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Learning Sparrow Algorithm With Non-Uniform Search for Global Optimization

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ABSTRACT

Sparrow Algorithm as a New Swarm Intelligence Search Algorithm, the sparrow algorithm has good optimization ability, but in complex environments, it still has certain limitations, such as weak learning ability. Therefore, this paper proposes a learning sparrow search algorithm for non-uniform search(Sparrow search algorithm with non-uniform search, NSSSA). A learning behavior selection strategy is proposed, and saltation learning and a random walk learning are introduced respectively. To a certain extent, the algorithm avoided alling into the local optimum, and a non-uniform variable spiral search is proposed to balance the development and search capabilities of the algorithm. In the experimental simulation, the effectiveness of the NSSSA algorithm is verified by using the benchmark function, and it is tested on the CEC 2013 test set. Compared with the algorithms with better performance in recent years, the results show that the NSSSA algorithm has better universality . Finally, the NSSSA algorithm is applied to the WSN coverage optimization problem. The results show that NSSSA achieves more than 90% and 96% coverage on the two models of 50×50 and 100×100, respectively, which verifies the practicability of the algorithm.

KEYWORDS

CEC 2013, Non-Uniform Spiral Search, Random Walk Learning, Saltation Learning, Sparrow Search Algorithm, WSN

1. INTRODUCTION

In nature, all kinds of organisms have their behavior strategie0d ways in the process of evolution. Inspired by these phenomena, people put forward many new methods and concepts to solve practical problems. The swarm intelligence optimization algorithm is an evolutionary algorithm of random search. The main idea is to simulate the foraging behavior of group creatures, such as fish schools, bird groups, and wolves. They will search for food in a cooperative way and constantly exchange food in the process. information to get more quality food as quickly as possible. Swarm intelligence has strong robustness, and the interacting individuals in the group are distributed, have no direct

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control center, and will not affect the solution of the problem due to the failure of a small number of individuals. The structure is simple and easy to implement, each individual can only perceive local information, and the rules that individuals follow are simple.Many classical algorithms such as particle swarm optimization (PSO) (Kennedy, James, and Russell C. Eberhart, 1997), Grey wolf optimization algorithm (GWO) (Mirjalili et al., 2014), ant colony algorithm (ACO)(Dorigo M et al., 2006), whale optimization algorithm (WOA) (Mirjalili S et al., 2016), and beetle antennae search algorithm(BAS)(Jiang X and Li S, 2017). They have been successfully applied in path planning (Wu Q et al., 2019), nonlinear control (Khan A H., 2019), image processing (Maitra M and Chatterjee A, 2008), and other fields.

The Sparrow Search Algorithm (SSA) is a new swarm intelligence optimization algorithm proposed in 2020 (Xue J and Shen B, 2020), Its principle is simple, the parameters are few, and the convergence speed is fast. It is more efficient than PSO, GWO, CO, and other algorithms in function optimization. Advantage. At present, SSA is also widely used in many practical engineering problems, such as vibration classification of rheostat transformers (Wu Y, 2021;Wang H and Xianyu J, 2021), flexible traction power supply systems (FTPSS) (Chen M et al., 2021), maximum power problems in the photovoltaic system(Zafar M H et al., 2021), the multi-objective problem of heater(Sukpancharoen S, 2021), prediction of water quality parameters in rivers (Song C et al., 2021), prediction of carbon price (Zhou J and Chen D, 2021;Zhou J and Wang S, 2021), Noise removal of measurement signals for concrete face rock fill dams (Xu L et al.2021), strength prediction of reinforced concrete(Li G et al.2021) bearing fault diagnosis (Xing Z et al., 2021), diabetes prediction (Wang Y and Tuo J, 2020).

However, it also has its shortcomings. For example, in the face of high-dimensional and complex problems, the optimization process always relies on a certain role, which reduces the learning ability of the algorithm and falls into a local optimum; on the other hand, there are more random parameters in the algorithm, resulting in the results being contingent.

In order to improve the above-mentioned defects of SSA, scholars have also proposed some schemes to improve the optimization effect of SSA. Liu et al. (2021) used the chaotic mapping strategy to initialize the population to make the population distribution more uniform, and then introduced and reintroduced the development and search capabilities of the adaptive thought balancing algorithm, and finally introduced Gaussian mutation to prevent the algorithm from stagnant.It is applied to three-dimensional UAV path planning, and good results are obtained.Liang et al. (2021)used the homogeneous chaotic system to provide adequate preparation for the algorithm optimization, also used the adaptive idea to improve the algorithm optimization ability, and finally proposed an improved boundary processing method to make the search scope more reasonable and effective. When it is applied to the antenna matrix problem, its optimization effect is more advantageous. Song et al.(2020) proposed chaos initialization population is a skewed tent, promoted the exploration and development of space with non-linear decreasing weight, and finally used mutation strategy and chaos search to update the poor and better individuals simultaneously, balancing the searchability of the algorithm. Wang et al.(2021) used Bernoulli chaos to initialize the population, a dynamic adaptive parameter adjustment algorithm to optimize, Then use the reverse learning strategy and the Cauchy mutation strategy to prevent the algorithm from stagnating. Apply the improved algorithm to the microgrid cluster with good results.Yuan et al.(2021)The population is initialized by using the center of gravity reverse learning, so that the individual distribution in the population is more uniform, and the global vision of the algorithm is opened up. Then the learning factor is proposed to speed up the information exchange between the populations. Finally, the mutation strategy is used to reduce the algorithm from falling into the local optimum. The probability. The improved algorithm is applied to maximum power point tracking (DMPPT), which has a better stability.Lei et al.(2020) uses Levy flight to improve the flexibility of the sparrow search algorithm and to apply it to positioning problems in wireless sensor networks, which has a good effect. In addition, Liu et al.(2021) have applied it to the diagnosis of diseases with good diagnostic results.Zhang et al.(2021)introduced the sine-cosine search algorithm and proposed a cooperative idea, which can be applied to the adaptive enhancement classifier with better binary classification results.Lu Xin et al(2021) introduced the idea of the bird swarm algorithm and proposed an improved sparrow search algorithm (ISSA), which is applied to the multi-threshold image segmentation field with better segmentation speed and accuracy. Ouyang et al.(2021) used lens learning to improve the searching ability of the discoverer, proposed a variable helix strategy to improve the flexibility of the algorithm, and finally fused the simulated annealing algorithm to refine the solution each time. Applying it to UAV path planning will make the planned route safer and simpler. Zhen zhang et al.(2022) proposed a new neighborhood search to update the quality of optimal individuals, and also used a new position update formula to speed up the convergence speed, which achieved better results in mobile robot path planning; Xu Hui et al.(2022) introduced tent chaotic mapping with golden sine search to improve the quality of initial and global optimal solutions;jun Dong et al.(2022) also used Levy flight to improve sparrow's flight. Many variants of SSA are being proposed one after another. The above authors have made some achievements in the performance of the algorithm, but there are still some shortcomings. The specific description is as follows:

1) The traditional chaos theory itself has randomness, the SSA algorithm has strong randomness and good search performance, so the role of chaos theory is not significant.
2) The traditional opposition-based learning strategy solves backward only at the same latitude and is not flexible.
3) Adaptive thinking has some convergence effect, but it is easy to fall into local optimum when dealing with high-dimensional complex class problems.
4) Mutation strategy can prevent the algorithm from falling into the local optimum, but it has some invalidity.
5) Most algorithms optimize on a test function with an optimal value of 0 and lack universal adaptation.

Based on the work and shortcomings of the above literature, to improve the defect that the algorithm approaches the far point, and enhance the optimization ability of the algorithm. this paper presents a learning sparrow search algorithm with a non-uniform search. This algorithm uses a new selection behavior, introduces saltation learning, and presents a random walk learning strategy, which enables the two learning methods to be flexibly used, speeds up internal population communication, and opens up a vision for individual optimization. Finally, a non-uniform spiral search strategy is proposed, which can better develop and explore unknown regions and improve the global optimization ability of the algorithm. The contributions and workload of this paper are as follows:

1) A new learning choice behavior is proposed, which chooses one of saltation learning and random walk learning according to the optimization situation.
2) A non-uniform spiral search strategy is presented, which makes the algorithm more flexible and overcomes the drawbacks of the traditional spiral search strategy.
3) NSSSA was compared with Chaos Sparrow Search Optimization Algorithm (CSSA)(Lv Xin et al., 2021), ISSA, SSA, PSO, Beetle swarm optimization algorithm (BSO) (Wang T and Yang L, 2018), GWO, Manta ray foraging optimization (MRFO) (Zhao W et al., 2020), Teaching-learning-based optimization algorithm (TLBO) (Rao, 2016)on six benchmark functions. At the same time, it also compares with other variants of the algorithm, and NSSSA can show better advantages. In the CEC2013 test set, NSSSA is compared with TDSD(Li X et al., 2020), FA_CL(Peng H et al., 2021), ASBSO (Yu Y et al., 2018) proposed in recent years, and all three algorithms pass the CEC test set. Verify the feasibility and validity of NSSSA.
4) NSSSA is applied to Wireless Sensor Network (WSN) coverage optimization problems to verify the usefulness of NSSSA.

The structure of this paper is as follows: Section 2 introduces the basic sparrow search algorithm. Section 3 describes and analyzes the NSSSA process. Section 4 describes the experiment and analysis of each algorithm on the benchmark function and the CEC 2013 test function. Section 5 describes the effectiveness of each algorithm in WSN coverage optimization. Section 6 summarizes the paper, and the last section suggests future directions for the work to address the shortcomings of the experiments.

2. A BRIEF INTRODUCTION TO SPARROW SEARCH ALGORITHM

The sparrow search algorithm is a swarm intelligence optimization algorithm, which is mainly inspired by the foraging behavior and anti-predation behavior of sparrows. In the process of sparrow foraging, there are discoverers and joiners, the discoverer is responsible for finding food in the population and providing foraging areas and directions for the entire sparrow population, while the joiner uses the finder to obtain food. Individuals in a population monitor the behavior of other individuals in the group, and attackers in the population compete with high-intake peers for food resources to increase their predation rates. In addition, sparrow populations engage in anti-predation behavior when they are aware of danger.

In SSA, finders with good fitness values prioritize food during the search. In addition, because the finder is responsible for finding food for the entire sparrow population and providing directions for all those who join. As a result, finders can obtain a larger foraging search range than those who join. Over the course of each iteration, the location of the finder is updated as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp(\dfrac{-t}{\alpha \cdot T}) & if \quad R_2 < ST \\ X_{i,j}^{t} + Q \cdot B & if \quad R_2 \geq ST \end{cases} \tag{1}$$

In equation (1), *i* represents the current iteration number and *T* is the maximum iteration number. $X_{i,j}$ is the position information of the first sparrow in the jth dimension. $\alpha\hat{I}(0,1]$ is a random number. R_2 and *ST* simulate warning and safety values respectively, and $R_2\hat{I}[0,1]$, $ST\,\hat{I}[0.5,1]$. *Q* is a random number that follows a normal distribution. *B* represents a 1*d matrix with an interior of all 1. When $R_2 < ST$, there are no predators within the population and the discoverer can search for food at will. When R_2 is greater than or equal to *ST*, predators appear within the population and signal danger, so the discoverer needs to lead other individuals away from their current location.

Followers perform local searches around the discoverer, and individuals with better fitness get food first. Follower's location update equations are as follows:

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

In equation (2), X_p is the optimal position occupied by the current discoverer, and X_{worst} represents the current global worst position. *A* represents a $1 \times d$ and each element is randomly assigned to 1 or -1, where $A^{+} = A^{T}(AA^{T})^{-1}$. When $i > n/2$, it means that the i-th follower with low fitness value does not get food, is in a very hungry state, and needs to fly to other places to find food to get more food.

In reality, sparrows are also in danger of being caught by natural enemies, so as to imitate the local optimal state in function optimization. Sparrows have scouts. The number of Scouts (ST) is randomly selected from the interior of discoverers and followers. When danger is found, an alarm will be generated, so that discoverers can lead other individuals to a safe place. Specific behavior equation:

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left| X_{i,j}^{t} - X_{best}^{t} \right| & if \quad f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{\left| X_{i,j}^{t} - X_{worst}^{t} \right|}{\left(f_i - f_w \right) + \varepsilon} \right) & if \quad f_i \le f_g \end{cases} \tag{3}$$

In equation (3), X_{best} is the current global optimal location. β as the step control parameter, it is a random number that obeys the normal distribution with a mean value of 0 and variance of 1. *KÎ*[-1,1] is a random number, and f_i is the fitness value of the current sparrow. f_g and f_w are the current global best and worst fitness values respectively. ε Is the smallest constant to avoid zero in the denominator. For simplicity, $f_i > f_g$ indicates that the sparrow is at the edge of the population and is extremely vulnerable to predators. When $f_i \le f_g$, it indicates that the sparrows in the middle of the population are aware of the danger and need to be close to other sparrows to minimize their risk of predation. *K* represents the moving direction of sparrows and is also a step control parameter.

3. LEARNING SPARROW ALGORITHM WITH NON-UNIFORM SEARCH

3.1 Why Each Modification Has Been Proposed

According to the above three equations, the search scope of SSA is good, but there are some defects in detail. In equation (1), α can make the discoverer traverse the whole space range, but it lacks detail. The larger T becomes, the lower the success rate of effective search. Equation (2) makes the location update of followers can only be updated under the search mode of the discoverers, which makes the search mode blind. equations (1) - (3) have the characteristic of approaching the origin, so the effect is obvious in the function optimization with the optimal value of 0.

In order to improve the defects of the discoverer search method, this paper proposes a non-uniform spiral search, which makes some changes over the traditional spiral search to reduce the invalidity of the algorithm. Then jump learning and random walk learning are introduced, and a behavior selection method is designed. Jumping learning can make different individuals communicate closely and get rid of the shackles of the original mechanism; Random walk learning can make individuals spread all over the whole space and avoid aggregation in the algorithm. The choice of the two behaviors increases the diversity of the algorithm population, effectively improves the flexibility of the algorithm, and gets rid of the defect that the algorithm approaches the origin.

3.2 Saltation Learning

In the process of sparrow optimization, individuals update with the change of discoverers, and lack of learning, resulting in all individuals easy to approaching the local optimal position. Finally, the optimization performance of the algorithm is limited. Therefore, we need a method that can enhance individual learning behavior to improve the optimization ability of the algorithm in different environments.

Saltation learning (SL) is a new learning strategy proposed by Penghu et al. (2021). It can learn between different dimensions, calculate candidate solutions through the best position, the worst position, and randomly selected positions, increase population diversity, and have good searchability. So as to reduce the probability of falling into local optimization. SL is specifically described as follows:

$$x_{i,j}^{t+1} = x_{best,k}^{t} + r \cdot \left(x_{a,l}^{t} - x_{worst,n}^{t} \right) \tag{4}$$

In equation (4), x_{best}^{t} and x_{worst}^{t} represent the best and worst positions of t iterations respectively. *K*, *l*, and *n* are three different integers selected from [1, *D*]. *D* represents the dimension, r is a random number of [- 1,1], and the positions in different directions are explored through the change of sign. *a* is a random integer belonging to [1, P], and P represents the population number. As shown in Figure 1, assuming that the dimension is 3, individuals with three different dimensions guide the selection of the next location, which speeds up the information exchange within the population and improves the optimization efficiency.

3.3 Random Walk Learning

In the optimization process of SSA, if it is far from the theoretical best quality, it means that it may fall into a local extremum. Therefore, it is necessary to call on all individuals to leave the current position. The behavior of the scout is contingent and there are few individuals, so it cannot be effective. Get rid of local extreme points. Therefore, this paper proposes a random walk learning strategy (Random walk learning, RWL), which is different from random walk in that it introduces the learning factors of the optimal and worst positions, so that there is a certain direction when the scout leaves, so that the Reduce unnecessary wandering.The specific mathematical model of RWL is as follows:

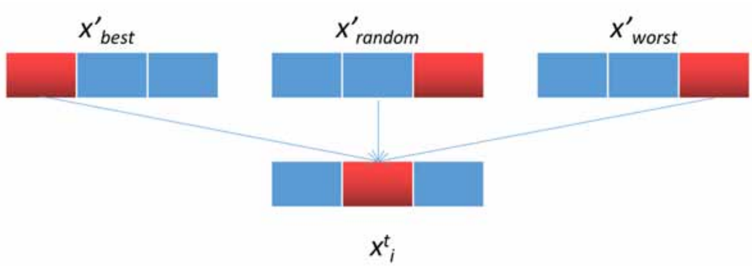
$$x_{i,j}^{t+1} = x_{best}^{t} + Z \cdot e^{\left(-\frac{t}{M}\right) \cdot \left(x_{i,j}^{t} - x_{worst}^{t}\right)} + \left(c_1 \cdot x_{best}^{t} - c_2 \cdot X_{i,j}^{t}\right) \tag{5}$$

In equation (5), *M* is the maximum number of iterations, C_1 and C_2 represent two learning factors, which obey the random number of normal distribution. $e^{\left(-\frac{t}{M}\right) \cdot \left(x_{i,j}^{t} - x_{worst}^{t}\right)}$ is the control step, $\left(c_1 \cdot x_{best}^{t} - c_2 \cdot X_{i,j}^{t}\right)$ is the direction of control. *Z* is a uniform random number between [0,1].It can be seen from the equation that the introduction of RWL makes individuals master global information and move toward a better position.

3.4 Choice of Learning Behavior

In the process of optimization, when the current position is farther from the optimal position than the worst position, it indicates that the algorithm has a process of falling into the local optimal point. It is necessary to change the current optimization mechanism and use RWL to lead all individuals to escape; On the contrary, it shows that the individual is in a normal state, and SL is used to speed up the convergence speed of the algorithm. The equation of behavior choice (BC) is as follows:

Figure 1. SL schematic diagram



$$C = \begin{cases} SL, if \ \ a < b \\ RWL, if \ \ a \geq b \\ a = \left| fit\left(X_{i,j}^{t}\right) - fit\left(x_{best}^{t}\right) \right| \\ b = \left| fit\left(X_{i,j}^{t}\right) - fit\left(x_{worst}^{t}\right) \right| \end{cases} \tag{6}$$

SL and *RWL* are Saltation learning and Random walk learning mentioned above, respectively, *fit* represents the fitness function.

3.5 Non-Uniform Spiral Search

The discoverer bears the main responsibility of population foraging, so his search method must be very flexible and detailed, which fully ensures the development and exploration of the overall situation, so as to lead other individuals to find the optimal solution and improve the optimization ability of the algorithm. The general spiral strategy can effectively improve the searchability of the algorithm, but the distance between the inner ring and the outer ring of the spiral is gradually increasing and more uniform. This uniform method has some limitations and can not effectively improve convergence accuracy. Therefore, this paper proposes a non-uniform spiral strategy, so that the distance between the inner coil and the outer coil does not show the same increasing trend.

The early algorithm of the sparrow search algorithm has good searchability, the early stage needs to speed up the search speed, and the later stage needs effective search ability so as to effectively get rid of the attraction of local extremes. The specific equations are as follows:

$$x_{i,j}^{t+1} = x_{best}^{t} + e^{bl} \cdot \cos\left(2\pi l\right) \cdot \left| x_{i,j}^{t} - x_{worst}^{t} \right| \tag{7}$$

$$l = 2 \cdot \left(\cos\left(\frac{\pi}{2} \cdot \frac{t}{M} \right) \right) - 1 \tag{8}$$

$\left| x_{i,j}^{t} - x_{worst}^{t} \right|$ represents the length of the helix and *l* represents the size of the helix shape. The *cos* function is used to reduce adaptively. The helix changes less in the early stage and faster in the later stage. The specific description is shown in Figure 2-3.

Figure 2. Uniform spiral search

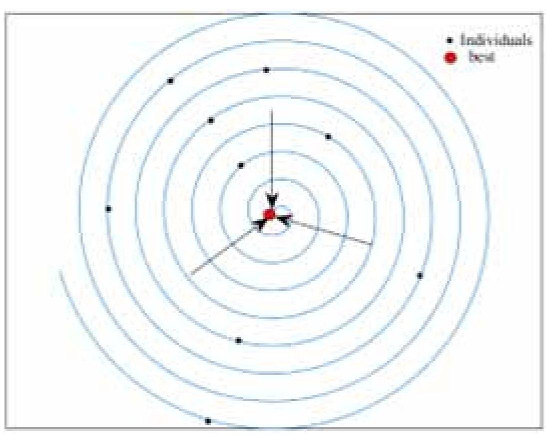


Figure 3. Non-uniform spiral search

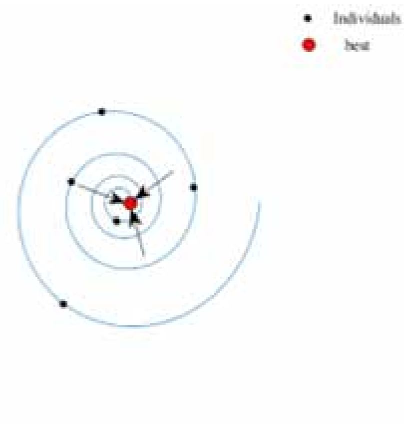


Figure 2 shows the general uniform spiral strategy. In a certain space, it can be seen that the distance between the inner and outer circles of the spiral search is the same, the early search accuracy is not high, and it takes a period of time to achieve a wide search. Figure 3 favorably avoids this drawback and can accelerate the convergence speed and improve the search ability of the algorithm in the early stage, and slowly reduce the search range in the later stage, which can further improve the local search ability of the algorithm and balance the local and global search ability of the algorithm in the whole process.

3.6. Learning Sparrow Algorithm with Non-Uniform Search

Sparrow search algorithm has weak learning behavior and can still have the probability of falling into local optimization. This paper presents a learning sparrow search algorithm based on the non-uniform helix. A selection behavior strategy is proposed, which introduces jump learning and random walk learning strategies respectively so that the algorithm has a better search mechanism. Then, a non-uniform spiral search is proposed in the discoverer stage, which makes its search more detailed and flexible. Comprehensively improve the optimization ability of the algorithm. The specific flow chart is shown in Figure 4:

3.7 Time Complexity Analysis

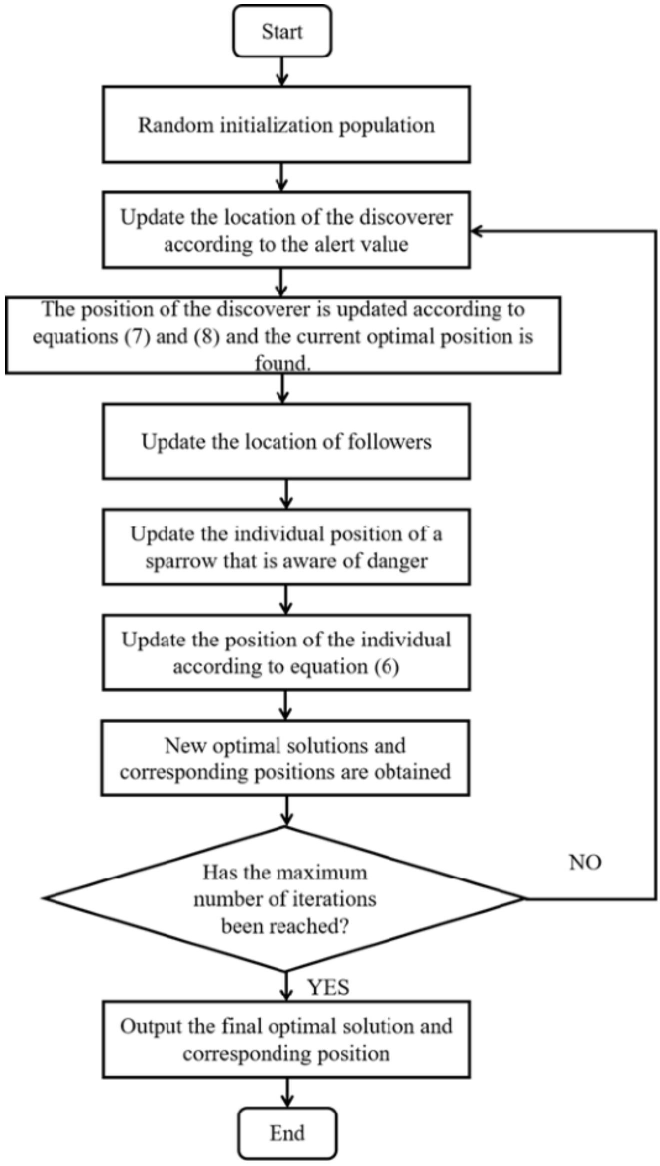
Time complexity is not only an important index to analyze an algorithm, but also an important reference index to measure the optimization speed of the algorithm. The time complexity of the NSSSA proposed in this paper is analyzed below.

Let the population number be n, the dimension of the problem be D, the initialization time be t_0, the time to randomly generate uniformly distributed random numbers in each dimension be t_1, and the time to solve the test function be f (D). Then the time of the initialization phase is

$$T_1 = O\left(t_0 + N\left(Dt_1 + f\left(D\right)\right)\right) \tag{9}$$

Let the proportion of discoverers be r_1, then its number is $r_{1\times}$N, the time to calculate the non-uniform spiral strategy is t_2, and its own calculation time is t_3, so the time complexity of the discoverer stage is

Figure 4. NSSSA flowchart



$$T_2 = O\left(r_1 N \left(t_2 + t_3\right)\right) \tag{10}$$

Similarly, the number of followers is $(1-r_1)\times N$. assuming that the calculation time of each dimension is t_4, the follower stage is

$$T_3 = O\left(\left(1 - r_1\right) ND\right) \tag{11}$$

If the proportion of vigilantes is r_2, the number is $r_{2\times}$N. Assuming that the update time in each dimension is t_5, the time complexity of the vigilant stage is

$$T_4 = O\left(r2NDt_5\right) \tag{12}$$

In addition, NSSSA adds a learning behavior selection strategy. If its calculation time is t_6, the calculation time of the newly added strategy is

$$T_5 = O\left(t6ND\right) \tag{13}$$

To sum up, the time complexity of NSSSA is

$$T = T_1 + G\left(T_2 + T_3 + T_4 + T_5\right) = O\left(D + f\left(D\right)\right) \tag{14}$$

4. PERFORMANCE TEST

The performance test is divided into two parts, the first part is the common standard test function, most of the theoretical optimal value of 0; the other part is the CEC 2013 test set, which contains 28 test functions and the theoretical optimal value of these functions is not in 0, and the optimal position is not all 0. Most of the current algorithms are tested only in the test of the optimal value of 0, which leads to the proposed algorithm being only applicable to some The purpose of doing so is to show the effectiveness and reasonableness of NSSSA.

4.1 Common Standard Function Tests

There are 6 common functions., Six standard test sets are shown in Table 1. 30 and 100 were tested respectively. F1-5 is a unimodal function and F6 is a complex multimodal function. The experimental environment is window10 64bit, the software is matlab2019b, the memory is 16GB, and the processor is Intel (R) Core (TM) i5-10200h CPU @ 2.40GHz. CSSA, ISSA, SSA, PSO, BSO, GWO, MRFO, WOA, and TLBO are compared with NSSA. The population number of each algorithm is 100 and the maximum number of iterations is 500.DS=0.2; ST=0.2; In PSO, $C_1 = C_2 = 1.429$ and the weight W = 0.729. Each algorithm runs 30 times in each function and calculates its average value, minimum value, and standard deviation to evaluate the optimization ability of each algorithm. The experimental results are shown in tables 2-3(The optimal value obtained by optimization has been expressed in bold).

It can be seen from tables 2 and 3 that NSSSA has achieved better results in all functions in both 30 and 100 dimensions, and has more advantages than other algorithms. It can find the optimal value 0 in F1-4, has better accuracy in F5, and can basically approach the optimal value every time in F6. On the other hand, the difference between the two dimensions of NSSSA is small, and the optimization ability is not reduced due to the improvement of dimensions. This shows that the selection behavior and the addition of non-uniform helix make NSSSA have better learning ability and play an important role in different dimensions.

In order to clearly see the convergence of each algorithm in each function, the convergence diagram of each algorithm in the 30-dimensional function is given, as shown in Figure 5.

It can be seen from Figure 5 that NSSSA converges faster in each function and has higher convergence accuracy. Especially in F3-4, it can quickly find the theoretical optimal value. In the multimodal function, it has a strong ability to resist local attraction.

Table 1. Benchmark function information table

F	DIM	Interval	MIN
$F_1\left(x\right)=\sum_{i=1}^{n}x_i^2$	30/100	[-100,100]	0
$F_2\left(x\right)=\sum_{i=1}^{n}\left\|x_i\right\|+\prod_{i=1}^{n}x_i$	30/100	[-10,10]	0
$F_3\left(x\right)=\sum_{i=1}^{n}(\sum_{j=1}^{i}x_j)^2$	30/100	[-100,100]	0
$F_4\left(x\right)=\max_i\left\{\left\|x_i\right\|,1\leq i\leq n\right\}$	30/100	[-100,100]	0
$F_5\left(x\right)=\sum_{i=1}^{n-1}\left[100(x_{i+1}-x_i^2)^2+(x_i-1)^2\right]$	30/100	[-30,30]	0
$F_6\left(x\right)=\sum_{i=1}^{n}-x_i\sin\left(\sqrt{\left\|x_i\right\|}\right)$	30/100	[-500,500]	-418.9829n

Table 2. Comparison table of optimization effects of various algorithms (30-dimensions)

Function	Algorithm	Best	Ave	Std
F_1(x)	**NSSSA**	**0**	**0**	**0**
	BSO	1.8337	9.2351	8.0567
	CSSA	**0**	**0**	**0**
	ISSA	**0**	**0**	**0**
	SSA	**0**	**0**	**0**
	MRFO	**0**	**0**	**0**
	WOA	3.1181E-104	1.0840E-95	4.5034E-95
	TLBO	4.0530E-86	2.9876E-85	2.1878E-85
	GWO	2.9726E-42	9.9797E-41	2.3113E-40
	PSO	1.562E-12	7.3034E-11	1.5384E-10
F_2(X)	**NSSSA**	**0**	**0**	**0**
	BSO	1.4341	4.9968	4.3319
	CSSA	**0**	3.1304E-206	**0**
	ISSA	**0**	2.1596E-142	1.1829E-141
	SSA	**0**	9.748E-180	**0**
	MRFO	4.2592E-237	1.5644E-229	**0**
	WOA	5.1550E-63	8.1673E-58	2.9729E-57
	TLBO	3.0778E-43	1.2493E-42	7.1358E-43
	GWO	1.0018E-24	5.1662E-24	3.7964E-24
	PSO	1.9393E-06	1.2453E-04	3.7942E-04

continued on following page

Table 2. Continued

Function	Algorithm	Best	Ave	Std
$F_3(X)$	**NSSSA**	**0**	**0**	**0**
	BSO	9.4317E-10	5.8438	19.6417
	CSSA	**0**	**0**	**0**
	ISSA	**0**	7.0814E-227	**0**
	SSA	**0**	7.0603E-92	3.8713E-91
	MRFO	**0**	**0**	**0**
	WOA	4721.7113	14247.7885	6987.8376
	TLBO	6.046E-17	1.7598E-15	1.8686E-15
	GWO	1.2722E-15	1.6521E-11	5.6379E-11
	PSO	2.4597	6.8764	4.6663
$F_4(X)$	**NSSSA**	**0**	**0**	**0**
	BSO	0.0417	1.5546	1.2080
	CSSA	**0**	**0**	**0**
	ISSA	**0**	3.7672E-158	2.0634E-157
	SSA	**0**	**0**	**0**
	MRFO	1.8994E-233	1.2937E-223	**0**
	WOA	1.3789E-07	29.9675	30.9981
	TLBO	7.5438E-35	2.2303E-34	1.1471E-34
	GWO	1.0249E-11	1.3528E-10	1.3629E-10
	PSO	0.06008	0.1756	0.08657
$F_5(X)$	NSSSA	**2.2729E-11**	**9.9476E-06**	**3.6349E-05**
	BSO	233.8862	971.7400	841.0884
	CSSA	3.47E-09	7.3760E-05	1.0942E-04
	ISSA	1.0562E-07	1.2681E-04	2.7208E-04
	SSA	7.6415E-09	**3.1722E-05**	5.9606E-05
	MRFO	20.0739	19.0914	0.3923
	WOA	26.3128	26.7973	0.2094
	TLBO	5.2658E-10	1.6085E-05	4.1716E-05
	GWO	45.1861	46.6720	0.7848
	PSO	10.0094	102.2121	51.6541
$F_6(X)$	NSSSA	**-12569.4842**	**-12253.2653**	804.4222
	BSO	-12569.4866	-11205.6626	1020.4548
	ISSA	-10141.2347	-9080.1757	568.2124
	CSSA	-10022.9333	-9045.4556	574.4343
	SSA	-10258.1903	-8724.1633	718.2918
	MRFO	-9687.4216	-9074.1013	**435.9415**
	WOA	-12569.4699	-11724.0348	1302.3261
	TLBO	-9264.3142	-7375.7309	1152.8942
	GWO	-8262.1714	-6362.1144	709.0298
	PSO	-8324.1386	-6844.9716	752.6817

Table 3. Comparison table of optimization effects of various algorithms (100-dimensions)

Function	Algorithm	Best	Ave	Std
$F_1(x)$	**NSSSA**	**0**	**0**	**0**
	BSO	195.6467	757.4745	391.4064
	CSSA	**0**	**0**	**0**
	ISSA	**0**	**0**	**0**
	SSA	**0**	**0**	**0**
	MRFO	**0**	**0**	**0**
	WOA	1.0469E-102	7.2231E-93	2.5499E-92
	TLBO	2.9527E-76	1.6114E-75	1.1585E-75
	GWO	5.0820E-18	2.6308E-17	2.1089E-17
	PSO	1.0668	12.4586	30.0289
$F_2(X)$	**NSSSA**	**0**	**0**	**0**
	BSO	1.2648	4.4716	2.5141
	CSSA	**0**	1.2353E-150	6.7659E-150
	ISSA	**0**	1.9139E-118	1.0483E-117
	SSA	**0**	1.7751E-138	9.7229E-138
	MRFO	8.2591E-234	8.7997E-228	**0**
	WOA	3.9713E-62	1.1101E-55	4.0498E-55
	TLBO	1.5899E-38	4.2526E-38	1.6467E-38
	GWO	1.1188E-23	1.0070E-22	8.1329E-23
$F_3(X)$	PSO	1.6825E-06	4.0864E-05	1.3518E-04
	NSSSA	**0**	**0**	**0**
	BSO	0.0680	154.2623	315.1105
	CSSA	**0**	1.9637E-206	**0**
	ISSA	**0**	**0**	**0**
	SSA	**0**	1.0517E-212	**0**
	MRFO	**0**	**0**	**0**
	WOA	458797.5073	673887.355	119006.9168
	TLBO	5.7047E-06	1.4581E-04	1.5072E-04
	GWO	0.4399	11.8139	13.5850
	PSO	6831.9888	4185.5172	7632.0184
$F_4(X)$	**NSSSA**	**0**	**0**	**0**
	BSO	0.04267	1.7935	1.3896
	CSSA	**0**	1.1926E-184	**0**
	ISSA	**0**	1.3563E-144	7.4285E-144
	SSA	**0**	1.9421E-165	**0**
	MRFO	1.0891E-224	6.0212E-219	**0**
	WOA	9.9712E-04	74.0677	29.3093
	TLBO	2.6417E-30	4.6349E-30	1.3566E-30
	GWO	2.0983E-03	0.05209	0.0865
	PSO	7.3782	9.5753	1.2667

continued on following page

Table 3. Continued

Function	Algorithm	Best	Ave	Std
$F_5(X)$	**NSSSA**	**7.1840E-12**	**6.3195E-06**	**3.1312E-05**
	BSO	1077.0368	1.3748E+04	1.3239E+04
	CSSA	4.2237E-08	2.5499E-04	3.4620E-04
	ISSA	2.1761E-07	2.6971E-04	6.66094E-04
	SSA	9.1735E-09	7.9045E-05	1.3805E-04
	MRFO	90.8234	92.3609	0.6613
	WOA	96.6794	97.2580	0.306837894
	TLBO	93.0637	91.1983	0.9548
	GWO	95.6787	96.9734	0.9208
	PSO	651.0884	3221.6846	6748.9024
$F_6(X)$	**NSSSA**	**-41898.2860**	**-40047.0781**	4825.5036
	BSO	-40261.0069	-33461.9674	3925.7756
	ISSA	-26395.4326	-24633.4955	**981.1676**
	CSSA	-26934.0704	-24515.6636	1327.8950
	SSA	-27320.1874	-24637.4984	1078.1888
	MRFO	-27791.1748	-25142.4131	1176.9092
	WOA	-41898.2647	-39015.2375	3769.7397
	TLBO	-27940.2584	-16598.4492	5164.0002
	GWO	-22404.2115	-16606.7711	2437.1531
	PSO	-23435.5935	-20056.7171	2277.0807

4.2 Comparison with Variants of Other Algorithms

In the previous section, NSSSA was mainly compared with variants of SSA and classical algorithms, and this section is compared with variants of other algorithms, including AGPSO3 (Mirjalili S et al., 2014), IGWO (Nadimi-Shahraki M H et al.2021), IPSO (Cui Z et al.2008), PSOGSA (Mirjalili and Hashim, 2010), TACPSO (Ziyu T and Dingxue Z, 2009). These algorithms have been mainly proposed by previous authors and tested on these common test functions. Dimension is 30.The population size and the number of iterations of each algorithm are consistent as above, the internal parameters of the other algorithms are shown in table 4, and the table of the optimization search results of each algorithm is shown in table 5.

As shown in table 5, it can be clearly seen that the performance index of NSSSA is the best in each function, and the other variants of the algorithm have poor performance in finding the optimal solution in the first five tested functions and cannot find the theoretically optimal solution. Taken together, NSSSA has better performance in these functions for finding the optimal solution, which has a great advantage over the previous algorithms and reflects the feasibility and novelty of NSSSA.

4.3 CEC 2013 Test

According to the test requirements of CEC 2013 (Liang J J et al., 2013), the computational complexity of each algorithm needs to be calculated, and the computational complexity of each algorithm is shown in table 6. t0 indicates the time to run the test program,Evaluate the computation time just for Function 14. For 200000 evaluations of a certain dimension D, it gives T_1; The complete computation time for the algorithm with 200000 evaluations of the same D dimensional benchmark function 14 is T2. $T_2^{'}$ is the average of 5 runs of T_2.

Figure 5. Convergence diagram of each algorithm function

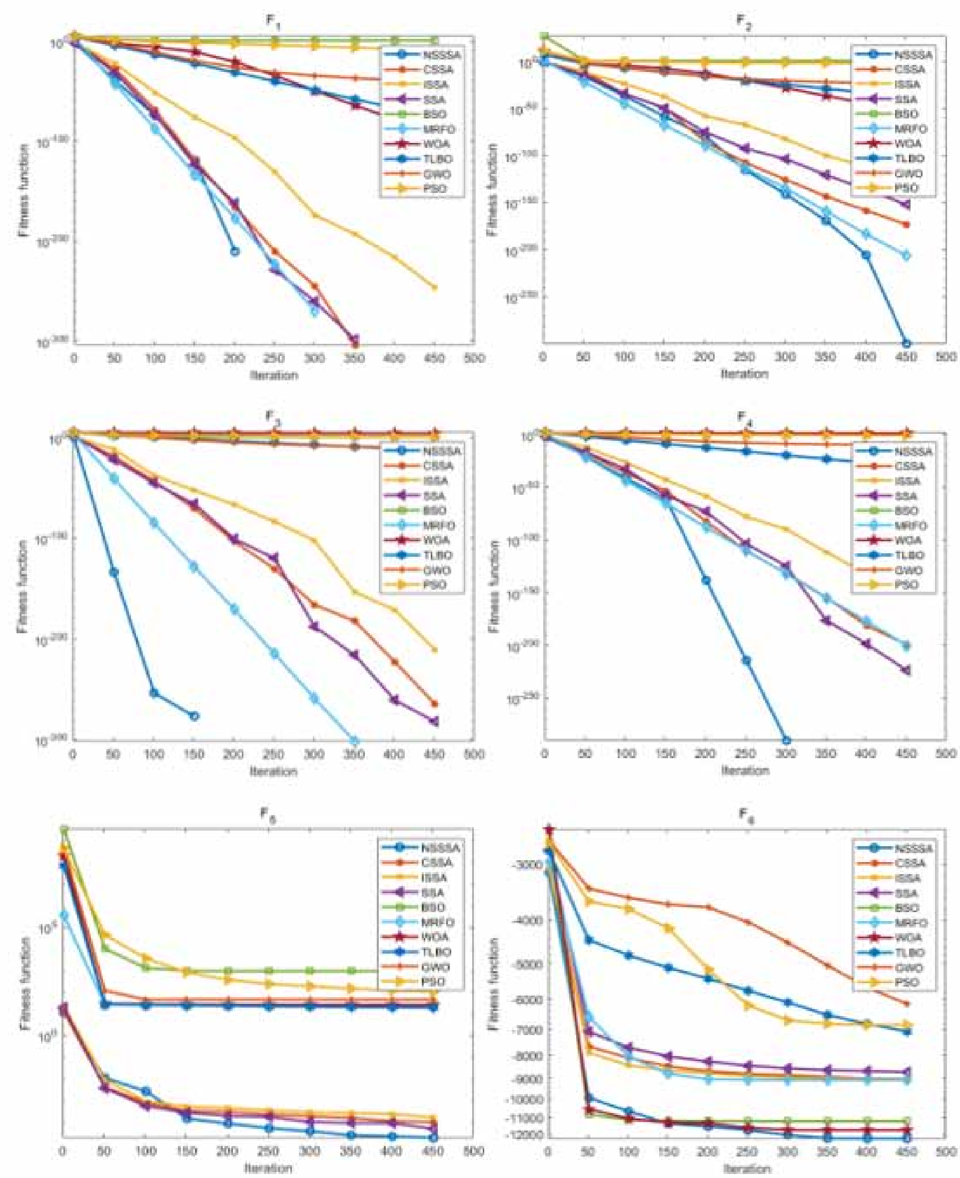


Table 4. Parameter information of the variants of the algorithm

algorithm	parameter
AGPSO3	Wmax=0.9,wmin=0.4,c1==c2=2
IGWO	a was linearly decreased from 2 to 0
IPSO	Wmax=0.9,wmin=0.4,c1==c2=2
PSOGSA	w=rand(1),c1=0.5,c2=1.5,G0=1,α=20
TACPSO	Wmax=0.9,wmin=0.4,c1==c2=2

Table 5. Comparison results with each algorithm variant

F	index	AGPSO3	IGWO	IPSO	PSOGSA	TACPSO	NSSSA
F1(X)	Best	1.76E-10	2.93E-43	1.56E-08	3.68E-19	2.32E-08	**0**
	Mean	6.20E-08	1.51E-41	1.19E-05	3.33E+02	4.66E-06	**0**
	Std	1.56E-07	1.67E-41	3.67E-05	1.83E+03	9.20E-06	**0**
F2(X)	Best	1.75E-04	1.68E-25	3.39E-05	2.70E-09	3.48E-04	**0**
	Mean	6.69E-01	1.05E-24	1.34E+00	2.83E+00	2.47E-02	**0**
	Std	2.54E+00	9.88E-25	3.45E+00	1.05E+01	5.98E-02	**0**
F3(X)	Best	6.09E+00	1.46E-11	6.26E+00	1.22E+03	4.95E+00	**0**
	Mean	2.06E+02	4.03E-09	4.08E+02	6.08E+03	5.52E+01	**0**
	Std	9.10E+02	8.84E-09	1.26E+03	3.00E+03	6.35E+01	**0**
F4(X)	Best	2.15E+00	4.70E-10	5.09E-01	1.62E+01	5.69E-01	**0**
	Mean	7.07E+00	2.86E-09	2.36E+00	3.77E+01	1.78E+00	**0**
	Std	3.13E+00	3.08E-09	9.29E-01	2.12E+01	7.63E-01	**0**
F5(X)	Best	1.79E+01	2.27E+01	1.60E+01	1.54E+01	9.24E+00	**2.27E-11**
	Mean	2.59E+02	2.32E+01	3.27E+03	3.04E+03	6.34E+01	**9.5E-06**
	Std	7.64E+02	2.83E-01	1.64E+04	1.64E+04	5.68E+01	**3.63E-05**
F6(X)	Best	-1.10E+04	-1.06E+04	-1.09E+04	-9.72E+03	-1.07E+04	**-1.26E+04**
	Mean	-1.03E+04	-8.53E+03	-9.88E+03	-8.26E+03	-9.40E+03	**-1.23E+04**
	Std	4.32E+02	1.73E+03	5.77E+02	9.01E+02	5.46E+02	8.04E+02

Table 6. Complexity information table

Time	T_0	T_1	T_2	$T_2^{'}$	$(T_2^{'} - T_1) / T0$
value	0.0694	13.3358	13.8916	13.8632	7.5994

In order to verify the optimization ability of the algorithm, and does not depend on the theoretical value of 0. This paper tests the algorithms on the CEC 2013 test set and compares the algorithms that have passed the test in recent years. The population number is 100, the evaluation time is 300000, and the dimension is 50. Most classical algorithms can find the theoretical optimal solution in some functions of 300000 times. Therefore, to measure the superiority of one algorithm over other algorithms, we should ensure the original ability and achieve better results. 300000 is a more appropriate evaluation number. DS=0.2; ST=0.6 In order to better demonstrate the global optimization capability of NSSSA, this paper compares it with TDSD, FA_CL, and ASBSO proposed in recent days. The results show that these three algorithms have achieved good results on the CEC test set. The parameter information of each algorithm is shown in Table 7. In this paper, the Wilcoxon rank test is used to illustrate whether there is a difference between the algorithms, and the test is carried out at the 5% significance level."+" indicates that the optimization performance of NSSSA is better than other algorithms, "-" indicates the opposite, "=" indicates that the optimization performance between the two algorithms is comparable, and N/A" indicates that the values of the two algorithms are the same and cannot be compared. Details The test results are shown in Table 5. The far right side of the table shows the theoretical optimal value of each function. The 30 running results of each algorithm are counted, and the optimal value, worst value, and median of each algorithm's running results are calculated. The five indicators of number, average, and standard deviation. In addition, the ranking of each algorithm on each function is calculated, and the average ranking is calculated to measure the universality of the algorithm. In order to intuitively see the stability of each algorithm Figure 6 shows the 30-time results of each algorithm in the functions F3, F9, F13, F18, F23, and F27.

From Table 4 and Figure 6, we can see that NSSSA has the most optimal indicators, and the number of optimal indicators of other algorithms is very small. Therefore, NSSSA has good results

Table 7. Parameters of each algorithm

Algorithm	SSA	CSSA	TDSD	ASBSO	FA-CL	NSSSA
Parameter	DS= $0.2\times N$ ST= $0.6\times$N	DS= $0.2\times N$ ST= $0.6\times$N	F_0=2.5 σ_0=0.5 μ=4 Z_0=0.152 P=0.988 $r=0.05$	$K=5$	α=0.01 β_{min}=0.2 β=1 γ=1	DS= $0.2\times N$ ST= $0.6\times$N

Table 8. Test results of each algorithm in CEC 2013(dim=50)

F	index	SSA	TDSD	CSSA	ASBSO	FA-CL	NSSSA	MIN
F1(x)	Best	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	-1.40E+03
	Worst	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	
	Median	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	
	Mean	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	**-1.40E+03**	
	Std	**0.00E+00**	1.24E-02	**0.00E+00**	2.74E-02	5.95E-01	**0.00E+00**	
	P	N/A(=)	1.21E-12(+)	N/A (=)	2.93E-05(+)	1.21E-12(+)		
F2(x)	Best	4.83E+06	4.27E+06	**8.59E+05**	1.52E+06	2.50E+06	9.40E+05	-1.30E+03
	Worst	2.96E+07	1.20E+07	**3.15E+06**	4.88E+06	1.21E+07	3.37E+06	
	Median	9.96E+06	8.54E+06	**1.49E+06**	2.68E+06	3.78E+06	1.93E+06	
	Mean	1.16E+07	8.34E+06	**1.57E+06**	2.91E+06	4.20E+06	2.00E+06	
	Std	5.34E+06	1.81E+06	**5.69E+05**	8.70E+05	1.92E+06	6.19E+05	
	P	3.02E-11(+)	3.02E-11(+)	2.60E-03(-)	5.97E-05(+)	6.72E-10(+)		
F3(x)	Best	1.59E+07	6.34E+09	2.35E+07	5.44E+07	1.30E+08	**1.23E+06**	-1.20E+03
	Worst	4.88E+09	1.80E+10	**1.13E+09**	1.47E+09	4.49E+09	1.16E+09	
	Median	2.39E+08	1.29E+10	2.01E+08	2.28E+08	7.51E+08	**1.91E+08**	
	Mean	6.99E+08	1.25E+10	2.93E+08	3.52E+08	1.21E+09	**2.69E+08**	
	Std	1.10E+09	2.88E+09	2.83E+08	2.87E+08	1.24E+09	**2.68E+08**	
	P	6.35E-02(=)	3.02E-11(+)	0.61(=)	0.09(=)	2.49E-06(+)		
F4(X)	Best	3.88E+02	7.43E+04	**-1.04E+03**	2.30E+04	3.44E+04	-6.61E+02	-1.10E+03
	Worst	5.96E+03	1.21E+05	**-9.10E+02**	5.98E+04	6.18E+04	1.40E+03	
	Median	2.42E+03	1.07E+05	**-9.84E+02**	3.69E+04	4.89E+04	-6.33E+01	
	Mean	2.73E+03	1.05E+05	**-9.80E+02**	3.69E+04	4.99E+04	1.04E+02	
	Std	1.45E+03	1.21E+04	**3.32E+01**	7.69E+03	6.75E+03	5.10E+02	
	P	1.96E-10(+)	3.02E-11(+)	3.02E-11 (-)	3.02E-11(+)	3.02E-11(+)		

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Table 8. Continued

F	index	SSA	TDSD	CSSA	ASBSO	FA-CL	NSSSA	MIN
F5(X)	Best	**-1.00E+03**	**-1.00E+03**	**-1.00E+03**	**-1.00E+03**	-9.99E+02	**-1.00E+03**	-1.00E+03
	Worst	**-1.00E+03**	-9.98E+02	**-1.00E+03**	**-1.00E+03**	-7.44E-02	**-1.00E+03**	
	Median	**-1.00E+03**	-9.99E+02	**-1.00E+03**	**-1.00E+03**	-9.99E+02	**-1.00E+03**	
	Mean	**-1.00E+03**	-9.99E+02	**-1.00E+03**	**-1.00E+03**	-9.33E+02	**-1.00E+03**	
	Std	**0.00E+00**	4.12E-01	**0.00E+00**	7.18E-03	2.51E+02	**0.00E+00**	
	P	N/A(=)	2.61E-11(+)	N/A(=)	3.02E-11(+)	2.61E-11(+)		
F6(X)	Best	-8.74E+02	-8.55E+02	-8.80E+02	-8.75E+02	-8.74E+02	**-8.98E+02**	-9.00E+02
	Worst	-7.53E+02	**-8.51E+02**	-7.96E+02	-7.52E+02	-7.47E+02	-8.23E+02	
	Median	-8.51E+02	-8.53E+02	-8.50E+02	-8.53E+02	-8.06E+02	**-8.85E+02**	
	Mean	-8.31E+02	-8.53E+02	-8.35E+02	-8.30E+02	-8.11E+02	**-8.71E+02**	
	Std	3.11E+01	**1.12E+00**	2.66E+01	3.31E+01	3.62E+01	2.51E+01	
	P	9.53E-07(+)	3.99E-04(+)	1.73E-06(+)	1.61E-06(+)	1.85E-08(+)		
F7(X)	Best	-6.81E+02	-6.85E+02	-6.79E+02	-7.18E+02	-7.03E+02	**-7.33E+02**	-8.00E+02
	Worst	-3.05E+02	**-6.35E+02**	-5.32E+02	-3.85E+02	-6.08E+02	-5.83E+02	
	Median	-6.11E+02	-6.62E+02	-6.26E+02	-6.47E+02	-6.49E+02	**-6.95E+02**	
	Mean	-5.95E+02	-6.61E+02	-6.23E+02	-6.15E+02	-6.54E+02	**-6.83E+02**	
	Std	8.99E+01	**1.09E+01**	3.86E+01	8.77E+01	2.13E+01	3.55E+01	
	P	1.36E-07(+)	1.81E-05(-)	3.52E-07(+)	1.11E04(+)	9.87E-02(=)		
F8(X)	Best	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	-7.00E+02
	Worst	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	
	Median	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	
	Mean	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	**-6.79E+02**	
	Std	3.33E-02	4.18E-02	3.79E-02	5.27E-02	**2.93E-02**	4.09E-02	
	P	5.11E-01(=)	7.28E-01(=)	6.35E-02(=)	5.87E-04(+)	2.97E-01(=)		
F9(X)	Best	-5.41E+02	-5.49E+02	-5.47E+02	-5.48E+02	-5.44E+02	**-5.75E+02**	-6.00E+02
	Worst	-5.26E+02	-5.42E+02	-5.30E+02	-5.32E+02	-5.29E+02	**-5.61E+02**	
	Median	-5.34E+02	-5.44E+02	-5.36E+02	-5.40E+02	-5.37E+02	**-5.67E+02**	
	Mean	-5.34E+02	-5.44E+02	-5.37E+02	-5.41E+02	-5.37E+02	**-5.67E+02**	
	Std	4.28E+00	**1.72E+00**	4.26E+00	4.48E+00	4.20E+00	3.10E+00	
	P	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)		
F10(X)	Best	**-5.00E+02**	-4.48E+02	**-5.00E+02**	-4.99E+02	-4.98E+02	**-5.00E+02**	-5.00E+02
	Worst	**-5.00E+02**	-4.02E+02	**-5.00E+02**	-4.98E+02	-2.27E+00	**-5.00E+02**	
	Median	**-5.00E+02**	-4.23E+02	**-5.00E+02**	-4.99E+02	-4.97E+02	**-5.00E+02**	
	Mean	**-5.00E+02**	-4.23E+02	**-5.00E+02**	-4.99E+02	-4.81E+02	**-5.00E+02**	
	Std	**7.27E-02**	1.39E+01	9.14E-02	1.72E-01	9.03E+01	8.11E-02	
	P	7.73E-01(=)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)		
F11(X)	Best	-9.55E+01	**-3.51E+02**	-9.16E+01	1.44E+02	7.99E+01	-3.23E+02	-4.00E+02
	Worst	2.85E+02	**-3.29E+02**	2.14E+02	5.01E+02	5.29E+02	-1.35E+02	
	Median	7.16E+01	**-3.41E+02**	3.38E+01	3.30E+02	2.39E+02	-2.55E+02	
	Mean	6.82E+01	**-3.40E+02**	3.46E+01	3.22E+02	2.60E+02	-2.50E+02	
	Std	9.33E+01	**5.92E+00**	7.64E+01	9.85E+01	1.11E+02	4.34E+01	
	P	3.02E-11(+)	3.02E-11(-)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)		

continued on following page

Table 8. Continued

F	index	SSA	TDSD	CSSA	ASBSO	FA-CL	NSSSA	MIN
F12(X)	Best	2.86E+02	7.68E+01	1.50E+02	2.27E+02	1.72E+02	**-1.96E+02**	-3.00E+02
	Worst	8.14E+02	**2.65E+02**	8.21E+02	7.08E+02	6.15E+02	2.85E+02	
	Median	5.87E+02	1.77E+02	3.85E+02	4.60E+02	3.74E+02	**-1.74E+01**	
	Mean	5.60E+02	1.68E+02	4.58E+02	4.79E+02	3.78E+02	**-6.50E+00**	
	Std	1.92E+02	**4.38E+01**	2.06E+02	1.10E+02	1.20E+02	1.05E+02	
	P	3.02E-11(+)	2.44E-09(+)	5.49E-11(+)	3.34E-11(+)	7.39E-11(+)		
F13(X)	Best	3.70E+02	3.71E+02	2.38E+02	5.96E+02	3.74E+02	**-4.45E+01**	-2.00E+02
	Worst	7.74E+02	4.62E+02	6.32E+02	9.56E+02	5.95E+02	**3.02E+02**	
	Median	5.28E+02	4.13E+02	4.36E+02	7.34E+02	4.62E+02	**1.17E+02**	
	Mean	5.62E+02	4.19E+02	4.47E+02	7.59E+02	4.59E+02	**1.34E+02**	
	Std	1.13E+02	**2.49E+01**	9.36E+01	9.97E+01	6.45E+01	8.14E+01	
	P	3.02E-11(+)	3.02E-11(+)	3.77E-04(+)	3.02E-11(+)	2.05E-11(+)		
F14(X)	Best	3.66E+03	**6.46E+02**	3.99E+03	5.74E+03	5.58E+03	3.50E+03	-1.00E+02
	Worst	7.33E+03	**1.45E+03**	6.64E+03	8.83E+03	1.36E+04	7.55E+03	
	Median	5.56E+03	**1.21E+03**	5.48E+03	7.21E+03	7.39E+03	5.48E+03	
	Mean	5.56E+03	**1.16E+03**	5.31E+03	7.27E+03	7.71E+03	5.38E+03	
	Std	7.81E+02	**1.84E+02**	7.19E+02	8.03E+02	1.53E+03	9.97E+02	
	P	6.00E-01(=)	3.02E-11(-)	0.7618(=)	4.00E-09(+)	3.20E-09(+)		
F15(X)	Best	6.72E+03	5.86E+03	6.43E+03	5.94E+03	7.20E+03	**3.28E+03**	1.00E+02
	Worst	1.11E+04	8.36E+03	9.93E+03	9.21E+03	1.46E+04	**6.10E+03**	
	Median	8.68E+03	7.46E+03	8.05E+03	7.82E+03	8.85E+03	**4.63E+03**	
	Mean	8.53E+03	7.40E+03	8.01E+03	7.67E+03	9.21E+03	**4.78E+03**	
	Std	9.03E+02	**5.63E+02**	8.73E+02	7.60E+02	1.96E+03	7.94E+02	
	P	3.02E-11(+)	4.08E-11(+)	3.02E-11(+)	3.69E-11(+)	3.02E-11(+)		
F16(X)	Best	2.01E+02	2.01E+02	2.01E+02	**2.00E+02**	2.02E+02	2.01E+02	2.00E+02
	Worst	2.03E+02	2.02E+02	2.03E+02	**2.01E+02**	2.04E+02	2.02E+02	
	Median	2.01E+02	2.02E+02	2.02E+02	**2.00E+02**	2.04E+02	2.01E+02	
	Mean	2.02E+02	2.02E+02	2.02E+02	**2.00E+02**	2.03E+02	2.01E+02	
	Std	8.02E-01	2.48E-01	6.56E-01	**1.55E-01**	3.63E-01	4.50E-01	
	P	1.71E-01(=)	1.11E-06(+)	4.00E-02(+)	4.50E-11(-)	3.02E-11(+)		
F17(X)	Best	8.05E+02	4.10E+02	6.71E+02	9.71E+02	1.09E+03	**3.96E+02**	3.00E+02
	Worst	1.41E+03	**4.39E+02**	1.24E+03	1.34E+03	1.69E+03	8.92E+02	
	Median	1.08E+03	**4.28E+02**	8.59E+02	1.18E+03	1.31E+03	4.91E+02	
	Mean	1.09E+03	**4.26E+02**	9.00E+02	1.17E+03	1.33E+03	5.79E+02	
	Std	1.52E+02	**8.05E+00**	1.70E+02	1.03E+02	1.58E+02	1.51E+02	
	P	6.47E-11(+)	5.40E-10(-)	3.87E-08(+)	2.92E-11(+)	2.92E-11(+)		
F18(X)	Best	1.13E+03	9.50E+02	9.69E+02	9.49E+02	1.06E+03	**5.21E+02**	4.00E+02
	Worst	1.60E+03	1.16E+03	1.59E+03	1.27E+03	1.65E+03	**7.65E+02**	
	Median	1.55E+03	1.07E+03	1.39E+03	1.09E+03	1.33E+03	**6.20E+02**	
	Mean	1.48E+03	1.07E+03	1.33E+03	1.09E+03	1.34E+03	**6.18E+02**	
	Std	1.33E+02	**4.22E+01**	2.27E+02	9.40E+01	1.59E+02	6.50E+01	
	P	3.00E-11(+)	3.00E-11(+)	3.00E-11(+)	3.00E-11(+)	2.97E-11(+)		

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Table 8. Continued

F	index	SSA	TDSD	CSSA	ASBSO	FA-CL	NSSSA	MIN
F19(X)	Best	5.18E+02	5.08E+02	5.16E+02	5.13E+02	6.69E+02	**5.03E+02**	5.00E+02
	Worst	5.54E+02	5.13E+02	5.41E+02	5.27E+02	8.34E+02	**5.08E+02**	
	Median	5.37E+02	5.10E+02	5.28E+02	5.18E+02	7.38E+02	**5.05E+02**	
	Mean	5.36E+02	5.10E+02	5.28E+02	5.18E+02	7.43E+02	**5.05E+02**	
	Std	1.04E+01	**1.06E+00**	6.84E+00	3.27E+00	4.65E+01	1.37E+00	
	P	2.98E-11(+)	2.98E-11(+)	2.98E-11(+)	2.98E-11(+)	2.98E-11(+)		
F20(X)	Best	6.21E+02	6.24E+02	6.20E+02	6.24E+02	6.23E+02	**6.13E+02**	6.00E+02
	Worst	6.25E+02	6.25E+02	6.25E+02	6.25E+02	6.25E+02	**6.15E+02**	
	Median	6.25E+02	6.25E+02	6.24E+02	6.24E+02	6.25E+02	**6.15E+02**	
	Mean	6.24E+02	6.24E+02	6.24E+02	6.24E+02	6.25E+02	**6.15E+02**	
	Std	7.11E-01	2.14E-01	1.14E+00	3.08E-01	4.53E-01	4.84E-01	
	P	6.47E-12(+)	6.48E-12(+)	6.48E-12(+)	6.48E-12(+)	2.40E-13(+)		
F21(X)	Best	1.54E+03	8.42E+02	1.54E+03	9.00E+02	9.28E+02	**8.00E+02**	7.00E+02
	Worst	1.82E+03	**9.31E+02**	1.82E+03	1.82E+03	1.82E+03	1.00E+03	
	Median	1.54E+03	**9.20E+02**	1.54E+03	1.54E+03	1.82E+03	1.00E+03	
	Mean	1.62E+03	**9.06E+02**	1.64E+03	1.57E+03	1.62E+03	9.45E+02	
	Std	1.33E+02	**3.12E+01**	1.40E+02	2.97E+02	3.02E+02	9.34E+01	
	P	1.16E-12(+)	2.93E-08(-)	1.59E-12(+)	1.38E-07(+)	1.38E-07(+)		
F22(X)	Best	5.91E+03	**1.91E+03**	5.63E+03	8.07E+03	7.53E+03	2.67E+03	8.00E+02
	Worst	1.01E+04	**2.69E+03**	9.94E+03	1.30E+04	1.38E+04	5.41E+03	
	Median	7.61E+03	**2.34E+03**	7.63E+03	1.11E+04	1.07E+04	4.18E+03	
	Mean	7.62E+03	**2.35E+03**	7.57E+03	1.10E+04	1.08E+04	4.09E+03	
	Std	1.07E+03	**2.26E+02**	1.02E+03	1.25E+03	1.67E+03	7.17E+02	
	P	3.02E-11(+)	3.34E-11(-)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)		
F23(X)	Best	8.35E+03	8.31E+03	7.18E+03	9.38E+03	7.38E+03	**4.91E+03**	9.00E+02
	Worst	1.34E+04	1.12E+04	1.40E+04	1.29E+04	1.53E+04	**7.91E+03**	
	Median	1.12E+04	9.81E+03	1.16E+04	1.11E+04	1.16E+04	**6.24E+03**	
	Mean	1.11E+04	9.77E+03	1.13E+04	1.10E+04	1.18E+04	**6.35E+03**	
	Std	1.62E+03	**6.64E+02**	1.41E+03	9.85E+02	1.81E+03	8.31E+02	
	P	3.02E-11(+)	3.02E-11(+)	4.50E-11(+)	3.02E-11(+)	4.50E-11(+)		
F24(X)	Best	1.36E+03	1.35E+03	1.36E+03	1.37E+03	1.36E+03	**1.27E+03**	1.00E+03
	Worst	1.41E+03	1.37E+03	1.40E+03	1.59E+03	1.42E+03	**1.32E+03**	
	Median	1.38E+03	1.36E+03	1.38E+03	1.43E+03	1.39E+03	**1.30E+03**	
	Mean	1.38E+03	1.36E+03	1.38E+03	1.44E+03	1.39E+03	**1.29E+03**	
	Std	1.21E+01	**4.67E+00**	1.36E+01	5.44E+01	1.68E+01	8.87E+00	
	P	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)	3.02E-11(+)		
F25(X)	Best	1.48E+03	1.50E+03	1.46E+03	1.58E+03	1.56E+03	**1.45E+03**	1.10E+03
	Worst	**1.53E+03**	**1.53E+03**	1.55E+03	1.70E+03	1.61E+03	**1.53E+03**	
	Median	1.51E+03	1.52E+03	1.50E+03	1.63E+03	1.58E+03	**1.48E+03**	
	Mean	1.51E+03	1.52E+03	1.50E+03	1.63E+03	1.58E+03	**1.48E+03**	
	Std	1.16E+01	**6.32E+00**	1.87E+01	2.80E+01	1.28E+01	1.66E+01	
	P	2.83E-08(+)	6.12E-10(+)	2.68E-06(+)	3.02E-11(+)	3.02E-11(+)		

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Table 8. Continued

F	index	SSA	TDSD	CSSA	ASBSO	FA-CL	NSSSA	MIN
F26(X)	Best	1.64E+03	**1.40E+03**	**1.40E+03**	**1.40E+03**	**1.40E+03**	**1.40E+03**	1.20E+03
	Worst	1.68E+03	**1.40E+03**	1.69E+03	1.68E+03	1.68E+03	1.60E+03	
	Median	1.67E+03	**1.40E+03**	1.66E+03	1.66E+03	1.64E+03	1.58E+03	
	Mean	1.67E+03	**1.40E+03**	1.65E+03	1.61E+03	1.54E+03	1.54E+03	
	Std	1.09E+01	**4.64E-01**	4.95E+01	1.05E+02	1.32E+02	7.97E+01	
	P	3.02E-11(+)	3.99E-04(-)	3.16E-10(+)	4.12E-06(+)	5.94E-02(=)		
F27(X)	Best	3.10E+03	**1.70E+03**	2.93E+03	3.17E+03	3.21E+03	2.31E+03	1.30E+03
	Worst	3.55E+03	3.22E+03	3.61E+03	3.82E+03	3.54E+03	**2.62E+03**	
	Median	3.32E+03	3.15E+03	3.35E+03	3.53E+03	3.27E+03	**2.49E+03**	
	Mean	3.32E+03	2.91E+03	3.34E+03	3.53E+03	3.32E+03	**2.47E+03**	
	Std	1.30E+02	5.53E+02	1.42E+02	1.78E+02	9.51E+01	**7.69E+01**	
	P	3.02E-11(+)	9.51E-06(+)	3.02E-11(+)	3.02E-11(+)	2.79E-11(+)		
F28(X)	Best	1.80E+03	1.81E+03	1.80E+03	7.59E+03	2.50E+03	**1.70E+03**	1.30E+03
	Worst	7.64E+03	1.83E+03	8.40E+03	1.15E+04	7.80E+03	**1.70E+03**	
	Median	1.80E+03	1.82E+03	1.80E+03	9.06E+03	6.45E+03	**1.70E+03**	
	Mean	3.99E+03	1.82E+03	4.16E+03	9.31E+03	6.20E+03	**1.70E+03**	
	Std	2.42E+03	4.01E+00	2.61E+03	9.40E+02	1.12E+03	**0.00E+00**	
	P	1.09E-12(+)	1.72E-12(+)	1.09E-12(+)	1.72E-12(+)	1.72E-12(+)		
+/=/-		21/7/0	20/1/7	21/5/2	26/1/1	26/2/0		

for CEC2013, especially F3, F5-6, F9, F12-13, F15-f16, F18, F20, F23-25, and F27-28, which have strong means of optimization and stability also good. From the statistical test results, NSSSA has more advantages than other algorithms. This reflects that it has certain advantages among various functions. According to the no free lunch in the world theorem, NSSSA shows good results in most functions, which indicates that NSSSA has good generalizability.

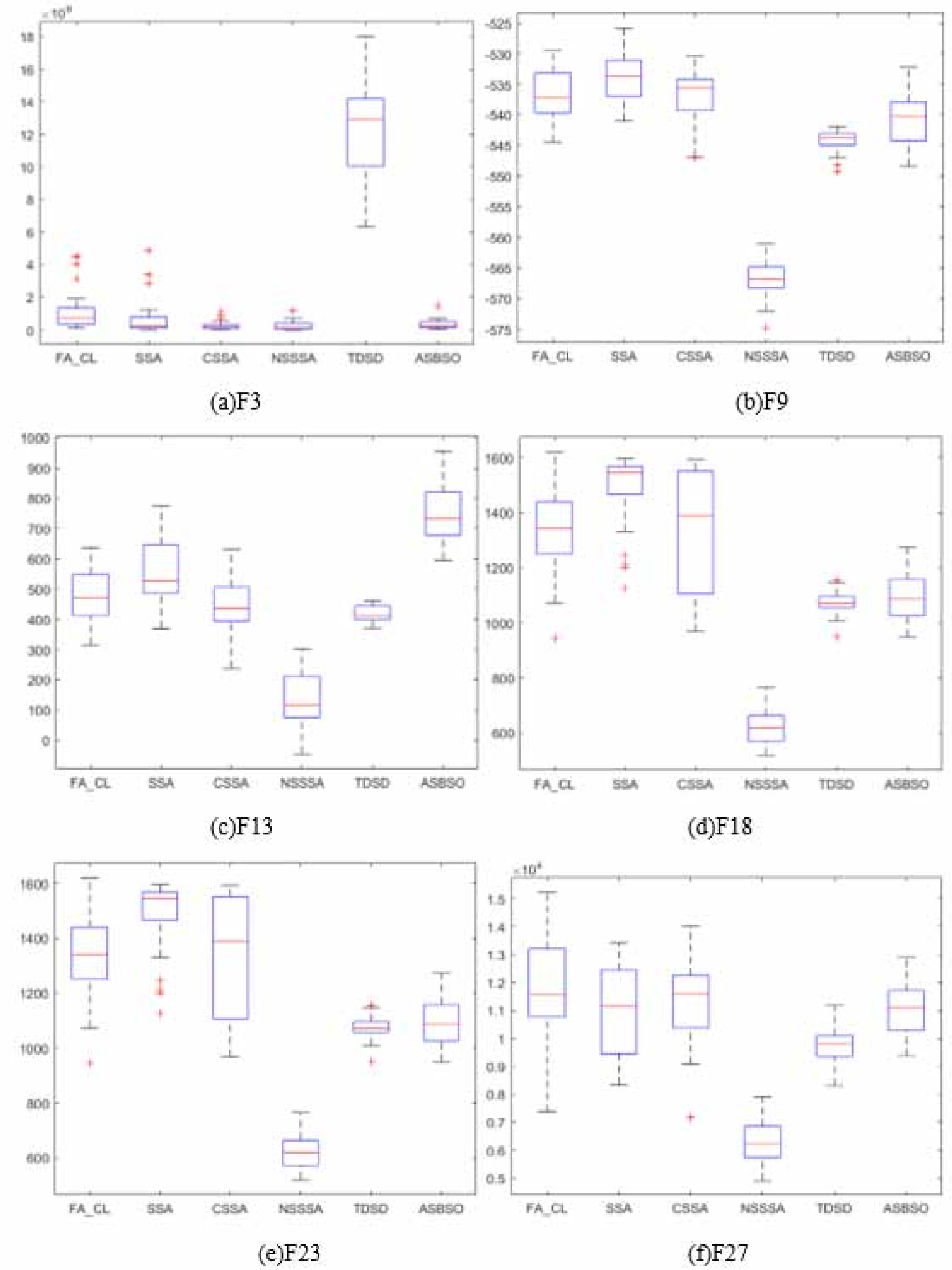
4.4 Comprehensive Analysis

In the above two parts of experiments, NSSSA not only unfolds the comparison with the more basic algorithms in the common test functions, but also compares with the variants of other algorithms, and the results show that NSSSA has significant optimization ability in the common test functions, basically, every index is the best, and most of them can find the theoretical optimal value precisely. In the comparison with popular algorithms proposed in recent years in CEC 2013, NSSSA also has the highest number of optimal metrics, beating ASBSO, TDSD, FA_CL, which are excellent algorithms verified by CEC.It can be seen that SL with random walk learning enables individuals to find high-quality solutions, while the non-uniform spiral search strategy can find more reasonable solutions in complex environments and get rid of the attraction of local extremes, which eventually makes the accuracy of solutions improve effectively.

5. COVERAGE OPTIMIZATION PROBLEM TESTING

The above content only verifies the effectiveness of the algorithm in function simulation, but the purpose of studying the algorithm needs to be implemented finally. In order to verify that NSSSA has good practicability, this paper uses two WSN coverage optimization problems of different scales to test. It is worth noting that at least two individuals have the same dimension when the SL strategy is used.

Figure 6. Statistical chart of optimization results of each algorithm



5.1 WSN Coverage Optimization Problem

This paper assumes that there are N homogeneous sensor nodes. In WSN, each sensor node has the same sensing radius R and communication radius R^c. To ensure the connectivity of the wireless sensor network, the communication radius of the node is set to be greater than or equal to twice the node's sensing radius. The set of nodes can be represented as $S = \left\{s_1, s_2, s_3, \ldots, s_n\right\}$ ..Collection $M = \left\{m_1, m_2, m_3, \ldots, m_n\right\}$, $\left(x_i, y_i\right)$ and $\left(x_j, y_j\right)$ corresponding to the two-dimensional spatial coordinates of s_i and m_j in the set respectively. In this paper, the Boolean perception model is used as a node perception model. As long as the monitoring area is within the range of the node perception radius, it is considered to cover the node. The Euclidean distance formula between sensor nodes and monitoring area nodes is as follows:

$$\mathrm{d}\left(s_i, m_j\right) = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{15}$$

The probability that the monitoring point m_j is perceived by the node s_i is expressed as follows:

$$p_{cov}\left(s_i, m_j\right) = \begin{cases} 1 & if \mathrm{d}\left(s_i, m_j\right) \le R \\ 0 & otherwise \end{cases} \tag{16}$$

The joint sensing probability of all sensor nodes to the monitoring point m is expressed as follows:

$$C_p\left(s_{all}, m_j\right) = 1 - \prod_{i=1}^{n}\left(1 - p_{cov}\left(s_i, m_j\right)\right) \tag{17}$$

Where S_{all} is all wireless sensor nodes in the monitoring area. It is assumed that the monitoring area is rectangular and the area is $L \cdot W$ m^2. For the convenience of calculation, the rectangle is divided into $L \cdot W$ grids with equal area, and the monitoring node m is located at the center of the grid. The joint perception probability of all monitoring points is calculated through the above formula (17), and the cumulative sum is the coverage area. Coverage C_r can be expressed as follows:

$$C_r = \sum_{x=1}^{L}\sum_{y=1}^{W} C_p\left(S_{all}, m_{(x-1)\cdot W + y}\right) / L \cdot W \tag{18}$$

The problem is described as follows:

$$f\left(I\right) = Max\left(C_r\left(I\right)\right) \tag{19}$$

5.2 Simulation Experiment

In order to fully verify the optimization performance of the NSSSA algorithm on WSN node coverage, the basic SSA algorithm and the classic PSO and GWO algorithms are selected for comparison. In addition, the simulation parameters of several comparative algorithms are consistent. In order to make the experiment more convincing, the simulation experiment of each comparison algorithm runs 30 times independently, and the maximum (best), minimum (worst), and average (ave) values of each algorithm are calculated 30 times. The average convergence diagram of each algorithm is given.

5.2.1 Coverage Optimization with Detection Area of 50×50

The maximum number of iterations of each algorithm is 500 and the population number is 50. Other parameters within the algorithm are the same as above. The experimental parameter settings are shown in Table 9. The optimal coverage planning diagram of each algorithm is shown in Figure 7. The average convergence of each algorithm is shown in Figure 8. The coverage effect is shown in Table 10.

As can be seen from Figure 7, the coverage of NSSSA is relatively dense, while the coverage of the GWO algorithm is very sparse. It can be seen from table 10 that NSSSA has a good coverage effect, preferably 91.48%, and good stability. The coverage of other algorithms is less than 90%. Figure 8 shows that NSSSA converges quickly and has high accuracy. The convergence has been completed in about 200 generations.

Table 9. Parameter setting

parameter	Value
Area	S=50m×50m
Pixel points	50×50
Number of nodes	V=35
Perceived radius	R=5m
Communication radius	Rc=10m

Figure 7. WSN coverage of each algorithm on 50×50 model

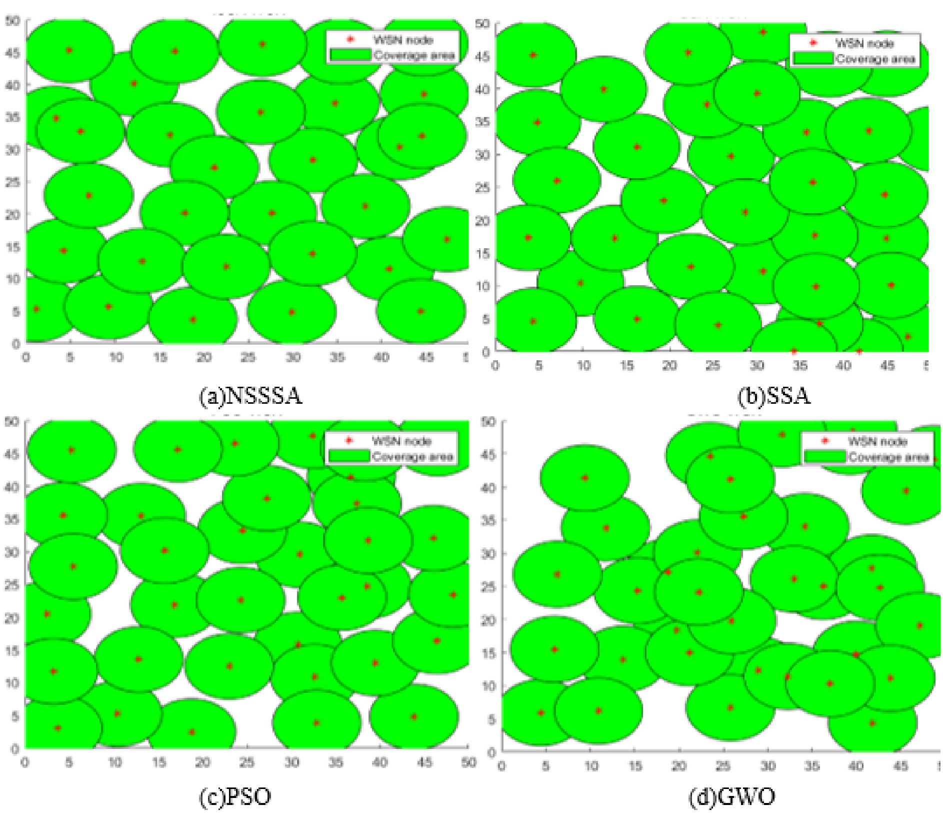


Figure 8. Average convergence diagram of each algorithm

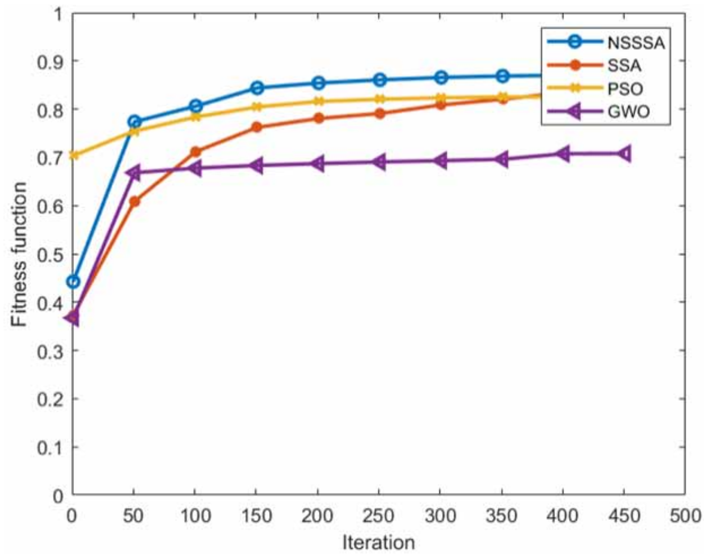


Table 10. Experimental results of each algorithm

performance index	NSSSA	SSA	PSO	GWO
Best	91.48%	86.24%	87.42%	74.04%
Ave	87.28%	84.44%	82.65%	72.96%
Worst	81.04%	82.16%	78.35%	70.48%

Table 11. Parameter setting

parameter	Value
Area	S=100m×100m
Pixel points	100×100
Number of nodes	V=40
Perceived radius	R=10m
Communication radius	Rc=20m

5.2.2 Coverage Optimization with Detection Area of 100×100

The maximum number of iterations of each algorithm is 200 and the population is 50. Other parameters within the algorithm are the same as above. The experimental parameter settings are shown in Table 10. The optimal coverage planning diagram of each algorithm is shown in Figure 9. The average convergence of each algorithm is shown in Figure 10. The coverage effect is shown in Table 11.

It can be seen from table 11 and figures 9-10 that the NSSSA coverage effect is better than 96%, and other algorithms are less than 90%. It can be seen that the stability of NSSSA on the 100×100 model still maintains a good state. It is close to the best coverage effect in about 60 generations.

Figure 9. WSN coverage of each algorithm

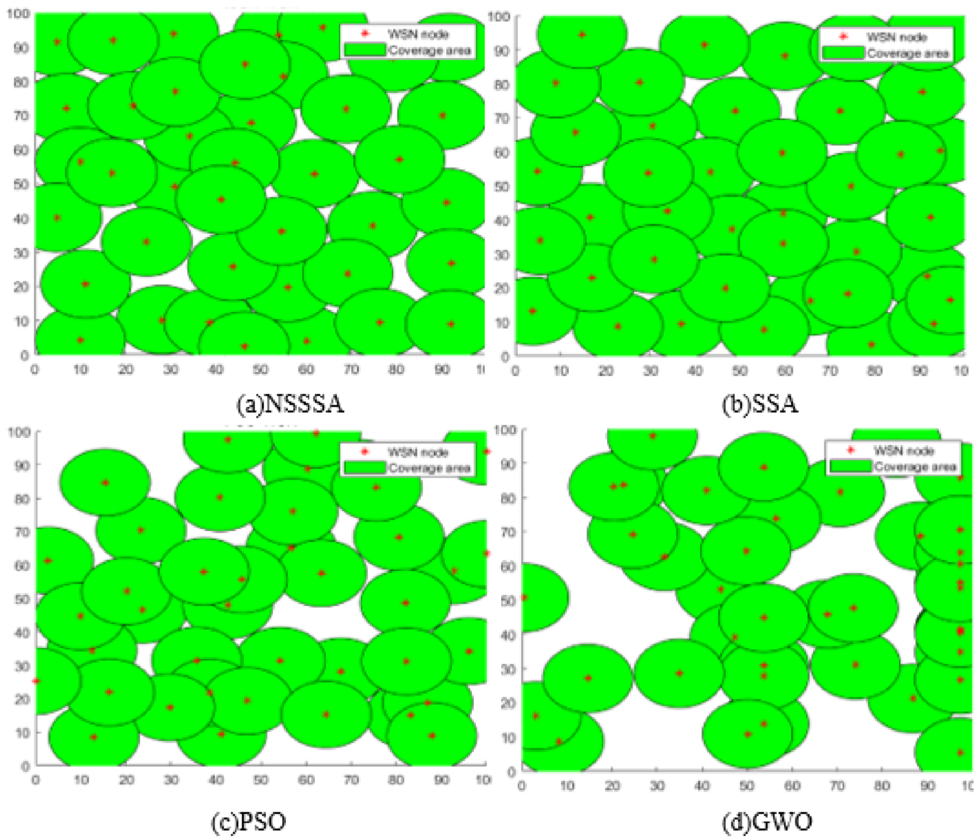


Figure 10. Average convergence diagram of each algorithm

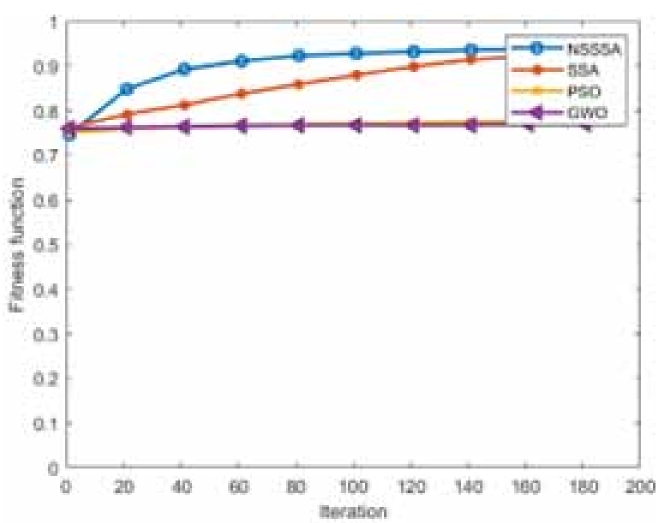


Table 11. Experimental results of each algorithm

performance index	NSSSA	SSA	PSO	GWO
Best	96.14%	86.24%	81.11%	79.47%
Worst	94.04%	84.44%	77.81%	76.97%
ave	92.32%	82.16%	73.55%	74.99%

Overall, NSSSA still maintains excellent performance in coverage problems of different scales and has obvious advantages in the convergence effect. Therefore, it can be seen that the introduction of multi-strategy makes the algorithm find a reliable solution faster and broaden the individual's vision in a certain space.

5.3 Comprehensive Analysis

From the two different models, it can be seen that NSSSA can both find the maximum coverage area faster than other algorithms, and at the same time has better stability. On the other hand NSSSA can get more than 90% coverage in both models, which shows that the behavioral selection can better judge the current advantage-seeking condition, while the non-uniform spiral search makes the individuals find better locations so that it can be the individuals fully spread throughout the space and determine the suitable layout location.

6. CONCLUSION

The sparrow search algorithm converges quickly, but it has insufficient accuracy. In order to improve its global optimization ability, a non-uniform learning sparrow search algorithm is proposed in this paper. The algorithm proposes a new learning selection strategy to enhance the learning ability of the algorithm in the optimization process and then proposes a non-uniform spiral strategy to balance the local development and global search ability of the algorithm. It has better optimization ability than the other nine algorithms on the six benchmark functions; Compared with different algorithms and their variants, the optimization results have obvious advantages and verify the effectiveness and novelty of NSSSA. At the same time, compared with SSA, CSSA, FA_CL, ASBSO, and TDSD on CEC 2013 test set, the results show that NSSSA has good universality. Finally, in the WSN coverage optimization problem with two different models, NSSSA can show better coverage effect, which verifies the practical value of NSSSA.

7. FUTURE WORK

Although the experimental results show that the algorithm has good results, NSSSA still has some shortcomings. From the test results of CEC 2013, the optimization ability of NSSSA is obviously stronger, but it cannot find the theoretical optimal solution in most functions, and the randomness still exists; on the other hand, from the effect of WSN coverage optimization, NSSSA cannot reach more than 90% coverage in the 50*50 model every time, and the coverage is not stable. Therefore, the randomness of NSSSA still has a large breakthrough space, and there is a need to further improve its optimization-seeking ability to achieve stable and significant results. We need to consider different improvement directions from different problems, so that it achieves top results in a practical problem and shows better practicality and value.

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DATA AVAILABILITY

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

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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