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Spectrum allocation for cognitive radio networks using the fireworks algorithm

Zhou Feng and Xue Weilian*

School of Management, Liaoning Normal University, Dalian 116029, China

The fireworks algorithm features a small number of parameters, remarkable optimization ability, and resistance to a local optimum. Based on the graph coloring model, the fireworks algorithm is introduced for the first time to solve the spectrum allocation problem for cognitive radio networks, thus maximizing utility and fairness of spectrum allocation. Two-layer binary coding is adopted for individual fireworks. The first layer refers to the coding of cognitive users used to determine channels that can be connected with the user. The second layer refers to the auxiliary coding of channels responsible for addressing mutual interference among multiple cognitive users when they connect with the same channel at the same time. Explosion operator, mutation operator, and the selection operation are designed to allocate the spectrum for the cognitive radio network. Simulation results demonstrate superiority and efficiency of the proposed algorithm in terms of spectrum allocation

Keywords: Fireworks algorithm; spectrum allocation; system utility; system fairness

1. INTRODUCTION

Rapid advances in wireless communications over recent years have witnessed a growing demand of the wireless network for spectral resources. Traditional spectrum allocation is inefficient because the spectrum is allocated in a fixed manner, resulting in a spectrum shortage. The cognitive radio technique is able to sense and utilize idle spectrum resources based on changes in the communication environment, thus improving the utilization of spectral resources and providing an effective approach to spectral shortages [1–2]. Hence, the cognitive radio technique has become a popular research area in wireless communications. It improves utilization of the spectrum by adaptively assigning spectral resources to be shared according to sensing results from the spectrum sensing module. The performance of the spectral resource allocation scheme can determine the spectrum utilization in the entire cognitive radio network.

Existing models for spectral resource allocation in cognitive radio networks can be classified into four types: graph-based coloring model [3–7], game-based model [8–11], auction model [12–18], interference temperature model [19–22], and other methods [23–30]. The first type of algorithm is more mature than the others.

The graph-based coloring model aims to maximize system utility or fairness. It is an NP-hard combinatorial optimization problem that can be solved by the dynamic programming method, branch-and-bound method, enumeration method, and other exact algorithms. For a large-scale combinatorial optimization problem, it is theoretically possible to obtain an optimal solution, but exact methods are too computationally intensive to be feasible in practice. Other options include inexact algorithms, like the heuristic method and intelligent optimization method. Greedy algorithms include the coloring method [31], color-sensitive graph-based coloring method [32–34], and distributed local bargaining method [35]. But these methods are challenged to formulate appropriate greedy rules and thus cannot guarantee an optimal solution. The swarm intelligent algorithm is able to search for an optimal solution in parallel and provides a remarkable optimization ability and robustness. Given these reasons, many swarm intelligent methods, such as

*Corresponding author. E-mail: xueweilian66@163.com

the genetic algorithm, particle swarm algorithm, and ant colony algorithm, are widely used to effectively address the spectrum allocation problem. However, they are limited in terms of global optimization and convergence.

The fireworks algorithm is a swarm intelligent method that is gaining popularity in recent years. Compared with other methods, it features a small number of parameters, remarkable optimization ability, and resistance to a local optimum [36–37]. In this paper, we pioneer the use of the fireworks algorithm for spectrum allocation. Simulation results indicate that the algorithm is able to satisfactorily avoid a local optimum and greatly improve allocation utility, system fairness, and convergence speed.

The rest of this paper is organized as follows. The related work is reviewed in Section 2. We propose the fireworks explosion algorithm for cognition radio spectrum allocation in Sections 3, respectively. In Section 4, extensive simulation experiments are conducted to evaluate the performance of the proposed algorithm. Finally, we conclude the paper in Section 5.

2. RELATED WORK

Allocating the spectrum for cognitive radio networks is a nonlinear discrete and multi-objective optimization problem. The focus of this paper is to find a solution to the graph coloring model using the swarm intelligent algorithm. We propose a method to solve the graph coloring model using the fireworks algorithm. Therefore, swarm intelligent approaches for spectrum allocation are reviewed in detail.

Mustafa et al. introduced the genetic algorithm (GA) for spectrum allocation [38] and optimized spectrum allocation using the greedy ability of GA to find an optimal solution iteratively. Although the final result was better than the traditional graph algorithm, it was inefficient and prone to get stuck in a local optimum. ZHAO et al. proposed a scheme for spectrum allocation using the quantum genetic algorithm (QGA) [39], where the quantum mutation and updating operation were introduced to improve the swarm's diversity and convergence. Although spectrum allocation utility and efficiency were enhanced, it was still prone to get stuck in a local optimum. In [40], ZHONG et al. introduced the adaptive genetic algorithm for spectrum allocation where the crossover and mutation operators were automatically adapted to the number of generations and convergence. Although the algorithm avoided a local optimum, optimization performance was poor and system overhead was heavy. Based on the diversity of spectrum allocation objectives in cognitive radio networks, YAO et al. [41] proposed to allocate the spectrum using the multi-objective genetic algorithm, finding a balance between system utility and fairness. In order to address the problem of the traditional genetic algorithm that it is prone to get stuck in a local optimum and is computationally intensive when used for spectrum allocation, YANG et al. introduced a hybrid adaptive idea to GA [42], where crossover and mutation operations were adapted to the number of generations. Moreover, the golden mean was used to compute the probability of crossover and mutation during spectrum allocation, resulting in greater allocation efficiency and utility. In [43], LI et al. proposed to combine GA with the ant colony algorithm for spectrum allocation in cognitive radio networks. System utility was improved, but allocation efficiency was low. In [44], ZHENG et al. attempted to allocate the spectrum by combining simulated annealing with GA. Although allocation utility was maximized, system overhead was heavy and system fairness was poor. In [45], WU et al. combined GA with the ant colony algorithm and randomly generated original solutions that were dispersed widely through GA. Afterwards, the set of original solutions was converted into the original distribution of pheromones that were processed by the ant colony algorithm. Finally, an optimal allocation scheme was determined using continuous positive feedback of information, which improved spectrum allocation utility and fairness. However, GA is a random algorithm that uses the greedy optimization strategy, thus its performance is unstable and is prone to get stuck in a local optimum.

In [46], ZHANG et al. proposed a spectrum allocation method based on the particle swarm algorithm, which determines an optimal solution based on the optimization of individual and the swarms. Given these properties, it greatly improves system performance, but is heavily dependent on the original solution and is prone to get stuck in a local optimum. In order to address the problem that the binary particle swarm spectrum allocation algorithm, REN proposed a PSO-based power and spectrum collaborative allocation algorithm [47], where PSO parameters (i.e., original position and speed of particles) were optimized. Power and channel allocation of the system could be updated in parallel during iterations, resulting in improved system throughput and convergence speed. In [48], QIAO et al. altered the original swarm through chaotic logistic mapping, and improved convergence speed by mutating the highly concentrated particles. Despite its ability to remember, the particle swarm algorithm finds the optimal solution based on local and global extreme points. Given this reason, it is highly dependent on the original solution and is prone to get stuck in a local optimum.

Other swarm intelligent algorithms include the method in [49] based on an ant colony, the method in [50] based on a leapfrog, and the method in [51] based on an artificial bee colony. These methods are not effective. Although synergy can be achieved by combining two or more algorithms, it is complicated to do and makes it a challenge to find a balance between system performance and fairness.

In this paper, the spectrum is allocated for cognitive radio networks by addressing the graph coloring model through firework explosion optimization. Block-based two-layer structures (i.e., master coding and auxiliary coding), an explosion operator, a mutation operator, and a selection strategy are designed based on characteristics of the problem. The proposed method maximizes spectrum allocation performance and fairness in the non-interference scenario and improves convergence speed.

3. MODEL AND ALGORITHM

3.1 Spectrum Allocation Model

According to spectrum allocation characteristics based on the graph coloring model, the problem of spectrum allocation is modeled as a graph coloring problem, i.e., coloring the graph $G = (U, E_C, L_B)$, where Udenotes the set of vertices in G that represent the set of cognitive users; L_B denotes the set of vertex colors and their weights; and E_C denotes the set of edges determined by the set of interferences. If $c_{n,k,m} = 1$, color m cannot be allocated to vertices n and k at the same time in order to avoid interference.

Suppose that the cognitive radio system has N cognitive users ($1 \sim N$) and M channels ($1 \sim M$). The security distance of each cognitive user is d_n ($n = 1, 2, ..., N$), the utility achieved by connecting authorized user n with channel m is $u_{n,m}$ ($n = 1, 2, ..., N, m = 1, 2, ..., M$), and the distance matrix between cognitive users is $B_{N\times N}$. A cognitive user can sense the nearby spectrum and make real-time adjustments by learning and understanding the external environment in order to update the non-interference matrix corresponding to each parameter.

1. Idle spectrum matrix (F): The idle spectrum consists of two situations. If an authorized spectrum is idle, other cognitive users regard this spectrum as idle and choose to connect. Each authorized user has its safety distance. Connecting the spectrum with other users within this distance causes interference for the authorized user. If the authorized spectrum is in service, the cognitive user beyond this distance can connect with the spectrum without causing interference for the authorized user. In this case, the authorized spectrum can be considered idle. That is, when $f_{n,m} = 0$, cognitive user n cannot connect to channel m; if $f_{n,m} = 1$, cognitive user n can connect to channel m. The idle spectrum matrix is:
$$F = \left\{f_{n,m} \left| f_{n,m} \in \{0, 1\}\right.\right\}_{N\times M} \quad (1)$$
2. Utility matrix (U): Utility is achieved when a cognitive user is connected to the authorized channel. Since different cognitive users may adopt different communication parameters, the connection of different cognitive users to the same authorized spectrum that stays idle may produce different utilities. This generates a utility matrix of cognitive users. Let $u_{n,m}$ denote the maximum utility achieved when cognitive user n is connected with idle channel m. The utility matrix is:
$$U = \left\{u_{n,m}\right\}_{N\times M} \quad (2)$$
3. Interference matrix (G): Like the authorized user, each cognitive user has a safety distance. When several cognitive users intend to connect with an authorized spectrum at the same time, we need to check whether these cognitive users fall beyond the safety distance of the authorized user, whether connecting them will cause interference for cognitive users already connected with the channel, and whether there is mutual interference among these cognitive users. If $g_{n,k,m} = 1$, connecting n and k to channel m at the same time will cause interference. Hence, users n and k must not be connected with m at the same time. If $g_{n,k,m} = 0$, there will be no mutual interference when n and k are connected with channel m at the same time. Hence, n and k are allowed to connect with m. The interference matrix is:
$$G = \left\{g_{n,k,m} \in \{0, 1\}\right\}_{N\times N\times M} \quad (3)$$
The interference matrix consists of idle spectrum matrix F, distance matrix B, and the safety distance of cognitive user d_n:
$g_{n,k,m} = 1$, if $f_{n,m} = 0$, or
$f_{k,m} = 0$, or
$f_{n,m} = 1$ and $f_{k,m} = 1$, but $b_{n,k}\langle \min(d_n, d_k)$
$g_{n,k,m} = 0$, if $f_{n,m} = 1$ and $f_{k,m} = 1$ and $b_{n,k}\rangle \max(d_n, d_k)$.
$g_{n,k,m} = 1 - f_{n,m}$, if $n = k$.
4. Interference-free allocation matrix (A): This represents an interference-free allocation scheme of the system. If $a_{n,m} = 1$, channel m is allocated to the cognitive user; if $a_{n,m} = 0$, cognitive user n cannot be connected with channel m.
$$A = \left\{a_{n,m} \left| a_{n,m} \in \{0, 1\}, a_{n,m} \le f_{n,m}\right.\right\}_{N\times M} \quad (4)$$
5. Maximum utility matrix ($U_{\max}$) of the spectrum: System utility is an important measure of a radio network's overall performance. Different utility functions represent different allocation objectives. In this paper, let U denote the utility function. The function for maximizing system utility is defined as:
$$U_{\max} = \max_{A\in\Omega N,M} \sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m}\cdot u_{n,m} \quad (5)$$
6. System fairness: Fairness is used to measure how fairly the spectrum is allocated among cognitive users. Fairness is measured by the bandwidth variance of cognitive users. Let $\bar{U}$ denote the average utility of cognitive users. Our objective is to minimize variance:
$$\text{fairness} = \min_{A\in\Omega N,M} \frac{1}{N}\sum_{n=1}^{N}\left(\sum_{m=1}^{M} a_{n,m}\cdot b_{n,m} - \bar{U}\right)^2 \quad (6)$$

3.2 Spectrum allocation in cognitive radio networks through firework algorithm

The fireworks algorithm (FWA) is a swarm intelligent algorithm inspired by the beautiful explosion of fireworks in the night sky. The basic principle of FWA is to regard the solution space of the optimized problem as a firework explosion space, and to regard candidate solutions of the optimized problem as the location of sparkles generated by the explosion and the location where they are set off. The fitness of sparkles and fireworks is evaluated using an objective function. The locations of well-fitted sparkles or fireworks are considered the solution that approximates to the optimal solution of the objective function. After comparing the fitness of all sparkles and fireworks, the locations of well-fitted sparkles and fireworks are selected as the locations where the next fireworks are set off. Sparkles and fireworks concentrate around the optimal solution during iterations. When the algorithm completes, the location of the most fitted fireworks and sparkles constitute the desired optimal solution to the objective function.

3.2.1 Coding

The fireworks algorithm was originally proposed to address the space optimization problem of continuous functions. In order to address discrete optimization problems more effectively, LI et al. proposed a binary fireworks algorithm [49]. Unlike the standard fireworks algorithm, their method encoded the problem and solution space using binary bits 1 and 0. If a real number is used for coding, mutated individuals may fall outside the range of the solution space. Furthermore, the binary coding operation is simple and shows remarkable optimization ability. Hence, the problem space is encoded using the binary coding scheme. We design a dual-layer binary coding scheme for spectrum allocation based on graph coloring model. The first layer refers to cognitive user-based code, which is the master code used to solve our problem. The second layer refers to channel-based code, which is a slave code used to control interference caused by the connection of multiple users on the same channel. Both of their code lengths is equal to the number of 1s in the availability matrix F, i.e. $l = \sum_{n=1}^{N} \sum_{m=1}^{M} f_{n,m}$.

Figure 1 shows an example of coding and decoding of evolved individuals given $N = 5$ cognitive users and $M = 5$ channels. Figure 1(a) is the availability matrix, where channels with a value of 0 are occupied by the master user and are unavailable to other cognitive users within its range. Only channels with a value of 1 are available to cognitive users. Only locations with a value of 1 are taken into account when we encode. From Fig. 1(a) it is observed that 13 elements are equal to 1 in the matrix. Therefore, the evolved individual is a $1 - D$ vector with a length of 13 as shown in Fig. 1(b). The corresponding interference-free matrix, A, is shown in Fig. 1(c).

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 & \end{bmatrix}$$

(a)

$$P_i = [1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1]$$

(b)

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

(c)

Figure 1 Illustration of coding and decoding structures.

In what follows, we describe the coding method in detail. The first layer is cognitive user coding, and its coding structure is shown in Fig. 2. In order to distinguish between users, we divide the master code into several blocks, each of which represents a cognitive user. The first row in Fig. 2 denotes the block number (or the cognitive user number). The second row represents the channels available to this user, and its value is determined by the availability matrix. It corresponds to the code of channel available to the user. The third row is the individual code which consists of several blocks. The number of digits in each block is determined by the number of channels available to the corresponding user. If it is "1", the corresponding channel is chosen and allocated to the user. If it is "0", the user does not choose the corresponding channel.

In order to avoid interference among cognitive users who use the same channel, we design a slave code. It is based on channel coding, and shares the same length and similar structure with the master code. The value of each digit in the slave code is determined by the master code. Its structure is shown in Fig. 3. The first row denotes the channel code. The second row represents the users that can be connected with the channel and its value is determined by the availability matrix. The third row is the individual code which consists of several blocks. The number of digits in each block is determined by the number of users that can be connected with the corresponding channel. If it is "1", the corresponding channel is allocated to the user. If it is "0", the corresponding channel is not allocated to the user. If two or more digits in each block are "1", it is necessary to guarantee there is no interference among users who are connected with the same channel.

3.2.2 Design of operators

The fireworks algorithm consists primarily of an explosion operator, a mutation operator, and a selection strategy. The quality of any of these three components has a direct impact on the algorithm's optimization performance.

(1) Explosion operator

Some fireworks are optimized in the solution space. The objective function is used to compute and evaluate the location of fireworks. Fireworks should be managed so that well-fitted ones are allocated more resources. In this way, they generate more sparks in a smaller search range, thus providing a greater ability to search the neighborhood. At the same time, fireworks with small fitness are allocated fewer resources so that they generate fewer sparks in a larger region, thus providing the ability to explore globally.

For the graph coloring-based spectral allocation problem, we design an explosion operator defined as the shift of 1 in the gene block, i.e., the cognitive user switches to another feasible channel. The number of sparks generated by the fireworks and the number of blocks converted by the explosion genes are determined based on the fitness of fireworks.

$$S_i = M \times \frac{f(x_i) - y_{\min} + \varepsilon}{\sum_{i=1}^{N}(f(x_i) - y_{\min}) + \varepsilon} \tag{7}$$

where $y_{\min} = \min(f(x_i))$, $(i = 1, 2, \cdots, N)$ denotes the smallest fitness of the current fireworks swarm, M is a constant that adjusts the number of sparks generated during an explosion, and ε denotes the machine-specific minimal value used to avoid division by zero. In order to prevent high-fitness fireworks from generating too many sparks and low-fitness fireworks from generating too few sparks, the number of sparks in Equation (7) is upper- and lower-bounded by thresholds:

$$S_i = \begin{cases} S_{\min}, S_i < S_{\min} \\ S_{\max}, S_i > S_{\max} \\ S_i, others \end{cases} \tag{8}$$

The number of modified blocks in the explosion gene relates to the number of generated sparks, and can be computed from

Block number (Cognitive users)	1		2			3		4				5	
Channel number	1	5	2	3	5	1	3	1	2	4	5	2	4
Individual coding	1	0	0	1	0	1	0	0	1	0	0	0	1

Figure 2 Structure of the master code.

Block number (Channel)	1			2			3		4		5		
Cognitive users	1	3	4	2	4	5	2	3	4	5	1	2	4
Individual coding	1	1	0	0	1	0	1	0	0	1	0	0	0

Figure 3 Structure of the slave code.

Equation (9). Let A_i denote the number of mutated gene blocks: if 1, a gene block is randomly selected from the individual for a "1" shift operation; if 2, two gene blocks are randomly selected from the individual for a shift operation; otherwise, three gene blocks are randomly selected for a shift operation.

$$A_i = \begin{cases} 3, \quad S_i \le S_{\min} + 1/3(S_{\max} - S_{\min}) \\ 2, S_{\min} + 1/3(S_{\max} - S_{\min}) < S_i \\ \qquad \le S_{\min} + 2/3(S_{\max} - S_{\min}) \\ 1, S_i > S_{\min} + 2/3(S_{\max} - S_{\min}) \end{cases} \tag{9}$$

(2) Mutation operator

Consider randomly selecting a gene bit and computing the complement probabilistically. To this end, a random number in the range 0-1 can be generated, and if the number is less than 0.5, the gene bit remains the same. Otherwise, compute the complement of the bit and the values of relevant bits may need to be adjusted accordingly.

(3) Selection strategy

The fireworks algorithm is expected to eliminate undesirable individuals and pass desirable individuals to the next generation. After the explosion process produces exploded sparks and mutated sparks, the algorithm computes the fitness of these sparks and fireworks using the objective function. Individuals with good locations will be selected from the population as the locations for the next round of fireworks explosions.

Let K denote the set of candidates and N denote the size of the fireworks population. Individuals with the highest level of fitness are selected from the candidates (mutated sparks, exploded sparks, and fireworks) as the next generation of fireworks. The remaining $N-1$ fireworks in the population are selected through a roulette process. Hence, the probability that candidate x_i is selected can be computed as:

$$p(x_i) = \frac{R(x_i)}{\sum_{x_j \in K} x_j} \tag{10}$$

$$R(x_i) = \sum_{x_j \in K} d(x_i - x_j) = \sum_{x_j \in K} \left\| x_i - x_j \right\| \tag{11}$$

Where denotes the sum of distances from the current individual to each element in K. For any individual in the set of candidates, if the nearby density of individuals is high, the probability that this individual is selected decreases.

3.2.3 Fitness Function

The fitness function is computed as shown in Equations (5) and (6).

3.2.4 Algorithm Process

In order to simulate a real-world environment for spectrum allocation in a cognitive radio network and to evaluate algorithm performance accurately, we generate the spectrum availability matrix (F), utility matrix (U), cognitive user distance matrix (B), and safety distance using a random process. The steps of the algorithm are shown in Fig. 4. Details are provided as follows:

1. Initialization: Randomly initialize the spectrum availability matrix (F), utility matrix (U), cognitive user distance matrix (B), and the vector of safety distances (D).

2. Data pre-processing: Generate a valid utility matrix using the spectrum availability matrix (F) and utility matrix (U). Generate the interference matrix (G) using the spectrum availability matrix (F), cognitive user distance matrix (B), and safety distance of each cognitive user.

3. Define algorithm parameters: Set up fireworks algorithm parameters $T\_\max$ and$S$, where $T\_\max$ is the maximum number of iterations and S is the number of fireworks, i.e., the original size of the population.

4. Randomly generate a population of S fireworks and process all individuals in a constrained manner through auxiliary coding.

5. Use the objective function to compute the fitness of individuals that are to be optimized in the solution space. Check

whether the algorithm's termination condition is met. Output the optimal solution if the termination condition is met. Otherwise, proceed to the next step.

6. Compute the number of sparks and the number of transformed blocks in the explosion gene based on Equations (7), (8), and (9). Let the fireworks explode.

7. Let the fireworks mutate.

8. Compute the fitness $f(X_i)$ of the original fireworks in the population and the sparks generated from the explosion. Select the spark or firework with the highest fitness from the solution space as the location of the next generation of fireworks. Next, select $N-1$ sparks (fireworks) as the next generation of individuals and return to Step 5.

Termination condition: reach the maximum number of iterations or the optimal solution remains no variation in over five consecutive rounds.

4. SIMULATION AND ANALYSIS

Simulations are performed to evaluate the spectrum allocation performance of the fireworks algorithm. Results are compared with those obtained using the genetic algorithm and particle swarm algorithm. In order to ensure the conclusiveness of simulation results, algorithm performance is measured by system utility and fairness. Simulation parameters are provided in the following table.

Parameter	Value
Size of distribution space /m^2	Varies
Number of master users	Varies
Number of cognitive users	Varies
Number of spectrums in system	Same as number of master users
Protective range of master user /m	2
Maximum transmission radius of slave user /m	4
Minimum transmission radius of slave user /m	1

The topological structure of the cognitive radio network is assumed to remain unchanged throughout an allocation cycle. In other words, the spectrum availability matrix F, utility matrix U, and interference matrix G do not change during an allocation cycle. These matrices are generated randomly in the simulation in order to compare algorithm performance more intuitively. Each of the compared matrices share the same F, U, and G for each round of simulation.

The parameter settings for the proposed algorithm are as follows: population size $M = 10$ and number of iterations T_max=300. For the particle swarm method, c1=c2=2, r1=r2=rand, and the weight of the population size w=0.5. For the genetic algorithm, crossover probability pc1=0.8, mutation probability pc2=0.01, number of iterations is 300, and the original number of fireworks is 30.

First, 20 rounds of independent simulations were performed on the fireworks algorithm (FWA), particle swarm optimization (PSO) algorithm, and genetic algorithm (GA). Let the abscissa denote the serial number of experiments and the ordinate denote system utility. Figure 5 shows that the system utility of FWA is higher than PSO and GA, except for some points where the system utility is close to one another. This demonstrates the superiority of the proposed algorithm over the other methods in terms of system utility.

In order to further evaluate the ability of FWA to converge when it is used for spectrum allocation, we assume 10 master users and 10 cognitive users. Let the abscissa denote the serial number of experiments and the ordinate denote system utility. Figure 6 shows the variation of system utility over 300 rounds of iterations. The proposed algorithm converges faster than the other methods and provides the highest system utility. This demonstrates the superiority of the proposed algorithm over the other methods in terms of system utility and convergence speed.

The number of cognitive users and channels in the cognitive radio network changes in real time due to variations in the communication environment. In order to emulate a real-world cognitive radio network, we study the variation in system utility with the number of master users and cognitive users. First, we set the number of cognitive users to 10 and assume the number of master users (M) ranges from 10 to 30, as shown in Fig. 7. There are fluctuations in the increase in system utility because there are as many spectrums as master users. Given the same number of cognitive users, adding one more master user to the cognitive radio network means there is one more potential spectrum resource available. Given this reason, the system utility allocated to cognitive users increases with the number of master users. Furthermore, the proposed method yields more system utility than the other two algorithms with an increase in the number of master users.

In order to evaluate the variation of system utility with the number of cognitive users, we assume 10 master users. Let the ordinate denote system utility and the abscissa denote the number of cognitive users, which ranges from 2 to 10. Fig. 8 shows the variation in system utility with the number of cognitive users. System utility is shown to decrease with the number of cognitive users. This could be attributed to the fact that the fixed number of master users means that spectrum resources are fixed in the system. In this context, the increasing number of cognitive users causes a worsening shortage of spectrum resources and fierce competition among cognitive users, resulting in reduced system utility. Despite this, the proposed algorithm decreases more slowly and outperforms the other methods.

Extensive simulations were performed above to demonstrate the superiority of the proposed method in terms of system utility. We also evaluate algorithm performance with system fairness as the objective function. Let the abscissa denote the serial number of experiments and the ordinate denote system fairness. Fig. 9 shows the variation of system fairness over 20 rounds of simulations. The proposed algorithm is vastly superior to GA and outperforms PSO by a small margin.

In order to further evaluate the ability of the methods to con-

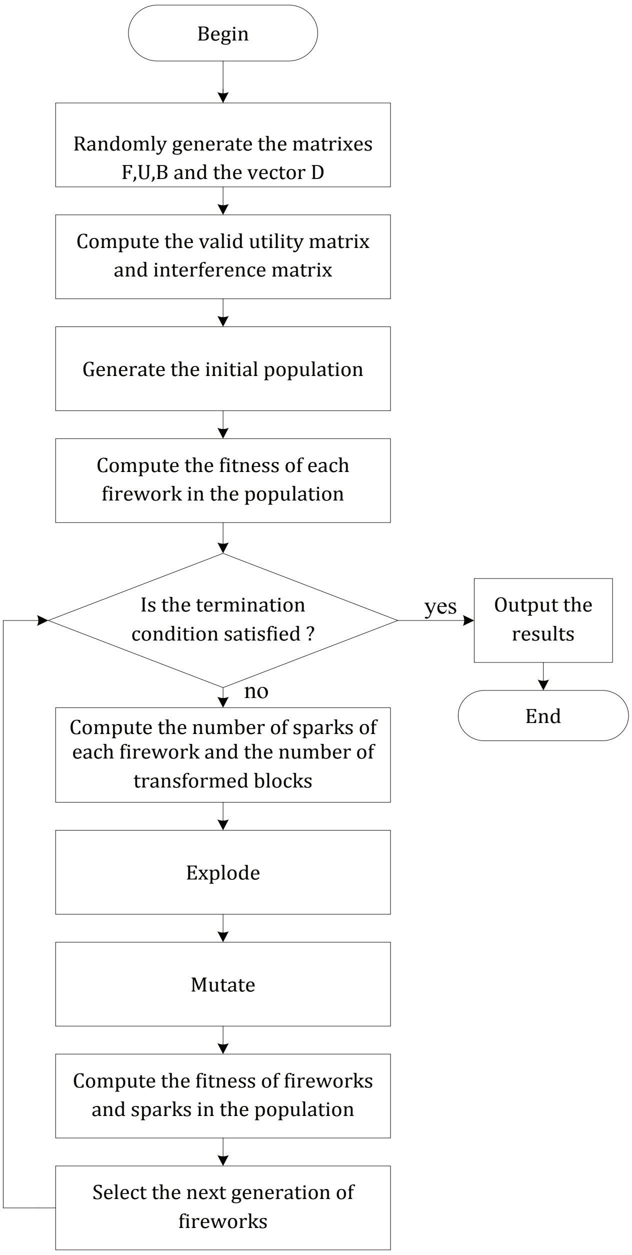

Figure 4 Steps for spectrum allocation based on the fireworks algorithm.

verge when system fairness is defined as the objective function, we assume 10 master users and 10 cognitive users. Let the abscissa denote the serial number of experiments and the ordinate denote system fairness. Fig. 10 shows the variation of system fairness over 300 rounds of iterations. The proposed algorithm provides the fastest convergence and greatest system fairness, thereby being superior to the other methods.

Suppose there are 10 cognitive users and that the number of master users ranges from 10 to 30. Next, we study the variation of system fairness with the number of master users. As shown in Fig. 11, system fairness increases with the number of master users. More master users in the system means that more spectrum resources are available. Thus, competition among users and interference are alleviated, resulting in greater system fairness. Also note that the proposed algorithm provides the greatest system fairness when master users change, further demonstrating superiority of the proposed method.

In order to further study the variation of system fairness with the number of cognitive users, we assume 10 master users and that the number of cognitive users ranges from 2 to 10. Simulation results in Fig. 12 show that given the same number of master users, system fairness decreases with the number of cognitive users. This is due to the fact that more cognitive users results in more fierce competition for spectrum resources. Hence, spectrum resources are allocated in an unbalanced manner, leading to reduced system fairness. In this regard, the performance of the proposed algorithm is similar to the other methods.

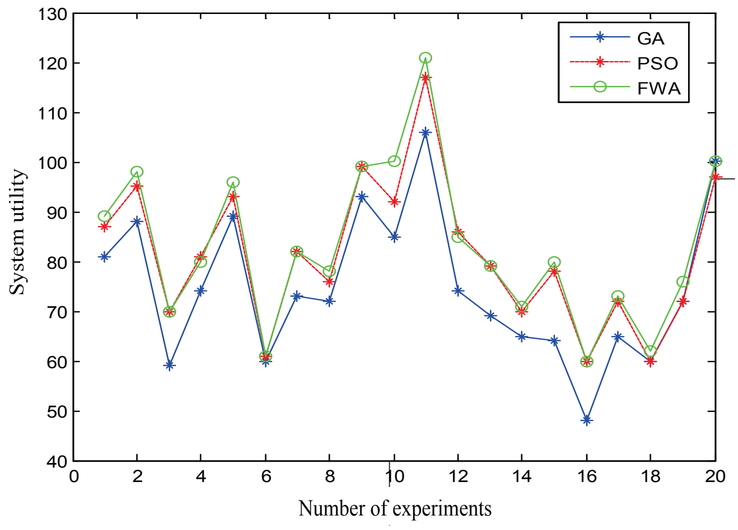

Figure 5 Variation of system utility with the serial number of experiments.

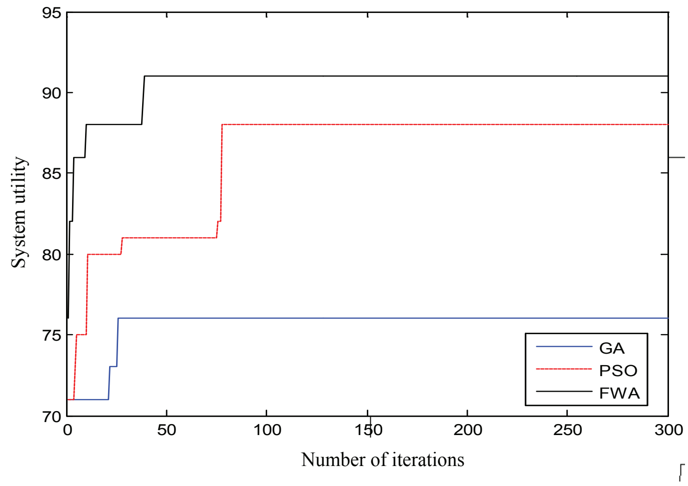

Figure 6 Variation of system utility with iterations.

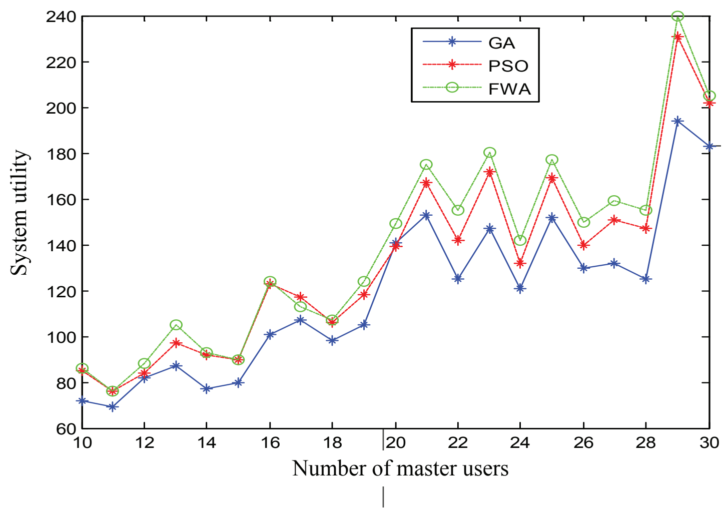

Figure 7 Variation of system utility with the number of master users.

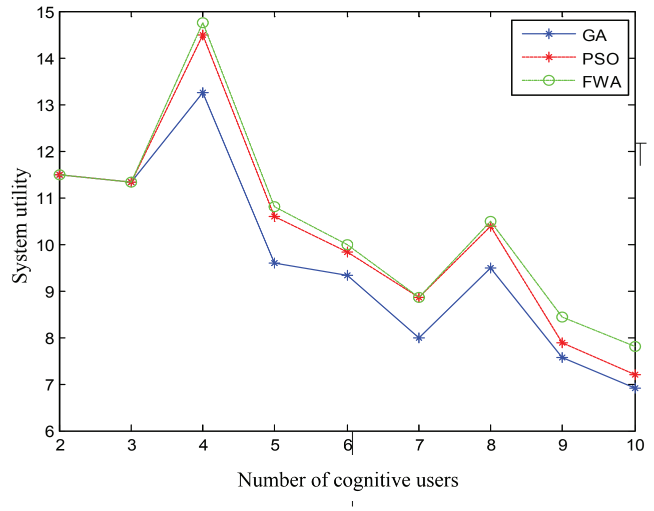

Figure 8 Variation of system utility with the number of cognitive users.

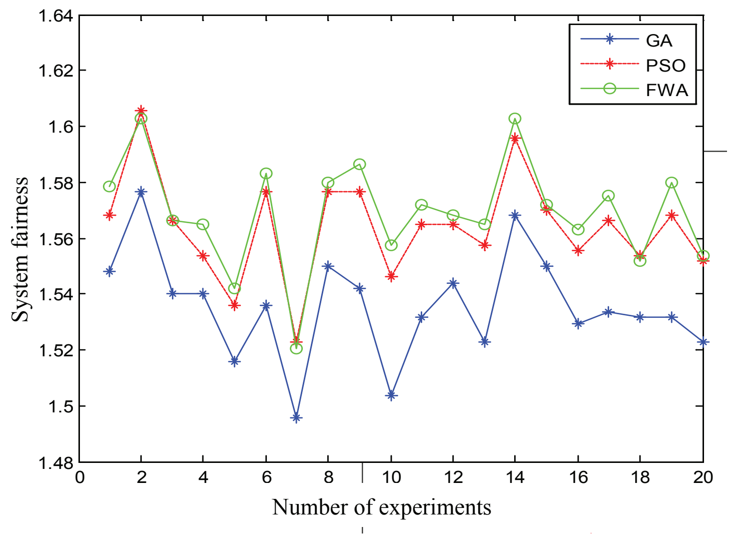

Figure 9 Variation of system fairness with the serial number of experiments.

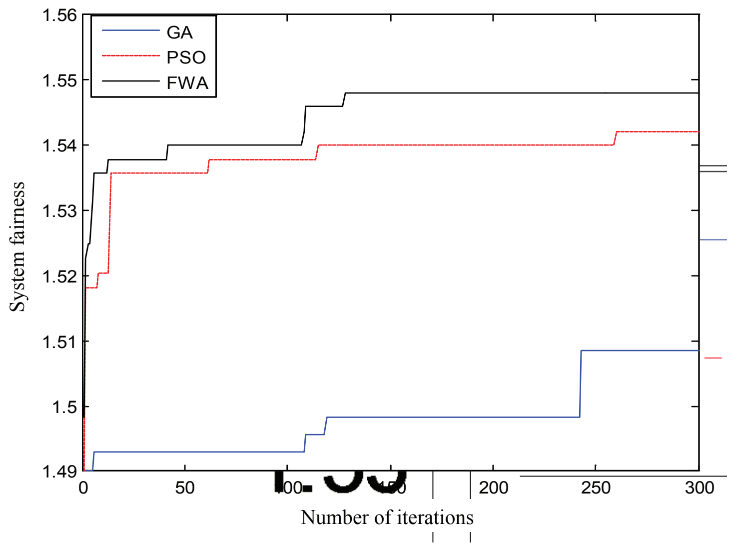

Figure 10 Variation of system fairness with iterations.

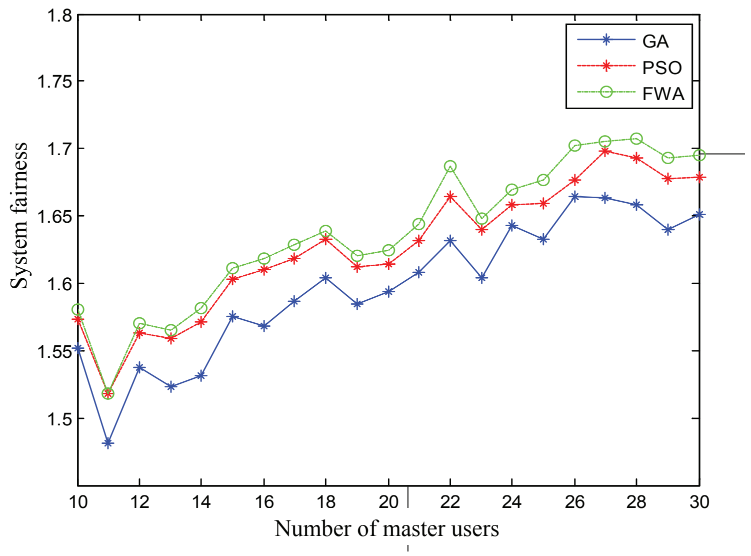

Figure 11 Variation of system fairness with the number of master users.

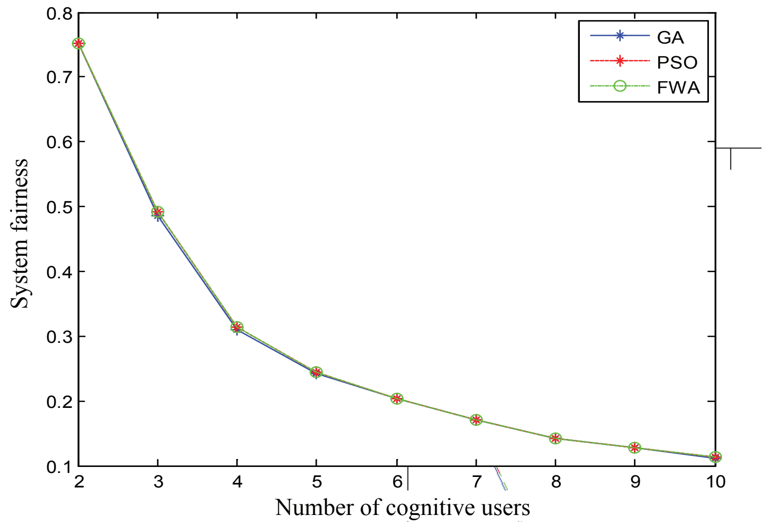

Figure 12 Variation of system fairness with the number of cognitive users.

5. CONCLUSION AND FUTURE WORK

Traditional swarm intelligence algorithms are prone to get stuck in a local optimum and to converge slowly when used to allocate the spectrum for cognitive radio networks. The fireworks algorithm has fewer optimization parameters, is less likely to get stuck in a local optimum, and provides excellent global optimization. Given these reasons, the fireworks algorithm is introduced for the purpose of spectrum allocation. Simulation results demonstrate the superiority of the proposed method in terms of convergence speed, system utility, and fairness. However, the time overhead of the proposed method is heavier than GA and PSO. This problem will be studied in the future.

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