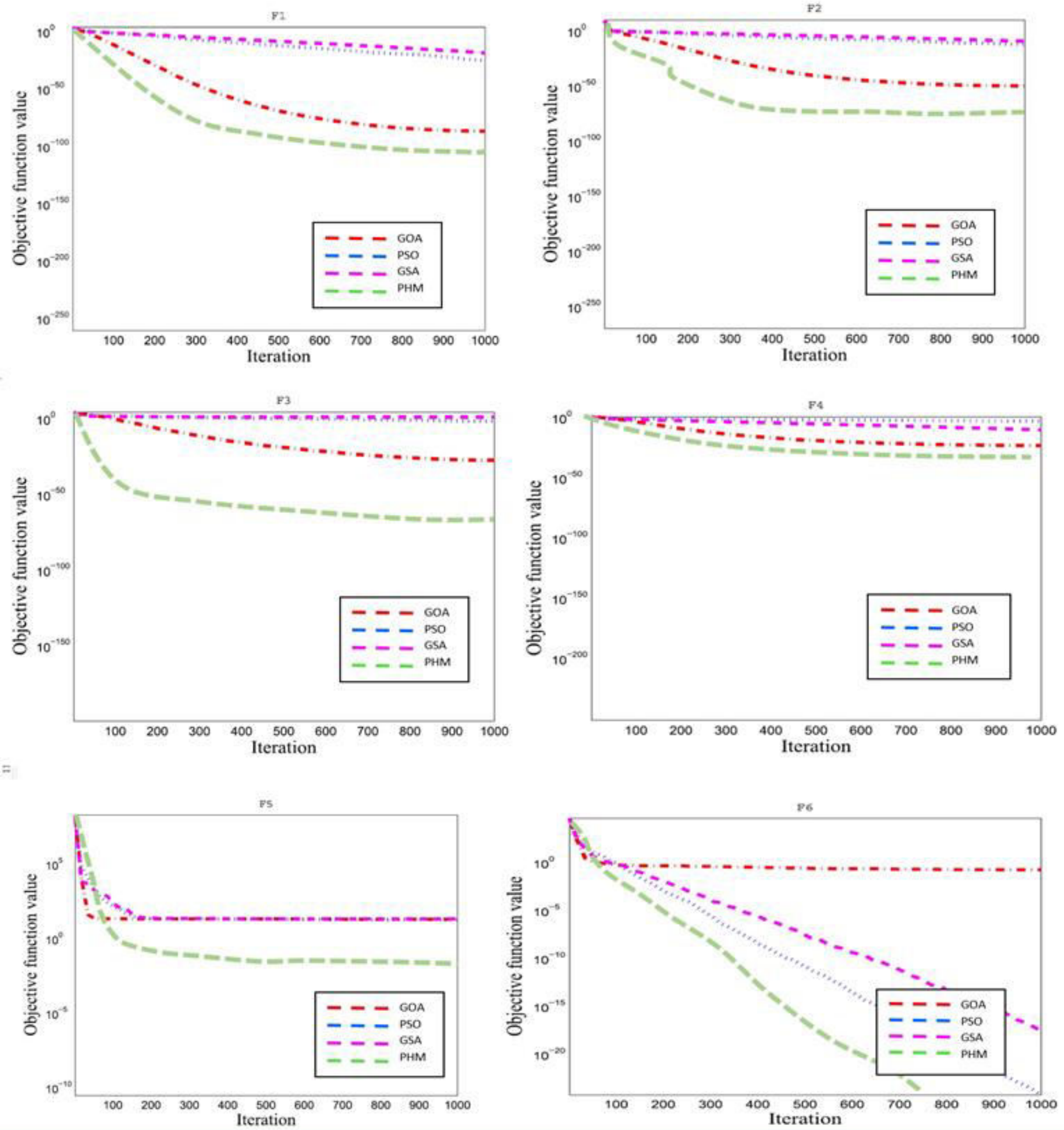

Figure 7.A -the test's convergence characteristics for GOA, PSO, GSA, and HPM function

ISSN: 1005-0086

Volume 41 Issue 8, 2022

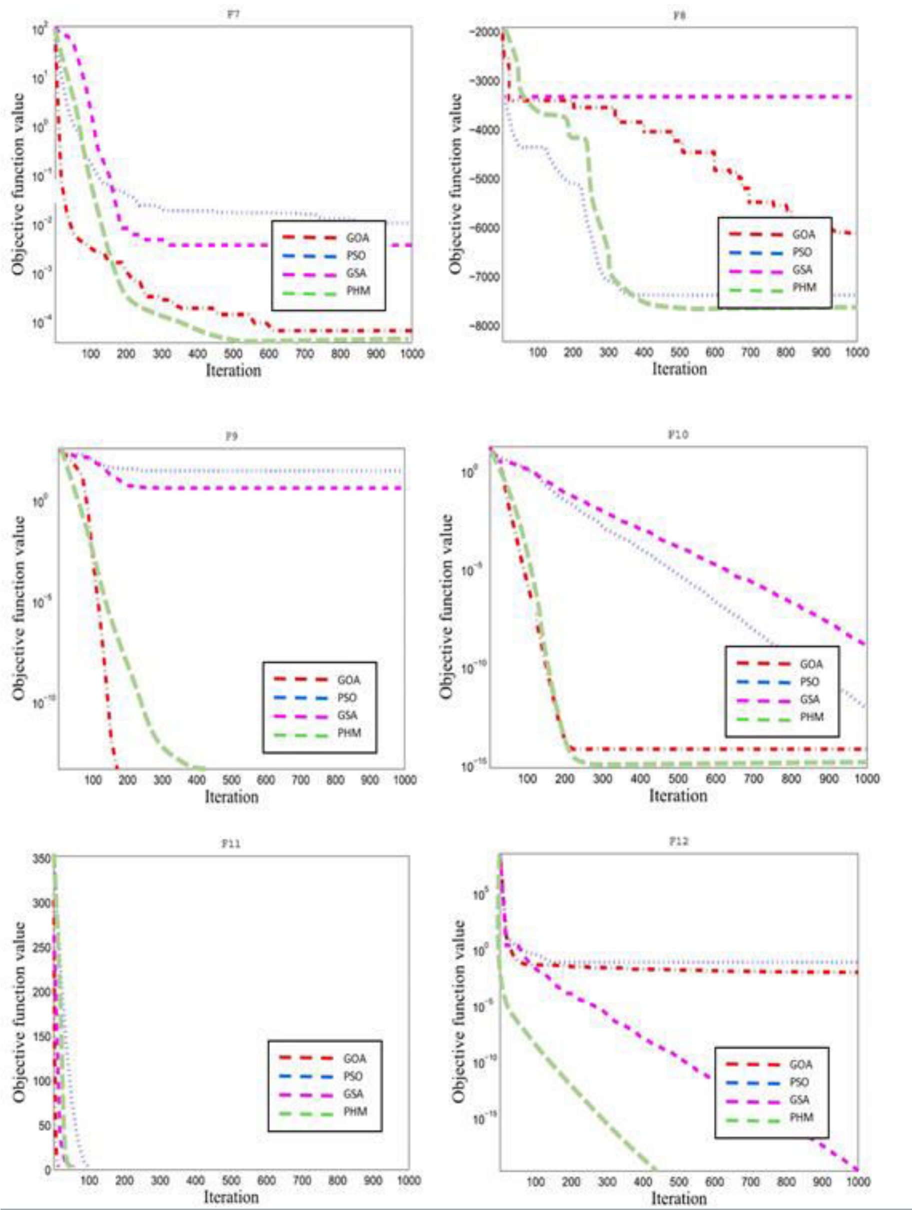

Figure 7.B -Convergence properties of GOA, PSO, GSA and HM on test

DOI: 10050086.2022.08.90

JOURNAL OF OPTOELECTRONICS LASER ISSN: 1005-0086

Volume 41 Issue 8, 2022

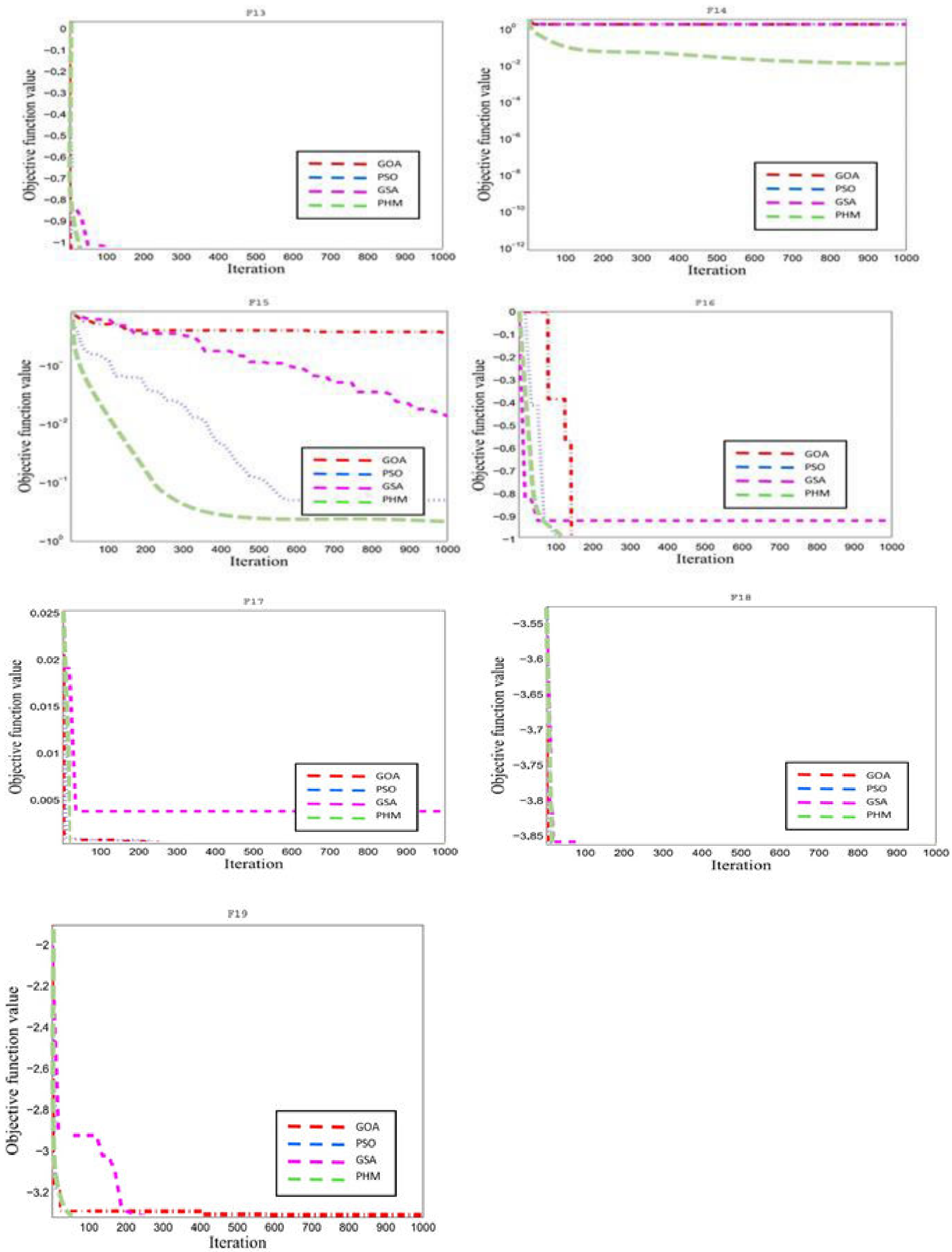

Figure 7.C -Convergence properties of GOA, PSO, GSA and HM on test

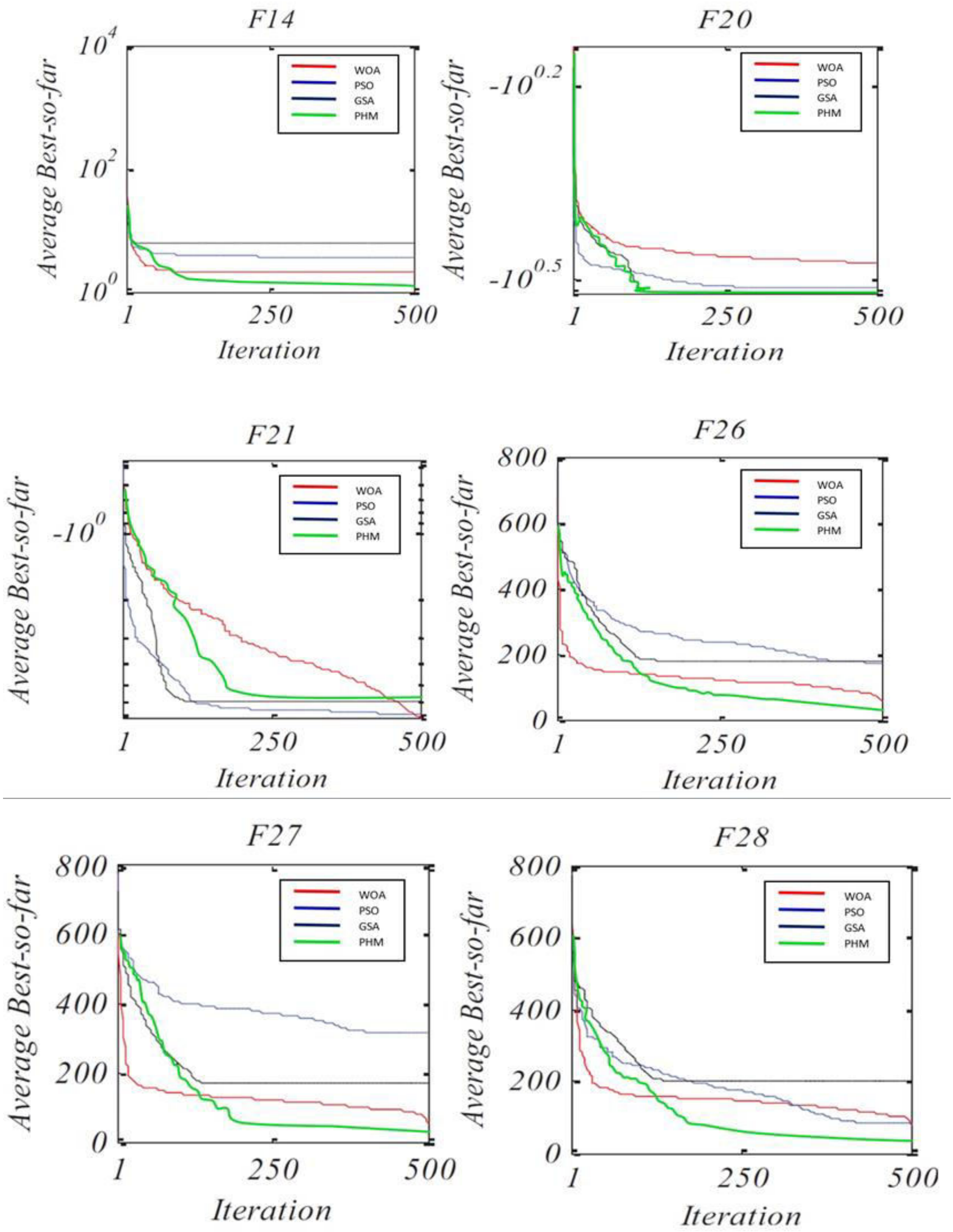

Figure 8.B -Convergence properties of WOA, PSO, GSA and PHM on test