# A CWMN Spectrum Allocation Based on Multi-strategy Fusion Glowworm Swarm Optimization Algorithm

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**Abstract.** In cognitive wireless mesh networks, genetic algorithm based spectrum allocation has the problems of easily falling into local optimum, low accuracy and slow convergence. Aiming at the problems, glowworm swarm optimization is applied into spectrum allocation, and a multi-strategy fusion glowworm swarm optimization algorithm is proposed in this paper, in which step size and fluorescein volatilization factor are dynamically optimized and positions of the glowworms that has fallen into local optimum can be disturbed by Gauss mutation operator. Compared with genetic algorithm and basic glowworm swarm algorithm, the theoretical analysis and simulation results show that the proposed algorithm can avoid falling into local optimum, converge more quickly to the global optimal solution, and obtain higher system bandwidth reward.

**Keywords:** Cognitive wireless mesh network (CWMN) · Spectrum allocation Glowworm swarm optimization (GSO) · Multi-strategy fusion

## 1 Introduction

Cognitive radio (CR) [1] is a new technology implementing dynamic spectrum access of wireless network, while cognitive wireless mesh network (CWMN) [2, 3] is a wireless mesh network integrating the technology of cognitive radio. The significant feature of CWMN is the absence of infrastructure, where each mesh node is the cognitive node. Based on the mechanism of spectrum allocation and sharing, mesh node has the ability of perceiving the surrounding wireless environment and intelligently get access to the bands that not used by the primary user (PU), for the purpose of solving the increasingly serious problem of lacking of spectrum resource.

In CWMN, when cognitive nodes dynamically using licensed bands must guarantee that it has no effect on the communication quality of the primary user. So the current main research problem is how to properly allocate unused authorized spectrum holes to cognitive mesh nodes. In recent years, the commonly used wireless spectrum

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dynamic allocation methods mainly include game theory [4], auction theory [5], evolutionary theory [6–9] and the graph coloring [10], where graph theory method has become the key point method of spectrum allocation for its flexibility and efficiency. But there unavoidably exists unfair allocation and high time cost in graph theory method. Later, some classical evolutionary algorithms combined with graph theory coloring method are proposed applying to the research of spectrum allocation.

In evolutionary theory, glowworm swarm optimization algorithm (GSO) is a new kind of bionic swarm intelligent stochastic optimization algorithm proposed in recent years, which has been successfully applied to different fields with strong ability of problem solving [11–14]. Literature [15] aims at the problem of precocity and stagnation of multi peak function when using basic GSO, an adaptive step size algorithm was put forward that enable avoiding glowworms falling into the local optima to a certain extent. But there were no in-depth studies on the parameter optimization and other applications of algorithm. To overcome the shortcoming, this paper proposed a CWMN network spectrum allocation algorithm based on multi-strategy fusion glowworm swarm optimization combined with the graph coloring model of spectrum allocation. The step size and volatile factor are optimized for adaptive adjustment in the algorithm. Besides, the updating formula of glowworm dynamic decision domain radius is adjusted for avoiding the existence of isolated glowworms, and Gauss mutation is applied to glowworms falling into the local optimum in the process of evolutionary. What's more, when necessary, the algorithm would retrospect after the disturbance. Through the improvement of the above aspects, the simulation results show that the multi-strategy fusion glowworm swarm optimization algorithm improves the optimization ability and convergence rate in spectrum allocation.

## 2 Network Model and Problem Description

Similar to the traditional wireless mesh network, cognitive wireless mesh network has the ability of cognition, reconfiguration and self-organizing, and could automatically establish nodes and maintain network connectivity. Cognitive Mesh nodes (Mesh router, client nodes and other network devices) in CWMN improve network performance through the search and sharing of the available authorized spectrum. Target for channel allocation in cognitive wireless mesh networks is assigning the available channels to SU (secondary user) in order to improve the spectrum utilization rate and maximizing reduces the interference to the PU (primary user) user. Figure 1 illustrates the structure of cognitive wireless mesh networks.

Correspondingly, CWMN network spectrum allocation model based on graph theory shown in Fig. 2 can be described as channel availability matrix, channel reward matrix, interference constraint matrix and valid channel allocation matrix. Supposing that there are $N$ cognitive users waiting to communicate at a certain time, while there are $M$ idle frequency bands can be used at the same time. The definition of the matrix is as follows:

(1) Channel availability matrix $L_0 L = \left\{ l_{n,m} \middle| l_{n,m} \in \{0,1\} \right\}_{N \times M}$ represents the channel availability. If $l_{n,m} = 1$, then channel $m$ is available for cognitive user $n$.

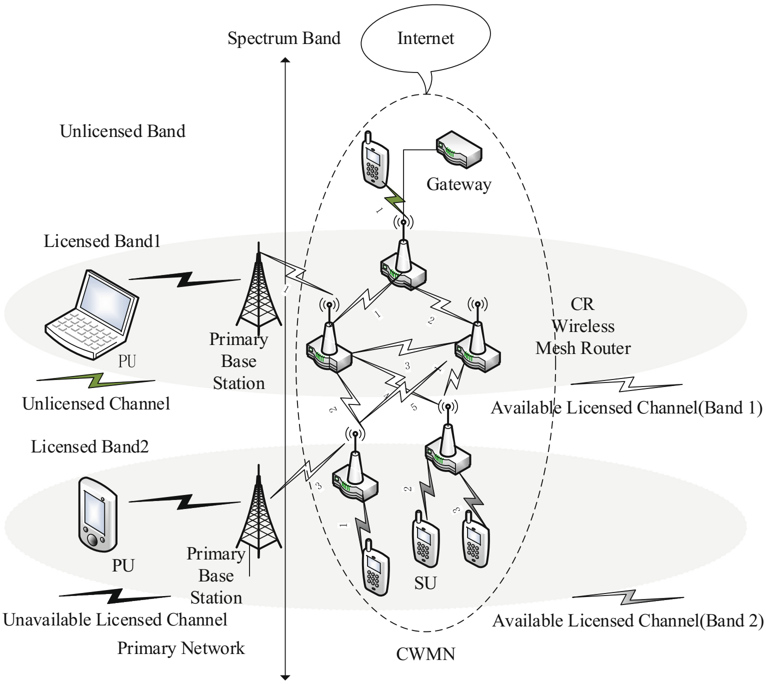


**Fig. 1.** Structure of cognitive wireless mesh network

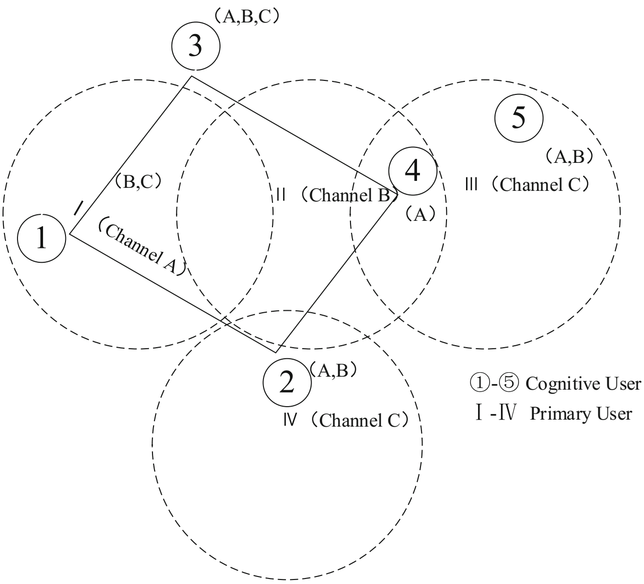


**Fig. 2.** Graph theoretic model for cognitive radio systems

(2) Channel reward matrix $B_0B = \{b_{n,m}\}_{N \times M}$, $b_{n,m}$ represents the channel reward of cognitive user $n$ using channel $m$.
(3) Interference constraint matrix $C_0C = \{c_{n,k,m} | c_{n,k,m} \in \{0,1\}\}_{N \times N \times M}$, if $c_{n,k,m} = 1$, then it means that cognitive user $n$ and $k$ using the frequency band $m$ simultaneously will cause conflict.
(4) Valid channel allocation matrix $A_0A = \{a_{n,m} | a_{n,m} \in \{0,1\}\}_{N \times M}$, if $a_{n,m}$=1, then it means that channel $m$ is assigned to cognitive user $n$.

$$\begin{cases} a_{n,m} \cdot a_{k,m} = 0 \\ c_{n,k,m} = 1 \end{cases} ; 0 \leq n, k < N, 0 \leq m < M \tag{1}$$

(5) Under the premise of valid channel allocation matrix, the total system bandwidth reward can be described as follows:

$$U = \sum_{n=1}^{N} \sum_{m=1}^{M} a_{n,m} \cdot b_{n,m} \tag{2}$$

# 3 Multi-strategy Fusion Glowworm Swarm Optimization Algorithm

Aiming at the shortness of the basic glowworm swarm optimization algorithm, a multi-strategy fusion glowworm swarm optimization algorithm (MSF-GSO) was proposed in this paper, which mainly realizes the following improvements:

(1) To avoid glowworms falling into the local optimum, the Gauss mutation is used to help glowworms jump out of the local optimum, and to search for the global optimum.
(2) Step size $s$ was adjusted to make adaptive adjustment to coordinate the relationship between global search and local search.
(3) Volatile factor $\rho$ was adjusted to make adaptive adjustment to improve the convergence speed and accuracy of the algorithm.
(4) In formula of updating neighborhood radius, the first parameter in adjusted to a parameter changing max from 0 to 0.1 to avoid the presence of isolated glowworms.

## 3.1 Gauss Mutation Operator

Aiming at the problems that glowworm swarm optimization algorithm easily falls into the local optima and has rather slow convergence speed. Gauss mutation was introduced, which adds random vectors obeying the Gauss distribution to the state of the original individual. The definition of Gauss mutation is as follows:

$$X_i = X_i \times [1 + k \times N(0,1)] \tag{3}$$

Where $X_i$ represents the state of the first $i$ glowworm individual, $k$ is the decreasing variable varying from 1 to 0, $N(0,1)$ is the random vector of the Gauss distribution with the mean of 0 and the variance of 1. Formula (3) adds decreasing stochastic disturbance term of Gauss distribution $X_i \times k \times N(0,1)$ to original $X_i$, which makes full use of the interference of the current population information, increases the diversity of the population, and helps glowworm jump out of the local optima to search the global optima, improves the search speed, also. In the iterative process of algorithm, once glowworms fall into local optima, the convergence rate of the algorithm would be affected greatly. So, it's urgent that the worst states of glowworm need to be eliminated, which are replaced by historical best glowworm. Then the intermediate populations of glowworm are obtained, which would need to carry out Gauss mutation. To check whether the results are improved with the increase of the number of iterations, the algorithm sets up a bulletin board to record the state of the best glowworm in history and the value of the objective function. When the bulletin board has not be changed or changed a little (e.g. the amplitude of change is less than $\mu$) in the three successive iterations. At the time, we can see the glowworm as fallen into local optima, then the mutation operation need to be carried out, where $\mu$ is the parameter to control Gauss mutation, the greater the parameter $\mu$, the greater the probability of Gauss mutation, the faster the convergence speed will be, but it will increase the amount of computation. Therefore, the value of $\mu$ should not be too large, generally take the number between $10^{-4} - 10^{-5}$.

In addition, the process of retrospect is increased in the iterative process. If the value of the step size is still larger, the algorithm then shifts to the location updating after the disturbance and start a new round of optimization.

### 3.2 Variable Step Size Strategy

In the glowworm swarm optimization algorithm, the experimental results can be limited by two aspects for step size is constant. If step size is smaller, the convergence of the algorithm would be affected; if step size is larger, it's very easy to skip the global optimum in the search process. In the later period of algorithm, the glowworm individuals would face oscillation phenomenon in the vicinity of the peak, which would lead to the decrease in the accuracy of search. Therefore, the constant step size can't be well used to solve the problem of different need of step size in the period of early stage and later stage. To solve the problem, an improved variable step size optimization algorithm was proposed, formula (4) and (5) are used to adjust the step size. It can be seen that $c$ is negative value, $s(t)$ is in the slow decline with the number of iterations increasing. It means that allocating larger step values for the glowworm individuals in early iterations to improve the search speed, and allocating smaller step values for the glowworm individuals in later iterations to avoid skipping optimal to achieve the purpose of optimization.

$$c = \frac{1}{t_{\max}} \ln\left(\frac{S_{\min}}{S_{\max}}\right) \tag{4}$$

$$s(t) = S_{\max} e^{c \cdot g_t} \tag{5}$$

In the formula (4) and (5), current iteration number and the maximum number of iterations are respectively expressed as $g_t$ and $t_{\max}$, the minimum value and maximum value of $s$ are respectively expressed as $S_{min}$, $S_{\max}$. All those are given values in the simulation.

### 3.3 Parameter Adaptive Strategy

In addition, there are also some important factors affecting the convergence speed and the accuracy of algorithm, such as volatile factor. In the glowworm swarm optimization algorithm, the value of volatile factor is a constant value. The limitation of constant $\rho$ is very obvious. If $\rho$ is relatively small, the updating of fluorescein would be greatly affected by previous accumulated fluorescein, which seriously weakens the search randomness and easily falling into local optimum, therefore it is not conducive to the expansion of space of algorithm. If $\rho$ is relatively larger, the updating of fluorescein would reduce effects from previous accumulated fluorescein, which then strength $\rho$ hens the search randomness, but it results in lower convergence speed. Therefore, this paper improves the performance of the algorithm by means of adaptive variation of the fluorescein volatile factor $\rho$, and the adaptive adjustment is based on the formula (6). Besides, with the increase of the number of iterations, it becomes a trend that glowworm individuals would gather together gradually. Then there would be a large number of glowworms in a small neighborhood. Therefore, the dynamic decision domain radius of glowworm easily reduces to 0, which leads to the formation of isolated glowworms and is not conducive to share group information and conduct cooperative search. Therefore, to avoid the existence of isolated glowworm, the dynamic decision domain radius needs to be adjusted as shown in the formula (7).

$$\rho = \begin{cases} 1 - \rho_{\max} \exp\left(-ct^{\frac{1}{N}}\right) & \rho < \rho_{\max} \\ \rho_{\max} & \rho \geq \rho_{\max} \end{cases} \tag{6}$$

In the formula (6), $t$ means the number of iterations, $c$ means regulator, $N$ means the number of cognitive radio users, $\rho_{\max}$ means the maximum value of $\rho$, which is set to the prevent convergence speed reducing for $\rho$ is too larger.

$$r_d^i(t+1) = \min\left\{ r_s, \max\left\{ 0.1 \times \frac{i}{T-1}, r_d^i(t) + \beta(n_l - |N_i(t)|) \right\} \right\} \tag{7}$$

In the formula (7), the value of $i$ is $0, 1, 2, 3, \ldots.., T-1$, which is to make the first parameter value between $0 - 0.1$.

### 3.4 Multi-strategy Fusion Glowworm Swarm Optimization Algorithm

The glowworm swarm optimization algorithm is as follows:

**Algorithm 1.** Glowworm swarmoptimization algorithm

Set number of dimensions and glowworms<br>
Let $s$ be the step size<br>
Initialize all other parameters<br>
For $i=1$ to $n$ do $l_i(0)=l_0$<br>
Set maximum iteration number $=T_{max}$<br>
Set $t=1$;<br>
**while** $t \le T_{max}$ **do**<br>
    **for** each glowworm $i$ **do**<br>
        **for** each glowworm $i$ $j \in N_i(\mathrm{t})$ **do**

$$l_i(t)=(1-\rho)l_i(t-1)+\gamma J(\chi_i(t)) \quad (8)$$

$$p_{ij}(\mathrm{t})=(l_j(\mathrm{t})-l_i(\mathrm{t}))/\sum_{k\in N_i(\mathrm{t})}(l_k(\mathrm{t})-l_i(\mathrm{t})) \quad (9)$$

$$j=select\_glowworm(\vec{\mathrm{p}})$$

$$x_i(\mathrm{t+1})=x_i(\mathrm{t})+\mathrm{s}((x_j(\mathrm{t})-x_i(\mathrm{t}))/(\|(x_i(\mathrm{t})-x_i(\mathrm{t})\|)) \quad (10)$$

$$r_d^{\,i}(\mathrm{t+1})=\min\{r_s,\max\{0,r_d^{\,i}(\mathrm{t})+\beta(\mathrm{n_t}-|N_i(\mathrm{t})|)\}\} \quad (11)$$

        **end for**<br>
        $index=\max(l)$<br>
        $x_{index}=brighest$<br>
        $t=t+1$;<br>
    **end for**<br>
**end while**

Where $t$ means the number of iteration, $\rho$ means the fluorescein volatile factor, $\gamma$ means the fluorescein update rate, $l_i(0)$ means the fluorescein initial value, $n$ means the total number of glowworms, $T_{max}$ means maximum number of iterations, $r_s$ means the sensing radius of glowworm individual, $\beta$ means the renewal rate of dynamic decision domain, $n_t$ means the threshold of the number of glowworm within neighborhood.

The multi-strategy fusion glowworm swarm optimization algorithm is as follows:

**Algorithm 2.** Multi-strategy fusion glowworm swarm optimization algorithm

1: *Step 1:* Initialize population
Generate glowworms in the solution space randomly and initialize a series of parameters.
2: *Step 2:* Initialize the bulletin board
Make the location of the glowworm to meet the constraints and calculate the initial value of the target function of the glowworm and initialize the bulletin board.
3: *Step 3:* Bulletin board update
Calculate the current target function value of the glowworm, if it's better than the bulletin board information, then update the bulletin board.
4: *Step 4:* Gauss mutation
Current worst glowworm population is replaced by the best glowworm in history to obtain the intermediate glowworm population.
5: *Step 5:* Fluorescein value update
All glowworms update the fluorescein value according to formula (8).
6: *Step 6:* Glowworm motion stage
Calculate neighborhood set of each glowworm. Select the moving direction according to the roulette method. Then the position would be updated according to the formula (10) and the radius of the decision domain would be updated according to formula (11).
7: *Step 7:* Retrospect determine
Carry out the glowworm swarm disturbance once again, then check the value of step size. If the step size is still larger, then retrospect again, that's turning to step 2. Otherwise, turning to step 8.
8: *Step 8:* Termination determine
Complete one iteration and check whether reaching the maximum number of iterations $T$, if not satisfied, then turn to Step 2 to start the optimization process of next generation of glowworm, otherwise end the iteration.

The flow chart of the MSF-GSO algorithm is as follows (Fig. 3):

## 4 Experimental Result and Analysis

To verify the performance of the multi-strategy fusion glowworm swarm optimization algorithm, the original glowworm swarm optimization algorithm and genetic algorithm in spectrum allocation, system reward obtained by different algorithms are compared. In the simulation, the number of cognitive users is 20; the number of available channel is 12. We use MATLAB to simulate. In order to simplify the problem, we assume that available channel and interference relations of each cognitive user remain the same, and all cognitive users have the same interference radius in the complete process of spectrum allocation.

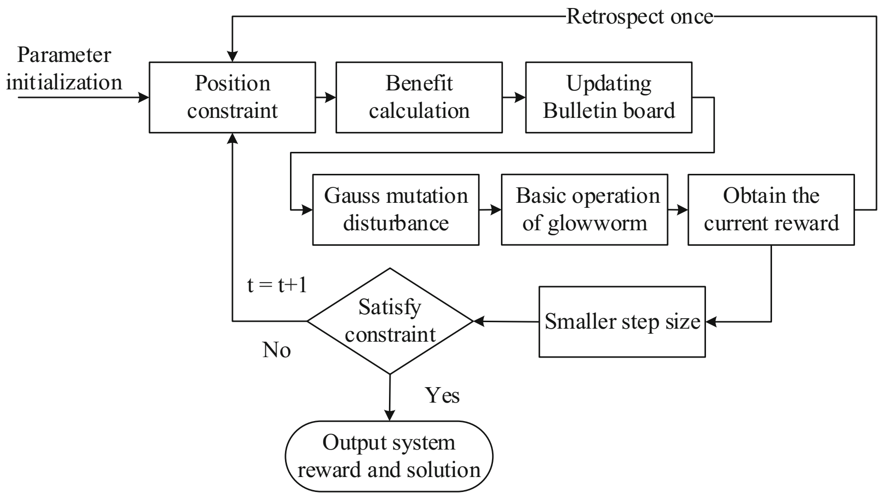


**Fig. 3.** Flow chart of MSF-GSO

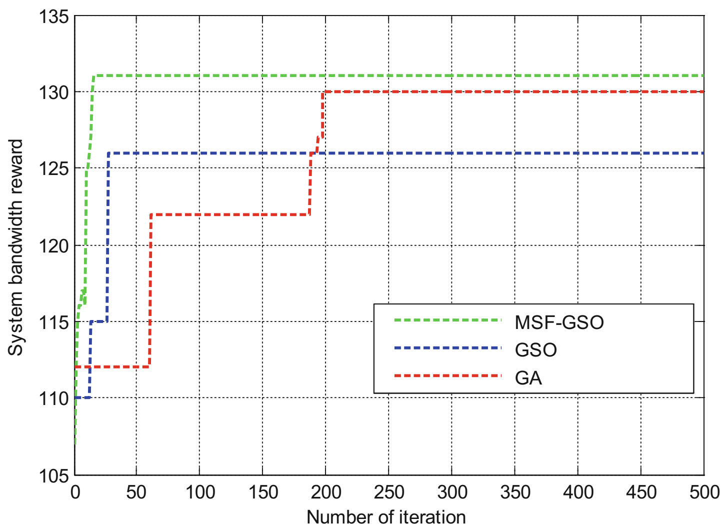


**Fig. 4.** The changes of system bandwidth reward with the number of iterations

Figure 4 shows the curve of system bandwidth reward changing with the number of iterations by using genetic algorithm, glowworm swarm optimization algorithm and multi-strategy fusion glowworm swarm optimization algorithm respectively. As can be seen from the above figure, the convergence speed of glowworm swarm optimization algorithm is faster than the genetic algorithm, but the system reward is a bit worse. The convergence speed of multi-strategy fusion glowworm swarm optimization algorithm is

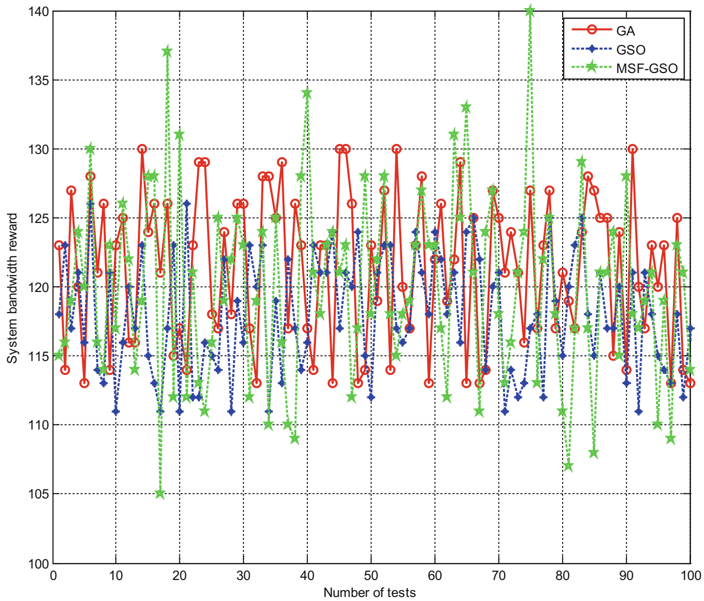


**Fig. 5.** The changes of system bandwidth reward with the number of tests

faster, and the maximum system reward reaches to 132, which are obtained at the 15 times of the iteration, and the system reward is better than that of the genetic algorithm.

Figure 5 shows the system bandwidth reward changes with the number of tests. It can be seen from the figure that the system reward obtained by multi-strategy fusion glowworm swarm optimization algorithm is obviously superior to the other two algorithms. Although every result is not the optimal result, but the average value is optimal. This is due to the MSF-GSO algorithm is a randomized algorithm. The performance of algorithm is easily affected by population size, maximum number of iterations and the threshold of neighborhood glowworm. So in practical application, the parameter should be adjusted properly based on the different conditions to obtain optimal results.

## 5 Conclusion

The key-point of spectrum allocation in cognitive wireless mesh network is to search the optimal solution to system maximum reward. A multi-strategy fusion glowworm swarm optimization algorithm is proposed based on the original glowworm swarm optimization algorithm in this paper. Firstly, the algorithm optimize the step size and volatile factor setting, which make both adaptive change with the number of iterations.

And adjust the updating formula of glowworm decision domain radius, which could effectively avoid the presence of isolated glowworm. Secondly, the process of Gauss mutation is added to the process of algorithm to disturb the local optima of the glowworm. After the disturbance, the step size needs to be checked. When necessary, the algorithm needs to retrospect. The simulation results show that compared with the glowworm swarm optimization algorithm and genetic algorithm, the multi-strategy fusion glowworm swarm optimization algorithm not only converges faster, but also has better system reward.

In future, we are planning to show the comparison with the genetic algorithm and glowworm swarm optimization and the changes of system bandwidth reward with the number of cognitive users. Moreover, we are also developing a model to analyze the transmission power consumption of the system by using different spectrum allocation algorithm.

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