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An improved monarch butterfly spectrum allocation algorithm for multi-source data stream in complex electromagnetic environment

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Abstract

In the era of the Internet of Everything, various wireless devices and sensors use spectrum, which is a precious and non-renewable resource, to communication. Due to the characteristics of massive, heterogeneous, and multi-source, the generated multi-source data stream brings difficulties to spectrum cognition. As a result, unreasonable spectrum allocation strategy leads to low utilization of spectrum resources. Optimizing spectrum allocation strategy can effectively improve spectrum utilization. Aiming at the problem of trapped local optimum solution in the genetic algorithm (GA) and particle swarm optimization algorithm (PSO), an improved monarch butterfly algorithm is proposed. Firstly, this paper employs the simulated annealing algorithm to select the migration rate, which increases the diversity of monarch butterfly population. Secondly, chaos mapping algorithm is utilized to improve the optimization ability and convergence speed. Finally, in the view of the problem that the monarch butterfly algorithm is easy to fall into the local optimal solution, there is no better way to escape from the local optimal solution. The Wolf pack updating operator is selected to improve the diversity of the population to generate new monarch butterflies. This method updates the population by generating new monarch butterfly individuals, so as to increasing the diversity of the population. The experimental results show that the improved monarch butterfly algorithm outperforms the other two algorithms in terms of convergence speed and system revenue.

Keywords: Multi-source data stream, Spectrum allocation, Monarch butterfly algorithm, Graph theory model

1 Introduction

With the advent of the 5G communication technology, smart city, smart home, smart medical and intelligent transportation come into our lives. While various frequency devices and sensors show explosive growth, the generated data have the characteristics of massive, heterogeneous, and multi-source [1]. The multi-source data stream makes the electromagnetic environment, which is inherently dynamic and changeable, more intricate and complex. It leads to difficulties in electromagnetic spectrum cognition and inaccurate analysis of frequency occupancy. It is conducive to sensing spectrum occupation by utilizing the intelligent data mining algorithm to extract features of multi-source data stream, while laying a good foundation for spectrum prediction and spectrum allocation, which solve the problem of low spectrum [2].

The main reason for the low utilization of spectrum resources is not the lack of spectrum resources, but failing to making full use of spectrum resources. At present, spectrum management agencies mainly divide the spectrum into multiple segments and then allocate these spectrum resources to different frequency agencies. The amount of spectrum resources allocated to communication systems is fixed. In order to avoid interference among different frequency bands, these frequency bands are usually separated by a certain frequency band as a protection band. The divided frequency band has a definite use time for the frequency mechanism. When the lease time expires, it is necessary to lease again. For the current rapidly developing 5G era, it is obvious that the fixed frequency band is not flexible enough to allocate spectrum resources, which greatly reduces the utilization rate of frequency resources.

In order to solve the problem of low utilization of spectrum resources, cognitive radio arises. Cognitive radio is widely used in vehicles [3], such as the Internet of Things, where it is mainly used to adjust power distribution [4]. Cognitive radio mainly includes spectrum sensing [5], spectrum management [6] and spectrum sharing. Based on the current network situation, cognitive radio selects the appropriate and effective spectrum resources to use. Through cognitive radio spectrum allocation strategy, one cognitive user can use the available spectrum resources only when one primary user cannot be interfered. Spectrum resource allocation is similar to a multi-objective optimization problem, which needs to consider the frequency of multiple users. For spectrum resource allocation, classical spectrum allocation methods include graph theory model [7, 8], game theory model [9, 10], interference temperature model [11] and auction model [12, 13].

The graph theory model mainly considers the relationship between frequency equipment and spectrum. It describes the relationship between frequency equipment and frequency equipment through the graph theory idea and then solves this graph theory problem by using graph theory coloring algorithm. Game theory model mainly refers to the cognitive users to improve their own signal-to-noise ratio to improve the transmission power. Cognitive users constantly adjust the transmission power and game, convergence to the Nash equilibrium point. The interference temperature model is mainly used when cognitive users and authorized users share the same frequency band. In order to ensure that cognitive users do not interfere with authorized users, the interference temperature model is used to quantify the maximum interference that authorized users can bear, so as to determine whether cognitive users interfere with authorized users. To ensure the stability and reliability of authorized user communication, the auction model is similar to the auction and auction of a commodity. Cognitive users bid for spectrum resources by taking the economic benefits of a certain frequency band for cognitive users as the auction price. The auction model mainly considers the network environment and the use of spectrum resources by primary users to set an appropriate price for spectrum resources and then allocates the spectrum to the users with the highest spectrum benefits according to the auction strategy.

However, these are traditional spectrum allocation solutions, and the popular ones are swarm intelligence algorithm and multi-agent reinforcement learning. Swarm intelligence algorithm is a new bionics algorithm. It has strong robustness and good results for solving nonlinear multi-objective optimization problems. Meanwhile, as an optimization algorithm, swarm intelligence algorithm is widely used in signal recognition [14, 15] and signal classification [16, 17].

In [18], the authors used genetic algorithm and particle swarm optimization algorithm to allocate spectrum resources. By comparing the obtained rewards and convergence times, the authors found that particle swarm optimization algorithm could obtain more rewards and less convergence times. In [19], an improved ant colony algorithm is proposed. By using the pheromone of ant colony to select channel, experimental results show that channel allocation and throughput can be significantly improved. In [20], an immune parallel artificial bee colony algorithm is proposed to improve the utilization rate of spectrum resources, and the experimental results show that the proposed algorithm is significantly better than the traditional ant colony algorithm and particle swarm optimization algorithm. Literature [21] proposed an improved artificial bee colony algorithm based on firefly algorithm to solve the spectrum allocation problem, and experimental results found that the algorithm was significantly better than other swarm intelligence algorithms. Literature [22] proposes an artificial bee colony algorithm, which reduces the probability of false alarm and greatly improves the throughput of the algorithm by predicting and sensing the main user. Literature [23] puts forward a soft computing heuristic framework, which uses evolutionary algorithm to allocate spectrum. In [24], a spectrum allocation algorithm based on particle swarm optimization (PSO) is proposed to select appropriate subcarriers for sub-users.

In this paper, an improved monarch butterfly optimization algorithm for spectrum allocation problem is proposed. The algorithm mainly considers frequency allocation as the optimization objective. It can effectively avoid falling into the local optimal solution and has good optimization performance. The algorithm has three main improvements, which are as follows:

1 Inspired by the annealing algorithm, the migration rate of monarch butterfly algorithm is improved to increase the population diversity;
2 By introducing chaotic mapping mechanism, the updating algorithm of monarch butterfly adjustment operator is improved;
3 The migration behavior of wolf pack is introduced as the updating method for population updating.

In Sect. 2, the graph theory model is introduced. The interference matrix, availability matrix, benefit matrix and non-interference allocation matrix of graph theory model are introduced in detail. When spectrum allocation scheme is determined, the graph theory model can be used to obtain spectrum allocation benefits. Section 3 mainly introduces the traditional monarch butterfly algorithm migration operator (MO), butterfly adjustment operator (BAO) and the implementation steps of the algorithm. Section 4 mainly introduces the improvement method of monarch butterfly algorithm and the algorithm flow of monarch butterfly algorithm. In Sect. 5, the performance of the improved algorithm is analyzed by experimental results.

2 System model of spectrum allocation

It is difficult to solve the spectrum allocation problem of cognitive radio directly by swarm intelligence algorithm. Graph theory colorization model can be used to describe spectrum allocation in cognitive radio. In the model, the node represents the frequency device, and the edge connecting two nodes means that the two nodes cannot use the same color, which means that two frequency devices do not share the same frequency point in the spectrum allocation problem. The graph theory model mainly has four matrices, which are availability matrix L, benefit matrix B, interference matrix C and non-interference allocation matrix A.

1 Available matrix $L_{N\times M}$ is used to describe all of the available spectrum resources available in the spectrum of frequency equipment. $L(n,m)=1$ means frequency point m, n available for use frequency equipment. n means that the current cognitive radio environment are n use frequency equipment, and m means that the current cognitive radio environment are m a spectrum.

2 Benefit matrix $B_{N\times M}$ is mainly used to describe the revenue obtained when frequency points are obtained by frequency equipment, and the revenue generally refers to the throughput, etc. For solving the cognitive radio spectrum allocation problem, the benefit matrix has a great influence on it, and the solution is generally based on the revenue matrix to maximize the revenue of spectrum allocation. $\mathrm{B}(n,m)=$ reward represents the reward obtained when frequency device n is used to select spectrum m.

3 Interference matrix $C_{N\times N\times M}$, which is the edge of graph theory coloring model, mainly describes whether multiple frequency devices can share the same frequency point. $C(n_1,n_2,m)$ indicates that when the frequency point m is used simultaneously by the frequency-using device and the frequency-using device, communication interference will be caused.

4 Allocation matrix $A_{N\times M}$ mainly represents the spectrum allocation scheme solved according to the currently available matrix L, benefit matrix B and interference matrix C. $A(N,M)=1$ indicates that the frequency point m is allocated to the frequency device n. At the same time, the spectrum allocation should meet the constraints to ensure that there is no interference between the frequency devices.

5 R_{sum} represents the income obtained by the spectrum allocation scheme.

$$R_{sum}=AB=\sum_{n=1}^{N}\sum_{m=1}^{M}a_{n,m}\times b_{n,m}. \tag{1}$$

The spectrum allocation scheme obtained from the availability matrix, interference matrix and benefit matrix is A, and the spectrum allocation revenue can be obtained by multiplying with the revenue matrix.

Figure 1 shows a graphic representation of the graph-theoretic model. The dots in the figure represent frequency equipment. It can be seen that the available frequency

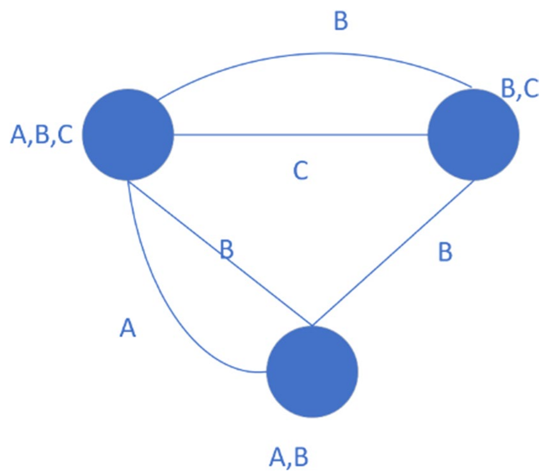

Fig. 1 A graphic representation of the graph-theoretic model

points of the three frequency devices are ABC, BC and AB. That is the relation of the available matrix. The line between two dots is an edge, which means that two frequency devices cannot use the same frequency point at the same time. Generally, when the frequency devices are close to each other, they cannot share the same frequency point; otherwise, interference will occur. That represents the relationship between the interference matrices. And the benefit matrix is not shown here.

The graph theory model mainly consists of interference matrix, availability matrix, benefit matrix and spectrum allocation matrix. The interference constraint relationship between frequency points and frequency devices is mainly represented by interference matrix. Whether the spectrum pair can be allocated to the frequency device is mainly represented by the available matrix. Spectral throughput and so on are mainly represented by benefit matrix. The distribution matrix can obtain the spectrum distribution relationship, and it can be seen that the graph theory model can describe the spectrum distribution relationship well.

In order to solve the spectrum allocation problem in complex environment, if interference matrix C, utility matrix B and available matrix are used directly to solve the problem, the solution complexity will be very high. With the increase of the number of frequency devices and frequency points, the scale of the problem increases sharply, which will increase the search space of the algorithm and the difficulty of searching the optimal solution. It's hard to get good results. However, it can be noted that the 0 element of the available matrix L has no role in spectrum allocation, because at the position of L 0, the representing frequency device cannot use that frequency point. After optimizing and solving by intelligent algorithm, the distribution result of 1 dimension is obtained. In order to obtain the correct distribution matrix A, the available matrix can be used to map the spectrum allocation scheme to 2 dimensions. So, we can solve the spectrum allocation problem just by recording the position of element 1 in the available matrix. This mapping scheme can greatly reduce the complexity of spectrum allocation. Figure 2 shows the mapping of the available matrices.

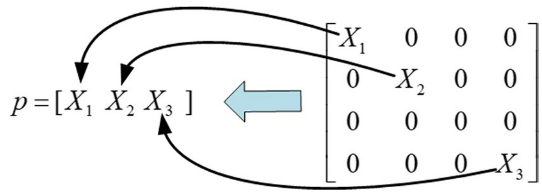

Fig. 2 Available matrix mapping relationships

3 The basic principle of monarch butterfly optimization algorithm

The monarch butterfly is a kind of migratory butterfly in North America [25]. It migrates every year because of climate change and carries out reproductive behavior in the process of migration. Monarch butterfly optimization algorithm is a new swarm intelligence algorithm based on the characteristics of monarch butterfly migration according to the season. In the algorithm of monarch butterfly, population P is divided into population $SP1$ and $SP2$ according to fitness. Monarchs in population $SP1$ would periodically migrate to individuals in population $SP2$ to replace individuals in $SP2$, so as to realize population renewal, while individuals in population $SP2$ mainly carried out internal renewal.

The number of monarch butterfly population is NP. When monarchs were divided into population $SP1$ and population $SP2$, the population scale factor needs be divided. The specific formula is written as

$$NP_1 = ceil(NP * pair), \tag{2}$$

$$NP_2 = NP - NP_1, \tag{3}$$

where $pair$ is the proportion of population $SP1$ in population SP, NP_1 is the number of monarch butterflies in population $SP1$, NP_2 is the number of monarch butterflies in population $SP2$.

The value of $SP1 + SP2$ is equal to 1, so the size of $SP1$ is determined, and the size of $SP2$ can be determined. The population 1 divided by $SP1$ is mainly to perform the migration operator, which will be updated within the population. The population 2 divided by $SP2$ is mainly to perform the adjustment operator, which will randomly generate the population to avoid falling into the local optimal solution. Therefore, choosing one large $SP2$ can better avoid the algorithm falling into the local optimal solution. Monarch butterfly algorithm realizes swarm intelligence algorithm optimization through migration operator (MO) and butterfly adjustment operator (BAO). The migration operator is mainly used for the information exchange of subpopulation $SP1$ and subpopulation $SP2$. The specific formula is written as

$$x_{i,k}^{t+1} = \begin{cases} x_{r1,k}^{t}, & \text{if } r \leq \mathrm{P} \\ x_{r2,k}^{t}, & \text{if } r > \mathrm{P} \end{cases}, \tag{4}$$

where $x_{i,k}^{t+1}$ is the position of the k-dimension component of the ith individual in $SP1$ population when iterated to $t+1$, $x_{r1,k}^{t}$ is the position of the k-dimension component of a randomly selected individual in $SP1$ population when iterated to generation t, and $x_{r2.k}^{t}$ is the position of the k-dimension component of a randomly selected individual in $SP2$

population when iterated to generation T. The variable $r = Rand * peri$, where $Rand$ is a random number generated between 0 and 1, and $peri$ is mobility. The larger P is, the more monarchs migrated and the higher population migration rate are.

The adjustment operator mainly updates the individuals in the population $SP2$ to generate new individuals to update the population, so as to promote the algorithm to converge to a better result more quickly. The updating formula of the adjustment operator is written as

$$x_{j,k}^{t+1} = \begin{cases} x_{best,k}^{t}, & rand \ \leq \mathrm{P2} \\ x_{r3,k}^{t}, & rand > \mathrm{P2} \end{cases}, \tag{5}$$

where $x_{best,k}^{t}$ is the k-dimension component of the individuals with the best fitness in population $SP1$ and $SP2$ at the t iteration. x_{r3}^{t} is the k-dimension component of randomly selected individuals in population $SP2$ at the t th iteration. P2 is the probability of population selection type.

Further variation occurs when the adjustment operator is used for updating. When $rand()$ >BAR, monarch butterflies in population $SP2$ will undergo further variation and update according to the following formula:

$$x_{i,k}^{t+1} = x_{i,k}^{t} + \alpha(dx_k - 0.5), \tag{6}$$

$$dx = Levy(x_i^{t+1}), \tag{7}$$

where BAR is the adjustment probability. α is the weight factor. $\alpha = \frac{1}{t^2}$, t is the current iteration number of the population. dx is the step length at which individual I performs the Levy walk. BAR is the adjustment probability.

To show the process of monarch butterfly algorithm in detail, Fig. 3 is the flowchart of monarch butterfly algorithm.

4 The proposed improved monarch butterfly algorithm

The traditional monarch butterfly algorithm is a continuous interval allocation problem, which is not suitable for the binary allocation problem of spectrum allocation. In order to make the monarch butterfly algorithm be applied to spectrum allocation, the algorithm will be discretized. At the same time, the MO and BAO operators of monarch butterfly are improved by introducing simulated annealing mechanism and chaos mechanism. The algorithm proposed in this paper can improve the defects of monarch butterfly algorithm and the efficiency of allocation.

4.1 Simulated annealing factor

When monarch butterflies in population $SP1$ are updated by MO operator, they will randomly select monarch butterflies in $SP1$ or $SP2$ according to probability to replace the current individual. In the early stage, MO operator will play a great role in updating the algorithm. However, when the population tends to converge, $SP1$ will select more individuals in $SP2$ for updating. Because $SP2$ population is updated by BAO operator, it is easy to generate newer and better individuals, and the individual diversity is more obvious than that of $SP1$ population.

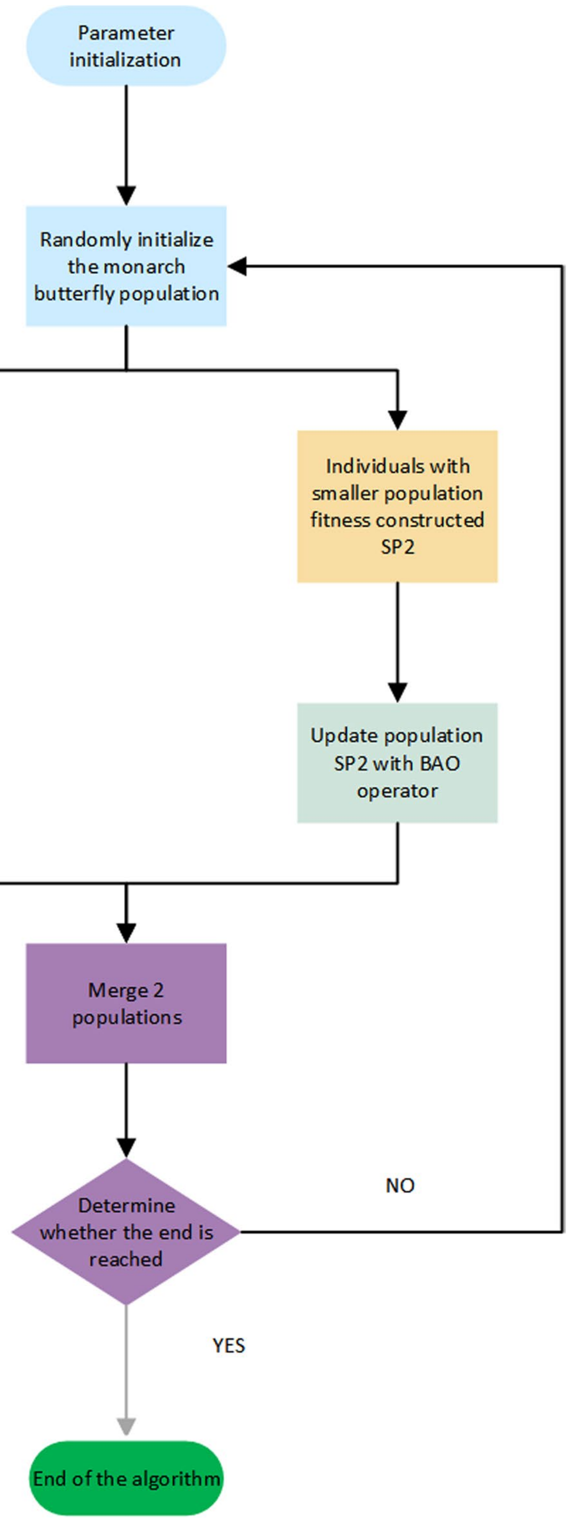

Fig. 3 Flowchart of the monarch butterfly algorithm

Simulated annealing algorithm is a kind of random search algorithm which is easy to solve complex optimization problems. The simulated annealing algorithm is based on the process of heating a solid until it melts, and then waiting for the melted individual to cool and solidify into a solid. The simulated annealing algorithm proposed in this paper is applied to the selection probability p of MO operator. The algorithm formula is written as

$$p = \begin{cases} \exp\left(\frac{(R\_N2 - R\_N1)}{\mathrm{T}^t}\right), & R\_N2 \leq R\_N1 \\ 1, & R\_N2 > R\_N1 \end{cases}, \tag{8}$$

$$T^{t+1} = \beta T^t, \tag{9}$$

where R_N2 is the average fitness of monarch butterflies of population $SP1$. R_N2 is the average fitness of monarchs in population $SP2$. T is the simulated annealing temperature, and β is the annealing coefficient.

When the average fitness of monarch butterflies in population $SP1$ is higher than that of monarch butterflies in population $SP2$, individuals will be randomly selected from $SP1$ to replace the current individuals in population $SP1$ when the population $SP1$ migrates. When the average fitness of monarch butterflies in population $SP1$ is lower than that in population $SP2$, the algorithm will use simulated annealing algorithm to select the appropriate migration factor P, so as to avoid the algorithm falling into the local optimal solution and increase the diversity of the population.

4.2 Chaotic mapping operator

In the process of updating the MBO operator, if rand()>BAR, further updates are made. However, when spectrum allocation is carried out by the updating algorithm, the updating algorithm is more traditional and cannot find a good solution, so that algorithm is easy to fall into the local optimal solution. In order to improve the probability of finding the optimal solution, chaotic mapping algorithm is introduced to this paper.

Chaotic sequence is a kind of sequence with randomness, ergodicity and regularity. It can search the solution space with a higher probability, and find a better solution to avoid the algorithm falling into local optimal solution, while ensuring the diversity of population. The algorithm has the following formula:

$$x_{i,k}^{t+1} = x_{i,k}^t + r^t(x_{r,k}^t - x_{i,k}^t), \tag{10}$$

$$r^{t+1} = \begin{cases} 2r^t, & r \leq 0.5 \\ 2(1 - r^t), & r > 0.5 \end{cases}, \tag{11}$$

where r^t is the chaotic mapping variable. $x_{r,k}^t$ is the individual with the best fitness in the population or an individual randomly selected in the population $SP2$. $x_{i,k}^t$ is the value of the k-dimension component of the ith individual at the t updating iteration.

Through the Chaotic update algorithm, the algorithm can avoid the blindness of monarch butterfly when searching for update.

4.3 Wolf pack travel update operator

Differential evolution algorithm is often used to generate new individuals in improved intelligent algorithms to improve population diversity and avoid falling into local optimal solutions. However, in the late period of population renewal, the individuals of the population have already converged to a relatively good value. At this time, the differential evolution operator will use the individuals in the population to randomly generate an individual. Since the population randomness generated by the differential evolution operator is relatively large, the probability of generating individuals with low fitness value is relatively high. The Wolf pack operator will conduct fine exploration around the optimal individual, so as to obtain a better solution in the later period of population renewal.

Wolves are social animals. When they are looking for food, they work together to find prey. When a subset of wolves smells prey, that subset of wolves will carefully explore the surroundings of the current location, bringing the wolf closer to the prey, and possibly even directly to the prey. Monarch butterfly migration algorithm mainly relies on MO and BAO operators to update and search for optimization, but it is easy to fall into local optimal solution. In order to make the monarch operator find better results and avoid falling into local optimal solutions, the wolf pack wandering behavior is introduced into the algorithm updated in this paper. The algorithm formula is written as

$$x_{i,k}^{t+1} = x_{i,k}^{t} + \sin(2 * pi/direction) * 2, \tag{12}$$

$$num\_ser = population * ratio, \tag{13}$$

where *direction* is the direction that the monarch butterfly can choose when exploring. The larger *direction* is, the finer the exploration will be. *ratio* is the number of monarchs performing migration behavior.

After the MO and BAO operations of the monarch butterfly algorithm are completed, the wolf pack wandering behavior will be carried out. Some monarch butterflies with high fitness value will wander in the current position for a certain number of times to find the individual with better fitness than the current one, and put the current individual into the population. And through the survival of the fittest, the individuals with low fitness were eliminated, so that the number of monarch butterflies did not change, so as to improve the population diversity.

4.4 Discretization of monarch butterfly algorithm

Monarch butterfly is an algorithm for continuous space, and the problems solved are generally continuous space problems. For the problem of spectrum allocation, the position of monarch butterfly needs to be discretized. The common discretization functions are generally sigmoid and arctan function. In this paper, sigmoid function is adopted, and the formula is written as

$$temp = \frac{1}{1 + \exp(-1 * x_{i,k}^{t})}, \tag{14}$$

$$x_{i,k}^{t} = \begin{cases} 1, & temp \le 0.5 \\ 0, & temp > 0.5 \end{cases}. \tag{15}$$

4.5 The process of monarch butterfly algorithm

As a swarm intelligence algorithm, the improved monarch butterfly algorithm has the following specific process:

Initialize the number of frequency devices and frequency spectrum. The available matrix, interference matrix and utility matrix of the graph theory model are randomly initialized, and the spectrum allocation problem is constructed using the graph theory model and other parameters. The fitness of the randomly generated population of monarch butterflies is sorted, and the individuals with greater fitness are divided into $SP1$, and the individuals with less fitness are divided into $SP2$. The migration operation of modified simulated annealing update operator is carried out for $SP1$ population.The MAO operator is used to update the population $SP2$, and in some cases, the transformation of the monarch butterfly is used by the chaotic mapping method. The population $SP1$ and $SP2$ are merged, and then the wolf swarm walking algorithm is used to generate new individuals. Some of all monarch butterflies will be eliminated by the survival of the fittest algorithm, so that the number of monarch butterflies remains P, which determine whether the algorithm is over.

Algorithm 1 Improved Monarch Butterfly Algorithm

```
Input: Number of frequency spectrum and number of frequency equipment
initialize the interference matrix, utility matrix, benefit matrix,P,T,BAR
while ( k ≤ T_max )
    k = k + 1
    The migration operation of modified simulated annealing update operator is carried out for SP1 population.
    The operation of the MAO operator is used to update the population SP2.
    The population SP1 and SP2 are merged, and then the wolf swarm walking algorithm is used to generate new individuals.
end while
OutPut:A
```

5 Simulation analysis

5.1 Parameter settings

Particle swarm optimization (PSO) and genetic algorithm (GA) are classical optimization algorithms, which obtain better optimization results for most optimization problems. In some cases, the improved intelligent algorithms are only applicable to partial optimization and are not universal. Therefore, particle swarm optimization algorithm and genetic algorithm are used as comparison algorithms.

The improved monarch butterfly algorithm is compared with the traditional particle swarm optimization algorithm and genetic algorithm. The performance of the algorithm is analyzed mainly through the spectrum allocation revenue, the number of iterations required for the convergence of the algorithm, and the impact on the algorithm when cognitive users and available spectrum change.

The experimental parameters are set as follows: the number of monarch butterflies is 20, the number of algorithm iterations is 100, the initial simulated annealing temperature is $T = 3000$, the temperature degradation coefficient β is 0.93, the proportion coefficient of $SP1$ in population is 0.3, and the proportion coefficient of $SP2$ in population is 0.7. *Ratio* is set to 0.5. The cognitive user is set to $N = 10$, and the number of available channels is set to $M = 10$.

5.2 Simulation results

The results shown in Fig. 4 show that the proposed algorithm is significantly better than other traditional algorithms. The algorithm converges when the number of iterations of the algorithm is 15 times, while the genetic algorithm needs 100 times to converge, and the particle swarm optimization needs 70 times to converge.

Figures 4, 5, 6 and 7 show that when the simulated annealing temperature is set to 3000, 6000, 9000 and 12,000, the spectrum allocation income of the improved monarch butterfly algorithm, particle swarm optimization algorithm and genetic algorithm changes with the number of iterations. It can be seen from the figures that compared with genetic algorithm and particle swarm optimization algorithm, the improved monarch butterfly algorithm obviously solves the better distribution returns, and the distribution returns shown in the figure are significantly better than those of the other two algorithms.

From the point of view of the convergence speed of the algorithms, the improved monarch butterfly algorithm converges to the equilibrium position quickly. Although the genetic algorithm converges quickly, the spectrum allocation income is poor. When the simulated annealing temperature increases, the number of allocation convergence of

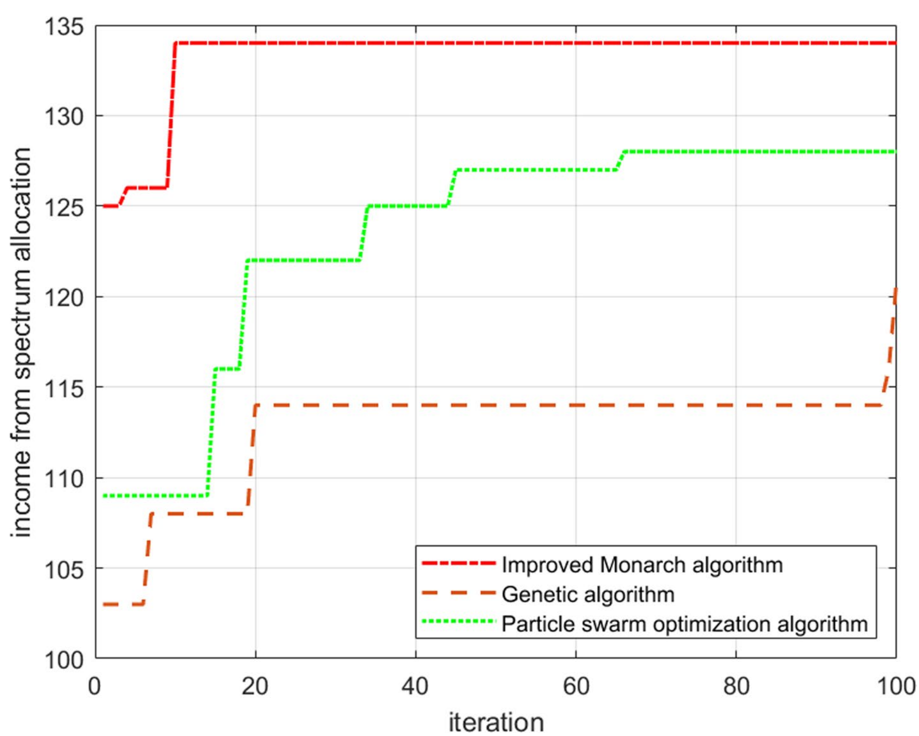

Fig. 4 Spectrum allocation income changes of the improved monarch butterfly algorithm, genetic algorithm and particle swarm optimization algorithm when $T = 3000$

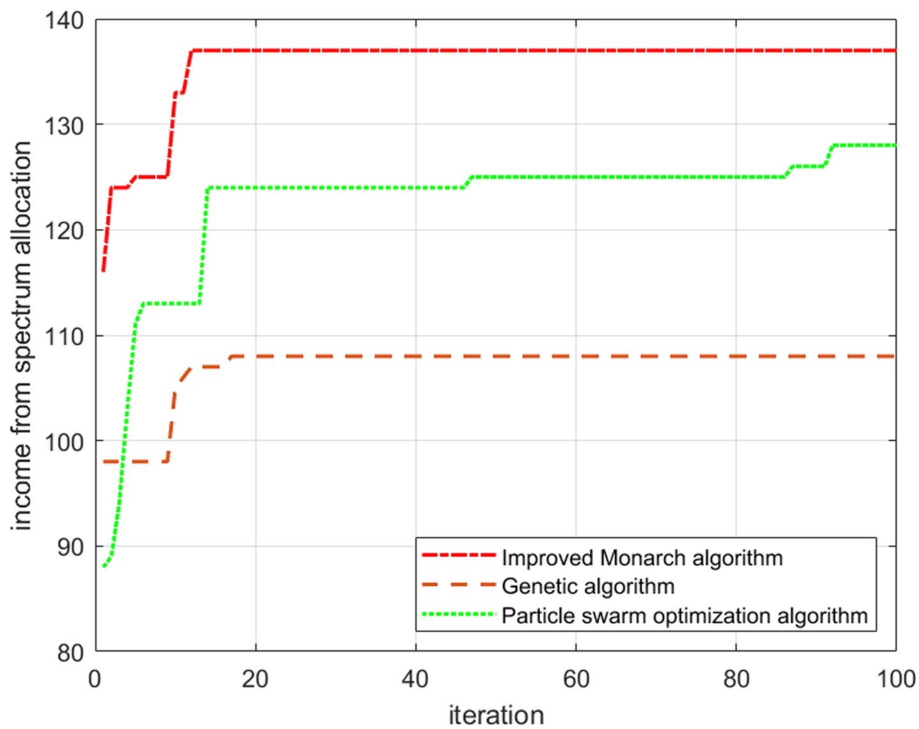

Fig. 5 Spectrum allocation income changes of the improved monarch butterfly algorithm, genetic algorithm and particle swarm optimization algorithm when $T = 6000$

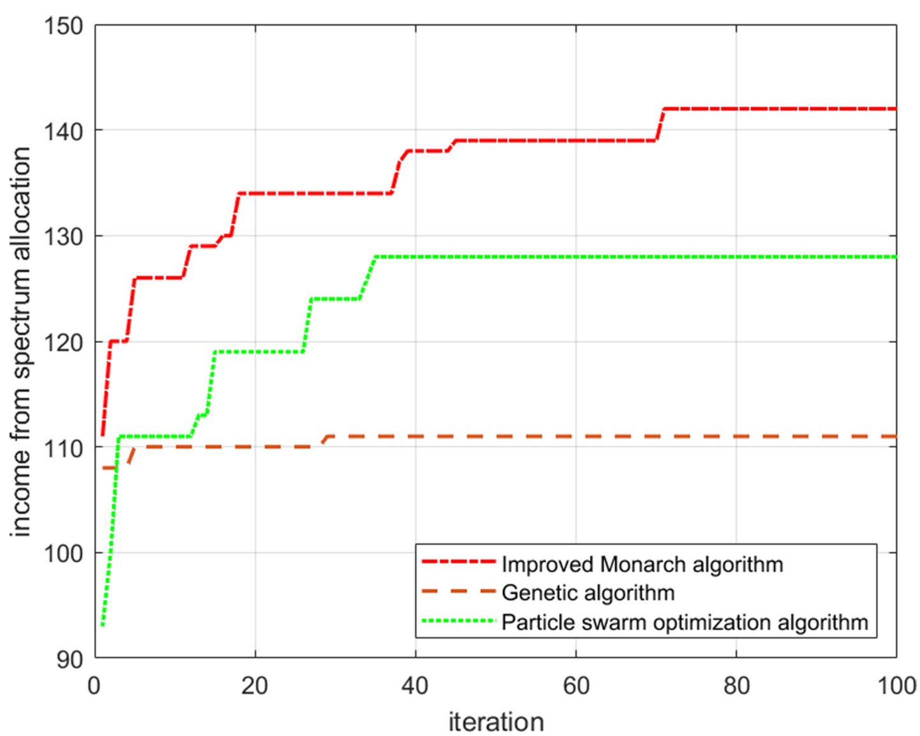

Fig. 6 Spectrum allocation income changes of the improved monarch butterfly algorithm, genetic algorithm and particle swarm optimization algorithm when $T = 9000$

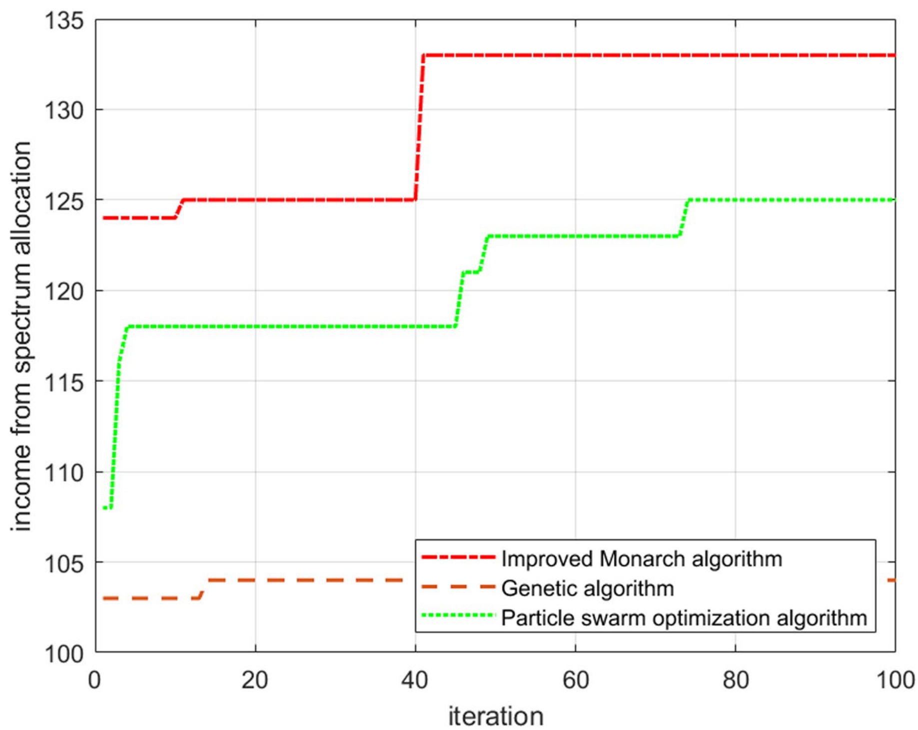

Fig. 7 Spectrum allocation income changes of the improved monarch butterfly algorithm, genetic algorithm and particle swarm optimization algorithm when $T = 12000$

the algorithm increases, and the spectrum allocation income obtained by the algorithm also changes. But the spectrum allocation income of the improved monarch butterfly algorithm is still higher than those of other algorithms. It indicates that the simulated annealing operator has a great influence on the improved monarch algorithm. Monarch butterfly algorithm has fast convergence is mainly due to the migration behavior of wolves algorithm introduced. Through increasing the diversity of population to avoid the algorithm trapped in local optimal solution, the algorithm can quickly converge to global optimal point rather than local optimal point.

Figures 8 shows the curve of the average network income as the number of cognitive users changes. In the experiment, the number of available spectrum is 15, and the number of cognitive users is 5-35 (with an interval of 5). The experimental results show that the improved monarch butterfly algorithm is significantly better than the two other algorithms in different cognitive user scenarios. However, when the number of cognitive users increases and the number of spectrum remains unchanged, the gap between the three algorithms becomes smaller and smaller. The main reason is that with the increase of frequency devices, spectrum resources are gradually insufficient, and the possibility of frequency conflict between cognitive users is increasing, so that the network income decreases significantly. However, it can be seen from the figure that even in this case, the improved monarch butterfly algorithm still performs better.

The results shown in Fig. 9 show that the proposed algorithm is significantly better than the other traditional algorithms. With the increase of frequency devices, the proposed algorithm is obviously better than the other traditional algorithms.

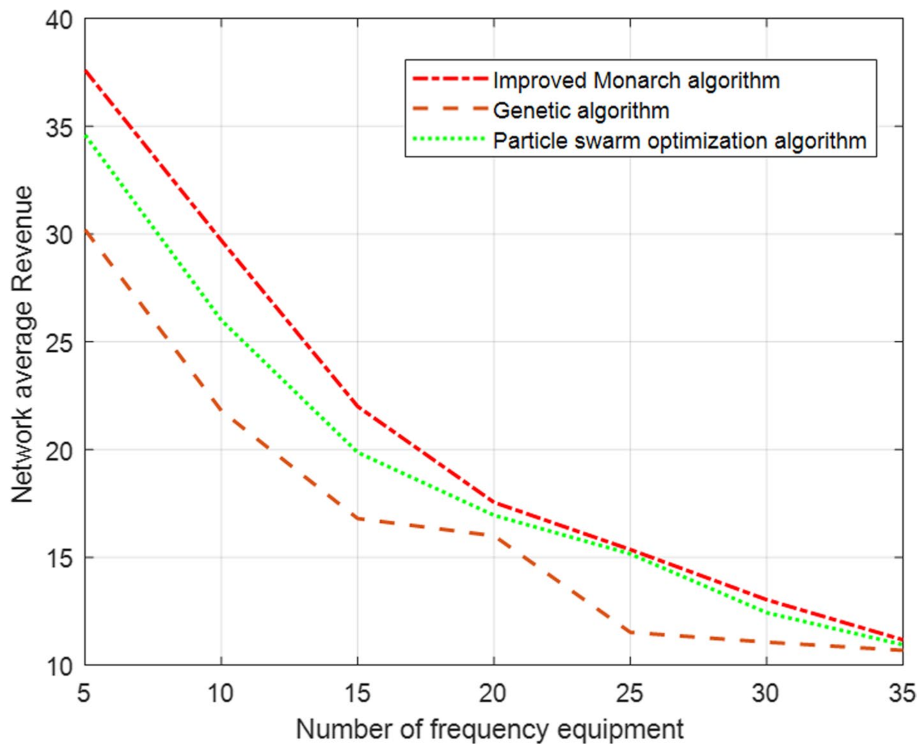

Fig. 8 When $T = 3000$, the average income transformation of the network when the number of frequency equipment changes

When the number of spectrum changes, the performance of spectrum allocation algorithm will be affected. The network average income of the three algorithms is compared when the amount of available spectrum changes, i.e., the simulated degradation temperature T is 3000, 6000 and 9000, respectively. Figures 9, 10 and 11 show the performance gap between the improved monarch algorithm and the other algorithms when the amount of spectrum available changes. Here, the number of the cognitive user takes 15, and the amount of spectrum available varies between 5 and 35 (with an interval of 5). The experimental results show that when the number of available spectrum increases gradually, the gap between the improved monarch algorithm and other algorithms becomes larger and larger. Since the number of cognitive users is set to 15, when the number of the spectrum is relatively small, the probability of conflict between cognitive users is very high, so that the average revenue of the three spectrum allocation algorithms is not much different in spectrum allocation. However, as increasing the number of available spectrum, the gap of the average network revenue gradually increases between the improved monarch butterfly algorithm and the other two algorithms. Due to the introduction of chaotic mapping operator into the monarch butterfly algorithm, the improved algorithm has better search ability.

Tables 1 and 2 show the iteration times when the three algorithms achieve convergence under different numbers of cognitive users and spectrum. Compared with genetic algorithm and particle swarm optimization algorithm, the convergence times of the proposed algorithm are changed as increasing the number of cognitive users and spectrum. However, the improved monarch butterfly algorithm is significantly better than the other

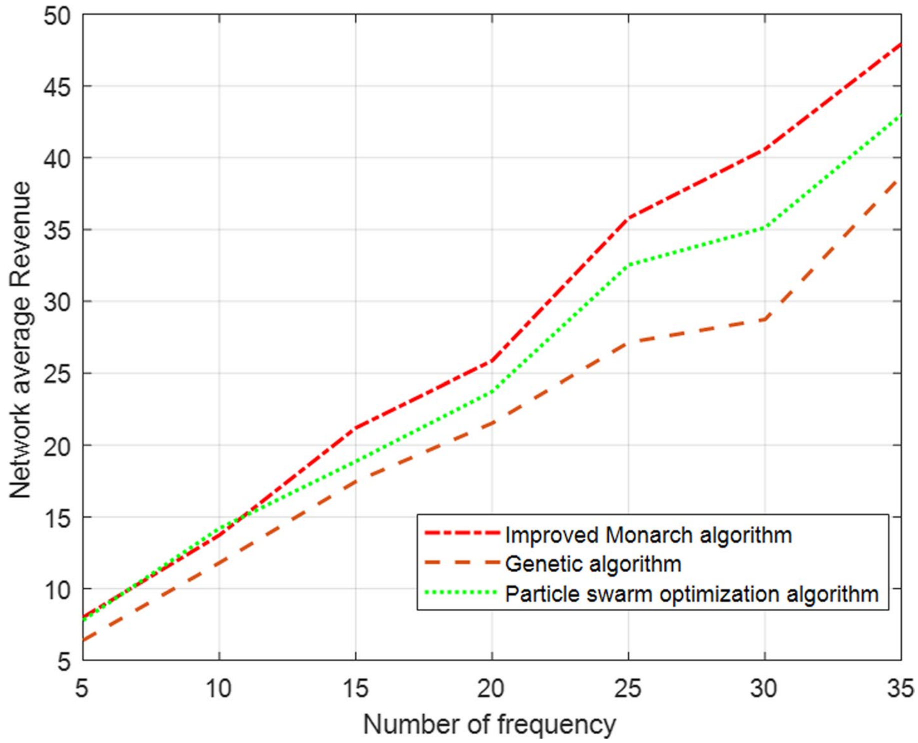

Fig. 9 Average income transformation of the network, when $T = 3000$ and the number of spectrum changes

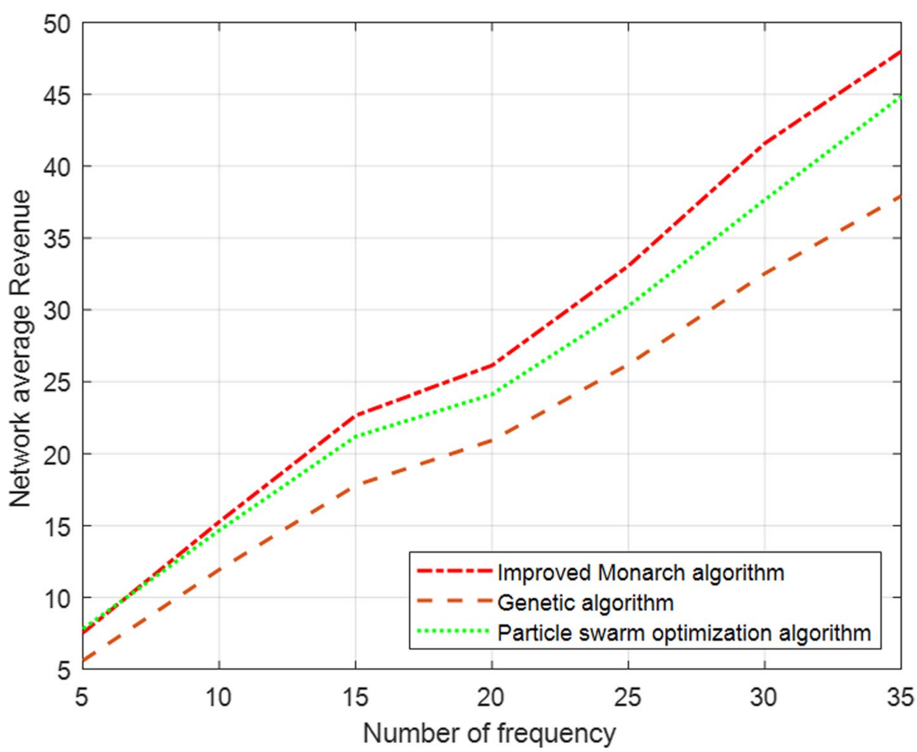

Fig. 10 Average income transformation of the network, when $T = 6000$ and the number of spectrum changes

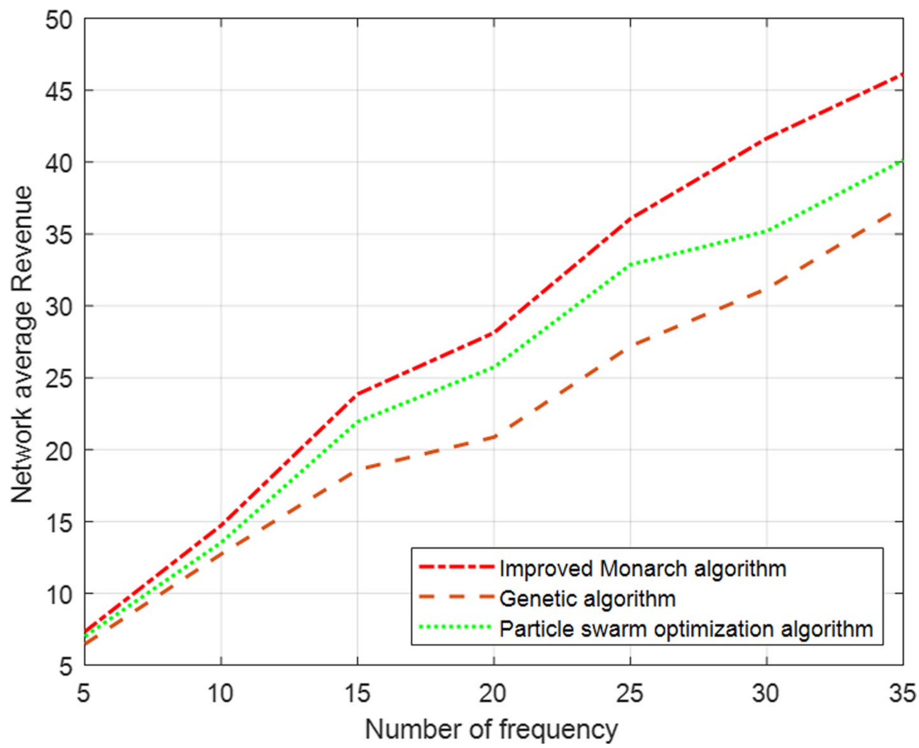

Fig. 11 Average income transformation of the network, when $T = 9000$ and the number of spectrum changes

Table 1 Convergence times of the three algorithms when recognizing user changes

Number of equipment	Improved Monarch	GA	PSO
5	22	79	71
10	12	39	92
15	18	88	72
20	22	6	78
25	7	6	85
30	5	5	24
35	4	4	62

Table 2 Convergence times of the three algorithms when recognizing user changes

Number of equipment	Improved Monarch	GA	PSO
5	38	6	94
10	18	45	95
15	58	82	55
20	4	8	40
25	42	76	42
30	40	72	41
35	18	8	53

two algorithms, and more stable than the other two algorithms. The main reason is that monarch butterfly algorithm increases the wandering behavior of wolf pack algorithm to update the population and annealing selection operator, so that the algorithm has better exploration ability and can find the global optimal solution relatively quickly.

6 Conclusion

In this paper, an improved monarch butterfly algorithm was proposed to solve the problem of trapped local optimum solution for spectrum allocation. The proposed algorithm utilized the simulated annealing factor to select the appropriate mobility and employed the chaotic mapping operator and the wolf pack travel update operator to improve the population diversity. Simulation results showed that when the number of frequency devices and frequency resources are fixed, the improved monarch butterfly algorithm is obviously superior to particle swarm optimization algorithm and genetic algorithm. Moreover, the convergence speed of the proposed algorithm is better than those of the two other algorithms. When the numbers of the frequency devices and available frequency resources change, the improved monarch butterfly algorithm still performs the two other algorithms. Therefore, the improved monarch butterfly algorithm has a good optimization performance and obtain outstanding spectrum allocation income and convergence speed.

Abbreviations

PSO	Particle swarm optimization algorithm
GA	Genetic algorithm
MO	Migration operator
BAO	Butterfly adjustment operator

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Declarations

Ethics approval and consent to participate
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