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Application Research of Chaotic Binary Particle Swarm Optimization Algorithm in Dynamic Spectrum Allocation

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Abstract. Dynamic spectrum allocation (DSA) in cognitive radio system has become a hot topic to solve the spectrum scarcity. Particle swarm optimization (PSO) has shown great flexibility in solving the spectrum allocation problem, and many related studies have been proposed. However, there is still room for improvement in the problem that PSO will have a slow convergence rate in the DSA and the latter particle search is easy to fall into the local optimum. In this paper, a dynamic time-varying spectrum allocation scheme based on chaotic binary particle swarm optimization is proposed. The improved algorithm introduces the idea of chaotic map to optimize the initial population and the optimal position of each generation of particles, and utilizes the global ergodicity of chaotic map to overcome the shortcomings of the algorithm. Based on the graph theory model, a mathematical model of dimensionality reduction spectrum allocation is built to realize DSA for users. The experimental results show that the convergence time cost of the improved algorithm is low, and the higher network rewards can be obtained under different experiments, and the fast and efficient spectrum allocation is realized to satisfy the demands of cognitive radio communication.

Keywords: chaotic map, cognitive radio, network rewards, particle swarm optimization

1 Introduction

Cognitive radio is a new intelligent radio communication system based on software radio system, which can perceive the idle licensed spectrum around in real time and access the authorized frequency band with less interference [1]. DSA is one of the key technologies in cognitive radio [2]. In this network, high-priority primary users (PUs) and opportunistic secondary users (SUs) are defined [3]. SUs need to ensure no interference to the normal operation of PUs and surrounding SUs after it is connected to the authorized frequency band [4]. In order to reduce interference and improve the utilization of allocated spectrum, it is particularly important to establish an appropriate spectrum allocation mechanism.

In recent years, spectrum allocation has been studied a lot. At present, research models for spectrum allocation mainly include game theory, auction theory, graph coloring problem, etc [5]. By coordinating the competition among SUs and improving the allocation efficiency, the problems related to interference and network rewards are eliminated. The graph coloring model is simple and efficient to suppress interference and improve network rewards, but the constructed spectrum allocation model is a nonlinear 0-1 programming problem, and such problem is a NP-hard problem [6]. Many researchers introduce intelligent evolutionary algorithm into graph theory model to solve the spectrum allocation problem. The studies show that evolutionary algorithms can efficiently solve NP-hard problem and obtain good allocation rewards [7]. However, the global development ability and local exploration ability of the

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algorithm need to be further improved. Experiments show that evolutionary algorithms such as genetic algorithm (GA), ant colony optimization (ACO) and PSO have been successfully applied, and better network rewards have been obtained. Among them, PSO has fewer parameters to adjust and strong global search ability. Therefore, this paper proposes an improved PSO combined with graph theory model to make up for the shortcomings of the algorithm and obtain better network rewards.

In this paper, we adopt the graph theory model and the improved PSO to solve spectrum allocation problem in cognitive radio networks. The main contributions of our work are as follows: A dynamic time-varying spectrum allocation scheme based on chaotic logistic binary particle swarm optimization (CLBPSO) is proposed. Combining chaotic map system with PSO, the initial population and the optimal position of each generation are optimized by using the global ergodicity and randomness of chaotic map, the global search ability of PSO is improved and jumped out the local optimal solution to obtain the ideal optimal solution.

The rest of this paper is organized as follows. Section 2 gives a survey of the related works on spectrum allocation. The spectrum allocation model is described in Section 3. Section 4 designs an improved PSO in detail. Section 5 describes the spectrum allocation strategy based on CLBPSO. Section 6 provides the simulation results and analysis. Finally, the conclusions and future research are presented in Section 7.

2 Related Works

Most of the existing spectrum allocation algorithms mainly solve the problems of improving spectrum utilization, reducing user interference and improving network rewards. Because the graph theory model is ideal and simple to solve the spectrum allocation problem, the intelligent evolutionary algorithm based on graph theory model has been widely studied [8]. Chaotic optimization system and PSO show excellent performance in solving spectrum allocation by evolutionary algorithms. In [9], authors proposed a chaotic quantum cloning algorithm (CQCA) to solve the spectrum allocation problem. It used chaotic map to optimize the initial population and used quantum revolving door to screen for cloned variant individuals, which improved traditional clonal algorithm in order to solve multi-object spectrum allocation problem and could obtain high performance precision. Nevertheless, the calculation process was complicated and the calculation time was long. In [10], the constraint operator for BPSO was designed, its main role was to constrain users who disturbed each other when they used spectrum. The improved algorithm was applied to the spectrum allocation to verify that it could guarantee the fair occupancy of spectrum among cognitive users. However, binary particle swarm optimization (BPSO) had the disadvantages of single search direction and slow convergence in the later stage, which still made the allocation scheme inadequate. In [11], a spectrum allocation scheme based on improved binary particle swarm optimization (IBPSO) was designed, the scheme discretized the particle velocity equation. The improved equation was used to update the particle position to ensure the continuity of evolution, but the algorithm was difficult to get the ideal solution. In [12], authors proposed a spectrum allocation scheme based on the population aggregation degree of BPSO. It improved the defect of the original algorithm which was difficult to find the global optimal solution and premature maturity. However, the relationship between the number of available spectrum and the global optimization of the algorithm was not considered, and the universality of the algorithm was reduced. In [13], authors considered the users' requirements and spectrum characteristics, and proposed an enhanced PSO to better balance the spectrum utilization and fairness among users. However, the network rewards was low and convergence rate was slow. In [14], A PSO spectrum allocation algorithm based on bit error rate, total power usage and individual transmission rate was designed. This method could provide higher transmission rate in real time, but the algorithm allocation time was too long to meet the actual communication requirements.

The above studies do not well overcome the shortcomings of the algorithm, and the convergence time and network rewards of spectrum allocation need to be further improved. In order to solve the problems of CQCA and IBPSO in the process of spectrum allocation, which are complex calculation, multiple convergent iterations and easy to get partial optimal results. In this paper, a list of reduced-dimensional spectrum is designed, and a chaotic optimization system is introduced to improve PSO. A spectrum allocation scheme based on CLBPSO is proposed. The simulation results show that convergence time of the scheme is short, and the system network rewards is high.

3 Spectrum Allocation Model

The spectrum allocation of cognitive radio needs to allocate available spectrum for SUs while ensuring the normal communication of PUs. The spectrum allocation scheme should ensure three elements [15]: the first is to ensure no interference among SUs, the second is to maximize network rewards, and the third is to reduce allocation time. Therefore, based on the graph theory model, this paper builds the reduced dimension spectrum allocation list and designs the spectrum allocation scheme of an improved PSO, which maximizes network rewards and cuts allocation time to meet the communication demands of cognitive radio systems.

3.1 Graph Theory Spectrum Allocation Model

In the cognitive radio system, PU and SU adjust communication range by changing transmit power. As shown in Fig. 1, there are 3 PUs, 8 SUs, and 3 available channels in this system model. The number of available channels is the same as the number of PUs. The SUs in the PU communication range can't use the channel occupied by the PUs to ensure that the SUs don't affect the normal operation of the PUs when they are occupying the channels. That is, SU_1, SU_2 and SU_3 in the Fig. 1 cannot use channel A occupied by PU_1, while SU_3, SU_4, SU_5, SU_6, SU_7 and SU_8 outside the communication range of PU_1 can occupy channel A. The availability of other channels is analogous to this. It is also necessary to note that the communication scopes of SU_3 and SU_4 are overlap in the Fig. 1, indicating that the two cannot use the same channel at the same time, otherwise there will be communication interference.

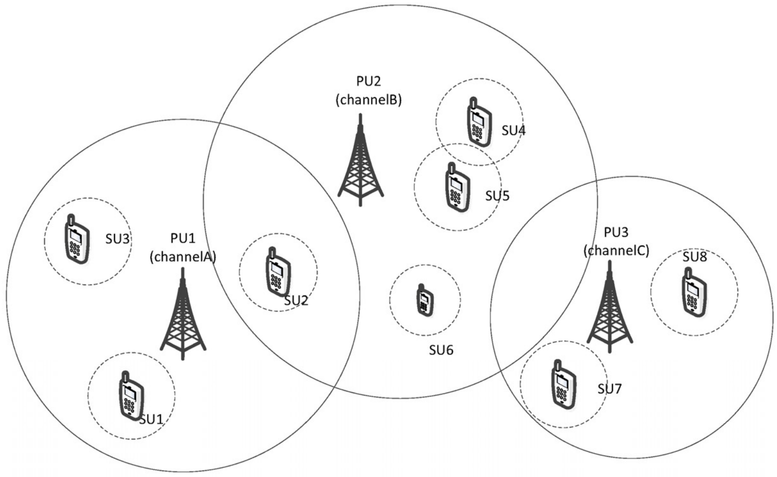

Fig. 1. Model of cognitive radio system

The spectrum model of graph theory in this paper is described by available matrix *L*, reward matrix *B*, interference matrix *C* and Non-interference allocation matrix *A*, where *N* and *M* are SUs sets and available spectrum sets, and the specific descriptions are as follows.

(1) Channel availability matrix *L*

$$L=\{l_{n,m}|l_{n,m}\in\{0,1\}\}_{N\times M}. \quad \textbf{(1)}$$

L represents the relationship between the cognitive user *N* and the spectrum *M*. If $l_{n,m}=1$, indicates that the cognitive user *n* can use spectrum *m*. Then $l_{n,m}=0$, it means that the cognitive user cannot use spectrum *m*. The actual meaning is expressed as that cognitive users outside the licensed spectrum *m* can use this spectrum, cognitive users within the range of coverage are not allowed to use it.

(2) Reward matrix *B*

$$B=\{\mathrm{b}_{n,m}\mid \mathrm{b}_{n,m}>0\}_{N\times M}. \quad \textbf{(2)}$$

B represents the rewards that can be obtained when cognitive user *n* uses channel *m*, which is greater than zero. Because different cognitive users have different distances from spectrum *m*, the transmit power and modulation method will also be different, so the rewards obtained by each user must be different. In actual communication, the rewards obtained by cognitive users are proportional to the communication coverage area. And it is worth noting that when $l_{n,m}=0$, then $b_{n,m}=0$.

(3) Interference matrix C

$$C=\{c_{n,k,m}\mid c_{n,k,m}\in\{0,1\}\}_{N\times N\times M}. \quad \textbf{(3)}$$

C indicates whether multiple cognitive users occupy the same channel at the same time to generate interference. If $c_{n,k,m}=1$, it means that cognitive users n and k will interfere when they use spectrum m at the same time, and they cannot be used at the same time. In the actual communication, it is indicated that the communication coverage range of cognitive user n and cognitive user k is overlapped, when they occupy the channel m. That is, the communication interference is generated. If $c_{n,k,m}=0$, indicating that simultaneous occupancy will not cause interference. And the interference matrix C is determined by the availability matrix L, that is $c_{n,k,m}\le l_{n,m}\times l_{k,m}$, when n=k, $c_{n,n,m}=1-l_{n,m}$.

(4) Non-interference allocation matrix A

$$A=\{a_{n,m}\mid a_{n,m}\in\{0,1\}\}_{N\times M}. \quad \textbf{(4)}$$

A represents the spectrum condition allocated by each cognitive user, which means a feasible spectrum allocation scheme. If $a_{n,m}=1$, indicating that the cognitive user n has allocated spectrum m. On the contrary, it means that the cognitive user n is not allocated spectrum m. Spectrum allocation must meet the non-interference constraint defined by the interference matrix C, conditions are as follows: $a_{n,m}+a_{k,m}\le 1$ and $c_{n,k,m}=1,\ \forall n,k\in[1,N],\mathrm{m}\in[1,M]$.

3.2 Fitness Function

In the spectrum allocation algorithm, a specific spectrum scheme is given to the SU n, Then total rewards obtained by the SU n is as follows: $\alpha_n=\sum_{m=1}^{M}a_{n,m}\cdot b_{n,m}$. The total reward U of all cognitive users is $U=\sum_{n=1}^{N}\alpha_n$. That is, the objective function of this paper is expressed as:

$$U=\sum_{n=1}^{N}\alpha_n=\sum_{n=1}^{N}a_{n,m}\cdot b_{n,m}, \quad \textbf{(5)}$$

$$A^*=\underset{A\in\Lambda(\mathrm{L},\mathrm{C})_{N,M}}{\arg}\ \max\sum_{n=1}^{N}\sum_{m=1}^{M}U. \quad \textbf{(6)}$$

The Eq. (5) represents the total maximum network rewards, Where α_n is the total reward of a single user n. The Eq. (6), all non-interference available spectrum matrices meeting the constraint condition are denoted as the set of A. The purpose of this paper is to find the optimal distribution matrix A^* according to the Eq. (5).

4 Binary Particle Swarm Algorithm with Chaos Optimization

4.1 Standard Binary Particle Swarm Optimization

PSO has been widely researched and applied since it was put forward due to its simple implementation and better global optimization capability [16]. But PSO is only suitable for continuous space optimization, such as continuous function and continuous variable operation. In order to solve the limitation of PSO in discrete space, in 1997, Dr. J. Kennedy and R.C. Eberhart proposed BPSO based on PSO [17]. Since the spectrum allocation problem in this paper is a discrete space optimization problem, BPSO is used to find the optimal solution.

In BPSO, the position of each particle is represented by binary variables, that is, each dimension of particle position is 0 or 1. The particle velocity equation is the same as the PSO velocity equation such as the Eq. (7), indicating the probability of a change in particle position 0 or 1. Equations of the particle velocity and position are as follows:

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 (p_{id}^{t} - x_{id}^{t}) + c_2 r_2 (p_{gd}^{t} - x_{id}^{t}), \tag{7}$$

$$x_{id}^{t+1} = \begin{cases} 1, & \eta < \theta(v_{id}^{t+1}) \\ 0, & \eta \geq \theta(v_{id}^{t+1}) \end{cases}. \tag{8}$$

In the Eq. (7), where v_{id}^{t+1} is the d-dimensional velocity of the next-generation particle i, which is the step size of the search space. p_{id}^{t} is the optimal position of the d-dimensional position of particle i after the t iteration. p_{gd}^{t} is the d-dimensional position of the particle population optimal position after the t iteration. x_{id}^{t} is the d-dimensional position of the current particle i after the t iteration. r_1 and r_2 are random numbers uniformly distributed in the (0, 1), c_1 and c_2 are learning weights, generally c_1=c_2=2, w is the inertia weight, which is the degree of reference to the original rate vector [18]. In the Eq. (8), x_{id}^{t+1} is the d-dimensional position of the next generation particle i, where η is a random number generated randomly between [0, 1], $\theta(v_{id}^{t+1})$ is a Sigmoid function that limits the continuous value of velocity between [0, 1], which is as follows:

$$\theta(v_{id}^{t+1}) = \frac{1}{1+\exp(-v_{id}^{t+1})}. \tag{9}$$

From the Eq. (9), it can be seen that the higher speed result in $\theta(v_{id}^{t+1})$ closer 1. The Eq. (8) can be understood as x_{id}^{t+1} is 1, when the value is greater than the random number η. That is, after the t+1 iteration, the value on the d-dimension of the particle i is 1, otherwise, it is set to 0.

4.2 Chaotic Map Optimization of Particle Position and Velocity

The particles generated by PSO in initial population process are randomly distributed in the solution space, quality of the initial population will have an impact on the results of the later iterations. Therefore, chaos map is introduced in the initial period of population. The initial population particles are distributed globally in the solution space by using its global ergodicity and initial sensitivity [19]. It is convenient for particles to search globally and find the initial global optimal solution. BPSO tends to fall into local optimum in search process of later algorithm. Therefore, the chaotic optimization is performed for each generation of particle velocity, so that the particles approach the global optimum through the evolution in the search iteration.

This paper adopt Logistic map to generate chaotic variables, the equation is as follows:

$$y_{s+1} = \mu y_s (1 - y_s). \tag{10}$$

where y_s is the chaotic variable of particle position optimization generated by the s iteration, $y_s \in [0,1]$, μ is a parameter to control the traversal state, when μ=4, the variable will traverse to the entire search space [19], that is, all states are in the chaotic space [0, 1]. In order to ensure the value range [0, 1] of chaotic sequence elements and conform the spectrum allocation binary coding method. In this paper, the integral function is introduced to modify the variables after chaotic map. So that, the work of binary encoding and decoding is omitted and computing time is cut down. The revised equation is as follows:

$$x_i = round(y_{s+1}). \tag{11}$$

where $round()$ is an integer function, x_i is the corrected particle position. Besides, we need to transform between chaotic space and variable space in the process of updating chaos in each iteration. The conversion process requires map and inverse map to implement, which are as follows:

$$p^0 = (v_{id}^t - v_{min})/(v_{max} - v_{min}), \quad \textbf{(12)}$$

$$v_{id}^t = v_{min} + p^s(v_{max} - v_{min}). \quad \textbf{(13)}$$

where the Eq. (12) is a map equation that maps a velocity variable to a chaotic variable, p^0 is the initial value of the chaotic variable, v_{id}^t is the real value of particle i in the d-dimension after the t iteration. v_{max} and v_{min} are the maximum and minimum of the speed value. The Eq. (13) is an inverse mapping equation that maps a chaotic variable to a velocity variable. p^s is the state value after the s iteration chaos optimization, v_{id}^t is the value of speed after t iteration chaos optimization.

5 Spectrum Allocation Strategy Based on CLBPSO

In this paper, the spectrum allocation problem is mapped to the optimization problem of particles. In CLBPSO, the particles contain position variables and velocity variables. We adopt chaotic map to optimize the position and velocity of particles. The location of particles represents a feasible spectrum allocation scheme, the velocity of the particle is the basis for updating the optimized position. The objective function is to maximize network rewards and solve the most efficient spectrum allocation scheme.

5.1 Algorithm Implementation Process

The algorithm randomly generates initial particle population position and velocity variables, the initial particle position is optimized by using the random ergodicity of chaotic map. So that, the particle traverses the initial solution space and improves the global search property of the initial particles. Calculating the adaptive function values of the optimized particle and evaluate *pbest* and *gbest*. Particle velocity represents the search step size, in order to avoid the particles falling into the local optimal. Similarly, the particle velocity is optimized by mapping and inverse mapping. The particle position is updated according to the particle velocity, and the information of each generation is evaluated. The algorithm stops running until the maximum number of iteration is reached. The specific implementation process of the algorithm is shown in Fig. 2.

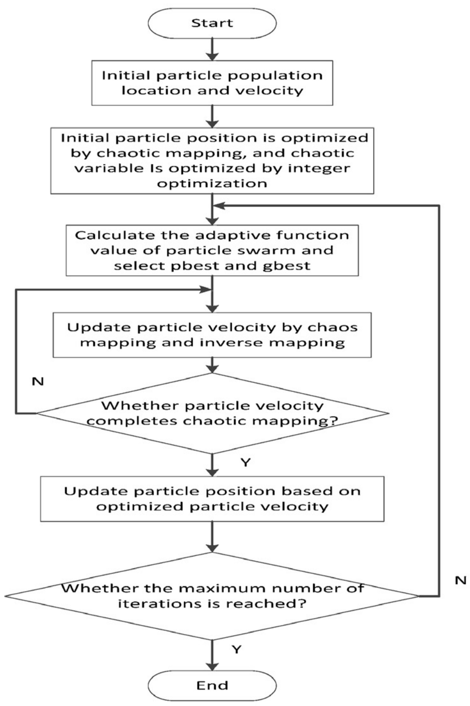

Fig. 2. The diagram of algorithm

5.2 Key Technologies

5.2.1 Spectrum Encoding Mapping

This paper adopts binary spectrum coding, 1 indicates that the channel can be used, and 0 indicates that the channel cannot be used. Aiming at the single authorization network, the number of cognitive users *N* is more than available spectrum *M*. Because the 0 element in *L* is not available for the cognitive user *n*, so we just encode the spectrum *m* represented by the 1 value. That is, the dimension of the particle is determined by the number *q* of 1 in *L*. The corresponding feasible allocation scheme has $F = 2^q - 1$, the corresponding encoding relationship between *L* and particle position *x* is shown in Fig. 3.

$$L = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}, \quad X = [x_1, x_2, x_3, x_4, x_5, x_6] = [l_{1,2}, l_{1,3}, l_{2,1}, l_{3,2}, l_{4,1}. l_{4,3}].$$

Fig. 3. Coding mapping of matrix *L* and particle location *x*

5.2.2 Particle Correction

When updating the position of particles, it is necessary to modify the particles that do not meet the conditions of non-interference constraint and spectrum availability. First, the solution of the particle position is mapped to the non-interference allocation matrix *A*. Then, we find all conditions that satisfy $c_{n,k,m} = 1$ and $n \neq k$ to any *m* and check whether the state variables on row *n* and row *k* in column *m* of *A* are both 1. If it is 1, one of the elements is randomly changed to 0, and the other remains unchanged. The modified matrix *A* is a new feasible solution.

5.2.3 Dimension Reduction Spectrum Allocation List *D*

Spectrum coding reduces the search space dimension from *N*×*M* to *q*, which reduces the search space and cuts down the search time. *A* reduced dimension spectrum allocation list *D* is established in order to make the faster and more efficient search.

Definition $D = [D_1, \cdots, D_f, \cdots, D_F]^T$, which is a list of all possible situations that represents the plans of cognitive users searching for spectrum, where $D_f = [d_1, d_2, \cdots, d_q]$, *F* is the total number of feasible spectrum schemes, *q* is the number of available spectrum, $d_q \in \{0,1\}$, $(d_1, d_2, \cdots, d_q)$ is ordered in binary way.

5.3 CLBPSO for Spectrum Allocation

(1) Initialize algorithm parameters include c_1 and c_2, *w* in the Eq. (7), maximum number of iterations *T*, particle population number *E* and number of chaotic iterations *S* in Eq. (10).

(2) Create an initial particle swarm. x_i represents a feasible spectrum allocation scheme. $x_i^t = (x_{i,1}^t, \cdots, x_{i,q}^t, \cdots, x_{i,Q}^t), i = 1, 2, \cdots, E$, $x_{i,q}^t \in \{0,1\}$. We use Eqs. (10) and (11) to optimize the chaotic map of the initial population. v_i represents the step length of the search spectrum allocation list $v_i^t = (v_{i,1}^t, \cdots v_{i,q}^t, \cdots, v_{i,Q}^t), i = 1, 2, \cdots E$, where $-F \leq v_{i,q}^t \leq F$, *F* is the number of spectrum schemes.

(3) Calculate the fitness function of the initial population according to Eq. (5). Then, select *pbest* and *gbest* and save the largest adaptive function value of the initial generation. At the same time, the location of the particle and the optimal spectrum allocation scheme are preserved.

(4) Update the speed of each particle. Because the velocity of the particle, v_i, represents the step length of the search spectrum scheme list, x_i represents a feasible scheme in the spectrum allocation scheme list. Therefore, we need to adjust the transformation based on the Eq. (7). The modified equation

is

$$v_{iq}^{t+1} = wv_{iq}^{t} + c_1 r_1 (p_{iq}^{t} - f_{iq}^{t}) + c_2 r_2 (p_{gq}^{t} - f_{iq}^{t}). \quad \textbf{(14)}$$

Where f_{iq}^{t} is q dimension position of particle i corresponding to the spectrum allocation scheme label after t iterations, p_{iq}^{t} is q dimension position of particle i corresponding to the optimal spectrum allocation scheme label after t iterations, p_{gq}^{t} is q dimension position of particle population corresponding to the optimal spectrum allocation scheme label after t iterations. According to Eqs. (12) and (13), the transformation between real values and chaotic variables is used to generate chaotic sequences.

(5) Update the position of each particle according to the Eqs. (8) and (9).

(6) Update *pbest* and *gbest*. If the fitness value x_i^t is greater than *pbest*, *pbest*= x_i^t. Otherwise, *pbest* does not change. If the fitness value x_g^t is greater than *pbest*, *pbest*= x_g^t. Otherwise, *gbest* does not change.

(7) If the maximum iterations T is reached, the algorithm obtains the optimal spectrum allocation scheme, *gbest*; Otherwise, skip to step (3) to continue to update the search..

6 Simulation and Analysis

In order to verify the validity of the CLBPSO in spectrum allocation, the network rewards is used as the criterion. In the Matlab R2012a programming environment, the proposed algorithm is compared with CQCA and IBPSO.

6.1 Simulation Parameters Setting

The specific simulation parameters are as follows [20].

Table 1. Simulation parameters setting

Simulation parameters	Value
Distribution area/m^2	200×200
Secondary user N	[1, 20]
Available spectrum M	[1, 30]
Reward matrix B	[0, 16]
Available matrix L	[0, 1]
Interference matrix C	[0, 1]
Spectrum allocation list D	0, 1 elements are ordered in binary form

6.2 Algorithm Parameter Setting

As shown in Table 2, $c1$, $c2$ and w are the standard value of the PSO algorithm. The value of the chaos control μ ensures the complete chaos, the values of population size E, maximum iteration T and chaotic map S are related to the simulation system.

Table 2. Algorithm parameter setting

Parameter	c_1	c_2	w	E	T	S	μ
Value	2	2	1	30	200	20	4

6.3 Simulation Results and Analysis

Table 3 is the specific network rewards obtained by the three algorithms for the specific iteration at M=N=5. The data is the average of 100 iterations of the algorithm.

Table 3. The comparison of algorithm network rewards under different iterations

Iteration \ Algorithm	CLBPSO	CQCA	IBPSO
50	103.24	101.46	96.64
100	111.59	107.23	97.87
200	112.67	109.49	98.66

According to the analysis in Table 3, CLBPSO algorithm is better than CQCA algorithm and IBPSO algorithm in terms of the total network rewards at 50, 100 and 200 iterations, which obtains the global optimal reward is the highest among the three algorithms. The total network rewards of CLBPSO algorithm is 2.9% higher than the CQCA algorithm and 14.2% higher than the IBPSO algorithm.

When M=N=5, 50 simulation experiments are performed to compare the performance of the three algorithms in the network performance. As shown in Fig. 4, among the 50 experimental samples, the network rewards obtained by the CLBPSO algorithm is significantly better than the other two algorithms, which proves that the CLBPSO algorithm can obtain the ideal network rewards.

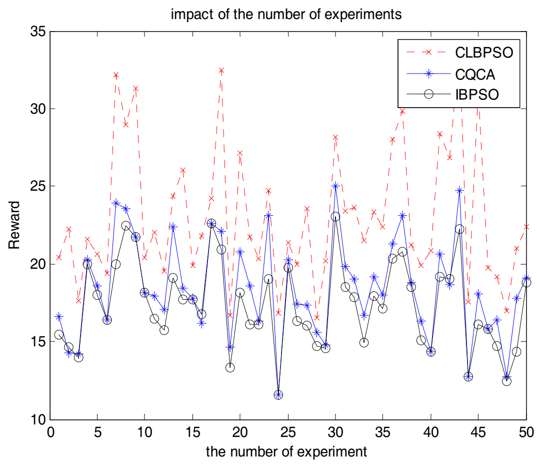

Fig. 4. the total network rewards of the algorithm under different experiments

When N=10, PUs K=20 and M is increased from 5 to 30. 100 experiments are performed as shown in Fig. 5. As the number of available spectrum increasing, the total network rewards is increasingly augment, and the increase of network rewards of CLBPSO algorithm is better than the other two algorithms. Since the CLBPSO algorithm adopts chaotic map from the initial population to the late search, it traverses all possible distributions and finds the optimal optimal solution with the highest rewards. The CQCA algorithm has lower reward and the IBPSO algorithm has the lowest reward.

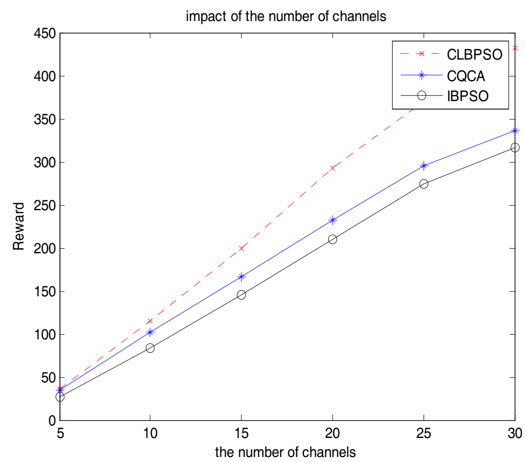

Fig. 5. Network reward versus number of available spectrum

When $M = 10$, PUs $K = 20$ and N is increased from 5 to 20, 100 experiments are performed as shown in Fig. 6. In the case of constant spectrum number, the total network rewards is decreasing in the process of increasing the number of SUs， which is the result of the multiple SUs competing for small amount of spectrum resources. With the decrease of network rewards, the CLBPSO algorithm still gains better network rewards, CQCA algorithm performs slightly better, and IBPSO algorithm performs worst.

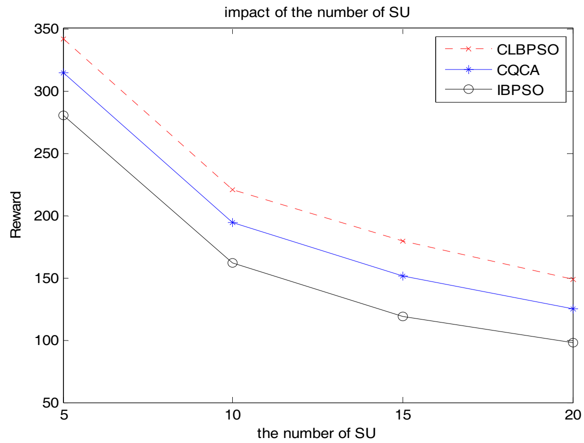

Fig. 6. Network reward versus number of cognitive users

When $M = 10$, $N = 20$ and PUs K is increased from 5 to 50, 100 experiments are performed as shown in Fig. 7. Under the condition that available spectrum and SUs are unchanged, the total network rewards decreases with the increasing of the PUs. Because the PU has absolute priority on the spectrum, and the PUs compete for limited spectrum resource. The CLBPSO algorithm gains the best network rewards among three algorithms.

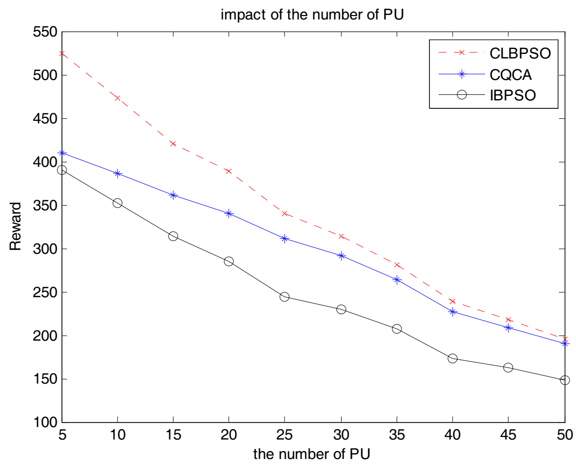

Fig. 7. Network reward versus number of primary users

6.4 Algorithm Operation Time Overhead Comparison

Table 4 shows the overhead of the three algorithms in computing time. It can be seen that the running time of the CLBPSO algorithm in the Clock computing time mode is lower than the CQCA algorithm, and it is longer than the IBPSO algorithm by about 0.5908 seconds. The run time of the CLBPSO algorithm in the TIC and TOC calculation time mode is minimum. Combining with the two time calculation methods, the CLBPSO algorithm has lower computational time overhead, which is superior to the other two algorithms.

Table 4. Time-consuming results of different algorithms

Algorithm	TIC and TOC(s)	Clock(s)
CLBPSO	1.418562	1.6143
CQCA	1.807544	1.0235
IBPSO	4.083665	4.7034

7 Conclusions

In this paper, the ergodicity of chaotic map is used to improve the deficiencies of PSO. The initial population and the position of each generation of particles are globally optimized and CLBPSO is proposed. Based on the graph theory model, the reduced dimension spectrum allocation list is built, and the dynamic spectrum allocation strategy based on CLBPSO is designed. The simulation results show that the proposed algorithm can obtain high network rewards, fast convergence rate and strong robustness. Next, we will study the relationship between the w value and the algorithm fitness to balance the global exploration ability and local development ability of the algorithm and further improve network rewards and fairness in spectrum allocation.

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