Resource Allocation with Proportional Rate In Cognitive Wireless Network: An Immune Clonal Optimization Scheme

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Received January 28, 2012; revised April 9, 2012; accepted May 9, 2012; published May 25, 2012

Abstract

In this paper, the resource allocation problem with proportional fairness rate in cognitive OFDM-based wireless network is studied. It aims to maximize the total system throughput subject to constraints that include total transmit power for secondary users, maximum tolerable interferences of primary users, bit error rate, and proportional fairness rate among secondary users. It is a nonlinear optimization problem, for which obtaining the optimal solution is known to be NP-hard. An efficient bio-inspired suboptimal algorithm called immune clonal optimization is proposed to solve the resource allocation problem in two steps. That is, subcarriers are firstly allocated to secondary users assuming equal power assignment and then the power allocation is performed with an improved immune clonal algorithm. Suitable immune operators such as matrix encoding and adaptive mutation are designed for resource allocation problem. Simulation results show that the proposed algorithm achieves near-optimal throughput and more satisfying proportional fairness rate among secondary users with lower computational complexity.

Keywords: Immune clonal algorithm, cognitive wireless network, OFDM, proportional fairness rate, resource allocation, subcarrier allocation, power allocation

This research was supported by the following Foundation Items: the National High Technology Research and Development Program (863 Program) of China (No. 2009AA12Z210), the National Natural Science Foundation of China (No. 61001202, 61003199 and 61072139), the National Research Foundation for the Doctoral Program of Higher Education of China (No. 20090203120016 and 20100203120008).We express our thanks to Dr. Richard Berke who checked our manuscript.

http://dx.doi.org/10.3837/tiis.2012.05.002

1. Introduction

Spectrum shortage crisis is becoming more and more severe with the increasing growth of wireless communication demands. It was reported by Federal Communications Commission (FCC) that most of the licensed wireless spectrum is not currently utilized [1]. It is far more underutilized rather than naturally scarce [2]. Cognitive wireless network (CWN) is a kind of intelligent communication system, which can improve the utilization of spectrum resources to fulfill the requirements of spectrum-hungry applications [3][4]. According to FCC regulations [1][5], spectrum holes exist in the licenced spectrum, and secondary users (SUs) can share the spectrum bands opportunistically with primary users (PUs) under interference restriction. To meet this requirement, the physical layer of a CWN should be very flexible. Orthogonal frequency division multiplexing (OFDM) offers fascinating performance in physical layer and has been used in many other wireless communications[6].Hence, OFDM system has the inherent flexibility in resource allocation, making it the favorite to be the CWN interface. It is of great significance for allocating resources to secondary users in OFDM-based cognitive wireless network so as to use the spectrum effectively. A comprehensive survey about adaptive resource allocation in conventional multi-user OFDM systems can be found in [7]. In cognitive OFDM network, SUs and PUs co-exist in a same band, so the mutual interferences between them are key issues and must be fully taken into account. These interference constraints are the main differences between the optimization problem in OFDM-based CWN and the conventional (non-cognitive) multi-user OFDM systems considered in [7].

The resource allocation problem in OFDM-based CWN has attracted more attentions in recent years. A lot of works have been investigated on it with different scenarios [8][9][10][11][12][13]. In [8], an optimal resource allocation using integer linear programming was proposed, which was computationally complex. In [9], a goal programming approach was used to transform the problem into a single objective nonlinear optimization problem. In [10], it was pointed out that the resource allocation problem was a large non-linear integer programming problem and two heuristics were proposed. In [11], it was also exhibited that the resource allocation problem was a nonlinear programming problem. Computationally efficient suboptimal algorithms were proposed in these schemes [8][9][10][11]. In addition, the algorithms in [8][9][10][11] didn't consider the proportional fairness demand among SUs. Actually, different SUs have different throughput requirements, which can be achieved by pre-defined service levels. In [12], the proportional rate constraint was added to the existing resource allocation problem. However, the introduction of this constraint makes the optimization problem more complicated thus increasing the difficulty in finding the optimal solution because the feasible set is not convex. In short, the resource allocation problem in CWN is a nonlinear optimization problem[8][9][10][11][12], for which obtaining the optimal solution is known to be NP-hard. The optimal resource allocation is computationally complex for practical applications [8][9][10][11][12]. In [9][10][11][12], it is shown that efficient suboptimal algorithms exhibit near-optimal performances and significantly reduce the computational complexity compared with the optimal solution.

It is known that bio-inspired methods are ideal for such nonlinear optimization problems [13][14]. Some bio-inspired methods have been employed in conventional (non-cognitive) OFDM based resource allocation system, such as genetic algorithm [15][16][17] and particle swarm optimization [18]. It is shown that these schemes have achieved better results compared with normal iterative algorithms. Artificial immune system (AIS) is a kind of promising

computational intelligence method which draws inspiration from the human immune system [19]. An AIS-based optimization algorithm, called immune clonal selection algorithm[20], which has been widely used in engineering-oriented fields in recent years, such as network routing [21], job scheduling [22][23], image recognition [24][25], multi-user detection [26] and so on. All the successful applications prove that immune clonal selection algorithm performs well in the domain of optimization.

In this study, an improved immune clonal selection algorithm is introduced to solve resource allocation problem in OFDM based CWN. The inspiration comes from the fact that clonal selection algorithm is ideal for non-liner optimization problems with a large feasible solution space where a quick sub-optimal solution will suffice. Also, the fact that immune clonal algorithm is seldom used in OFDM based CWN further deepens our inquisitiveness to explore this option.

In this paper, the resource allocation problem is to maximize the system throughput, with constraints including SU's total power, proportional fairness rate, bit error rate (BER) and maximum interference power that PU can tolerate. In [13][18], it was shown that resource allocation can be solved sub-optimally by separating subcarrier allocation and power allocation. Hence, the proposed scheme is divided into two steps. That is, subcarriers are firstly allocated to secondary users assuming equal power, and then the power allocation is performed with an improved immune clonal algorithm. Through the proportional clonal, mutation and clonal selection, the proposed algorithm performs a greedy search which reproduces antibodies and selects their improved offspring after the affinity maturation process. Theoretical analysis indicates that it is very suitable for the resource allocation. Extensive experiment results show that the performances of the proposed algorithm outperform the existing ones. Compared with the optimal resource allocation scheme in[8], the proposed one obtains very close to the throughput as the optimal algorithm does but with a significantly lower computational complexity. Compared with the sub-optimal proportional fairness resource allocation method in [12], the proposed scheme achieves high system throughput with more satisfying proportional fairness rate among SUs. The proposed algorithm exhibits a good tradeoff between system throughput maximization and proportional fairness rate.

The rest of this paper is organized as follows. In Section II, the system model is described and the problem of resource allocation is formulated. In Section III, the proposed algorithm is presented. Simulation results are provided in Section IV. The conclusions (concluding remarks) are summarized in Section V.etwork operators and system administrators are interested in the mixture of traffic carried in their networks for several reasons. Knowledge about traffic composition is valuable for network planning, accounting, security, and traffic control. Traffic control includes packet scheduling and intelligent buffer management to provide the quality of service (QoS) needed by applications. It is necessary to determine to which applications packets belong, but traditional protocol layering principles restrict the network to processing only the IP packet header.

2. System model

In this paper, resource allocation of an OFDM based CWN is considered, in which a base station (BS) serves one primary user (PU) and M secondary users (SUs)[8][12]. The regulations are that the SUs can not interfere normal transmission of the PU. The signals of the PU and SUs can cause mutual interferences. The interference generated by PU to SUs can be seen as the noise power which only affects the signal-to-interference-noise-ratio (SINR) and

can be measured by base station (BS) which controls all users. But the interference power generated by SUs to the bandwidth occupied by PU cannot exceed the threshold. It is assumed that the channel is slowly time-varying, and the BS is assumed to have perfect channel state information for all SUs and subcarriers. The SUs has band of width W_c Hz and total N subcarriers are available. In order to avoid unacceptable interference to PU, SUs have to sense the environment and rapidly adapt their transmission parameter values. The total throughput of the SUs is denoted as R_{sum}, while R_m is the throughput of secondary user m $(1 \le m \le M)$. The resource allocation problem can be formatted into [8][9][10][11][12]:

$$\max R_{sum} = \max \sum_{m=1}^{M} R_m \qquad (1)$$

Furthermore, let $b_{m.n}$ denote the throughput transmitted on subcarrier n for user m in a symbol period, while $\lambda_{m,n} \in \{0,1\}$ is a subcarrier allocation indicator such that $\lambda_{m,n}$=1 if and only if subcarrier n is allocated to secondary user m. That is:

$$R_m = \sum_{n=1}^{N} \lambda_{m,n} b_{m,n} \qquad (2)$$

Hence, from equation (1) and equation (2), it can be deduced that

$$\max R_{sum} = \max \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{m,n} b_{m,n} \qquad (3)$$

Following [8,9,10,12], $b_{m.n}$ is set to:

$$b_{m.n} = \left\lfloor \log_2 (1 + \frac{p_{m,n} g_{m,n}^2}{\delta (N_0 W_c + S_{mn})}) \right\rfloor \qquad (4)$$

where $\lfloor\ \rfloor$ denotes the integer function, $p_{m.n}$ is the power allocated to secondary user m on subcarrier n, $g_{m,n}$ is gain from BS to user m on subcarrier n, δ is the SNR gap which can be represented as δ=-ln($5p_e$)/1.5 for an MQAM with a specified p_e (bit error rate) [10,12,27,28].The one-sided noise power spectral density (PSD) is denoted as N_0 .The interference power caused by the primary user to subcarrier n at user m is S_{mn}.

Therefore, from equation (1) ,(2),(3) and (4), it can be deduced that

$$\max R_{sum} = \max \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_{m.n} \left\lfloor \log_2 (1 + \frac{p_{m,n} g_{m,n}^2}{\delta (N_0 W_c + S_{mn})}) \right\rfloor \qquad (5)$$

Hence, the resource allocation problem in this paper is expressed as follows [8][9][10][11][12]:

$$\max R_{sum} = \max \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_{m.n} \left\lfloor \log_2 (1 + \frac{p_{m,n} g_{m,n}^2}{\delta (N_0 W_c + S_{mn})}) \right\rfloor \qquad (6)$$

Subject to

$$\sum_{m=1}^{M} \lambda_{m,n} = 1 \qquad \text{(a)}$$

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_{m,n} p_{m.n} \le p_{total} \qquad \text{(b)}$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{m.n} p_{m.n} I_n \le I_{th} \qquad \text{(c)}$$

$$R_1 : R_2 : \ldots : R_M = \alpha_1 : \alpha_2 : \ldots : \alpha_M \qquad \text{(d)}$$

Where, constraint (a) ensures that each subcarrier can only be allocated to one secondary user,

constraint(b) ensures that the total transmit power of all the SUs must be lower than p_{total}, constraint (c) ensures that the interference caused by SUs to PU cannot exceed the predefined threshold upper I_{th} of primary user, I_n denotes the interference factor caused by SUs to PU on subcarrier n ,constraint (d) is the proportional rate restriction. $\alpha_1 : \alpha_2 : ... : \alpha_M$ is a set of pre-determined values which are used to ensure proportional fairness among SUs.

From the described above, we know that the resource allocation includes subcarrier allocation and power allocation. In [7], it is shown that resource allocation problem can be solved sub-optimally by separating subcarrier and power allocation. Therefore, we solve the resource allocation problem in two steps in this study. Firstly, subcarriers are assigned to SUs with basic proportional fairness assuming equal power. Secondly, the immune clonal optimization is used to allocate power ensuring maximum throughput with proportional fairness rate. The constraints are dealt with by repairing the solutions.

3. Proposed Algorithm

In this section, we describe the two-step resource allocation (subcarrier allocation and power allocation) scheme in detail.

3.1 Subcarrier Allocation

Subcarrier allocation aims to allocate subcarriers to SUs subject to the described constraints. Available conventional methods allocate subcarriers to SUs with maximum channel gain on it in order to obtain highest rate [7], which may lead to increasing interference gain for PU in the cognitive OFDM system, then the SUs will strongly be restricted with the transmit power of PU so that the SUs will not get the ideal throughput instead [29][30].So the subcarrier allocation algorithm proposed in [7] is not suitable for it. In this paper, the channel gain of the subcarrier and the mutual interferences are jointly considered. A subcarrier allocation scheme is presented under the interference of PU can tolerate.

The details are as follows.

As mentioned above, after a simple transform of equation (4), the incremental power $\Delta p_{m.n}$ required for transmitting one bit to secondary user m on subcarrier n is given by[31][32][33]

$$\Delta p_{m.n} = \frac{N_0 W_c + S_{m,n}}{g_{m,n}^2} 2^{b_{m.n}} \qquad (7)$$

Recalling that the notations used in here have been explained in section 2. Accordingly, the incremental interference $\Delta I_{m.n}$ to the primary user caused by such a transmission is given by

$$\Delta I_{m.n} = \Delta p_{m.n} I_n \qquad (8)$$

Here, I_n denotes the interference factor caused by SUs to PU on subcarrier n. Assuming that N_m is the set of subcarriers assigned to secondary user m, $\varnothing$ is empty set, $E = \{1, 2, ... N\}$ is the total subcarrier set, n_p is denoted as the subcarrier with minimum incremental power for SUs, n_I is denoted as the subcarrier with minimum incremental interference to PU. P is the total power required for transmitting to the SUs, I is the interference introduced for PU. Recalling that $b_{m,n}$ is denoted as the throughput (maximum number of bits) in a symbol period on subcarrier n for secondary user m, while R_m is the throughput of secondary user m.

The flowchart of the subcarrier allocation algorithm is given below in **Fig. 1**.

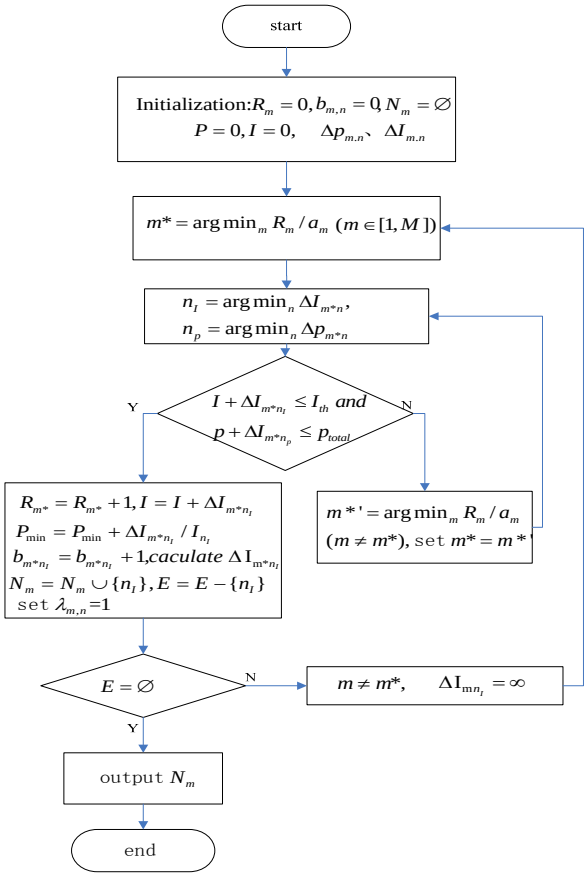

Fig. 1. flowchart of subcarrier allocation algorithm

The detailed description of the algorithm is given below[31] (*Step1*- *Step2*).

Step1.Initialization.

set $R_m = 0,\ b_{m,n} = 0$, $N_m = \varnothing$, $P = 0, I = 0$,

calculate $\Delta p_{m.n}$、$\Delta I_{m.n}$（$m \in [1, M], n \in [1, N]$）。

Step2 for $m \in [1, M]$, do the followings：

Step2.1 find $m^* = \arg\min_m R_m / \alpha_m$,

Step2.2 find $n_I = \arg\min_n \Delta I_{m^*n}$; $n_p = \arg\min_n \Delta p_{m^*n}$;

Step2.3 if $p + \Delta p_{m^*n_p} \le p_{total}$ and $I + \Delta I_{m^*n_I} \le I_{th}$, do the following updates:

（1） $R_{m^*} = R_{m^*} + 1, I = I + \Delta I_{m^*n_I}$,

（2） $P = P + \Delta I_{m^*n_I} / I_{n_I}$,

（3） $b_{m^*n_I} = b_{m^*n_I} + 1$, calculate $\Delta I_{m^*n_I}$, $\Delta p_{m^*n_I}$.

（4） $N_m = N_m \cup \{n_I\}, E = E - \{n_I\}$,set $\lambda_{m,n}$=1 .

（5）if $E = \varnothing$, then output N_m , subcarrier allocation is ended. otherwise，for all $m \ne m^*$, set $\Delta I_{mn_I} = \infty$, $\Delta p_{mn_I} = \infty$; go to *Step2.1*

Step2.4 if $I + \Delta I_{m^*n_I} > I_{th}$ or $p + \Delta p_{m^*n_I} > p_{total}$, then：

Set $m*' = \arg\min_m R_m / a_m (m \neq m*), m* = m*'$ (i.e. set $m*$ is the next SU with higher R_m / α_m), go to *Step2.2*.

Additionally, after the subcarrier allocation, the throughput for secondary user m is described as:

$$R_m = \sum_{n=1}^{N_m} \lambda_{m.n} b_{m,n} = \sum_{n=1}^{N_m} \left\lfloor \log_2 (1 + \frac{p_{m,n} g_{m,n}^2}{\delta(N_0 W_c + S_{mn})}) \right\rfloor \quad (9)$$

For general explanation, each SU obtains a subcarrier during the first round allocation, which enables the SU to achieve the highest possible R_m / α_m rate. After the first round selection, the poorest user who suffers the severest unfairness is immediately given a privilege to choose another subcarrier with the highest R_m / α_m rate among the remaining subcarriers. The allocation process is repeated until all the subcarriers are completely allocated. After the subcarrier allocation, the proportional rate fairness among secondary user is given roughly. The exact satisfaction of maximum system throughput, as well as the requirement of the proportional rate fairness, will be ultimately achieved by the following power allocation algorithm based on immune optimization in section 3.2.

3.2 Power Allocation Optimization Based On Immune Clonal Algorithm

Theoretically, the optimal power distribution scheme can be obtained by solving a set of nonlinear equations. But it is impractical for practical systems because of the high complexity and the NP-hard nature of the optimization problem [9][10][11][12]. Here, we propose a novel suboptimal power allocation scheme based on immune clonal algorithm.

3.2.1 Immune Clonal Selection Theory

The clonal selection theory [19] is used in immunology to describe the basic features of an immune response to an antigen stimulus. Clonal selection is a dynamic stimulation process of the immune system self-adaptive against antigen. According to Burnet [19], clonal selection occurs in accordance with the degree that a B-cell matches an antigen. A strong match causes much cloning of B-cell, and a weak match results in little cloning. The clonal selection algorithm for optimization has been popularized mainly by de Castro and Von Zuben's CLONALG[20] and widely used in engineering-oriented fields[21][22][23][24][25][26].

These clonal selection based algorithms essentially evolve solutions by repeated process of cloning, affinity maturation (via mutation) and selection for candidate solutions, and remaining good solutions in the population.

3.2.2 Summary of related terms in this paper

We describe the terms in our algorithm as follows:

(1) Antigen. In this paper, antigen refers to the power allocation problem to be solved in CWN.

(2) Antibody and its encoding. In this paper, an antibody represents a candidate power allocation scheme. We adopt matrix representation rather than binary string representation [16][17] since the matrix encoding is clear and easy to realize for power allocation. Here, a $M \times N$ matrix denoted as $\mathbf{p}$ is used to encode the power allocation, where the row is denoted as the secondary user m $(m = 1, 2....M)$, column is denoted as the subcarrier n $(n = 1, 2....N)$, the matrix element $p_{m.n} (1 \leq m \leq M, 1 \leq n \leq N)$ is denoted as the gained power to user m on subcarrier n, that is

$$\mathbf{p}=\begin{bmatrix} p_{1,1} & p_{1,2} \cdots\cdots p_{1,N-1} & p_{1,N} \\ p_{2,1} & p_{2,2} \cdots\cdots\cdots p_{2,N-1} & p_{2,N} \\ \cdots & \cdots\cdots p_{m,n} \cdots\cdots & \cdots\cdots \\ p_{M-1,1} & p_{M-1,2} \cdots\cdots\cdots p_{M-1,N-1} & p_{M-1,N} \\ p_{M,1} & p_{M,2} \cdots\cdots p_{M,N-1} & p_{M,N} \end{bmatrix}$$

In this study, $\mathbf{p}$ is referred as an antibody. Antibody population $\mathbf{A}=(\mathbf{p}_1,\mathbf{p}_2,....,\mathbf{p}_k)$ is a k-dimensional group of antibody $\mathbf{p}$, where the positive integer k is the size of antibody population $\mathbf{A}$. $p_{m.n}(1\le m\le M,1\le n\le N)$ is a gene bit of antibody $\mathbf{p}$.

(3) Affinity. Affinity is the fitness measurement for an antibody. For power allocation problems, the optimization model is described in equation (6). The affinity is a mapping of the value of equation (6) for a given antibody $\mathbf{p}$ (power allocation scheme). Because equation (6) is to be maximized, it can be stated that the higher affinity of an antibody has, the better the antibody is.

3.2.3 Realization Of Power Allocation Based On Immune Clonal Algorithm

In this section, we describe a novel power allocation optimization algorithm. It improves the population by three main operators: the proportional clonal operator, the adaptive mutation operator and the selection operator. The constraints are dealt with by repairing the solutions.

The basic flowchart of power allocation based on clonal selection algorithm is described in **Fig. 2**:

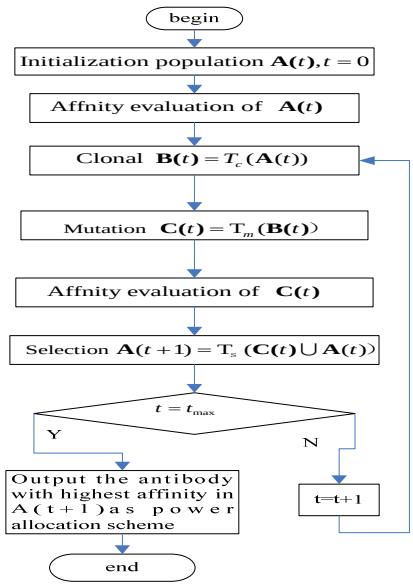

Fig. 2. Flowchart of immune-based power allocation algorithm

The algorithm is implemented as follows (Step1-Step7)

Step1: Initialization

Set the maximum evolutionary generation $t_{\max}$. Set $t=0$, where t is termed as current evolutionary generation. Create an initial antibody population $\mathbf{A}(t)$ with size k in accordance with antibody encoding in section 3.2.2. That is, $\mathbf{A}(t)=(\mathbf{p}_1(t),\mathbf{p}_2(t),....,\mathbf{p}_k(t))$. $\mathbf{p}_i(1\le i\le k)$ is a

candidate power allocation scheme, $\mathbf{A}(t)$ is a set of candidate power allocation schemes.

Here, some pre-knowledge are used to initialize the antibody $\mathbf{p}_i$ in order to accelerate algorithm convergence, which is proved by the latter simulation experiments. From constraint (a), it is known that each subcarrier can only be allocated to one secondary user at any given time, which can be expressed in the matrix $\mathbf{p}_i$ that each column only has one non-zero element $p_{m.n}$ .Recalling that N_m has been determined after subcarrier allocation is finished. Since the total power p_{total} is allocated equally for subcarrier allocation, so the element $p_{m.n}$ of matrix $\mathbf{p}_i$ must satisfy $p_{mn} \in [0, \frac{N_m}{N} p_{total}]$. Each antibody $\mathbf{p}_i (1 \le i \le k)$ that satisfies the constraints (b) and (c) will be a candidate.

Step2: Affinity evaluation

Calculate the affinities of all antibodies in $\mathbf{A}(t)$ according to equation (6). It is denoted as: $f(\mathbf{A}(t)) = (f(\mathbf{p}_1(t), f(\mathbf{p}_2(t)), ..., f(\mathbf{p}_k(t))$ .Here, a higher affinity of an antibody $\mathbf{p}_i(t)(1 < i < k)$ has, the better an antibody (power allocation scheme) is.

Step3: Proportional Clonal $\mathrm{T_c}$

In immunology, cloning means asexual propagation so that a group of identical cells can be descended from a single common ancestor [20]. In this study, we obtain B(t) by applying clonal proliferation $\mathrm{T_c}$ to $\mathbf{A}(t)$. It is defined as follows:

$$\mathbf{B}(t) = T_c(\mathbf{A}(t)) = [T_c(\mathbf{p}_1(t)), T_c(\mathbf{p}_2(t)), ..., T_c(\mathbf{p}_k(t))] \quad (10)$$

Here, the clonal scale q_i for each antibody $\mathbf{p}_i (1 \le i \le k)$ is proportional to its affinity $f(\mathbf{p}_i(t))$. That is, $q_i(t) = Int(n_c \times \frac{f(\mathbf{p}_i(t))}{\sum_{i=1}^{k} f(\mathbf{p}_i(t))})$, where $Int(\,)$ denotes the integer function, n_c is a given value $(n_c > k)$. The antibody with larger affinity value (objective function value of equation (6)) has a larger q_i . Let $z = \sum_{i=1}^{k} q_i$, then $\mathbf{B}(t)$ can be expressed as $\mathbf{B}(t) = \{\mathbf{p}'_1(t), \mathbf{p}'_2(t), ..., \mathbf{p}'_z(t)\}$ .Actually, clonal proliferation on antibody $\mathbf{p}_i(t)$ is to make multiple identical copies of it.

Step 4: mutation T_m

In immunology, mutation means the immune system recognizes external pattern by antibody gene mutation in order to gain higher affinity [19,20]. In this study, it is defined as $\mathbf{C}(t) = \mathrm{T}_m(\mathbf{B}(t))$. An adaptive mutation which associates the mutation probability m_p with the evolutionary generation is designed. That is, $m_p = m_p \times (1 - \frac{t}{t_{\max}})$, t is current evolutionary generation, $t_{\max}$ is the maximum evolutionary generation. The advantages of the mutation lie in its searching ability in a large scope in early evolution process while it searches in a local scope in latter evolution process, which will accelerate the convergence. After mutation, the population becomes:

$$\mathbf{C}(t) = \{\mathbf{p}''_1(t), \mathbf{p}''_2(t), ..., \mathbf{p}''_z(t)\}$$

In this paper, the mutation is done by exchange the non-zero elements of two columns with probability m_p in matrix $\mathbf{p}$. The proposed mutation is easy to realize and doesn't violate the constraints. Obviously, it can ensure that each subcarrier is only allocated to one secondary

user and all antibodies generated by mutation still meet the constraints, so they are still feasible power allocation solutions. An example is given below where the second column and the $N-1$ th column are exchanged. $\mathbf{p}'$ becomes $\mathbf{p}''$ after mutation. Actually, mutation is to exchange the power allocation of two secondary users and generate a new candidate power allocation scheme.

$$\mathbf{p}' = \begin{bmatrix} p_{1,1} & p_{1,2} \cdots\cdots p_{1,N-1} & p_{1,N} \\ p_{2,1} & p_{2,2} \cdots\cdots p_{2,N-1} & p_{2,N} \\ \cdots & \cdots\cdots & \cdots \\ p_{M-1,1} & p_{M-1,2} \cdots\cdots p_{M-1,N-1} & p_{M-1,N} \\ p_{M,1} & p_{M,2} \cdots\cdots p_{M,N-1} & p_{M,N} \end{bmatrix}, \mathbf{p}'' = \begin{bmatrix} p_{1,1} & p_{1,N-1} \cdots\cdots p_{1,2} & p_{1,N} \\ p_{2,1} & p_{2,N-1} \cdots\cdots p_{2,2} & p_{2,N} \\ \cdots & \cdots\cdots & \cdots \\ p_{M-1,1} & p_{M-1,N-1} \cdots\cdots p_{M-1,2} & p_{M-1,N} \\ p_{M,1} & p_{M,N-1} \cdots\cdots p_{M,2} & p_{M,N} \end{bmatrix}$$

Step5：Affinity evaluation

Calculate the affinities of all antibodies in $\mathbf{C}(t)$ according to equation (6). It is defined as: $f(\mathbf{C}(t)) = (f(\mathbf{p}_1''(t), f(\mathbf{p}_2''(t)), \ldots, f(\mathbf{p}_z''(t))$.

Step6: Clonal Selection T_s

Clonal Selection T_s is defined as:

$\mathbf{A}(t+1) = \mathrm{T}_s(\mathbf{C}(t) \cup \mathbf{A}(t)) = (\mathbf{p}_1(t+1), \mathbf{p}_2(t+1), \ldots, \mathbf{p}_k(t+1))$ .That is, select k antibodies having higher affinity from $\mathbf{C}(t)$ and $\mathbf{A}(t)$ to form the next population $\mathbf{A}(t+1)$.

Step 7: Termination Test

If $t_{\max}$ is satisfied, stop the algorithm. Output the antibody with the maximum affinity in $\mathbf{A}(t+1)$ as the result of power allocation. Otherwise, $t = t+1$, go to Step 3.

After immune clonal optimization, the power is allocated among SUs with proportional fairness demand.

3.2.4 Advantages Of The Proposed Algorithm

(1) The suitable matrix encoding is designed which is clear and easy to realize.
(2) Initialization of antibody population with pre-knowledge accelerates the convergence.
(3) Adaptive mutation probability combines the mutation operator with the evolutionary generation, which reduces the blindness of the mutation and further accelerates the convergence. The proper mutation method ensures that the generated antibody still meets the constraints.

3.3 Computational Complexity

The computational complexity of the proposed algorithm is composed of two parts: the computational complexity of subcarrier allocation and that of power allocation. From section3.1, we know that the subcarrier allocation has a worst computational complexity of $O(N \times M)$, where N denotes the number of subcarrier, M denotes the number of secondary users. For the immune-based power allocation in section3.2, the total computational complexity is mainly composed of that for initialization, affinity evaluation, colnal, mutation, and selection. Given the population size k , colnal scale n_c ($n_c > k$)and the maximum generation $t_{\max}$, the procedure of population initialization, affinity evaluation and proportional colnal (step1-step3) has the same computational complexity of $O(k \times M \times N)$ in each generation, while the procedure of mutation, affinity evaluation, selection（step4-step6）has the computational complexity of $O(k \times n_c \times M \times N)$ in each generation. Hence, for each generation, the total computational complexity

is $O(3(k \times M \times N) + 3(k \times n_c \times M \times N))$ .Since $n_c > k$, according to the properties of Symbolic O [10,34,35,36], it can be denoted as $O(n_c \times M \times N))$ .When the power allocation is finished, it has the total computational complexity of $O(t_{\max} \times (n_c \times M \times N))$. Therefore, the proposed algorithm has a computational complexity of $O(N \times M) + O(t_{\max} \times (n_c \times M \times N))$.

The computer simulations show that $t_{\max}$ implicitly depends on M and N (see section 4.1). The more complex the search space is, the larger the number of generations should be. Thus, for given n_c and $t_{\max}$, the gradual computational complexity of the proposed algorithm is $O(N \times M)$ in accordance with the properties of symbolic O , which is lower than that of the algorithm in [12]($O(N(M+N))$)and the algorithm in[8]($O(N^2 M)$).

4. Simulation Results And Discussion

4.1 Experimental Environments And Parameter Settings

The experiments are done in windows XP, MATLAB7.0 is used to program. The parameter settings are as follows [8][9][10][11][12]: It is assumed that the subcarrier gains $g_{m,n}$ are outcome of identically distributed Raleigh random variables. The simulation system consists of one PU and M SUs. The SUs has a bandwidth of 5 MHz and consists of 64 subcarriers, each with a bandwidth, W_c , of 0.3125 MHz. The Additive White Gaussian Noise (AWGN) PSD, N_0 , is set to 10^{-8} W/Hz. The BER of SUs, p_e , is set to 10^{-3} , so the δ is 5 dB. The interference of PU to SUs, $S_{m,n}$,is set to $10^{-6} w$ .In order to evaluate the algorithm performance in various interference constraints, the total power of SUs, P_{total} , ranges from 0.5W to 1.5W. The interference of the PU can tolerance, I_{th} , ranges from $10^{-3} w$ to $10^{-2} w$ .The number of SUs, M , ranges from 2 to 20.

The proportional rate constraints are as same as those in[12]:

Table 1. proportional fairness settings

index	*proportional rate settings*
1	$\alpha_1 : \alpha_2 : a_3 : \alpha_4 = 1:1:1:1$
2	$\alpha_1 : \alpha_2 : a_3 : \alpha_4 = 1:2:4:8$
3	$\alpha_1 : \alpha_2 : a_3 : \alpha_4 = 1:1:1:8$
4	$\alpha_1 : \alpha_2 : a_3 : \alpha_4 = 1:1:1:16$

4.2 Sensitivity In Relation To The Immune Algorithm Parameters

Four parameters are to be settled at the initialization phase: the antibody population size k , the clone population size n_c , the mutation probability m_p , and the maximum number of generations $t_{\max}$. k and n_c directly affect the computational complexity of the algorithm[33][34][35]. Given k and n_c large enough, the diversity of the population can be enhanced and the prematurity can be avoided in some extent. But the computational complexity will also be very large. $t_{\max}$ depends on M and N obviously. The more complex

the search space is, the larger the number of generations should be. m_p is very important for local search in algorithm. A larger m_p has the ability to produce more new antibodies, but it also has the probability to destroy some good antibodies. When m_p is too small, the convergence speed is not quick enough to find the best solution in appointed generations.

Since the optimal choice is hard to determine by theoretical analysis, it is important to analyze the performance affected by experiments in different cases. After trial and error, the parameters employed in the proposed immune algorithm are: number of generations $t_{\max} = 200$, population size $k = 10$, clonal scale $n_c = 25$, mutation probability m_p=0.3. The algorithm run for $t_{\max}$ generations, the antibody associated with the maximal affinity value at this point will be the resource allocation result.

4.3 The Performances Of The Proposed Algorithm

The total throughput is used to measure the performance of the proposed algorithm. The total throughput versus number of secondary users and maximum tolerable interference are shown in **Fig. 1**, **Fig. 2** and **Fig. 3**.

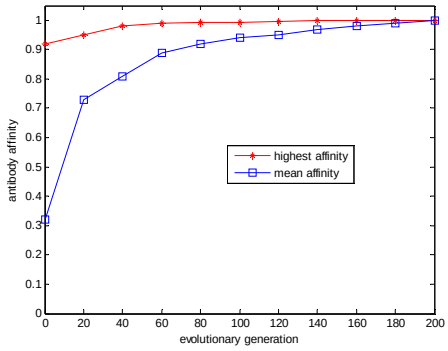

Fig. 3. Antibody affinity versus evolutionary generation

Fig. 3 shows the antibody affinity verse evolutionary generation. It can be seen that the individual affinity converge to the best affinity with the generation increasing, which proves that the proposed algorithm can realize the proportional rate among secondary users. Additionally, it also can be seen that the proposed algorithm converge rapidly because the pre-knowledge is introduced for the initialization of antibody population and the suitable operators are designed in the algorithm. Theoretical analysis and experimental results are well consistent.

Fig. 4 shows the total throughput R_{sum} versus the number of SUs with different I_{th}. A total of 100 time samples are used for each number of secondary users. Assuming that $P_{total} = 1w$, the other parameter settings are shown in section 4.1, the index of proportional fairness rate is set to 1. It can be seen from figure4, the system throughput R_{sum} is increasing with the number of secondary user, which is the result of the added multi-user diversity gain. But subject to the constraint of subcarriers, the increasing extent is becoming rather slow. Meanwhile, the system total throughput R_{sum} increases with I_{th} ,the higher interference I_{th} the PU can tolerate, the higher power the SUs can have, so the system total throughput R_{sum} is becoming higher, which is reasonable.

Fig. 5 shows the total throughput R_{sum} versus the maximum tolerable interference power I_{th} with different P_{total} . Here M=4, the other parameter settings are shown in section 4.1, the index of proportional rate is set to 1. As to be expected, R_{sum} increases with I_{th} . It also can be seen that the total throughput increases with the increasing P_{total} .The difference is larger for small values of I_{th} , but the difference is becoming minor with increasing I_{th} . The reason is that with the increasing interference, the system becomes interference-limited, and the available transmission power for SUs isn't a major factor. For a given P_{total} , the throughput reaches a limit, this is because that the system is no longer subject to interference power that primary user can tolerate.

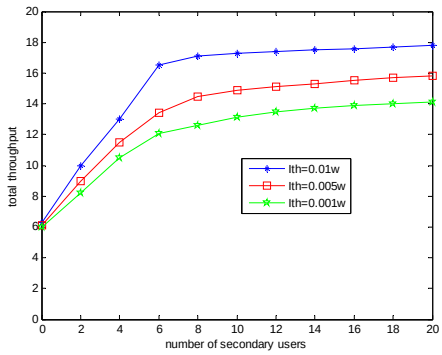

Fig. 4. total throughputs versus number of secondary users

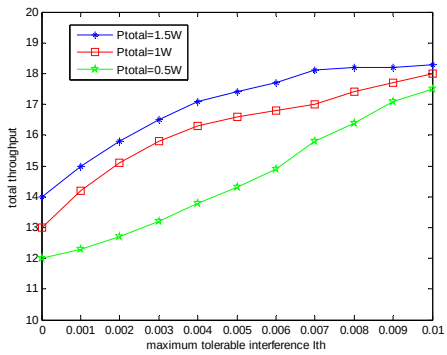

Fig. 5 total throughput versus maximum tolerable interference I_{th}

4.4 Comparisons With Related Algorithms

In order to evaluate the performances of the proposed algorithm, it is also compared with typical algorithms in [8] and [12] under the same experiment settings. Algorithm in [8] is an optimal algorithm with maximum system throughput, while algorithm in [12] is a resource allocation with proportional rate. Both of them are excellent and typical algorithms. The total throughput and fairness are used to measure the performances.

Fig. 6 and **Fig. 7** show the throughput and fairness of the proposed algorithm compared with that in [8] and [12]. **Fig. 6** shows the system throughput as a function of different proportional fairness index (see table1). The parameter settings are as follows: $P_{total} = 1w$,

$I_{th} = 0.01w$, other parameter settings are shown in section 4.1. It can be seen that the system throughput is maximized in [8] and it remains the same because it doesn't consider the proportional fairness. The total throughput of the proposed algorithm changes with proportional fairness. As the proportional fairness requirements for SUs become less uniform, the total throughput decreases. This is because that the diversity of multi-user reduces effectively and the proposed algorithm removes some allocated bits to satisfy the proportional rate constraint resulting in some loss for system throughput. It can also be seen that the proposed algorithm can obtain very close to the optimal throughput as the optimal algorithm in [8] and can achieve consistent greater throughput than sub-optimal algorithm in [12], which show that the proposed algorithm gains better trade-off between throughput and fairness.

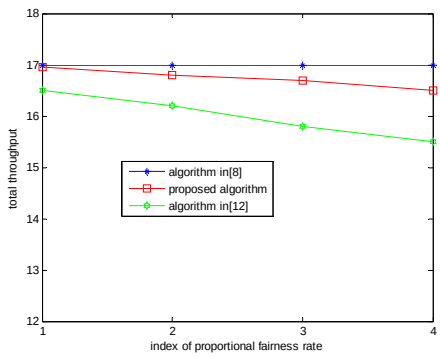

Fig. 6 total throughput with different index proportional fairness

Fig. 7 directly displays the distribution of the total throughput among SUs with proportional fairness rate $\alpha_1 : \alpha_2 : a_3 : \alpha_4 = 1:1:1:16$. The first column denotes algorithm in [8], the second column denotes the ideal distributions. That is, the total throughput is allocated according to the proportional rate with the value $F'_m = \frac{\alpha_m}{\sum_{i=1}^{M} \alpha_i}$. The fairness of secondary user m actually gotten is expressed as $F''_m = \frac{R_m}{\sum_{i=1}^{M} R_i}$.The third column denotes the proposed algorithm in this paper, the fourth column denotes algorithm in [12]. It can be seen that the total throughput is allocated proportionally among SUs in our algorithm, which is very close to ideal fairness ratio and better than algorithm in [12]. Subcarriers are allocated to the SUs with best gain on it and don't consider the fairness in [8]. Hence, when secondary user 4 has better channel conditions, it obtains almost all the resource and other SUs can hardly obtain throughput.

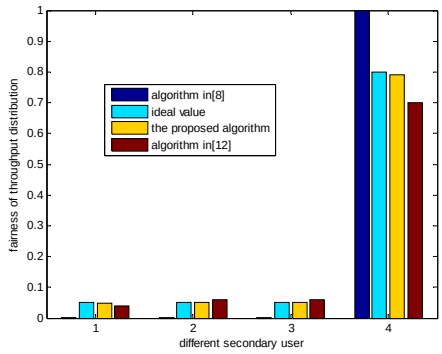

Fig. 7 throughput distributions among different secondary user

5. Conclusions

Resource allocation is a key issue in cognitive wireless network. In this paper, joint subcarrier and power allocation with proportional fairness rate in OFDM-based CWN is studied. It is hard to obtain the optimal solution directly because the resource allocation is a nonlinear optimization problem. Hence an immune clonal based sub-optimal algorithm is proposed. The total power and interference threshold constraints are jointly considered, which is different from the conventional (non-cognitive) scheme. Theoretical analysis and computer simulations show that the proposed algorithm can achieve near-optimal performance with lower computational complexity and outperform some other approaches with proportional rate constraint. It obtains better trade-off between total throughput and proportional fairness. Its application into different practical systems, such as cognitive ad hoc system, is also quite worth studying, which may be the future research of this work.

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