INTERNATIONAL JOURNAL OF COMMUNICATION SYSTEMS
Int. J. Commun. Syst. 2016; **29**:64–83
Published online 19 May 2014 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/dac.2797

Discrete polynary coding immune clonal selection-based joint subcarrier and power allocation in uplink cognitive OFDM network

Ronghua Shang*,†, Kun Zhang, Licheng Jiao and Jianshe Wu

Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education, Xidian University, Xi'an 710071, China

SUMMARY

Cognitive radio has been considered to be one of the main technologies to solve the problem of low spectrum utilization, while the adaptive allocation of network resource is one of the key technologies. A discrete polynary coding immune clonal selection (DPICS)-based joint subcarrier and power allocation algorithm is proposed to solve the resource allocation problem in uplink cognitive OFDM networks. The novelties of DPICS include the following: A unique coding method is adopted to deal with multi-value discrete variables. Compared with the traditional methods, the proposed method can acquire the shortest code. Meanwhile, the constraints of the subcarrier allocation are avoided. A heuristic mutation scheme is used to direct the mutation. Subcarriers are reallocated randomly to the secondary users with larger homotactic noise, which has a large probability to produce the optimal solution and improves the searching process. Subcarriers and power are allocated simultaneously, which is different with the traditional biphasic resource allocation algorithms. The biphasic resource allocation algorithms cannot acquire the subcarrier allocation result and power allocation result simultaneously, which makes the final result imprecise. The proposed algorithm avoids this situation and improves the accuracy of the final result. Compared with state-of-the-art algorithms, the proposed algorithm is shown as effective by simulation results.

Received 22 May 2013; Revised 14 January 2014; Accepted 24 March 2014

KEY WORDS: cognitive radio; immune clonal selection; spectrum allocation; power allocation; OFDM

1. INTRODUCTION

The spectrum licensing mechanism is adopted now to manage the spectrum resource. According to this mechanism, the spectrum resource is allocated to a certain number of users (licensed user or primary user) to send a message in the long term. At this time, whether the spectrum is in use or not, other users have no right of access. Therefore, when the spectrum channel remains unused, it will not be effectively taken advantage, which makes the utilization of spectrum channels very low and change in a wide range. Some researches point out that according to different times and different areas, the utilization of different channels changes from 15% to 85% [1, 2]. Moreover, the development of modern radio communication technology strains the spectrum resource. Therefore, how to improve the utilization of spectrum resource becomes a more and more important issue. The cognitive radio technology is proposed for solving this

*Correspondence to: Ronghua Shang, Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education, Xidian University, Xi'an 710071, China.
†E-mail: rhshang@mail.xidian.edu.cn

problem [3]. Under the current spectrum management scheme, this technology can effectively improve the utilization of spectrum without affecting the primary user. And finally, a cognitive network without the concept of primary user will come true, which will change the current spectrum management scheme.

Cognitive radio can dynamically change its transmitter parameters to interact with the surrounding environment [2, 4] and choose an appropriate unused channel to communicate. According to the definition of cognitive radio, two core abilities are included, which are the cognitive ability and the reconfiguration ability [2]. Cognitive ability refers to the ability that the cognitive radio can sense the variation of the surrounding spectrum environment, while the reconfiguration ability means that the cognitive radio can dynamically adjust its transmitter parameters to the surrounding environment. The main challenges and development of cognitive radio are discussed in [2] and [4].

Orthogonal frequency-division multiplexing technology is one of the main technologies that are used in the transport layer in modern radio networks [5]. This paper focuses on the power and spectrum resource allocation in OFDM-based cognitive network, which is called cognitive OFDM network [5, 6]. In cognitive OFDM network, for different users, each channel has different transport characteristic. Through the appropriate use of this characteristic, cognitive OFDM can improve the utilization of spectrum resource [6]. Since being proposed, cognitive OFDM technology has attracted a great attention from researchers, and a great development has been made. Meanwhile, some cognitive OFDM model has been formulated. As an example, a greedy algorithm is proposed to optimize distributed joint frequency, data transmit speed, and the power allocation on every subcarrier [7]. However, the proposed algorithm has a high complexity, which limits its practical use. For this reason, biphasic resource allocation algorithms are proposed in [8] and [9], which can acquire suboptimal solutions. In the proposed algorithm, subcarriers are firstly allocated under the assumption of equal distribution of power on every channel, and then the power will be reallocated. The proposed algorithm can efficiently reduce the time complexity with suboptimal solutions. The basic resource allocation schemes with optimal and suboptimal solutions are discussed in [10]. In addition, according to different applications, researchers have proposed different cognitive OFDM resource allocation schemes. In [11] and [12], the resource allocation algorithms in distributed wireless cognitive network are proposed, and such algorithms in ad hoc networks are discussed in [13] and [14]. In [15], the resource allocation algorithm in uplink cognitive OFDM network is proposed, and another algorithm in uplink WiMAX networks is discussed in [16], while references [17] and [18] discuss in detail the resource allocation problem in different conditions in cognitive OFDM.

In most common conditions, the allocation problem of wireless cognitive network resource is a nonlinear problem, which is called an 'NP-hard' problem [19]. Such a problem is difficult to solve with traditional schemes. However, the proposition of intelligent algorithm based on bio-inspiration offers a new way to solve these problems [20]. There are some works in applying the intelligent algorithm to the allocation problems in recent years. As an example, the design of parameters in cognitive radio using the genetic algorithm is proposed in [21]. Meanwhile, some genetic algorithms are proposed in [22] and [23] to solve the problem of resource allocation in cognitive radio. In [24] and [25], the genetic algorithm is used to solve the problem of collaborative spectrum sensing and allocation. In reference [26], the optimal resource allocation problem under different optimization criteria using intelligent algorithm is discussed in cognitive network. However, the traditional intelligent algorithm takes too much time to deal with the optimization problem. For the resource allocation problem in OFDM network, the power and subcarrier have to be allocated separately, making the final result imprecise, so in this paper, a new intelligent algorithm is designed to solve the subcarrier and power allocation problem in cognitive OFDM network.

The novelties of the proposed algorithm are as follows:

In the proposed algorithm, in order to reduce the time consumption, the solutions near the optimal point are used as the initialized population, which is different with the traditional intelligent algorithms that use randomly created solutions as the initialized population.

Meanwhile, a new coding method that reduces the number of variables is adopted. As a result, the mutation scheme is redesigned. Prior information is used to direct the mutation operation and makes such an operation become more effective.

DOI: 10.1002/dac

Subcarriers and power are allocated simultaneously, which guarantees the precision of the final solution.

The basic process of the proposed algorithm includes initialization of population, clone, mutation, fitness evaluation, and update population. In the initialization of population, the approximately greedy scheme is used to allocate the subcarriers to the secondary users with the minimum noise. In the clone and update process, the traditional operation is adopted. And in the mutation and fitness evaluation process, new mutation operation and fitness function according to the problem model are designed. The antibodies in the population are coded as possible subcarrier allocation solutions, and the allocation of power is operated in the fitness evaluation process.

The rest of this paper is organized as follows: the second part introduces the basic model of cognitive OFDM resource allocation; the third part gives a detailed description of the proposed algorithm; in order to evaluate the effectiveness of the proposed algorithm, a series of experiments are designed, and the experimental results are given and analyzed in the fourth part; future work is discussed in the fifth part.

2. SYSTEM MODEL

Consider a single base station cognitive OFDM network with m secondary users and n subcarriers and assume that the parameters of the network have been acquired by the process of spectrum sensing and analysis. The serial data are coded to be an OFDM symbol and is transmitted by the subcarriers and power allocated by the algorithm. Here, we assume that one subcarrier can only be occupied by one secondary user at the same time. Therefore, there is no interference when the secondary user transmits its information. When the interference between different base stations is ignored, the noise of every subcarrier only includes the environment noise, which is white Gaussian noise.

We use N_0 to denote the noise spectral density of every channel and W_c to denote the channel bandwidth of the subcarrier. Then the Gaussian noise of the subcarrier can be represented as follows [27]:

$$P_n = N_0 {*} W_\mathrm{c} \tag{1}$$

According to the Shannon formula, in the ideal condition, the channel capacity of every subcarrier can be represented as

$$C = W_\mathrm{c} {*} \log\left(1 + \frac{P_\mathrm{s}}{P_n}\right) \tag{2}$$

In formula (2), C denotes the system capacity, and P_s denotes the signal power. In a practical case, the channel capacity is also affected by the channel gain and BER. In such a case, the data transmitter rate of secondary user i on channel k can be represented as follows [27]:

$$R_{ik} = \frac{1}{n} W_\mathrm{c} \log\left(1 + \frac{P_{ik} g_{ik}{}^2}{\delta N_0 W_\mathrm{c}}\right) \tag{3}$$

In formula (3), R_{ik} denotes the maximum system transmit rate of secondary user i on channel k, with transmit power p_{ik}. p_{ik} denotes the power of secondary user i on channel k. g_{ik} denotes the channel gain of channel k when secondary user i uses this channel. Generally, because of the multipath effect, g_{ik} will be a Rayleigh distributed random number [28]. δ denotes a function of BER, and in the Rayleigh channel, δ can be calculated as follows [29]:

$$\delta = \left(\frac{0.2}{P_\mathrm{e}} - 1\right) \bigg/ 1.5 \tag{4}$$

From the preceding analysis, for the i-th secondary user, the data transmit rate under the subcarrier allocation proposal Ω can be calculated as follows [27]:

DOI: 10.1002/dac

$$R_i = \sum_{k=1}^{n} \omega_{ik} R_{ik} \tag{5}$$

In formula (5), R_i denotes the acquired data transmit rate of secondary user i, while $\Omega = \{\omega_{ik} | \omega_{ik} \in \{0, 1\}, 1 \le i \le m, 1 \le k \le n\}$ denotes a possible channel allocation proposal. And when $\omega_{ik} = 1$, it means the i-th secondary user uses channel k; otherwise, the i-th secondary user does not use channel k.

In cognitive radio, according to the different demands for service, there are different optimization criterions, demanding different optimization functions. Among them, three are common [19, 20], ones that are shown as follows:

(1) Max-Sum-Reward (MSR), this criterion can be expressed as follows:

$$U(R) = \sum_{i=1}^{m} R_i \tag{6}$$

(2) Max-Min-Reward (MMR), which means maximizing the data transmit rate of the secondary user that acquires the smallest rate. It can be expressed as follows:

$$U(R) = \min(R_i) \qquad i = 1, \cdots, m \tag{7}$$

(3) Max-Proportional-Fair (MPF), which means that the transmit rate should be proportionally distributed among the secondary users while maximizing the data transmit rate, which can be expressed as follows:

$$U(R) = \prod_{i=1}^{m} R_i \tag{8}$$

Except this expression of MPF, some researchers also propose different expressions of this criterion [21, 22]. Different expressions can acquire different effects, such as in reference [27], which can realize any proportional distribution of the transmit rate in secondary users.

For the power allocation, to realize the maximization of the earlier criterion, different power allocation proposals will be acquired. Meanwhile, there are some constraints on the power allocation. Firstly, for every subcarrier, because it can only be allocated to one user at the same time, it will cause interference if other secondary users do not use this subcarrier load power on the subcarrier. Therefore, the power allocation proposal $P = \{p_{ik} | 1 \le i \le m,\ 1 \le k \le n\}$ in secondary users should meet the following constraints [27]:

$$p_{ik} \begin{cases} > 0, & \omega_{ik} = 1 \\ = 0, & \omega_{ik} = 0 \end{cases} \qquad i = 1, \cdots, m, k = 1, \cdots, n \tag{9}$$

Secondly, because of the restriction of the device, the transmit power of every secondary user is limited. For this reason, the power allocation proposal P should meet the constraints of transmit power, which can be expressed as follows [29]:

$$\sum_{k=1}^{n} \omega_{ik} {}^{*} p_{ik} \le P_i \qquad i = 1, \cdots, m \tag{10}$$

where P_i denotes the maximum transmit power of secondary user i.

At last, to guarantee the communication quality of the primary user, the power loaded on each subcarrier should remain in the tolerable range of the primary user. The interference temperature model [2] describes in detail the necessity of interference constraint, which can be expressed as follows:

$$\sum_{i=1}^{m} p_{ik} I_{ik} \le Q_k \qquad k = 1, \cdots, n \tag{11}$$

DOI: 10.1002/dac

where I_{ik} denotes the interference constraint of secondary user i on the subcarrier k and Q_k denotes the ceiling of the interference constraint of the primary user on subcarrier k.

To realize the joint optimal allocation of subcarrier and power, with the preceding optimization criterion, the optimal subcarrier allocation proposal Ω^* and power allocation proposal P^* can be calculated as follows [26]:

$$(\Omega^*, P^*) = \arg\max U(R) \quad \text{for all } (\Omega^*, P^*) \tag{12}$$

The MSR criterion is considered in this paper, which means that the algorithm will realize the maximum system transmit rate through reasonable subcarrier and power allocation proposals.

3. THE PROPOSED ALGORITHM

A discrete polynary coding immune clonal selection (DPICS)-based joint subcarrier and power allocation algorithm is adopted in this paper to allocate the subcarrier and power jointly in the uplink OFDM network. There is a basic process in such an algorithm, which includes the population initialization, clone, mutation, fitness evaluation, population updating, and so on. Each antibody in the population denotes a possible subcarrier allocation proposal; as a result, the operation on antibodies is equal to the operation on the subcarrier allocation proposal. The power allocation is completed in the fitness evaluation operation. The MSR criterion is used as the fitness value of every subcarrier and power allocation proposal. After several iterations of elimination of low fitness antibody, the proposed algorithm can acquire the optimal solutions.

3.1. The implementation principle of the proposed algorithm

The reason the proposed algorithm can acquire the optimal solution is that, in the execution of the algorithm, the solution will evolve in the right direction continuously by eliminating the bad antibodies and generating better antibodies randomly. The behavior of the population in the execution of the algorithm can be shown in Figure 1. In Figure 1, the dashed line denotes the population range after clone and mutation. The solid line represents the population range after the population update. Solid arrows indicate the direction of the evolution of the antibodies in the population, and the direction of the population is represented by the bold arrow.

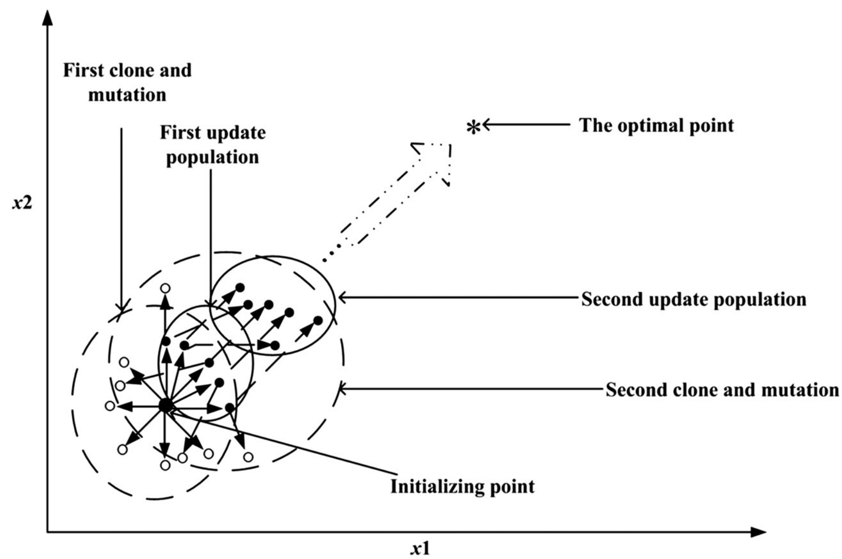


Figure 1. The illustration of the algorithm in this paper.

DOI: 10.1002/dac

Figure 1 can be explained as follows: in the initialization process, the proposed algorithm uses a similar greedy method, making the antibodies in the population gather near the optimal solutions and overlap with each other. After the first clone and mutation operations, the antibodies of the population begin diffusion in different directions, which are shown by the solid points and hollow points in the dashed circle in Figure 1. However, because the mutation operation in the algorithm is based on the heuristic method, by using the prior knowledge to guide the process of mutation, the antibodies in the population have a high possibility of evolving in the right direction. Therefore, it is easy to acquire a better solution. In the population updating operation, the antibody with the right direction will be kept (as shown by the solid point in the solid line circle in Figure 1), while the one with the wrong direction will be eliminated (as shown by the dashed point in the dashed circle). The newly formed population will carry the clone and mutation operations again. The preceding process will be repeated iteratively, driving the population to evolve in the right direction. Finally, the optimal solutions will be acquired. The evolution direction is shown by the bold arrow in Figure 1.

3.2. The realization of the proposed algorithm

3.2.1. Related terms. There are some terms in immune clonal selection-based algorithm, and the definitions of the related terms are given as follows.

Antibody: Antibody consists of genes. In the proposed algorithm, an antibody is a row vector, which will be described in Section 3.2.2.

Gene: Gene is the element of antibody. In the proposed algorithm, a gene is an element in the row vector (antibody); n genes compose an antibody. Here, n is the number of subcarriers. The relationship of gene (x_i) and antibody ($\boldsymbol{x}$) is described in Section 3.2.2.

Population: A population consists of several antibodies; the number of antibodies a population consists of is the scale of the population. In the proposed algorithm, the population is a two-dimensional matrix. The row of this matrix is an antibody, and every element in this matrix is a gene. The number of rows in the matrix is the scale of the population.

Fitness: Fitness value is the value of the objective function. Each antibody has a fitness value, which represents whether the antibody is suitable to be the final solution. The higher the fitness value, the more suitable is the antibody as the final solution. In the proposed algorithm, the objective function is the MSR criterion; therefore, the fitness value is the system transmit rate.

Population coding: How to use the antibody to represent the resource allocation result and how to acquire the resource allocation result from an antibody are very important. In the proposed algorithm, the resource allocation result is coded as a row vector.

Population initialization: This step gives every gene and antibody in the population initial value. In the proposed algorithm, it means that every element of the matrix is initialized with an integer value.

Clone operation: Create more of the same antibodies using one antibody. In the proposed algorithm, it means creating more of the same row vectors using a row vector, which will make the matrix (population) bigger.

Mutation operation: Change the value of some genes of an antibody, which adjusts the resource allocation result in a small extent. In the proposed algorithm, it means changing the value of a randomly picked element in a row vector.

Fitness evaluation: Calculate the fitness value (the value of objective function) for every antibody. In the proposed algorithm, it means the system transmit rate.

Population update: Use antibodies with high fitness values to replace antibodies with low fitness values. In the proposed algorithm, it means the row vectors with low fitness values are replaced with those having high fitness values.

3.2.2. Population coding. In the proposed algorithm, a unique coding method is adopted, which is described as follows.

Because one subcarrier can only be allocated to one user at the same time, all the subcarriers are coded. The length of the code is n (the number of subcarriers), and the value of each bit of the code

DOI: 10.1002/dac

ranges in the interval [1, m] while keeping it as an integer, which is, in other words, a multi-value discrete variable. The value represents the number of secondary users who use the subcarrier. We use $\boldsymbol{x}$ to represent a possible subcarrier allocation proposal, which is an antibody in the population. We use x_k to represent the allocation result of subcarrier k, which is the k-th gene of the antibody and means that the subcarrier k is allocated to secondary user x_i [30]. Then the antibody $\boldsymbol{x}$ can be expressed as follows:

$$x = (x_1, x_2 \ldots x_k \ldots x_n) \tag{13}$$

Compared with other coding methods [19, 22], this kind of code has the least variables, which can reduce the dimension of decision space and can speed up the convergence of the proposed algorithm.

3.2.3. Population initialization. Different from the random distributed initialized population in traditional immune clonal selection algorithms, the similar greedy method is adopted in the population initialization process [21, 22]. The homotactic noise c_i is defined as follows:

$$c_i = \frac{{g_{ik}}^2}{\delta N_0 W_\mathrm{c}} \tag{14}$$

Without the consideration of the variation of the power, it can be known from formula (14) that the higher the value of c_i, the higher the data transmitter rate. As a result, for every subcarrier, the secondary user with the highest c_i value is allocated to it.

When taking the power into consideration, because the subcarrier allocation result will affect the allocation of power, this method could not find the optimal population, but the suboptimal. A subsequent adjustment is needed to acquire the optimal solutions.

The initialization of the population can be expressed as follows:

$$\boldsymbol{A}(1) = (A_1(1), A_2(1), \ldots, A_n(1)) \tag{15}$$

Because the random scheme is not introduced in the initialization process, the antibodies in the initialized population are equal, that is, $A_1(1) = A_2(1) = \ldots = A_n(1)$.

3.2.4. Clone operation. In the traditional immune clone selection algorithm, the fitness is calculated firstly, and the proportion of clone is decided by the fitness value. However, in the proposed algorithm, in order to reduce the time complexity, we assume that the fitness of all antibodies is the same; therefore, the proportion of clones is the same as all antibodies. If this proportion takes a small value, which means a small scale of the population, the population is not conductive to expand its search in the follow-up operation, while a large proportion of clones will increase the time assumption in the follow-up operation. Therefore, a suitable proportion is explored. The experiments show that a proportion of 4 could lead the proposed algorithm to acquire a good effect, the value of which is taken in the proposed algorithm.

The population after clone operation can be expressed as follows:

$$\boldsymbol{B}(it) = \left(B_1(it), B_2(it), \ldots, B_{4*_n}(it)\right) \tag{16}$$

where it denotes the current generation. The clone operation can be expressed as follows:

$$\boldsymbol{B}(it) = clone(\boldsymbol{A}(it)) = (clone(A_1(1)), clone(A_2(1)), \ldots, clone(A_n(1))) \tag{17}$$

When the proportion of clone is 4, then

$$Clone\ (A_i(it)) = \left(B_{1+4*(i-1)}(it), B_{2+4*(i-1)}(it), B_{3+4*(i-1)}(it), B_{4+4*(i-1)}(it)\right) \tag{18}$$

DOI: 10.1002/dac

And the following equation holds:

$$B_{1+4*(i-1)}(it) = B_{2+4*(i-1)}(it) = B_{3+4*(i-1)}(it) = B_{4+4*(i-1)}(it) \tag{19}$$

After the clonal operation, the scale of the population will expand four times.

3.2.5. Mutation operation. We propose a new mutation operation called the heuristic mutation scheme, which implements local search in the decision space by randomly picking up a gene in antibodies and changing its value. From the analysis in Section 3.2.2, if the subcarriers are allocated to the user with a large value of c_i, then a large system throughput will be achieved. Therefore, the heuristic method is taken in the mutation operation. That is, we use the c_i as prior knowledge to guide the mutation operation, making it easier for the user with large c_i to obtain the subcarrier. This method can increase the probability of optimal solution, therefore speeding up the convergence.

The heuristic mutation operation is described as follows: firstly, a gene is randomly picked up according to the probability for every antibody, which denotes a subcarrier. Secondly, calculate the value c_i for all secondary users on this subcarrier and assign the c_i value of the user who used the subcarrier before to be zero. Thirdly, the c_i value should be normalized and taken as probability. At last, a secondary user is picked up randomly according to the probability. The number of this user is taken as the value of the picked gene. The process of heuristic mutation operation is shown as Algorithm 1:

Algorithm 1: Mutation Operation

Input: *Pop*: the population consisting of the allocation of subcarriers
pm: the mutation probability
Output: *ChiPop*: the result population of mutation operation
The process of the proposed algorithm:

```
[N,C]← size of Pop
CI←g^2./δN_0W_c); % the division of matrix
[MN,MC=size(CI);
ChiPop=Pop
If MN>1
For i=1:N
    If rand(1,1)<pm
    Ma ← random integer from [1 C]
    CI1=CI
    CI1ChiPop(I,Ma)) ←0
    Cs←zeros(MN, 1;)
    For every element Cs(j)in Cs
       Cs(j)←sum(CI1(1:j, Ma))
    End of for
    Cs ← normalization of Cs
    Ran=rand(1,1)
    For every element Cs(j)in Cs
    If Cs(j-1)<Ran<Cs(j)
           ChiPop(i, Ma)=j
       End of if
    End of for
  End of if
End of for
End of if
```


DOI: 10.1002/dac

3.2.6. Fitness evaluation. The MSR criterion is used in this operation, which is described in formula (6), as the fitness function. The following process is included in this operation: firstly, acquire the power allocation proposal through the power allocation algorithm described in the following and then calculate the overall system transmitter rate through formulae (3), (5), and (6). The value is taken as the fitness value.

In the proposed algorithm, the power is allocated by the fitness evaluation operation. The water-filling algorithm is considered here. However, it is not suitable for two constraint optimization problems. We draw the thought in reference [29] and take the power allocation problem in two steps. We firstly consider the power constraint only and allocate the power. Then we consider the interference constraint and correct the first allocation result. That is, if the power exceeds the interference constraint, it will be replaced with the upper bound of the interference constraint.

The process of power allocation operation is described as follows: firstly, we should acquire the subcarrier allocation proposal through the antibodies in the population, and then we calculate the water-filling level through the water-filling theorem for every secondary user. The power is allocated for every subcarrier according to the water-filling level. Thirdly, we calculate the allocated power and find whether it exceeds the interference constraint, and if the power exceeds the interference constraint, it will be replaced by the upper bound of the interference constraint. The process is shown in Algorithm 2:

Algorithm 2: Power Allocation

Input: *Pop*: the population consisting of the allocation of subcarriers
Output: *PowPop*: the result population of allocating the power in transmitter
The process of the proposed algorithm:

```
[N, C ← size of Pop
CI←δN_0W_c./g; % the division of matrix
Q=ones(m,1)*Q; Cq←Q./I;
For i=1: N
    Cw←zeros(m,n)
    For j=1:n
      Cw(j, Pop(i, j)) ←1
    End of for
    CP_n←N_0*W_c*Cw
    CN← the nuber of subcarriers owned by every secondary user, which has m rows and 1column
    Cy←(Paver+sum(CP_n, 2./CN; where Paver is the power limitation of transmitter of every secondary user
    Cy =ones(m,1)*Cy; P←Cw .*(Cy-CI)
      For every element p_ik in P and corresponding element q_ik in Cq
          If p_ik>q_ik then
            p_ik←q_ik
          End of if
    End of for
  PowPop(i, :, :) ←P
End of for
```

3.2.7 Population updating. In order to reduce the time complexity of the proposed algorithm, a simple way is taken to update the population. We firstly sort all the antibodies in the population from large to small according to their fitness value. Then we take *CNM* antibodies in the front to form the new population. Here, *CNM* denotes the scale of the population.

3.2.8 The whole process of the proposed algorithm. The basic operation of the proposed algorithm includes population initialization, clone, mutation, fitness evaluation, population update, and so on.

DOI: 10.1002/dac

The antibody in the population represents the possible subcarrier allocation proposal. Therefore, the operation on the antibody corresponds to the subcarrier allocation adjustment. The power allocation is completed in the fitness evaluation operation in cognitive OFDM networks. Through iteratively eliminating the proposals with low fitness value and randomly acquiring better proposals, the optimal solution will finally be achieved. The whole process of the proposed algorithm is shown in Algorithm 3.

Algorithm 3: Immune clonal selection based joint subcarrier and power allocation in uplink cognitive OFDM network

---

variance: *Pop*: the population consisting of the allocation of subcarriers
gmax: the largest generation of the population
pm: the probability of mutation
ChiPop: the result population of mutation process
Pa, ChiPa: the fitness of the variance *Pop, ChiPop*
CNM: the size of the population

The process of the proposed algorithm:

```
Initialization of variance gmax, pm, CNM
Initialization of the Population Pop
ChiPop← Mutation of Pop
Pop←[ChiPop; Pop(1, :)]
Pa← the fitness of Pop
g ← 1
while g<gmax
    ChiPop← clone of Pop
    ChiPop← mutation of ChiPop
    ChiPa← the fitness of ChiPop
    ChiPop←[ChiPop; Pop]
    ChiPa←[ChiPa; Pa]
    (Pop, Pa)← update from (ChiPop, ChiPa)
    g← g+1
end of while
```

3.3 Convergence analysis

The proposed algorithm, which based on the immune clonal selection, converges with probability 1. The proof is given as follows.

We use $\vartheta(\boldsymbol{A})$ to represent the number of optimal solutions in population $\boldsymbol{A}$, while $\boldsymbol{A}_i$ is used to denote the population of the i-th generation. The optimal solution is obtained when and only when the following equation is satisfied:

$$p\{\vartheta(\boldsymbol{A}_i) > 0\} = 1$$

In the preceding equation, the left-hand side means the probability that there are optimal solutions in the population of the i-th generation. To verify the preceding equation, we should firstly resolve the probability that $p\{\vartheta(\boldsymbol{A}_i)=0\}$. According to Bayesian theorem, there is the following derivation:

$$\begin{aligned} p\{\vartheta(\boldsymbol{A}_i) = 0\} &= p\{\vartheta(\boldsymbol{A}_i) = 0|\vartheta(\boldsymbol{A}_{i-1}) > 0\}^* p\{\vartheta(\boldsymbol{A}_{i-1}) > 0\} \\ &+ p\{\vartheta(\boldsymbol{A}_i) = 0|\vartheta(\boldsymbol{A}_{i-1}) = 0\}^* p\{\vartheta(\boldsymbol{A}_{i-1}) = 0\} \end{aligned}$$

According to the population updating scheme in the proposed algorithm, there must be optimal solutions in population $\boldsymbol{A}_i$ if optimal solutions exist in population $\boldsymbol{A}_{i-1}$; therefore,

DOI: 10.1002/dac

$p\{\vartheta(\boldsymbol{A}_i) = 0 | \vartheta(\boldsymbol{A}_{i-1}) > 0\} = 0$

And $p\{\vartheta(\boldsymbol{A}_i) = 0\} = p\{\vartheta(\boldsymbol{A}_i) = 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\} * p\{\vartheta(\boldsymbol{A}_{i-1}) = 0\}$.

We use ξ to represent the minimum probability of $p\{\vartheta(\boldsymbol{A}_i) > 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\}$.

Then, $1 \geq p\{\vartheta(\boldsymbol{A}_i) > 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\} \geq \xi > 0$.

And $1 - \xi \geq 1 - p\{\vartheta(\boldsymbol{A}_i) > 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\} \geq 0$.

Because $p\{\vartheta(\boldsymbol{A}_i) = 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\} = 1 - p\{\vartheta(\boldsymbol{A}_i) > 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\}$, therefore,

$$\begin{aligned} p\{\vartheta(\mathbf{A}_i) = 0\} &= p\{\vartheta(\boldsymbol{A}_i) = 0 | \vartheta(\boldsymbol{A}_{i-1}) = 0\} * p\{\vartheta(\boldsymbol{A}_{i-1}) = 0\} \\ &= p\{\vartheta(\boldsymbol{A}_1) = 0\} * \prod_{j=2}^{i} p\left\{\vartheta\left(\boldsymbol{A}_j\right) = 0 | \vartheta\left(\boldsymbol{A}_{j-1}\right) = 0\right\} \\ &\leq p\{\vartheta(\boldsymbol{A}_1) = 0\} * (1 - \xi)^{i-1} \end{aligned}$$

Because $1 \geq p\{\vartheta(\boldsymbol{A}_1) = 0\} > 0$ and $\lim_{i\to\infty} (1 - \xi)^{i-1} = 0$, therefore, $\lim_{i\to\infty} p\{\vartheta(\boldsymbol{A}_i) = 0\} = 0$. That is, $\lim_{i\to\infty} p\{\vartheta(\boldsymbol{A}_i) > 0\} = 1$.

This means that the proposed algorithm converges with probability 1.

3.4. *Complexity of the proposed algorithm*

We use g to denote the generations of iteration, c to denote the scale of population, n to denote the number of genes for every antibody, and m to denote the size of the set of values. So the complexity of each run is as follows:

In the population initialization, the equivalent noise needs to be calculated one time, which has the complexity of O(mn), and this needs to be assigned to every antibody, so the complexity of the population initialization is O($cn + mn$).

In the clone operation, every antibody and every gene need to be traversed once, so the complexity of this operation is O(cn).

In the mutation operation, the scale of the population is 4*n, for every antibody, only one gene is picked up and operated, which means the complexity of mutation operation is O(c).

In the affinity evaluation operation, the decoding process and power allocation process need to be carried out. The affinity of all the antibodies needs to be calculated, so the complexity of the affinity evaluation is O(cmn).

In the population updating operation, all antibodies need to be sorted, which has a complexity of O($c$log(4c)).

All the preceding operations have a linear complexity. With g generations of iteration, the complexity of the proposed algorithm is O($gcmn$log(4c)).

From preceding analysis, it is indicated that the complexity is affected by the scale of the population and the iteration, which make it hard to compare the complexity of the proposed algorithm with that of the contrast algorithms. But the fact is that the complexity is proportional to the number of secondary users and the number of subcarriers, while the generations of iteration and the scale of population are determined not by the scale of problem, but by the algorithm. The complexity of the contrast algorithms is given in Table I.

Table I indicates the same complexity of the proposed algorithm with the algorithms in [27] and in [30], which is lower than the algorithm in [29].

4. EXPERIMENT AND ANALYSIS

4.1. *Parameter settings*

In this paper, we assume a cognitive OFDM network with a single base station, which has m secondary users and n subcarriers. The network is not affected by other networks. Because the

DOI: 10.1002/dac

Table I. The complexity of the contrast algorithms.

Different algorithms	Complexity
Algorithm in [29]	$O(n^2m)$
Algorithm in [27]	$O(nm)$
Algorithm in [30]	$O(nm)$
Our proposed algorithm	$O(gcmn\log(4c))$

multipath effect commonly exists in the modern communication system, the experimental network is thought to be affected by the multipath effect. And because of this influence of the multipath, the channel and interference temperature index obey the Rayleigh random distribution. Therefore, the Rayleigh random numbers with a mean value of 1 are taken to simulate the channel gain g_{ik} and interference temperature index I_{ik}. In addition, the other parameters are set as follows: all the channel widths are set as $W_c = 1$; the BER is set as $P_e = 10^{-3}$, according to formula (4), and δ is 132. The Gaussian white noise power spectral density is set to be 10^{-7} for all the channels.

In the experiment, the power constraints and interference constraints will change according to the experiment conditions, which is convenient for comparing different experiment results.

In the proposed algorithm, the scale of the population has a large effect on the performance of the proposed algorithm. A large scale of the population can avoid local optima, which is one of the difficulties of traditional algorithm dealing with optimization problems. A small scale of the population can reduce the time complexity of the algorithm but can make it easier to acquire local optimal solutions. Experiments show that a population with 30 antibodies and 50 generations is suitable for the proposed algorithm. Meanwhile, the proportion of clones is set to be 4, and the probability of mutation is set to be 1.

4.2. Convergence analysis

In order to evaluate the convergence of the proposed algorithm, the following experiment is considered: the proposed algorithm runs with the parameters described in Section 4.1, while the generation is not stationary at 50 but varies according to the experiment. We count the mean and the maximum of the system throughput in every generation. When these two values are approximately equal, the proposed algorithm converges. To test the convergence of the proposed algorithm, the generation that needs to converge is counted in this experiment.

The convergence process of the proposed algorithm is shown in Figure 2, with $m = 4$ and $n = 32$.

The deterministic subcarrier allocation scheme is taken in the proposed algorithm; therefore, all the antibodies in the population are equal after the population initialization, so as the system throughput. As a result, the mean and the maximum of the system throughput are equal too, and near the optima. But in the following generation, these two values are not equal because the

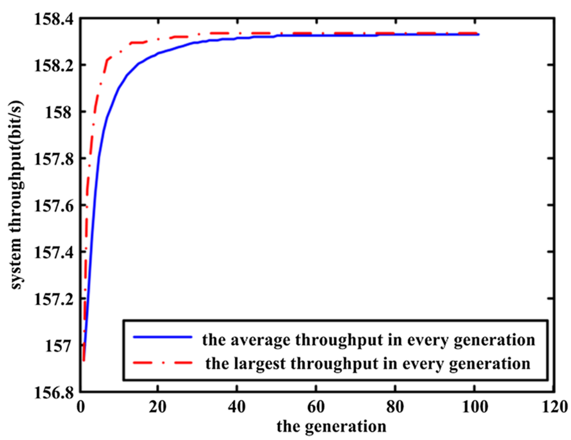


Figure 2. An illustration of convergence of the proposed algorithm.

DOI: 10.1002/dac

antibodies evolve in different directions in the clone and mutation operations, making different subcarrier allocation proposals involved in the population and leading the diversity of the population. The convergence of the proposed algorithm is illustrated in Figure 2.

Figure 2 shows that the maximum the system has already been acquired after 20 generations, while the mean value is acquired after many more generations than the maximum value. This process is beneficial. The maximum value converges fast, which shows the good ability of the proposed algorithm to find the optimal solution. The mean value converges slowly, which means that the population is good at keeping diversity and can search a broader range, which can avoid local optima and guarantee the maximum value to be the optimal solution.

Although the maximum value of system throughput converges to the optimal solution in the early stage of the proposed algorithm, the following generation is necessary. Because in the early stage, the mean value does not converge to the optimal solution, which means that the proposed algorithm is still in the process of searching optimal solutions. With the mean value close to the maximum value, the searching process converges gradually, which can guarantee the avoidance of local optima.

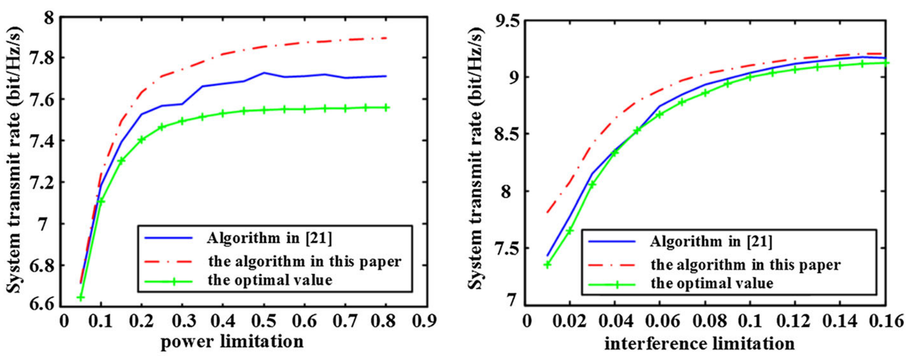
4.3. *The performance analysis under the MSR criterion*

It can be seen from the system model that the power allocation in the cognitive OFDM network has two kinds of constraints: the power constraint and the interference constraint. In order to test the performance of the proposed algorithm under different constraints, the improved water-filling algorithm in [29] is taken as the contrast algorithm. And two experiments are designed as follows:

Given the number of subcarriers $n = 32$ and the number of secondary users $m = 4$, the performance of these two algorithms under the following two conditions is tested. Firstly, taking the interference constraints to be $Q_k = 0.01 + AWGN$ where $AWGN$ denotes Gaussian white noise, the initial power constraints to be $P_i = 0.01$, and Q_k to be constant while P_i increases by 0.05 for 16 times, the performance of the proposed algorithm and the compared algorithm is tested. Its power is 0.01. Secondly, we take the same initial value of Q_k and P_i, but P_i is constant in this condition, while Q_k increases by 0.01 for 16 times. The results are shown in Figure 3.

Figure 3(a) presents the variation of the system transmit rate with transmit power. Figure 3(b) presents the variation of the system transmit rate with the interference temperature constraint. These three curves denote respectively the maximum result in initial population, the optimal solution obtained by the proposed algorithm in this paper, and the solution obtained by improved water-filling algorithm. From Figure 3(a, b), we can find that for both the proposed algorithm and the improved water-filling algorithm, the solutions are improved much compared with the result of the initial population. It suggests that the similar greedy method is not the optimal method, which needs the follow-up adjustment in order to acquire the optimal solution.

It can be seen from Figure 3(a) that when the power is low, which corresponds to the former curve, the performances of the proposed algorithm and the improved water-filling algorithm are roughly equal; but when the power is high, which corresponds to the latter curve, the



(a) (b)

Figure 3. The variation of system throughput versus power limitation (a) or interference limitation (b).

DOI: 10.1002/dac

performance of the proposed algorithm is much better than that of the improved water-filling algorithm. The reason is obvious. When the power is low, the power constraints play the major role to the resource allocation. Therefore, the improved water-filling algorithm is effective for the resource allocation, obtaining good performance. When the power is high, the interference constraints play the major role to the resource allocation. Therefore, the improved water-filling algorithm is invalid for the resource allocation, obtaining bad performance. Meanwhile, no matter which constraints play the major role, the proposed algorithm can acquire good performance.

From Figure 3(b), we can find that in the former curves, the interference is low and plays the major role. Therefore, the performance of the proposed algorithm is much better than that of the improved water-filling algorithm. In the latter curves, the condition is converse and the performance of both algorithms is roughly equal. The result of Figure 3(b) confirms the preceding analysis in Figure 3(a).

To verify the performance of both algorithms when there are many secondary users, we design this experiment. The condition is same with experiment 1 except for the following parameter: in condition 1, the initial value of P_i is 0.01, and the step is 0.02, which is repeated for 16 times; in condition 2, the value of P_i is 0.2, and the setting of Q_k is the same with that in experiment 1. The result is shown in Figure 4.

From Figure 4(a, b), we can find that when there are many secondary users, the result is similar with experiment 1. Meanwhile, when the power constraints play the major role, the proposed algorithm is better than the improved water-filling algorithm, which is different with experiment 1.

To verify the effect of the number of secondary users on the performance of both algorithms, we run both algorithms respectively under the condition of power taking the major role or the condition of interference taking the major role with different numbers of secondary users. The results are shown in Figure 5. In Figure 5(a), we set the power to be $P_i = 0.05$, and the interference temperature to be $Q_k = 0.01$. Meanwhile in Figure 5(b), we set the power to be $P_i = 10$, and the interference temperature to be $Q_k = 0.01$. The number of subcarriers is 32 in both conditions.

From Figure 5, we can find that, when there is only one secondary user, the results of both algorithms are the same and equal to the initial population, which means it is not necessary to allocate the network resource when there is only one secondary user. In addition, when the number of users is larger or the interference constraints play the major role, the performance of the proposed algorithm is much better than the improved water-filling algorithm.

4.4. The comparison of different criterions

In order to compare the performance under different criterions, which are mentioned in part 2, the following experiment is designed: we set $n = 32$, $Q_k = 0.01 + AWGN$, and $P_i = 0.01$. The initial number of secondary users is set to 4, the final number is set to 11, and the step is set to 1. The proposed algorithm runs under the MSR criterion, the MMR criterion, and the MPF criterion,

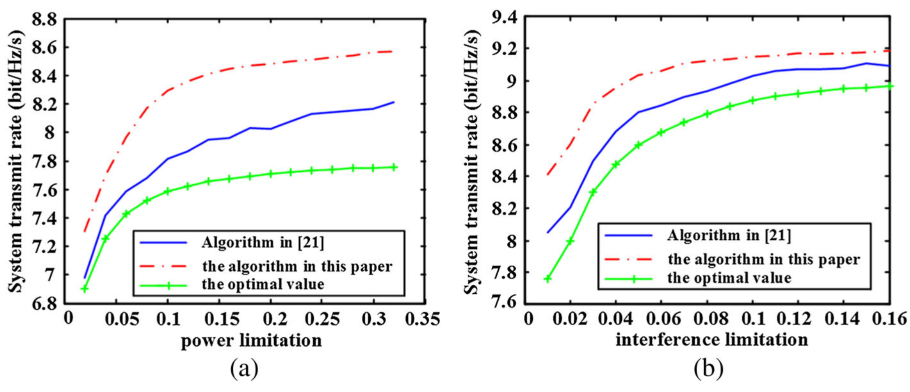


Figure 4. The variation of system throughput versus power limitation (a) or interference limitation (b), when $m = 12$.

DOI: 10.1002/dac

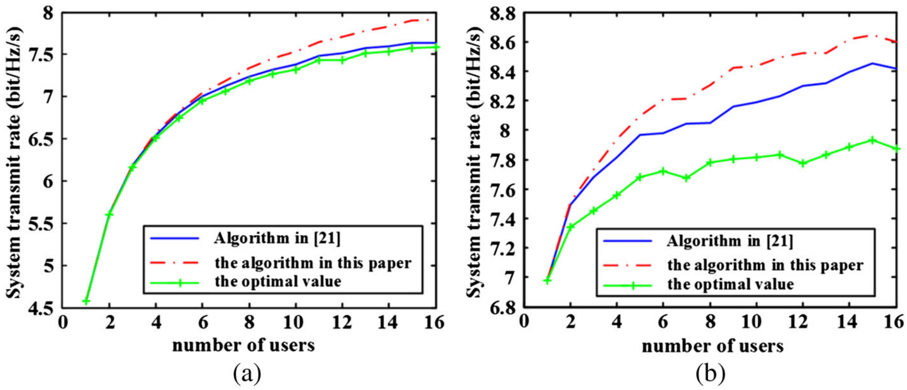


Figure 5. The variation of system throughput versus the number of secondary user when power constraints (a) or interference constraints (b) take the main effect.

respectively. We count the optimal result, the average system throughput, and the variance of secondary users to it under the aforementioned three criterions. The simulation results under different criterions are shown in Table II.

It can be seen from Table II that under the MSR criterion, the proposed algorithm can acquire the largest system throughput, while its variance is the largest too. This means an unfair allocation of data transmit rate between secondary users. Under the MMR criterion, the proposed algorithm acquires the least average system throughput with the least variance. This means that the MMR criterion emphasizes the fairness between secondary users most and sacrifices the data transmit rate. Under the MPF criterion, the average system throughput and the variance are middle in these three criterions. This means that the MPF criterion can make a compromise between the system throughput and the fairness among secondary users. Overall, these three criterions have their own characteristic. If we emphasize the system throughput, the MSR criterion is recommended. If the fairness among secondary users is more important, the MMR criterion should be considered. If both characteristics are in need, the MPF criterion should be in reference.

4.5. The effect comparison with other intelligent algorithms

For the resource allocation problem in the OFDM network, there are many intelligent algorithms proposed. We also take the algorithms in [27] and [30] as contrastive algorithms to testify to the effectiveness of the proposed algorithm. The OFDM network with one base station is assumed here, which has n subcarriers and m secondary users. The parameters of the network are set as in [30], which are listed as follows:

Table II. The simulation results under different criterions.

Number of secondary users	Fitness value			Average throughput of each secondary user			Variance of the throughput of each secondary user		
	MSR	MPF	MMR	MSR	MPF	MMR	MSR	MPF	MMR
4	156.44	2330221	38.26	39.11	39.08	38.89	71.45	2.45	1.58
5	165.55	39357489	31.60	33.11	33.10	32.66	32.92	21.95	8.65
6	175.23	6.12E+08	27.78	29.21	29.20	28.70	30.38	23.64	9.72
7	180.06	7.19E+09	23.59	25.72	25.68	24.68	99.39	30.27	13.77
8	185.33	8.23E+10	22.17	23.17	23.15	22.89	46.15	1.73	0.95
9	188.26	7.02E+11	18.51	20.92	20.84	20.47	110.44	45.82	27.85
10	192.98	6.76E+12	18.22	19.29	19.28	19.11	40.72	38.68	22.52
11	196.19	5.3E+13	13.44	17.84	17.76	17.02	88.22	24.21	20.04

MSR, Max-Sum-Reward; MPF, Max-Proportional-Fair; MMR, Max-Min-Reward.

DOI: 10.1002/dac

The number of subcarriers is 64.
The number of secondary users is set between 2 and 16.
The equivalent noisy power spectral density is 1.1565×10^{-8} W/Hz.
The channel bandwidths is 1 MHz.
The total power of the base station is 1 W.
The channel gains of the OFDM network are uniform random numbers in the interval [0 1].
The BER is set to be 10^{-3}.

At the same time, to testify the performance of the proposed algorithm under the MPF criterion, an MPF-based penalty term is added to the objective function [27], which is shown in formula (20). The penalty parameter is $w = 1.5$. In the experiment, the results of the proposed algorithm with and without the penalty term are presented.

$$f = U(R) + w^* \max\left(0, 1 - \left(\left(\sum_{i=1}^{M} R_i\right)^2 \bigg/ \sum_{i=1}^{M} {R_i}^2\right)\right) \tag{20}$$

In formula (20), $U(R)$ is calculated by formula (6).

In this experiment, four algorithms run for 100 times separately, the results are counted and presented in the form of a boxplot, and the average results are calculated and presented; Figures 6–8 show the experiment results.

Figure 6 shows the average results of four algorithms when the secondary users vary from 2 to 16 and are an even number. This figure tells us that when the number of secondary users increases, the system transmit rate of four algorithms increases too, which confirms the diversity effect of secondary users. The proposed algorithm can acquire a higher system transmit rate compared with both two contrastive algorithms. Meanwhile, from the proposed algorithm, we can find that the result does not change if the penalty term is added to the objective function, which means that the system transmit rate is uniformly distributed among secondary users and the MPF criterion can be guaranteed by the proposed algorithm.

To test the stability of the proposed algorithm, we take the number of secondary users to be six and use a boxplot to show the 100-run results of four algorithms in Figure 7.

From Figure 7, we can find that, compared with the two contrastive algorithms, the proposed algorithm shows very steady results. Meanwhile, we can also find that the result does not change if the penalty term is added to the objective function, which means the MPF criterion can be guaranteed by the proposed algorithm.

In order to further test the performance of the proposed algorithms under the MPF criterion, we count the transmit rate of every secondary user for four algorithms in every run and calculate the relative variance according to formula (21).

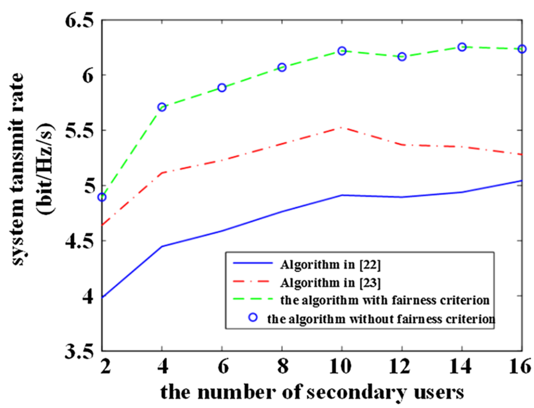


Figure 6. System transmit rate versus the number of secondary users.

DOI: 10.1002/dac

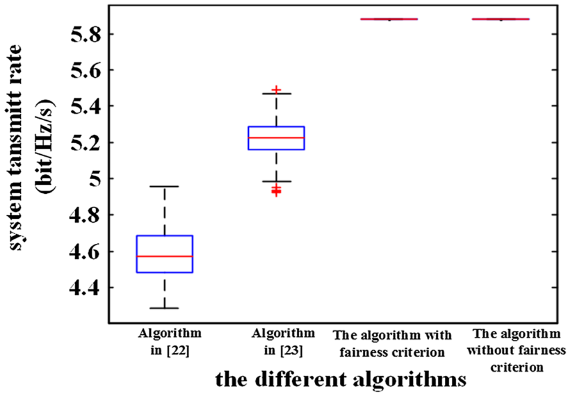


Figure 7. The statistic of 100 runs for different algorithms.

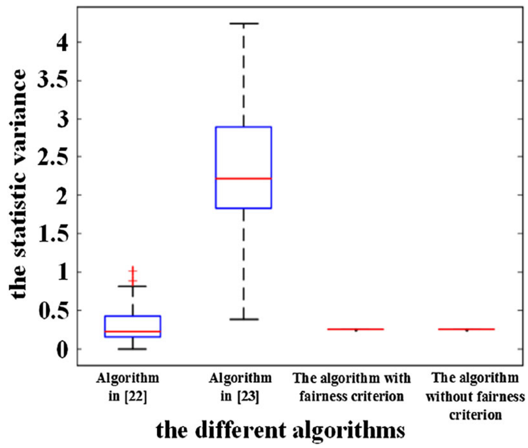


Figure 8. The statistic of variance of different users.

$$V(R) = \sum_{i=1}^{m} \left(\frac{R_i - R_{\text{aver}}}{R_{\text{aver}}} \right)^2 \tag{21}$$

In formula (21), the R_{aver} is calculated as formula (22)

$$R_{\text{aver}} = \frac{\sum_{i=1}^{m} R_i}{n} \tag{22}$$

From formula (21), we can find that the value of $V(R)$ is always positive; the smaller the value of $V(R)$ is, the smaller the difference of transmit rate among secondary users, which means the system transmit rate is distributed more even among secondary users; when the value of $V(R)$ is 0, the system transmit rate is distributed absolutely even among secondary users.

The relative variance of 100 runs for four algorithms is shown in Figure 8. We take the secondary users to be 4.

From Figure 8, we can find that both the proposed algorithm and the algorithm in [27] can realize the uniform distribution of the system transmit rate among secondary users, and the result of the proposed algorithm is very steady. In addition, from the results of the proposed algorithm with and without the penalty term, we can find that the penalty term hardly has any effect on the

DOI: 10.1002/dac

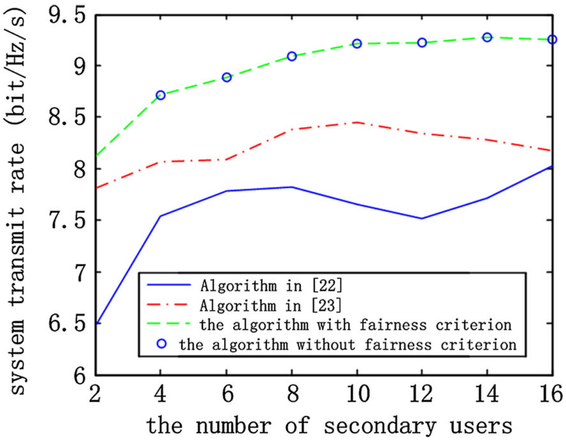


Figure 9. System transmit rate versus the number of secondary users.

performance of the proposed algorithm. The proposed algorithm can satisfy the MPF criterion even without the penalty term.

4.6. The effect of the proposed algorithm under imperfect channel state information

In a real communication network environment, the accurate channel parameters cannot be acquired because of the error and delay of channel information, which will lead to two influences: (1) this will cause channel parameter estimation errors and improve the BER and (2) parameter estimation results is outdated. To solve the delay problem of channel estimation, probability estimation methods (like maximum likelihood estimation) are used to estimate current channel state information, the channel information known in the past. In cognitive radio technology, the estimation of channel state information is completed in spectrum analysis, which is not the main purpose of the paper; however, the influence of the channel estimation error must be considered, which mainly causes the improvement of BER. In a real urban environment, because of multipath effects, channel gain generally obeys the Rayleigh distribution. When M-QAM modulation is used, the BER can be calculated using the following formula [31]:

$$P_e = c_1 \exp\left(\frac{-c_2\gamma_{ik}}{2^{R_{ik}} - 1}\right) \tag{23}$$

In the preceding formula, γ_{ik} denotes signal-to-noise ratio and c_1 and c_2 are the experience values, where c_1 is set to be 0.5 and c_2 is set to be 1.2[32].

In this experiment, the random numbers that obey Rayleigh distribution with average 1 are used to simulate the channel gains and interference temperature index. Meanwhile, the channel bandwidth is set to $W_c = 1$ MHz. The *AWGN* for every subcarrier is set to be the Gaussian number with an average of 10^{-7} W/Hz. The BER will be calculated using the preceding formula.

The number of subcarriers is set to be $n = 32$. Keep the interference temperature limit for every subcarrier to be $Q_k = 0.1 + AWGN$, while the number of secondary users is set to $m = 2$–16 and increases by 2. The effects of the proposed algorithm and the contrast algorithms are tested.

From Figure 9, we can find the stability of the proposed algorithm, which indicates the same conclusion as in Section 4.5.

5. CONCLUSIONS

The DPICS algorithm is proposed in this paper for the resource allocation problem in a cognitive OFDM network. Different from the traditional algorithm, the proposed algorithm codes the subcarrier and uses the discrete decision space. The main advantages of the proposed algorithm are the following:

DOI: 10.1002/dac

It codes the subcarrier. This coding has the shortest length compared with that of other algorithms. The length of this coding is affected only by the number of subcarriers. The variables take the integer value in the interval $[1\ m]$ and are affected only by the number of secondary users.

The mutation operation takes the heuristic method, which makes the search of new allocation proposal more effective than the traditional ones and reduces the time cost as a result. Meanwhile, this mutation operation can handle multi-value discrete variables.

The proposed algorithm allocates the subcarrier and the power at the same time with low time complexity, which is different with the two-step algorithms.

The proposed algorithm avoids the processing of subcarrier allocation constraints. The power allocation operation can handle the constraints effectively. As a result, the complexity is reduced.

A series of experiments are designed to verify the performance of the proposed algorithm. The results and analysis of the experiments show the good effectiveness of the proposed algorithm. But still, there are some problems that need to be solved, just like the time cost problem, the accuracy of the optimal solution, the adaptive control of the scale of the algorithm, and so on. Therefore, our future work will focus on these problems.

ACKNOWLEDGEMENTS

We would like to express our sincere appreciation to the anonymous reviewers for their insightful and valuable comments, which have greatly helped us in improving the quality of the paper. This work was partially supported by the National Basic Research Program (973 Program) of China under grant 2013CB329402; the National Natural Science Foundation of China, under grants 61371201, 61001202, 61203303, and 61272279; the Fundamental Research Funds for the Central Universities under grant K5051302028; the Fund for Foreign Scholars in University Research and Teaching Programs (the 111 Project) under grant B07048; and the Program for Cheung Kong Scholars and Innovative Research Team in University under grant IRT1170.

REFERENCES

1. FCC. ET Docket No 03-222 Notice of proposed rule making and order. December 2003.
2. Akyildiz IF, Lee WY, Vuran MC, Mohanty S. Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey. *Computers Networks (Elsevier)* 2006; **50**(13):2127–2159.
3. Safdar GA. Cognitive Radio Networks: Sensing, Access, Security. *LTE-Advanced and Next Generation Wireless Networks: Channel Modelling and Propagation*, de la Roche G, Glazunov AA and B Allen (eds.). John Wiley & Sons, Ltd: Chichester, UK, 2012; 443–472.
4. Wang B, Liu KJR. Advances in cognitive radio networks: a survey. *IEEE Journal of Selected Topics in Signal Processing* 2011; **5**(1):5–23.
5. Oh E, Woo C. Performance analysis of dynamic channel allocation based on the greedy approach for orthogonal frequency-division multiple access downlink systems. *International Journal of Communication Systems* 2012; **25** (7):953–961.
6. Wang S, Huang F, Yuan M, Du S. Resource allocation for multiuser cognitive OFDM networks with proportional rate constraints. *International Journal of Communication Systems* 2012; **25**(2):254–269.
7. Cheng P, Zhang Z, Qiu P. Optimal distributed joint frequency, rate, and power allocation in cognitive OFDMA. *IET Communication* 2008; **2**(6):815–826.
8. Kang X, Liang YC, Nallanathan A. Optimal power allocation for fading channels in cognitive radio networks: ergodic capacity and outage capacity. *IEEE Transactions on Wireless Communications* 2009; **8**(2):21–29.
9. Bai L, Chen C, Wu B, He J. Adaptive resource allocation for multicast orthogonal frequency division multiple access systems with guaranteed BER and rate. *International Journal of Communication Systems* 2013; **26**(7):912–926.
10. Bansal G, Hossain J, Bhargava VK. Optimal and suboptimal power allocation schemes for OFDM-based cognitive radio systems. *IEEE Transactions on Wireless Communications* 2008; **7**(11):4710–4718.
11. Zhang Yh, Leung C. A distributed algorithm for resource allocation in OFDM cognitive radio systems. *IEEE Transactions on Vehicular Technology* 2011; **60**(2):546–554.
12. Han Z, Ji Z, Liu KJR. Noncooperative resource competition game by virtual referee in multicell OFDMA networks. *IEEE Journal on Selected Areas in Communications* 2007; **25**(6):1079–1090.
13. Chowdhury K, Akyildiz I. OFDM based common control channel design for cognitive radio ad hoc networks. *IEEE Transactions on Mobile Computing* 2011; **10**(2):228–238.
14. Di Felice M, Chowdhury KR, Bononi L. Cognitive radio vehicular ad hoc networks: design, implementation, and future challenges. *Mobile Ad Hoc Networking: Cutting Edge Directions, Second Edition* 2013; 619–644.

DOI: 10.1002/dac

15. Huang J, Subramanian V, Berry R, Agrawal R. Joint scheduling and resource allocation in uplink OFDM systems for broadband wireless access networks. *IEEE Journal on Selected Areas in Communications* 2009; **27**(2):226–234.
16. Hwang BJ, Hwang I, Huang CW. Frame–based adaptive uplink scheduling algorithm in orthogonal frequency division multiple access-based Worldwide Interoperability for Microwave Access networks. *International Journal of Communication Systems* 2012; **25**(11):1381–1397.
17. Wang P, Zhao M, Xiao L, Zhou S, Wang J. Power allocation in OFDM-based cognitive radio systems. *Proc. IEEE Global Telecommun. Conf. (Globecom)*, 2007; 4061–4065.
18. Bansal G, Hossain MJ, Bhargava VK. Adaptive power loading for OFDM-based cognitive radio systems with statistical interference constraint. *IEEE Transactions on Wireless Communications* 2007; **10**(9):2786–2791.
19. Almalfouh SM, Stüber GL. Interference aware radio resource allocation in OFDMA based cognitive radio networks. *IEEE Transaction on Vehicular Technology* 2011; **60**(4):1699–1733.
20. Hossain E, Niyato D, Kim DI. Evolution and future trends of research in cognitive radio: a contemporary survey. *Wireless Communications and Mobile Computing* 2013. DOI: 10.1002/wcm.2443.
21. Liu Y, Jiang H, Huang YQ. Design of cognitive radio wireless parameters based on multi-objective immune genetic algorithm. *Proc. WRI Int. Conf. CMC* 2009; 92–96.
22. Guo AJ, Cheng P, Wang XB, Rui Y, Gan XY, Yu H. Evolution framework for resource allocation with local interaction: an infection approach. *IEEE International Conference on Communications* (*ICC*) 2011; 1–5.
23. Gözüpek D, Alagöz F. Genetic algorithm-based scheduling in cognitive radio networks under interference temperature constraints. *International Journal of Communication Systems* 2011; **24**(2):239–257.
24. Wang B, Liu KJ, Clancy T. Evolutionary cooperative spectrum sensing game: how to collaborate? *IEEE Transactions on Communications* 2010; **58**(3):890–900.
25. Wu Z, Cheng P, Wang X, Gan X, Yu H, Wang H. Cooperative spectrum allocation for cognitive radio network: an evolutionary approach. *IEEE International Conference on Communications* (*ICC*), 2011; 1–5.
26. Zhao Z, Peng Z, Zheng S, Shang J. Cognitive radio spectrum allocation using evolutionary algorithms. *IEEE Transactions on Wireless Communications* 2009; **8**(9):4421–4425.
27. Chai ZY, Liu F, Qi YT, Zhu SF. On the use of immune clonal optimization for joint subcarrier and power allocation in OFDMA with proportional fairness rate. *International Journal of Communication Systems* 2013; **26**(10):1273–1287.
28. B Wang, Z Ji, Liu KJR, Clancy TC. Primary-prioritized Markov approach for dynamic spectrum allocation. *IEEE Transactions on Wireless Communications* 2009; **8**(4):1854–1865.
29. Wang W, Wang W, Lu Q, Peng T. An uplink resource allocation scheme for OFDMA-based cognitive radio networks. *International Journal of Communication Systems* 2009; **22**(5):603–623.
30. Sharma N, Tarcar AK, Thomas VA, Anupama KR. On the use of particle swarm optimization for adaptive resource allocation in orthogonal frequency division multiple access systems with proportional rate constraints. *Information Sciences* 2012; **82**(1):115–124.
31. Chung ST, Goldsmith AJ. Degrees of freedom in adaptive modulation: a unified view. *IEEE Transactions on Communications* 2001; **49**(9):156–1571.
32. Attar A, Nakhai MR, Aghvami AH. Cognitive radio game for secondary spectrum access problem. *IEEE Transactions on Wireless Communications* 2009; **8**(4):212–2131.
33. Mahmoud H, Yucek T, Arslan H. OFDM for cognitive radio: merits and challenges. *IEEE Personal Communication* 2009; **16**(2):6–15.

DOI: 10.1002/dac