Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 4882521, 15 pages
https://doi.org/10.1155/2022/4882521

Research Article

Comparative Study and Improvement Analysis of Sparrow Search Algorithm

Shaoqiang Yan, Weidong Liu, Xinqi Li, Ping Yang, Fengxuan Wu, and Zhe Yan

Xi'an Research Institute of High Technology, Xi'an, Shaanxi 710025, China

Correspondence should be addressed to Shaoqiang Yan; yanshaoqiang668@163.com and Ping Yang; yyp_ing@163.com

Received 26 June 2022; Accepted 8 August 2022; Published 31 August 2022

Academic Editor: Chia-Huei Wu

To solve the problem that the emerging sparrow search algorithm (SSA) lacks systematic comparison and analysis with other classical algorithms, this paper first introduces the principle of the sparrow search algorithm and then describes the mathematical model and algorithm description of the sparrow search algorithm. By comparing several classical intelligent algorithms with particle swarm optimization (PSO), differential evolution (DE), and gray wolf optimizer (GWO), the sparrow search algorithm's theory and model are systematically compared and analyzed, and the advantages and disadvantages of SSA are summarized. Finally, based on the above research and previous research, the limitations of SSA and current improved SSA are analyzed, which provides ideas for further improvement of the algorithm.

1. Introduction

The concept of swarm intelligence (SI) was first proposed by Gerardo Beni and Jing Wang in 1989. It points out the characteristics of "a class of nonintelligent agents exhibiting intelligent behavior through self-organizing behaviors such as cooperation" [1]. Swarm intelligence optimization algorithm (swarm intelligence optimization algorithm) is a random optimization algorithm (also called probability search algorithm) that simulates the construction of the group behavior of natural organisms. Compared with most gradient-based optimization algorithms and traditional algorithms, the intelligence of the swarm intelligence optimization algorithm is mainly because the algorithm is independent of the optimization problem itself, insensitive to the initial conditions, self-organizing and self-adapting. The algorithm is simple in overall design, requires fewer parameters, is easy to implement, and can be processed in parallel, so it has the advantages of good fault tolerance, strong robustness, and stability [2].

Marco Dorigo's ant colony optimization (ACO) [3] and Kennedy and Eberhart's particle swarm optimization (PSO) [4] are the two most classical algorithms in swarm intelligence. With the introduction and improvement of the two classical algorithms, their theoretical system has gradually improved and matured and has now developed into a more complete algorithm in swarm intelligence algorithm.

The two classical swarm intelligence algorithms mentioned above, genetic algorithm [5], differential evolution algorithm [6], simulated annealing algorithm [7], and artificial neural network [8] also play an important role, which lays a foundation for the establishment and improvement of the entire intelligent algorithm system in recent decades and also provides a direction for the subsequent algorithm proposals and improvements, with far-reaching impact. So far, there are numerous scholars participating in the research. With the development of the whole intelligent algorithm system, more and more classical swarm intelligence optimization algorithms appear, see Table 1 for details.

Sparrow search algorithm (SSA) is a new swarm intelligence optimization algorithm proposed by Xue and Shen in 2020 based on the foraging, predatory, and antipredatory behaviors of the sparrow population [23]. It mainly includes the process of individual searching for food, grabbing food, being alert to threats, and avoiding predators to achieve the goal of optimization. Compared

Table 1: Literature of swarm intelligence algorithm.

Algorithm full name	Arbitrary name	Author(s)	Year
Artificial bee colony swarm algorithm [9]	ABC	Karaboga D, Basturk B.	2007
Firefly algorithm [10]	FA	Yang X S.	2010
Bat algorithm [11]	BA	Yang X S, Gandomi A H.	2012
Gray wolf optimization algorithm [12]	GWO	Mirjalili S, Mirjalili S M, Lewis A	2014
Chicken swarm optimization [13]	CSO	Meng X, Liu Y, Gao X, et al.	2014
Bird swarm algorithm [14]	BSA	Meng X B, Gao X Z, Lu L, et al.	2014
Pigeon-inspired optimization [15]	PIO	Duan H, Qiao P.	2014
Ant lion optimizer [16]	ALO	Mirjalili S	2015
Whale optimization algorithm [17]	WOA	Mirjalili S, Lewis A	2016
Salp swarm algorithm [18]	SSA	Mirjalili S, Gandomi A H, Mirjalili S Z, et al.	2017
Moth search algorithm [19]	MSA	Wang G G.	2018
Monarch butterfly optimization [20]	MBO	Wang G G, Deb S, Cui Z.	2019
Harris hawks optimization [21]	HHO	Heidari A A, Mirjalili S, Faris H, et al.	2019
Slime mould algorithm [22]	SMA	Li S, Chen H, Wang M, et al.	2020
Sparrow search algorithm [23]	SSA	Xue J, Shen B.	2020
Marine predator algorithm [24]	MPA	Faramarzi A, Heidarinejad M, Mirjalili S, et al.	2020
Hunger games search [25]	HGS	Yang Y, Chen H, Heidari A A, et al.	2021
Colony predation algorithm [26]	CPA	Tu J, Chen H, Wang M, et al.	2021
Weighted mean of vectors [27]	INFO	Ahmadianfar I, Heidari A A, Noshadian S, et al.	2022

with the research history of classical algorithms such as particle swarm optimization and genetic algorithm, the research and application of this algorithm is still in the initial stage and to be developed. With the advantages of SSA, compared with other swarm intelligence algorithms, such as faster convergence, stronger stability, and higher accuracy of optimization, it has great research potential and development prospects [28].

At the same time, since the sparrow search algorithm was proposed, it has been approved by a large number of scholars. However, it still has some drawbacks in common with other swarm intelligence optimization algorithms, such as uneven initial population distribution, inadequate convergence ability after iteration, easy to fall into local optimum, and prone to premature stagnation. At the same time, according to the no free lunch theorem (NFL theorem), it can be concluded that no algorithm performs well on any optimization problem; they only work well on one type of problem but perform poorly on another. Compared with the traditional intelligent optimization algorithm, the new intelligent optimization algorithm has different emphases on convergence speed, solution time, calculation accuracy, etc. Therefore, systematically comparing SSA with other classical group intelligence algorithms will help to improve SSA and apply it in engineering.

Therefore, this paper systematically studies and analyzes the principle of sparrow search algorithm and compares with other representative swarm intelligence optimization algorithms, analyzes the advantages and disadvantages of SSA, then summarizes the research status of SSA in recent years, and finally points out the future research and development on improving SSA.

The main contributions of this paper are as follows:

(1) The principle, mathematical model, and basic process of SSA are introduced systematically

(2) The representative swarm intelligence optimization algorithms (PSO, DE, and GWO) are selected to compare with SSA, and their optimization effects are compared and tested from the aspects of algorithm performance, population diversity loss, search mode, population exchange, etc.

(3) On the basis of the above experiments, it is further concluded that SSA has the advantages of faster convergence and faster loss of population diversity compared with other algorithms

(4) Finally, according to the above advantages and disadvantages, the research status of improving SSA in recent years is summarized, and the future research development of improving SSA is pointed out

2. Sparrow Search Algorithm

2.1. The Principle of Sparrow Search Algorithm. As a group bird, sparrows are active in places where humans live. They are very active, intelligent, and have a good memory. They are bold and like to be close to people, but they are very alert. During the sparrows' feeding process, individual populations have a clear division of labor and can be divided into discoverers and participants according to their suitability for the environment. Discoverers have a high degree of environmental adaptability and need to search extensively to discover food, guide individuals to obtain food, and master the search direction of the entire population. Participants were less adaptable to the environment than the discoverers, and to improve their own fitness, they followed the discoverers to obtain food. At the same time, the sparrow population is bound to encounter various threats from the external natural environment such as natural enemies during feeding. In order to improve the survival probability, the sparrow population will randomly allocate a part of the individual as a warner, keep alert to the surrounding environment, and alert the population to flee whenever a threat is found.

In the case of sparrow populations searching for lost grains in harvested fields, the discoverer is responsible for skipping across a wide range of fields to find lost grains and stopping eating when they discover them. When the participant notices that the discoverer has found food, he jumps straight to the location of the grain, grabs the food with the discoverer, and eats it in competition. However, due to the limited number of grains, there is no guarantee that each sparrow will be free from hunger among the participants, so sparrows farther away from the grain (i.e., less adaptable to the environment) will give up competing with the population for food and choose to fly elsewhere to feed alone. At the same time, in order to ensure the safe feeding of the population, the sparrow population will randomly arrange a certain number of sparrows for sentinel investigation in the periphery and interior of the population, so that the whole population can escape in time in response to emergencies. This is how the sparrow population feeds.

2.2. Mathematical Model of Sparrow Search Algorithm. In SSA, individuals can be classified as discoverers, participants, and alerters. The discoverer is responsible for finding food and leading the population search. The participants follow the discoverer to seize food. The alerter is alert to environmental threats and warns the sparrow population to move to a safe area.

To describe the sparrow feeding process through a mathematical model, rules need to be developed to simplify the sparrow's behavior as follows.

(1) The fitness of the environment in the sparrow population depends on the fitness evaluation of the objective function, and the finder's fitness is higher than that of the participants

(2) There is an internal competitive relationship between the participant and the discoverer. Some participants monitor the behavior of the discoverer to compete for food in order to improve their own energy

(3) Individuals of sparrows with lower energy may fly elsewhere to obtain higher energy

(4) Sparrows have flexible individual behavioral strategies that allow them to switch between discoverers and participants, making them discoverers with high fitness, but the proportion between discoverers and participants remains the same in the population

(5) Warners in a sparrow population alert when they detect an external environmental threat, and when the alert value is greater than the security threshold, the finder escapes from the current location and directs the population to a safe area

(6) When the alert is aware of external environmental threats or natural enemies, the alert will take the lead in escaping, the alert at the edge of the population will move near the population center, and the alert at the population center will move randomly from a feeding state to an active state, reducing the risk of their own predation

Based on the description of the above behavior rules, the mathematical model for designing SSA is as follows.

Assuming that the whole sparrow population size is N and the location of the ith sparrow individual t moment is $X_i^t = (x_{i,1}^t, x_{i,2}^t, \cdots, x_{i,d}^t, \cdots x_{i,D}^t)$ in a D-dimensional search space, then the whole sparrow population X can be expressed as

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2d} & \cdots & x_{2D} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nd} & \cdots & x_{ND} \end{bmatrix}. \tag{1}$$

When the discoverer did not find the threat ($R_2 < ST$), they were responsible for guiding the population to forage and conduct extensive search. When individuals in the population have found predators (natural enemies) and issued an alarm ($R_2 \geq ST$), it guides the population to the location of the safe area. The location update is described as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \exp\left(\dfrac{-i}{\alpha \cdot M}\right), & R_2 < ST, \\ X_{i,j}^t + Q \cdot L, & R_2 \geq ST, \end{cases} \tag{2}$$

where α is a random number belonging to $[0, 1]$. $R_2 \in [0, 1]$ represents the early warning value. $ST \in [0.5,1]$ represents the security threshold of the current environment. Q is responsible for controlling the step size, which is a random number subject to normal distribution. L is a Matrix of $1 \times d$, and all elements are 1, and d represents dimension.

In order to obtain food, the participants follow and supervise the discoverer to grab food ($i \leq N/2$) or look for food alone ($i > N/2$). Therefore, the location update description of the participants is as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{\text{worst}}^t - X_{i,j}^t}{i^2}\right), & i > \dfrac{n}{2}, \\ X_P^{t+1} + \left|X_{i,j}^t - X_P^{t+1}\right| \cdot A^+ \cdot L, & \text{otherwise}, \end{cases} \tag{3}$$

where X_{worst} represents the worst position of the current population and X_p is the best position currently occupied by the discoverer. A is a responsible for controlling the direction $1 \times d$ matrix, the element is only 1 or -1, and $A^+ = A^T(AA^T)^{-1}$.

When aware of the danger, the sparrow population will make anti predation behavior. When $f_i \neq f_g$, it means that the current sparrow is on the edge of the population and aware of the danger and needs to move closer to the population center to reduce the risk of predation. When $f_i = f_g$, it indicates that the sparrow in the center of the population is aware of the danger and needs to escape from its current position. The location update description of the alerters is as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^t + \beta \cdot \left| X_{i,j}^t - X_{\text{best}}^t \right|, & f_i \neq f_g, \\ X_{i,j}^t + K \cdot \left(\dfrac{\left| X_{i,j}^t - X_{\text{worst}}^t \right|}{(f_i - f_w) + \varepsilon} \right), & f_i = f_g, \end{cases} \tag{4}$$

where X_{best} represents the optimal location of the current population. β is responsible for controlling the step size, which is a random number subject to standard normal distribution. K controls the direction of sparrow movement and the moving step length. It is a random number belonging to $[-1, 1]$. f_i, f_g, and f_w represent the fitness value of the ith individual and the best and worst fitness values of the current population, respectively. To prevent the denominator from being 0, ε takes a minimal positive real number.

2.3. Basic Process. According to the description and analysis of the sparrow search algorithm in the previous section, the implementation steps of SSA are shown as follows:

Step 1: set initialization parameters including population size N; discoverer proportion PD; alerter proportion SD; objective function dimension D; upper and lower bounds ub, lb; maximum number of iterations T; and security threshold ST.

Step 2: initialize population.

Step 3: calculate the fitness f_i for each individual, rank the fitness, marking the optimal fitness f_g and its corresponding position X_{best}, the current worst fitness f_w, and its corresponding position X_{worst}.

Step 4: select the individual with pre-PN*N of fitness value as discoverer, update the discoverer's position according to formula (2), and record the optimal position X_P occupied by the current discoverer.

Step 5: pick the remaining individuals as accessions and update the location of the accessions as per equation (3).

Step 6: the individual with SN*N was randomly selected as the alerters, and the position of the alerter was updated according to formula (4).

Step 7: calculate fitness values updating the sparrow location and f_g, X_{best}, f_w, and X_{worst}.

Step 8: judge if the output condition is met, meet then the cycle ends, output the result; otherwise, repeat step 3 ~ 7.

3. Sparrow Search Algorithm Compared with Other Algorithms

3.1. Particle Swarm Algorithm. Particle swarm optimization (PSO) is a classical swarm intelligence algorithm, which imitates the biological characteristics of bird groups and uses the cooperation and competition between particles to seek the best solution [29]. Its main idea is to use the memory of particles to continuously search for the best solution, by learning from the best self-individuals in history and the best learning from the population. Similar to the human social behavior, when a person wants to make a decision, one is to analyze according to his own experience and experience, and the other is to learn from the population through social behavior such as network and communication [30].

Set in the D-dimensional search space, the position vector of the ith particle is $X_i = (X_{i,1}, X_{i,1}, \cdots, X_{i,D})$ and the velocity vector of the ith particle is $v_i = (v_{i,1}, v_{i,2}, \cdots v_{i,D})$, after t iterations, the historical best position of particle X_i is $p\text{best}_i^t$, and the population global best position is $g\text{best}^t$. The velocity and position of the particle are updated with the formula:

$$\begin{cases} v_{i,j}^{t+1} = w \cdot v_{i,j}^t + c_1 \cdot r_1 \cdot \left(p\text{best}_i^t - x_{i,j}^t \right) + c_2 \cdot r_2 \cdot \left(g\text{best}^t - x_{i,j}^t \right), \\ X_{i,j}^{t+1} = X_{i,j}^t + v_{i,j}^t, \end{cases} \tag{5}$$

where w is the inertia weight coefficient, which has a strong global search ability when w is large and a strong local search ability when w is small. c_1 and c_2 are individual learning factors and group learning factors, respectively, and r_1 and r_2 are random numbers that lie between $(0, 1)$ [31].

3.2. Differential Evolution Algorithm. The differential evolution (DE) algorithm is an evolutionary algorithm that simulates biological evolution and is essentially a greedy genetic algorithm with preserved dominant individuals based on real number coding [32], one of the original genetic algorithms (GA), but with much stronger homing performance than GA [33], which comes from the latter group. The main idea is to perform variation and crossover operations on the current population to produce a new population, while the latter, using the selection operations of greedy thinking to retain the dominant individuals, results in a more optimal population [34].

The simplest original variant manipulation (DE/rand/1) is used as an example [35]:

$$V_{i,j}^t = X_{r1,j}^t + F \cdot \left(X_{r2,j}^t - X_{r3,j}^t \right), \tag{6}$$

where $V_{i,j}^t$ is an intermediate individual after mutation operation, let population size be N; $r1$, $r2$, and $r3$ are mutually unequal and belong to $[1, N]$; F is the scaling factors and takes values ranging in $[0, 1]$.

Crossover maneuvers [36]:

$$U_{i,j}^t = \begin{cases} V_{i,j}^t, \text{if rand}(0,1) \le CR \text{ or } i = i_{\text{rand}}, \\ X_{i,j}^t, \text{otherwise}, \end{cases} \tag{7}$$

where $U_{i,j}^t$ is the intermediate individual after the hybridization operation, CR is the crossover probability, and i_{rand} is a random integer belonging to $[1, N]$.

The selection actions are [37]

$$X_{i,j}^{t+1} = \begin{cases} U_{i,j}^t, \text{if } f\left(U_{i,j}^t\right) \le f\left(X_{i,j}^t\right), \\ X_{i,j}^t, \text{otherwise}, \end{cases} \tag{8}$$

where f is the fitness function.

3.3. Gray Wolf Optimization Algorithm. The gray wolf optimizer (GWO) [38] is a typical emerging group intelligence algorithm that has emerged since the self-particle and ant colony algorithms, simulating the leadership hierarchy and hunting mechanisms of gray wolf populations in nature [39] and, in turn, achieves the goal of seeking optimal solutions. There was a strict hierarchy within the gray wolf population, with the top three best fit wolf in the mapping population designated α, β, and δ, and the remaining individuals collectively designated ω. α is the leader of the wolf pack, leading and directing the whole population to hunt; β is the " army surgeon " in the tarantula to assist α and manage δ and ω; δ is the " collar " in the tarantula and can only manage ω; ω is the " soldier " in the tarantula, hearing the first three, and is responsible for the equilibrium within the population [40]. It mainly consisted of two processes, bracketing of prey and hunting [41].

Surround prey:

$$\begin{aligned} D &= \left| C \cdot X_p^t - X_{i,j}^t \right|, \\ X_{i,j}^{t+1} &= X_p^t - A \cdot D, \end{aligned} \tag{9}$$

where D represents the distance between the individual and the prey, X_p^t is the location of the prey, X represents the location of the gray wolf, and A and C are the synergy vector coefficients, which were calculated as follows:

$$\begin{aligned} A &= 2 \cdot a \cdot r_1 - a, \\ C &= 2 \cdot r_2, \end{aligned} \tag{10}$$

where a is the convergence factor and decreases linearly from 2 to 0 with the number of iterations, r_1 and r_2 are random numbers of [0, 1]. When $|A| > 1$, the gray wolf was dispersed in position, and a global search was performed. When $|A| \le 1$, the gray wolf was positionally concentrated, and a local search was performed.

When the gray wolf has identified the location of the prey, β and δ guided the wolfring group to surround the prey, under the lead of α, and to hunt; the mathematical description follows:

$$D_\alpha = \left| C_1 \cdot X_\alpha^t - X_{i,j}^t \right|, X_1 = X_\alpha^t - A_1 \cdot D_\alpha, \tag{11}$$

$$D_\beta = \left| C_2 \cdot X_\beta^t - X_{i,j}^t \right|, X_2 = X_\beta^t - A_2 \cdot D_\beta, \tag{12}$$

$$D_\delta = \left| C_3 \cdot X_\delta^t - X_{i,j}^t \right|, X_3 = X_\delta^t - A_3 \cdot D_\delta, \tag{13}$$

$$X_{i,j}^{t+1} = \frac{X_1 + X_2 + X_3}{3}, \tag{14}$$

where X_α, X_β, and X_δ represent the position of optimal solution α, suboptimal solution β, third best solution δ, respectively. C_1, C_2, and C_3 represent a random variable.

3.4. Comparative Experiments. Particle swarm algorithm, differential evolution algorithm, and gray wolf algorithm are typical representatives of classical group intelligence algorithm, evolutionary algorithm, and emerging group intelligence algorithm, respectively, and comparative analysis of the above three algorithms with the sparrow algorithm is helpful for the systematic understanding of sparrow algorithms.

This paper studies the above algorithm with the help of six test functions, whose algorithm parameter settings are shown in Table 2, the test function is shown in Table 3, and the image of the function is shown in Figure 1. $F1$ and $F2$ are unimodal high-dimensional functions, $F3$ and $F4$ are multimodal high-dimensional functions, and $F5$ and F 6 are fixed dimensional functions. From the images of the functions, we can see that both $F3$ and $F4$ are high-dimensional multimodal test functions with more local optimal pitfalls, which can better examine the performance of each algorithm. Subsequent experiments mainly rely on $F3$ and $F4$. The number of populations was set to be 30, the number of iterations to 500, the dimension to 30, and each algorithm was run 30 times to record the optimal value, worst value, mean value, and standard deviation in the results, respectively, and according to the mean value, each algorithm was shown to the optimal value of each index was coarsened, and the results are shown in Table 4, and the convergence of the function fitness values is shown in Figure 2.

From Table 3, we can see that SSA is outstanding in the six test functions, each index is almost optimal, ranking first, indicating that SSA can get rid of some local optimal traps and has good optimization performance and high accuracy. From Figure 2, it can be seen that the function convergence curve of SSA decreases rapidly, indicating that SSA has a higher efficiency and a faster convergence rate.

Figure 3 shows the position change diagram of each of the above algorithms after one iteration, i.e., the step update diagram, where the population number of each algorithm is 100 and the dimension is 3 for easy observation. In the figure, "o" is the original population location, the straight line points to the location after an iteration, and the red "+" represents the theoretical optimal location. It can be seen that each PSO update has a smaller step size and other

Table 2: Parameter.

Algorithm	PSO	DE	GWO	SSA
Parameter	$c1 = 2$ $c2 = 2$ $W_{\text{mix}} = 0.2$ $W_{\text{max}} = 0.9$	$\text{CR} = 0.2$ $F_{\text{min}} = 0.2$ $F_{\text{max}} = 0.8$	$a = (2 \longrightarrow 0)$	$\text{ST} = 0.8$ $\text{PD} = 0.2$ $\text{SD} = 0.2$

Table 3: Test function.

Function	Dimensions	Interval	Min
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100,100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	[−100,100]	0
$F_3(x) = \sum_{i=1}^{n} - x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	30	[−500,500]	-418.98*dim
$F_4(x) = \frac{\pi}{n}\left\{10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \left[1 + 10 \sin^2(\pi y_{i+1})\right] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10,100,4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	[−50, 50]	0
$F_{15}(x) = \sum_{i=1}^{11} \left(a_i - \frac{x_1 (b_i^2 + b_1 x_2)}{b_i^2 + b_1 x_3 + x_4}\right)^2$	4	[−5, 5]	0.0003
$F_{22}(x) = \sum_{i=1}^{7} \left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	[0, 10]	-10.4029

algorithms have a larger step size update, but the DE location update is good or bad, and the search efficiency is low. GWO is a messy search that keeps approaching the optimal value. SSA can find the optimal value and jump directly to the near optimal value, which is more efficient.

Figure 4 shows the population diversity change of the above algorithm. From the diagram, it can be seen that the population diversity of PSO, DE, and GWO is decreasing and fluctuating in a small range. SSA is a fast convergence followed by a wide range of fluctuations in countertrend growth, which is due to the fast convergence of SSA, but the alerters keep on feeding back and escaping from the current position.

Figure 5 shows the exploitation and exploration phases of the above algorithms. From the diagram, it can be seen that PSO, DE, and GWO have a strong ability of global search in the early stage, local search in the later stage, and development capability. However, due to the fast convergence rate, SSA enters the development stage early, but due to the back-feeding behavior of the alerters, it keeps alternating the development and exploration stages and finally stabilizes within a certain range to fluctuate, which is used to jump out of local optimum.

4. Comparative Analysis

From the point of view of population communication mechanism, PSO communicates with individual historical and global optimal locations to determine the next move, which is very robust. DE randomly selects several individuals from the population for mutation and hybridization, which has some randomness but strong communication ability, and then relies on greedy strategies to ensure the effectiveness of communication. GWO relies on hierarchy to share information with optimal, suboptimal, and third-best solutions. It has better communication ability than particle swarm, but it can not guarantee the quality of the population after communication. SSA only relies on the participants to communicate with the best discoverers. Except for the best discoverers, the other discoverers have no communication behavior with the participants, which can easily lead to missed high-quality solutions. Generally speaking, the communication mechanism of SSA is poor and DE is good.

From the point of view of search mode, PSO keeps approaching the optimal solution purposefully by self-learning and social learning and updates the global and historical optimal solutions continuously along the way. PSO has strong global exploration ability but slow convergence rate. DE relies on mutation and hybridization for global search, which is extremely random but has no purpose. The whole search process relies on probability search to easily produce duplicate solutions. GWO uses the mechanism of enclosing prey to search and relies on the first three optimal solutions to search, which has strong global search ability but poor search accuracy. SSA uses the “discover-joiner” model to search. The discover is responsible for global

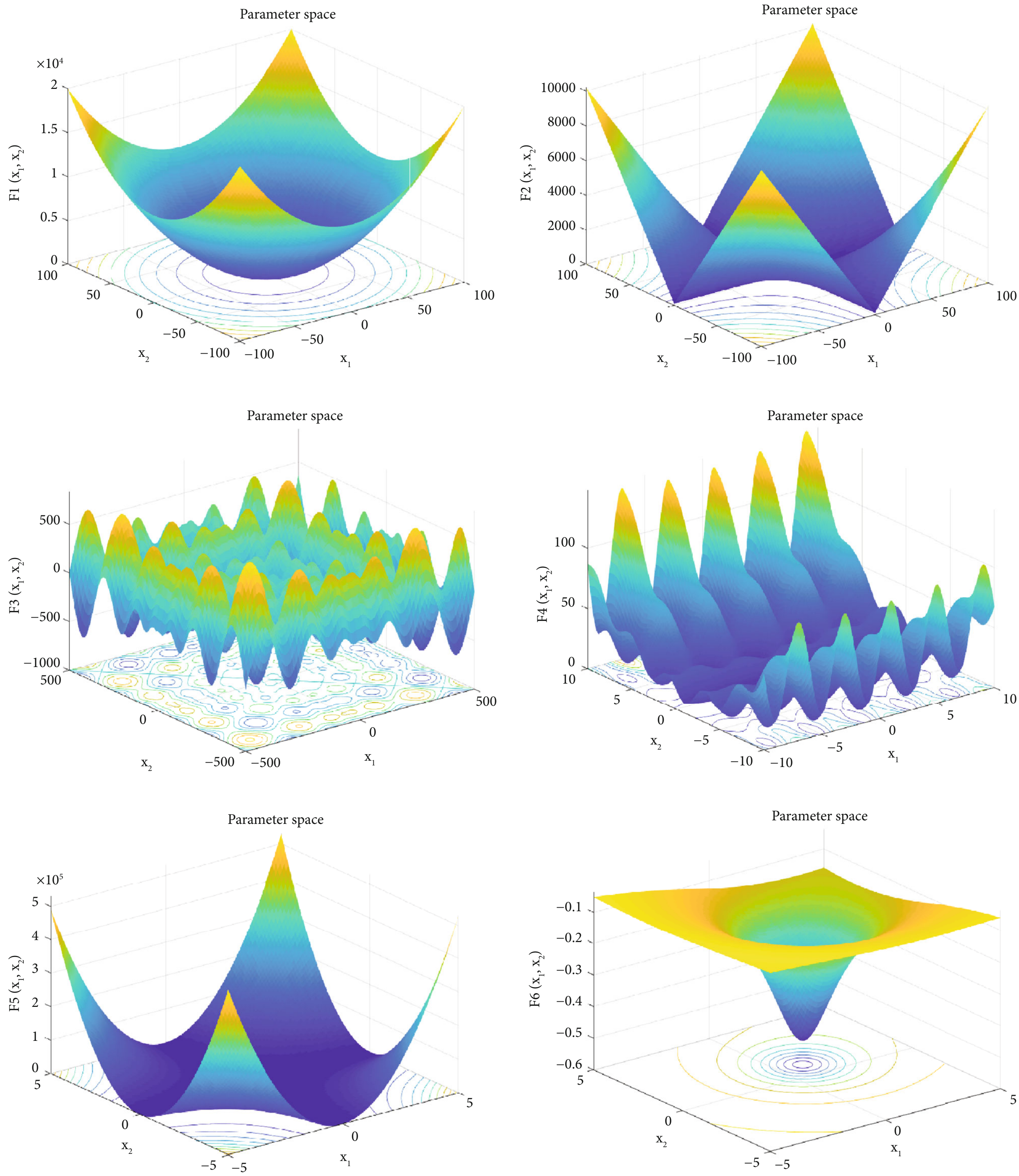

Figure 1: Test function diagram.

search. The joiner jumps directly to near the optimal solution for local search. A larger step leads to fast convergence, but the discover has a smaller proportion of the population and is easy to fall into the local optimal. Relatively, the participants account for a large proportion and carry out detailed local search with high search accuracy. In general, PSO has strong global search ability, SSA has strong local search ability and fast convergence speed.

From the loss of population diversity, PSO step size is small, convergence rate is very slow, and loss of population diversity is slow during the search process. DE relies on probability to optimize, sometimes with sudden changes,

Table 4: Comparison table of optimization effect.

F	Index/algorithm	PSO	DE	GWO	SSA
F1	Best	$8.93E-06$	$5.55E-14$	$6.31E-28$	0
	Worst	0.000836	44621.28	$4.66E-25$	$1.37E-67$
	Ave	0.000163	3314.816	$5.25E-26$	$4.58E-69$
	Std	0.000213	10734.63	$1.13E-25$	$2.51E-68$
	Rank	3	4	2	1
F2	Best	0.004097	5.607874	$1.47E-16$	0
	Worst	0.271186	$3.71E+13$	$1.61E-15$	$3.45E-40$
	Ave	0.040348	$1.28E+12$	$6.19E-16$	$1.15E-41$
	Std	0.05509	$6.77E+12$	$3.56E-16$	$6.30E-41$
	Rank	3	4	2	1
F3	Best	-7203.72	-12566.8	-10562.5	-12569.5
	Worst	-2664.29	-6671.64	-8506.23	-9495.96
	Ave	-5937.33	-10130.9	-9321.52	-10584.62
	Std	1187.275	1920.468	1570.104	2060.998
	Rank	4	2	3	1
F4	Best	5.13E-07	0.003551	0.006064	$1.57E-32$
	Worst	0.113749	0.092477	0.065291	$4.18E-08$
	Ave	0.039048	0.023993	0.022545	$2.15E-09$
	Std	0.021686	0.018595	0.014487	$8.19E-09$
	Rank	4	3	2	1
F5	Best	0.004097	5.607874	$1.47E-16$	0
	Worst	0.271186	$3.71E+13$	$1.61E-15$	$3.45E-40$
	Ave	0.040348	$1.28E+12$	$6.19E-16$	$1.15E-41$
	Std	0.05509	$6.77E+12$	$3.56E-16$	$6.30E-41$
	Rank	3	4	2	1
F6	Best	-10.4029	-6.43112	-10.4029	-10.4029
	Worst	-2.75193	-0.52836	-5.08767	-5.08767
	Ave	-8.58689	-1.75891	-9.33986	-9.87138
	Std	3.105192	1.362386	2.162441	1.621828
	Rank	3	4	2	1

the convergence speed is fast or slow, but the convergence speed is accelerated due to the influence of greedy strategy. GWO has a faster convergence rate when the global search capability is strong in the early stage, but a slower convergence rate in the later stage as the iteration number step decreases. The convergence rate of SSA is very fast due to the joiner mechanism, but the existence of the alerters' mechanism, the constant escape of some individuals from the current location will prevent some loss of population, resulting in adverse growth of later population diversity. Overall, the population loss rate of SSA is faster, but due to the warner mechanism, a portion of the population diversity is increased.

In terms of the ability to escape from local optimum, PSO can search in a wide range and detail due to its small step size. It is not easy to fall into local optimum, but it requires a large number of iterations and is not efficient. DE has a strong ability to jump out of the local optimum according to mutation operation, but it has some randomness. GWO has a good balance ability of exploration and development because it keeps approaching the optimal solution and the step size decreases continuously during the search process, but it is also prone to fall into local optimum because of its low search accuracy. Participants in SSA jump directly to the current optimal solution, with a large step size, which is easy to miss the good solution and fall into the local optimal. However, the warner mechanism can help to improve this problem by escaping from the current location. As the number of iterations increases, the warner's escape range becomes smaller and its ability to jump out of the local optimal becomes weaker. Generally speaking, DE has a strong ability to get rid of the attraction of local optimal values, while SSA has some ability to jump out of local optimal values but still can not meet the needs of optimization.

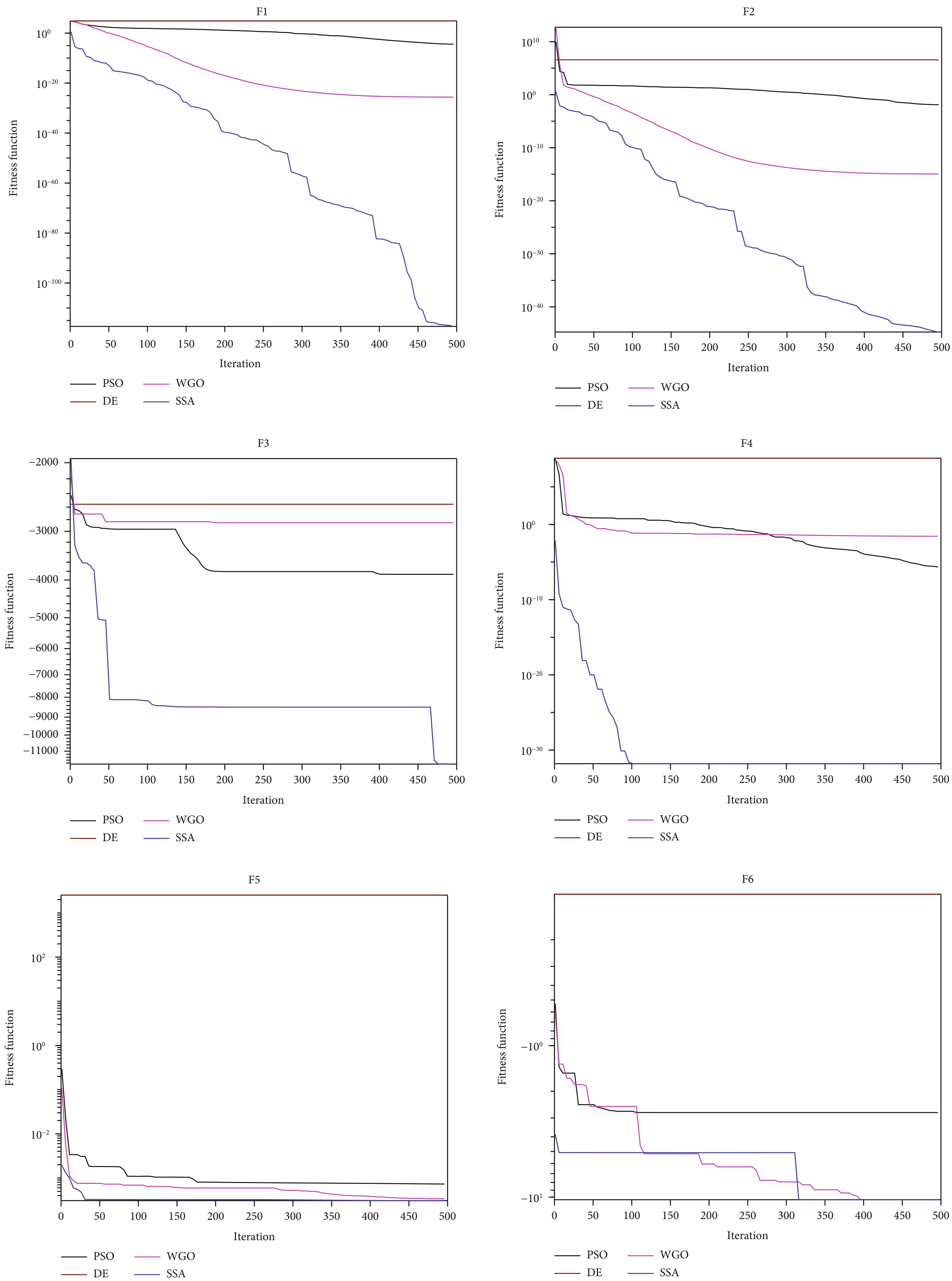

Figure 2: Fitness convergence curve.

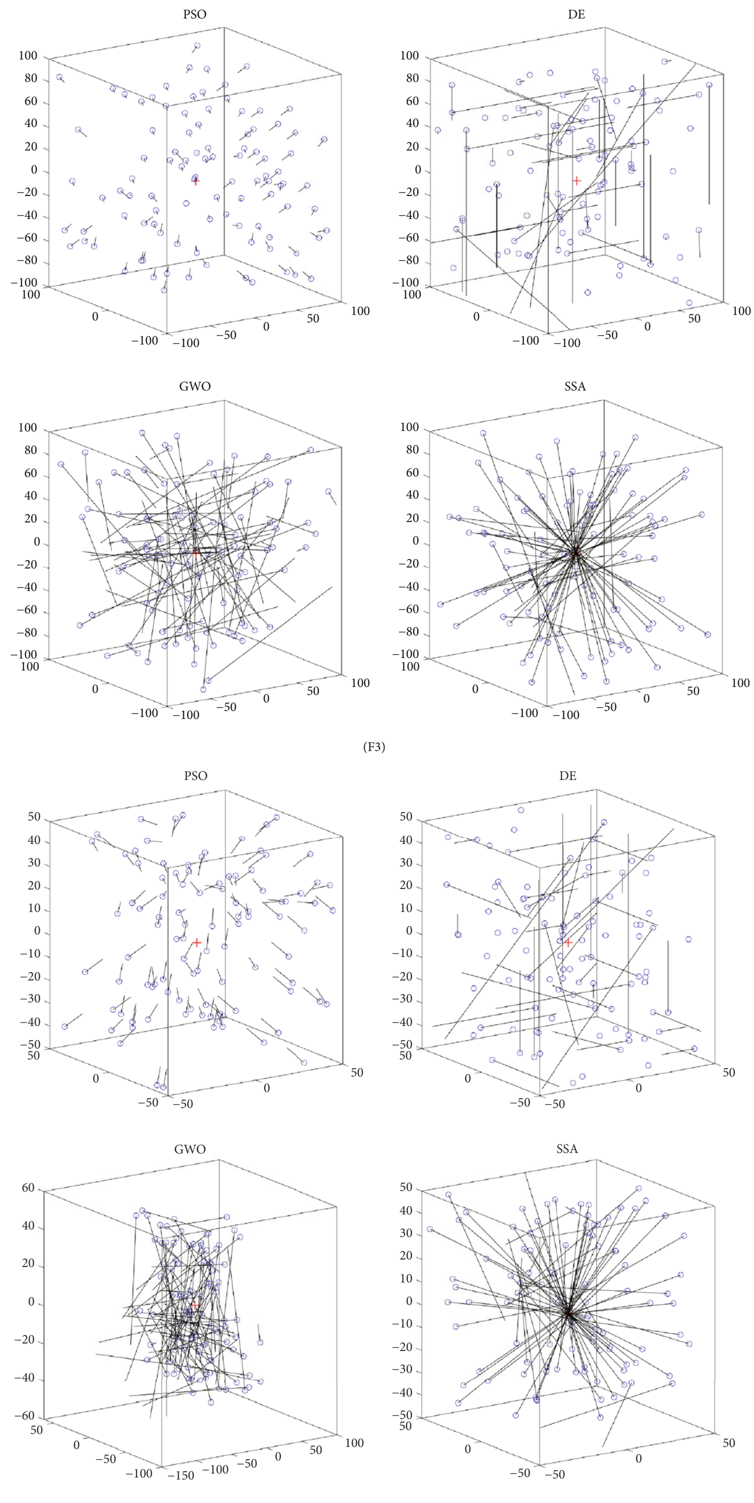

Figure 3: Step change chart.

In summary, the sparrow algorithm has the advantages of fast convergence and high accuracy, but less communication within the population, poor global search ability, fast loss of population diversity, and weak ability to jump out of local optimum.

5. Limitations and Improvement Analysis of Sparrow Algorithm

In the last section, the advantages and disadvantages of sparrow algorithm are analyzed and compared. Although SSA

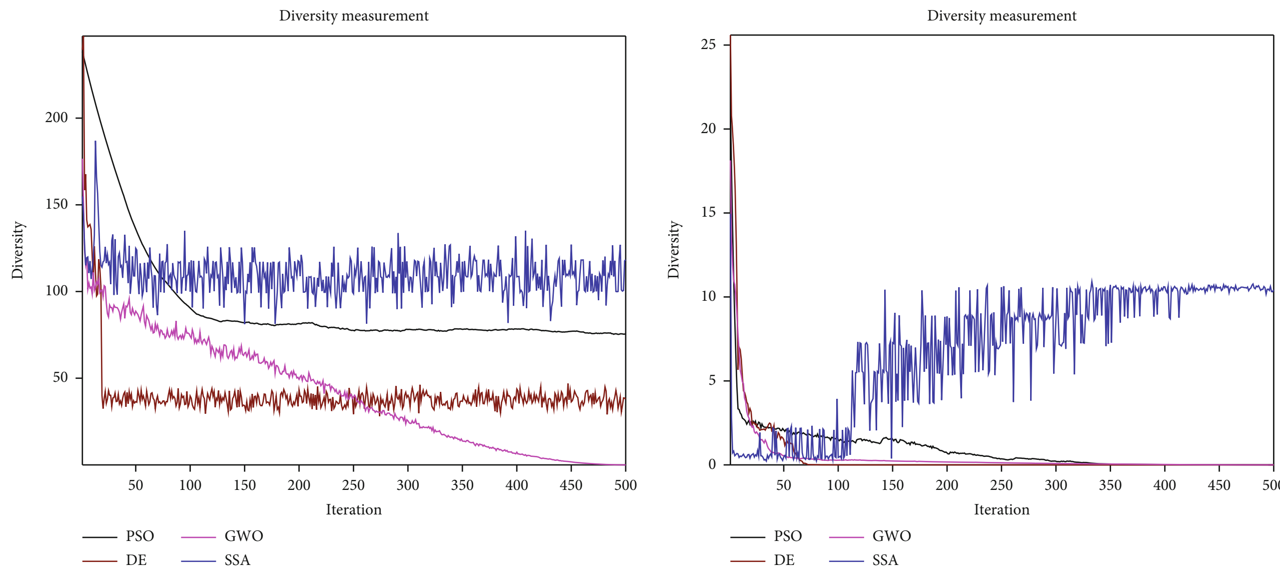

Figure 4: Population diversity.

can get better results in optimization problems, due to the general defects of swarm intelligence algorithm and its own behavior mechanism, there are still limitations, and many scholars have made improvements accordingly. The detailed analysis is as follows.

5.1. Initial Population Quality. The results show that the diversity of initial population can help to improve the accuracy and convergence speed of the algorithm [42]. Random initialization population is a common method of initialization population for the population intelligence algorithm [43]. The random and uneven initial population distribution under this method results in unstable initial population quality and poor population diversity [44], especially in high-dimensional space [45].

The same is true for SSA, where the sparrow algorithm is introduced for initializing population based on pseudorandom sequence such as chaotic mapping, such as the tent map [46], logistic map [42, 47], cube map [48], sin map [49], Bernoulli map [50], and circle map [51]. This method guarantees the quality of initial solution, improves the diversity of initial population, and facilitates later iteration optimization. At the same time, another method to initialize population based on learning mechanism has been proposed, such as center-of-gravity reverse learning [52], elite reverse learning [52, 53], and refractive reverse learning [54]. By using reverse solution to expand the initial range, and comparing with the original solution to select a better initial solution, the individual of the population is more flexible and diverse, and the search ability of SSA is improved.

However, there is still some randomness in the above improved population initialization methods, which can not guarantee absolute uniformity of each initialization. Choosing a better population initialization method can help to improve this problem. For example, good point set [55], a strategy with better initial population effect, can be added.

5.2. Interpopulation Communication. The communication between individuals in the sparrow algorithm population is limited to those who join the population and the finder with the best location. The communication between individuals is less and the communication of information is difficult. As a result, the effective information is "hidden" and the search efficiency is low.

Based on this, self-learning and social learning factors of particle swarm [56], equivalence mechanism [57] in gray wolf algorithm, mutation operation [58] in differential evolution algorithm, and cross-vertical and horizontal strategy [59] are introduced into the sparrow algorithm, which increases the number of communication objects within the population, makes communication more frequent, and makes information sharing enter the "highway."

However, the abovementioned improvement strategies do not make full use of the dominant group of discoverers, and sparrows cannot only grab food from those who get the most food. The next step is to try to make full use of the dominant group of discoverers to improve.

5.3. Biological Characteristics. Each species has its own unique population behavior and biological characteristics. Because the sparrow algorithm was proposed for a short time, many mechanisms based on sparrow-specific behavior have not been fully developed and improved. There is still room for improvement of the original algorithm.

The biological characteristics of SSA can be improved if the unique suicidal behavior [60] of sparrows, a bird, is incorporated into the original mechanism, i.e., the behavior of "being imprisoned and dying from fasting."

5.4. Global Search Capability. In SSA iterative optimization, the participants follow the discoverer to forage, which is a directed random search algorithm. The global search of the sparrow algorithm relies only on a small group of discoverers, which generally accounts for only 20%. Although half of the hungry individuals who join the algorithm search

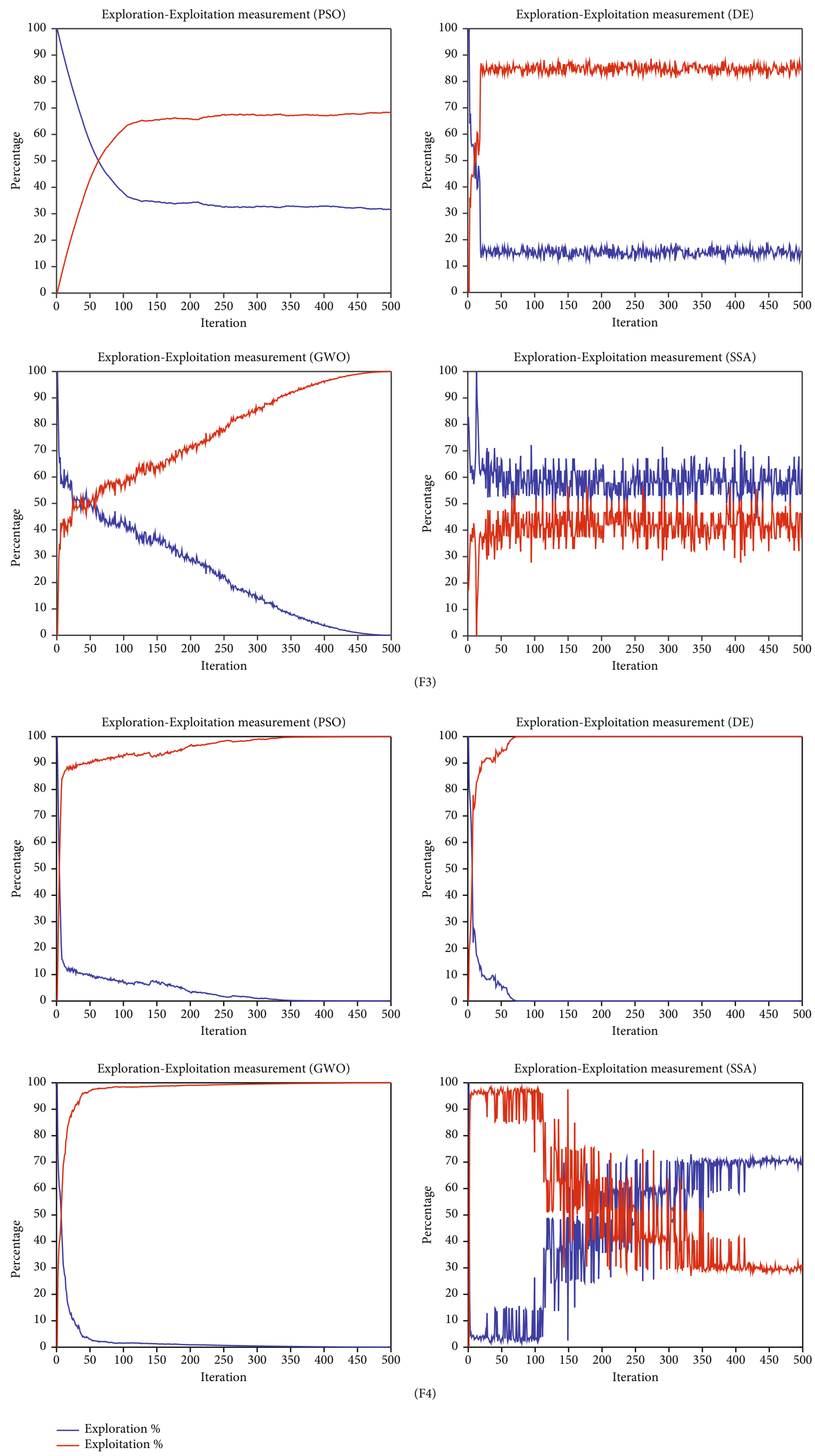

Figure 5: Exploitation phase and exploration phase.

randomly because they cannot get food, the search range of the participants is smaller than that of the discoverers, and their global search depends mainly on the discoverers. At the same time, although discoverers and participants update each other constantly and search is more flexible, the ratio between them is unchanged, and the ability of discoverers responsible for global search is not substantially improved, resulting in poor global search ability [61].

Based on this, a method combining the global search ability algorithms such as sine-cosine algorithm [62], bird swarm algorithm [63], firefly algorithm [53], and differential evolution algorithm [64] with the discoverers in SSA is proposed, which improves the global search ability of SSA with the excellent global search ability of other algorithms, “using other spears, strengthening our spears.” At the same time, another adaptive improvement strategy based on balanced exploratory development capability is introduced into SSA, such as nonlinear inertial weight [53, 65], adaptive distribution [66], and adaptive control step [67], to increase the global search capability by enhancing the previous exploratory capability.

The above improvements are mainly aimed at the discoverers who occupy a minority of the population and are responsible for guiding the direction of the population. They do not make full use of the hungry individuals who account for 40% of the population for random search. By expanding the search range of hungry individuals among the participants, the global search ability of the whole algorithm can be increased.

5.5. Loss of Population Diversity. In the "participant-discover" model of the sparrow algorithm, the joiner jumps directly to the location of the discoverer, and the convergence rate is faster, which leads to a rapid loss of population diversity. Although there is some development capability near the current location of the discoverer, there are problems that make insufficient use of the current individual, are easy to miss the good solution, and are not stable enough to guarantee the quality of the solution. Once trapped and unable to jump out of the local extreme state, the overall performance of the algorithm is limited.

Improvement strategies based on disturbance mechanism were introduced to SSA participants, such as Levy flight [68], chaotic disturbance [46], and Cauchy variation [69], to increase population diversity and alleviate rapid loss by updating the participant location.

However, the above improvement strategies still do not make full use of the high-quality solution to the current location, only to improve the updated location. If you can take full advantage of your current location [70], you can make your search more flexible and varied.

5.6. Jump Out of Local Optimum. Intelligent algorithms have the disadvantage of easily falling into local optimum. Warnings in SSA have antipredatory behavior, which can be improved by constantly escaping from the current location. However, as the number of iterations increases, the escape range of late population convergence of alerters decreases and their ability to escape from local optimum decreases. As a result, SSA's ability to jump out of local optimum is unstable, leading to sometimes being unable to get rid of the attraction of local optimum.

For the method of jumping out of local optimum, many researchers have done a lot of research, including mutation, reverse learning, and simulated annealing. Among them, Brownian motion [57], lens learning [71], and other strategies are introduced into SSA. The method of full-dimension probability updating has some randomness, but it can effectively improve the problem that it is easy to fall into the local optimal trap.

However, the abovementioned improvement strategy uses the way of full-dimension update and does not take into account the interference between dimension and dimension, which may lead to redundant jump out of local optimum operation in a certain dimension. At the same time, like the reverse learning strategy, once the chosen space is not better, it is still unable to jump out of the local optimum. Some dimension-by-dimension updates [60] will help improve its algorithm.

6. Conclusion

This paper first introduces the principle of SSA and then elaborates the optimization process of SSA with the help of sparrow feeding behavior. Then, based on the behavior characteristics of sparrows, the mathematical model of SSA and the basic flow of the algorithm are constructed. Then, the representative PSO, DE, and GWO algorithms are briefly introduced, and the advantages and disadvantages of SSA are obtained by comparing SSA with the above algorithms in many aspects such as the population communication mechanism. Finally, based on the general defects of the swarm intelligence algorithm and the defects of the behavior mechanism of SSA, the limitations of the algorithm are summarized, and the improvement of SSA by relevant scholars according to its limitations is listed, which provides ideas and directions for further improvement of the algorithm.

Mainly, the sparrow algorithm has the advantages of fast convergence and high accuracy, but less communication within the population, poor global search ability, fast loss of population diversity, and weak ability to jump out of local optimum.

Data Availability

The data used to support the findings of this study are available from the corresponding authors upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was financially supported by the regional foundation of the National Natural Science Foundation of China (No. 61703411).

References

[1] J. Kennedy, *Swarm Intelligence Handbook of Nature-Inspired and Innovative Computing*, Springer, Boston, MA, 2006.

[2] M. Kotti, B. Benhala, M. Fakhfakh et al., "Comparison between PSO and ACO techniques for analog circuit performance optimization," in *ICM 2011 Proceeding*, pp. 1–6, Hammamet, Tunisia, 2011.

[3] L. Shijie, D. Chen, C. Mingzhi, Z. Fan, and C. Jinghui, "A review of new swarm intelligence optimization algorithms," *Computer Engineering and Applications*, vol. 54, no. 12, pp. 1–9, 2018.

[4] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, pp. 1942–1948, Perth, WA, Australia, 1995.

[5] S. Mirjalili and S. Mirjalili, "Genetic Algorithm," in *Evolutionary Algorithms and Neural Networks*, pp. 43–55, Springer, Cham, 2019.

[6] A. K. Qin, V. L. Huang, and P. N. Suganthan, "Differential evolution algorithm with strategy adaptation for global numerical optimization," *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 2, pp. 398–417, 2009.

[7] P. J. M. Van Laarhoven and E. H. L. Aarts, "Simulated Annealing," in *Simulated Annealing: Theory and Applications*, pp. 7–15, Springer, Dordrecht, 1987.

[8] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *Journal of Pharmaceutical and Biomedical Analysis*, vol. 22, no. 5, pp. 717–727, 2000.

[9] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," *Journal of Global Optimization*, vol. 39, no. 3, pp. 459–471, 2007.

[10] X. S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *International journal of bio-inspired computation*, vol. 2, no. 2, pp. 78–84, 2010.

[11] X. S. Yang and A. H. Gandomi, "Bat algorithm: a novel approach for global engineering optimization," *Engineering Computations*, vol. 29, no. 5, pp. 464–483, 2012.

[12] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, 2014.

[13] X. Meng, Y. Liu, X. Gao, and H. Zhang, "A new bio-inspired algorithm: chicken swarm optimization," in *International Conference in Swarm Intelligence*, pp. 86–94, Cham, 2014.

[14] X. B. Meng, X. Z. Gao, L. Lu, Y. Liu, and H. Zhang, "A new bio-inspired optimisation algorithm: bird swarm algorithm," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 28, no. 4, pp. 673–687, 2016.

[15] H. Duan and P. Qiao, "Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning," *International journal of intelligent computing and cybernetics*, vol. 7, no. 1, pp. 24–37, 2014.

[16] S. Mirjalili, "The ant lion optimizer," *Advances in Engineering Software*, vol. 83, pp. 80–98, 2015.

[17] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Advances in Engineering Software*, vol. 95, pp. 51–67, 2016.

[18] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp swarm algorithm: a bio-inspired optimizer for engineering design problems," *Advances in Engineering Software*, vol. 114, pp. 163–191, 2017.

[19] G. G. Wang, "Moth search algorithm: a bio-inspired metaheuristic algorithm for global optimization problems," *Memetic Computing*, vol. 10, no. 2, pp. 151–164, 2018.

[20] G. G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," *Neural Computing and Applications*, vol. 31, no. 7, pp. 1995–2014, 2019.

[21] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: algorithm and applications," *Future Generation Computer Systems*, vol. 97, pp. 849–872, 2019.

[22] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: a new method for stochastic optimization," *Future Generation Computer Systems*, vol. 111, pp. 300–323, 2020.

[23] J. Xue and B. Shen, "A novel swarm intelligence optimization approach: sparrow search algorithm," *Systems Science & Control Engineering*, vol. 8, no. 1, pp. 22–34, 2020.

[24] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine predators algorithm: a nature-inspired metaheuristic," *Expert Systems with Applications*, vol. 152, article 113377, 2020.

[25] Y. Yang, H. Chen, A. A. Heidari, and A. H. Gandomi, "Hunger games search: visions, conception, implementation, deep analysis, perspectives, and towards performance shifts," *Expert Systems with Applications*, vol. 177, article 114864, 2021.

[26] J. Tu, H. Chen, M. Wang, and A. H. Gandomi, "The colony predation algorithm," *Journal of Bionic Engineering*, vol. 18, no. 3, pp. 674–710, 2021.

[27] I. Ahmadianfar, A. A. Heidari, S. Noshadian, H. Chen, and A. H. Gandomi, "INFO: an efficient optimization algorithm based on weighted mean of vectors," *Expert Systems with Applications*, vol. 195, article 116516, 2022.

[28] S. Yan, W. Liu, P. Yang, F. Wu, D. Zhu, and G. Chen, "Optimization of UAV Cooperative Path Planning Mathematical Model Based on Personalized Multigroup Sparrow Search Algorithm in Complex Environment," *Journal of Function Spaces*, vol. 2022, 2022.

[29] W. Qinghong, Z. Ying, and M. Zongmin, "A review of particle swarm optimization algorithms and their applications," *Computer Information*, vol. 26, no. 30, pp. 34-35+10, 2010.

[30] L. Haoran C. Jingchuan et al., "An improved extended particle swarm algorithm for geese swarms," *Journal of Metrology*, vol. 40, no. 3, pp. 498–504, 2019.

[31] Z. Yufei, Z. Jihui, and D. Ming, "Research on adaptive multiobjective particle swarm optimization algorithm based on decomposition," *Journal of Qingdao University: Engineering and Technology Edition*, vol. 33, no. 1, pp. 45–50, 2018.

[32] D. Yongzhao, F. Yuling, L. Peizhong, J. Tang, and Y. Luo, "Multi-population covariance learning differential evolution algorithm," *Journal of Electronics and Information*, vol. 41, no. 6, pp. 1488–1495, 2019.

[33] Z. Shuang, Z. Yasheng, and D. Huayu, "On-orbit reconfiguration configuration design of navigation constellation based on differential evolution algorithm," *China Space Science and Technology*, vol. 38, no. 4, p. 27, 2018.

[34] J. Wei and L. Gang, "Bayesian finite element model updating method based on multi-chain differential evolution," *Engineering Mechanics*, vol. 36, no. 6, pp. 101–108, 2019.

[35] W. Liujing, Z. Guijun, and Z. Xiaogen, "Strategic adaptive differential evolution algorithm based on state estimation feedback," *Journal of Automation*, vol. 46, no. 4, pp. 752–766, 2020.

[36] W. Tong and L. Qi, "Path planning for mobile robot based on improved genetic algorithm," *Journal of Beijing University of Aeronautics and Astronautics*, vol. 46, no. 4, pp. 703–711, 2020.

[37] C. Chuang, R. Chellali, and X. Yin, "Improving genetic algorithm to optimize BP neural network for speech emotion recognition," *Computer Applications*, vol. 36, no. 2, p. 344, 2019.

[38] Y. Tikhamarine, D. Souag-Gamane, A. N. Ahmed, O. Kisi, and A. El-Shafie, "Improving artificial intelligence models accuracy for monthly streamflow forecasting using grey wolf optimization (GWO) algorithm," *Journal of Hydrology*, vol. 582, article 124435, 2020.

[39] M. Shariati, M. S. Mafipour, B. Ghahremani et al., "A novel hybrid extreme learning machine–grey wolf optimizer (ELM-GWO) model to predict compressive strength of concrete with

partial replacements for cement," *Engineering with Computers*, pp. 1–23, 2022.

[40] W. Chen, H. Hong, M. Panahi et al., "Spatial prediction of landslide susceptibility using GIS-based data mining techniques of ANFIS with whale optimization algorithm (WOA) and grey wolf optimizer (GWO)," *Applied Sciences*, vol. 9, no. 18, p. 3755, 2019.

[41] A. Naserbegi, M. Aghaie, and A. Zolfaghari, "Implementation of grey wolf optimization (GWO) algorithm to multi-objective loading pattern optimization of a PWR reactor," *Annals of Nuclear Energy*, vol. 148, article 107703, 2020.

[42] X. Kuoming, G. Y. Jun, and D. Huiqiao, "Bat location algorithm based on good point set applied in WSN," *Journal of Sensing Technology*, vol. 30, no. 8, pp. 1252–1257, 2017.

[43] S. Jiaze and W. Gang, "White-box test case prioritization using a good point set genetic algorithm," *Computer Engineering and Science*, vol. 40, no. 10, pp. 1815–1821, 2018.

[44] M. Xianmeng and C. Cuicui, "Whale optimization algorithm based on elite reverse learning and Lleivy flight," *Electronic Measurement Technology*, vol. 44, no. 20, pp. 82–87, 2021.

[45] N. Rui, Z. Weiguo, L. Guangwen, and L. Xiaoxiong, "Adaptive chaotic hybrid multi-objective genetic algorithm based on tent map," *Journal of Beijing University of Aeronautics and Astronautics*, vol. 38, no. 8, pp. 1010–1016, 2012.

[46] M. Lu Xin, Z. J. Xiaodong, and W. Zhen, "Chaotic sparrow search optimization algorithm," *Journal of Beijing University of Aeronautics and Astronautics*, vol. 47, no. 8, pp. 1712–1720, 2021.

[47] C. Zhang and S. Ding, "A stochastic configuration network based on chaotic sparrow search algorithm," *Knowledge-Based Systems*, vol. 220, article 106924, 2021.

[48] T. Andy, X. Korean Tong, and X. L. Dengwu, "Unmanned aerial vehicle track planning method based on chaotic sparrow search algorithm," *Computer Applications*, vol. 41, no. 7, pp. 2128–2136, 2021.

[49] M. Tsinghua and Z. Qiang, "An improved sparrow algorithm combining Cauchy mutation and reverse learning," *Computer Science and Exploration*, vol. 15, no. 6, pp. 1155–1164, 2021.

[50] P. Wang, Y. Zhang, and H. Yang, "Research on economic optimization of microgrid cluster based on chaos sparrow search algorithm," *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 5556780, 2021.

[51] Z. Weikang, L. Sheng, and R. Chunhui, "Mixed strategy improved sparrow search algorithm," *Computer Engineering and Applications*, vol. 57, no. 24, pp. 74–82, 2021.

[52] J. Yuan, Z. Zhao, Y. Liu et al., "DMPPT control of photovoltaic microgrid based on improved sparrow search algorithm," *IEEE Access*, vol. 9, pp. 16623–16629, 2021.

[53] L. Changan, F. Xueling, S. Changhao, and Z. Lijuan, "Maximum 2-D entropy segmentation method based on improved sparrow algorithm," *Laser Technology*, vol. 46, no. 2, pp. 274–282, 2022.

[54] L. Ailian, Q. Ling, C. Guimei, and J. Peak, "Sparrow search algorithm combining sine-cosine and Cauchy mutations," *Computer Engineering and Application*, vol. 58, no. 3, pp. 91–99, 2022.

[55] J. Yuan, Z. Liu, Y. Lian et al., "Global optimization of UAV area coverage path planning based on good point set and genetic algorithm," *Aerospace*, vol. 9, no. 2, p. 86, 2022.

[56] Q. Marmenco, "Cross-cell scheduling problem optimization based on degree values and clustering coefficients," *Computer Application Research*, vol. 38, no. 9, pp. 2651–2656, 2021.

[57] T. Andy, X. Korean Tong, and X. L. Dengwu, "Chaotic sparrow search algorithm based on hierarchy and Brownian motion," *Journal of Air Force Engineering University (Natural Science Edition)*, vol. 22, no. 3, pp. 96–103, 2021.

[58] G. Biao, B. Runcai, L. Guangwei, W. Dong, L. Wei, and F. Jie, "An improved sparrow classification algorithm based on dynamic warning and selection variation," *Journal of Liaoning University of Engineering and Technology (Natural Science Edition)*, vol. 40, no. 6, pp. 496–502, 2021.

[59] D. Yuxian and L. Changyun, "Sparrow search algorithm based on SBOL sequence and crossover strategy," *Computer Applications*, vol. 42, no. 1, pp. 36–43, 2022.

[60] P. Yang, S. Yan, D. Zhu et al., "Improved sparrow algorithm based on game predatory mechanism and suicide mechanism," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 4925416, 2022.

[61] W. Ruogu, "Why do crows and sparrows commit suicide," *Forest and Human*, vol. 3, p. 11, 1998.

[62] M. Tsinghua, Z. Qiang, M. Chengcheng, and B. Jiaxuan, "Hybrid sine-cosine algorithm and sparrow algorithm for L vy flight," *Journal of Shanxi University (Natural Science Edition)*, vol. 44, no. 6, pp. 1086–1091, 2021.

[63] M. Lv Xin and Z. J. Xiaodong, "Multi-threshold image segmentation based on improved sparrow search algorithm," *System Engineering and Electronic Technology*, vol. 43, no. 2, pp. 318–327, 2021.

[64] W. Zeyu, X. Jun, X. Gang, and C. Xinying, "Multi-target sparrow search algorithm based on a new congestion distance," *Computer Engineering and Applications*, vol. 57, no. 22, pp. 102–109, 2021.

[65] W. Song, S. Liu, X. Wang, and W. Wu, "An improved sparrow search algorithm," in *2020 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*, Exeter, United Kingdom, 2020.

[66] C. Xin, X. Mingqing, S. Yin, W. Bincheng, L. Shuangxi, and Q. Cheng, "Fault diagnosis of fiber optic gyro based on improved sparrow search algorithm and support vector machine," *Journal of Air Force Engineering University (Natural Science Edition)*, vol. 22, no. 3, pp. 33–40, 2021.

[67] X. Wu, H. Zhenghua, W. Lianjiang, Z. Yuxiao, and J. Xu, "Intelligent on-demand control algorithm and key technology of mine airflow," *Journal of China University of Mining*, vol. 50, no. 4, pp. 725–734, 2021.

[68] W. Hairui and fresh in Jianchuan, "Application of improved sparrow search algorithm in distributed power configuration," *Computer Engineering and Applications*, vol. 57, no. 20, pp. 245–252, 2021.

[69] H. Tong, T. Andy, X. Zhou Huan, and X. L. Dengwu, "Collaborative track planning method for multiple unmanned aerial vehicles based on LASSA," *System Engineering and Electronic Technology*, vol. 44, no. 1, pp. 233–241, 2022.

[70] C. Gan, W. Cao, M. Wu, and X. Chen, "A new bat algorithm based on iterative local search and stochastic inertia weight," *Expert Systems with Applications*, vol. 104, pp. 202–212, 2018.

[71] S. Yan, P. Yang, D. Zhu, W. Zheng, and F. Wu, "Improved sparrow search algorithm based on iterative local search," *Computational Intelligence and Neuroscience*, vol. 2021, 31 pages, 2021.