Int. J. Electron. Commun. (AEÜ) 67 (2013) 29–34

Contents lists available at SciVerse ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

Power saving for real-time services in multiuser OFDMA-based cognitive radio systems under average interference constraint

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ARTICLE INFO

Article history:
Received 21 June 2011
Accepted 2 June 2012

Keywords:
OFDMA
Cognitive radio
Stochastic nature
Power saving
Real-time services

ABSTRACT

This paper considers a power minimization problem for Quality-of-Service provisioning in the downlink of multiuser OFDMA-based cognitive radio systems with real-time services by jointly optimizing over subcarrier and power allocation. An average interference constraint is imposed to protect the primary transmission. The optimal solution is obtained by using Lagrange methods. It can be seen that the optimal power allocation follows a modified water-filling approach with different water levels for different subcarriers and users. An optimal algorithm and a suboptimal algorithm based on stochastic nature are then proposed. Numerical comparisons show that the performance of the suboptimal algorithm with low complexity is close to that of the optimal one, which demonstrate that the suboptimal algorithm outperforms other algorithms.

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1. Introduction

Cognitive radio (CR) [1] is a promising idea to deal with the spectrum underutilization problem caused by the current fixed spectrum assignment policy. Cognitive radio users (CRUs) are allowed to identify and access available spectrum which is not currently used by primary users (PUs) as long as the total interference at each PU's receiver remains below a certain threshold. Orthogonal frequency division multiple access (OFDMA) is a potential candidate for CR systems because of its great flexibility in assigning resources among CRUs [2]. Since both PUs and CRUs may exist in side-by-side bands yet have different access technologies, mutual interference [3] between PUs and CRUs limits the performance of both systems. To realize the full potential of OFDMA-based CR systems, several challenging resource allocation problems need to be solved.

Power-saving is key to power-limited portable wireless devices, such as laptops, portable digital assistants (PDAs) and sensors working in poor conditions [4,5]. It has become even more important now especially in the context of green communications [6,7] when the cost of energy and the impact of information communication technology on carbon emission are taken into account. Therefore, techniques that minimize power consumption in multiuser OFDMA-based CR systems across varying traffic load conditions are required.

Resource allocation techniques have a potential to improve power efficiency greatly [7]. Most existing resource allocation schemes for OFDMA-based CR systems [8–12] have been designed to increase the spectral efficiency or sum-rate [13] subject to a set of constraints, while neglecting the power consumption. Since the number of available subcarriers is time-varying due to the nature of PUs' activities, traditional resource allocation algorithms for OFDMA systems [14–17] cannot be directly applied to OFDMA-based CR systems. Up to now, there have been few studies on power saving for Quality-of-Service (QoS) provisioning of real-time (RT) services in multiuser OFDMA-based CR systems. In [18], we minimized the transmission power for a single user scenario. Authors proposed a cross-layer approach in [19] to minimize the transmission power to meet the maximum delay of RT services in OFDMA-based CR systems. However, mutual interference between PUs and CRUs was not considered. Authors in [20,21] focused on minimizing the interference power to the PU in a single user scenario with constraints on the target rate requirement of the CRU and the total transmission power nevertheless without consideration of the interference to the CRU caused by the PU.

The main contribution of this paper is the joint optimization over subcarrier and power allocation in multiuser OFDMA-based CR systems with RT services which are characterized by strong time sensitivity and inelastic bandwidth requirements [22,23]. The average interference constraint is imposed to protect the primary transmission, which is also considered in [24–26] from the perspective of information theory to maximize the system capacity. The goal of this paper is to minimize the total transmission power while meeting the target rate requirement of each CRU and keeping the interference to the PU below a certain threshold, with the

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http://dx.doi.org/10.1016/j.aeue.2012.06.003

mutual interference between PUs and CRUs taken into account. It can be seen that for a given subcarrier assignment, the optimal power allocation follows a modified water-filling approach with different water levels for different subcarriers and users. To reduce the computational cost, a suboptimal algorithm based on stochastic nature is hence proposed. Finally, simulation results are presented.

The rest of this paper is organized as follows. Section 2 presents system models and describes the problem formulation. The solution to the optimization problem is obtained and then an optimal algorithm and a suboptimal algorithm are proposed in Section 3. Section 4 presents the numerical results. Conclusions are drawn in Section 5.

2. System models and problem formulation

2.1. System models

We study the downlink of a multiuser OFDMA-based CR system with a *single* PU and a CR base station (CRBS). The CRBS serves K CRUs with RT services and the total available bandwidth W is divided into N subcarriers, each having Δf bandwidth. The PU occupies W_p bandwidth which is assumed to be located in the middle of the available spectrum [3] as shown in Fig. 1.

We assume that each CRU first estimates its own channel state information (CSI) and then reports it to the CRBS via a feedback channel. The subcarrier and power allocation results are then sent to each CRU via a control channel [27]. Let $|h_{k,n}^{ss}|^2$, $|h_{k,n}^{ps}|^2$ and $|h_{k,n}^{sp}|^2$ denote the instantaneous channel power gain of the nth subcarrier from the CRBS to the kth CRU, the PU's transmitter to the kth CRU, and the CRBS to the PU's receiver, respectively. The fading coefficients are assumed to remain unchanged within each transmission frame but can vary from one frame to another [27]. Besides, we assume that the CRBS can estimate $|h_{k,n}^{sp}|^2$ by an active learning method [28]. But for some scenarios, it may be impossible for the CRBS to exactly know the instantaneous values of $|h_{k,n}^{sp}|^2$. However, the average channel gain of the PU can be predicted when the PU and CRBS are closely located. It is important to mention that in such case, interference constraint imposed to the PUs is met in an average sense.

Assume that $\varphi_{k,n}(f)$ is the baseband power spectral density (PSD) of the nth subcarrier in the kth CRU's band. It can be given by:

$$\varphi_{k,n}(f) = p_{k,n} T_s \left(\frac{\sin(\pi f T_s)}{\pi f T_s} \right)^2 \tag{1}$$

where T_s is the OFDM symbol duration, $p_{k,n}$ denotes the transmission power on the nth subcarrier of the kth CRU. The resulting interference, $I_{k,n}$ to the PU's band caused by the nth subcarrier can be written as [3]

$$I_{k,n}(d_n, p_{k,n}) = |h_{k,n}^{sp}|^2 \int_{d_n - W_p/2}^{d_n + W_p/2} \varphi_n(f) df = p_{k,n} S_{k,n}, \tag{2}$$

where $S_{k,n}$ is defined as:

$$S_{k,n} = |h_{k,n}^{sp}|^2 \int_{d_n - W_p/2}^{d_n + W_p/2} T_s \left(\frac{\sin(\pi f T_s)}{\pi f T_s} \right)^2 df. \tag{3}$$

In (3), d_n represents the frequency distance between the nth subcarrier and the PU's band.

The interference introduced to the nth subcarrier at the kth CRU's receiver by the PU can be written as [3]

$$J_{k,n}(d_n) = |h_{k,n}^{ps}|^2 \int_{d_n - \Delta f/2}^{d_n + \Delta f/2} \Phi_{RR}(e^{j\omega}) d\omega, \tag{4}$$

where $\Phi_{RR}(e^{j\omega})$ is the PSD of the PU signal.

In general, the number, $b_{k,n}$ of bits per OFDM symbols, which can be supported by the nth subcarrier of the kth CRU (in bps/Hz) can be given by [29]

$$b_{k,n} = \log_2(1 + p_{k,n}\alpha_{k,n}), \tag{5}$$

where $\alpha_{k,n} = |h_{k,n}^{ss}|^2 / \Gamma(\sigma_n^2 + J_{k,n})$ is the channel-interference-noise-ratio (CINR) on the nth subcarrier of the kth CRU, σ_n^2 denotes the variance of additive white Gaussian noise and Γ is an signal-to-noise (SNR) gap which is related with the required bit error rate [29]. For simplicity, we assume continuous modulation, i.e., $b_{k,n}$ can take on real values.

2.2. Problem formulation

The objective of the joint optimization is to minimize the total transmission power while satisfying the target bit rate requirements of all CRUs with RT services and limiting the interference to the PU below the certain threshold. Since each CRU experiences different fading, the channel gains vary from user to user at each subcarrier, and among all the subcarriers of a single CRU. Thus, the multiuser dynamic resource allocation problem is very complicated to solve.

We assume that a subcarrier cannot be shared by more than one CRU at a specific time and define $\rho_{k,n} \in \{0, 1\}$ as a subcarrier assignment indicator, indicating whether the nth subcarrier is assigned to the kth CRU or not.

In some scenarios, perfect CSI assumption is impractical due to the limited feedback bandwidth and the delay. However, the average channel gains of PUs can be predicted when PUs and CRBS are closely located. In such case, it is more desirable to impose an average-received interference constraint. Thus, the problem can be mathematically formulated as

$$OP1: \min_{\rho_{k,n}, p_{k,n}} \sum_{n=1}^{N} \sum_{k=1}^{K} \rho_{k,n} p_{k,n} \tag{6}$$

$$s.t. \sum_{n=1}^{N} \rho_{k,n} b_{k,n} \geq R_k^{req}, \quad \forall k \tag{7}$$

$$E\left\{ \sum_{n=1}^{N} \sum_{k=1}^{K} \rho_{k,n} p_{k,n} S_{k,n} \right\} \leq I_{th} \tag{8}$$

$$\sum_{k=1}^{K} \rho_{k,n} \leq 1, \quad \forall n \tag{9}$$

$$\rho_{k,n} \in \{0, 1\}, \quad \forall k, n \tag{10}$$

$$p_{k,n} \geq 0, \quad \forall k, n, \tag{11}$$

where R_k^{req} and I_{th} are respectively the target bit rate requirement of the kth CRU and the given average interference threshold of the PU. $E\{\cdot\}$ is the expectation operation. The constraint (8) provides more flexibility for dynamically allocating transmit power among CRUs over fading channels. In other words, even though there are large interference at some times, small interference at other times can compensate the performance of the PU in an average sense. Note that $OP1$ is a mixed integer programming problem. For the system with K users and N subcarriers, there are K^N possible subcarrier assignments since each subcarrier can be used by one user only.

3. Proposed resource allocation algorithms

To make the problem tractable, an approach is to relax the constraint (10) to allow $\rho_{k,n}$ to be a real number within the interval [0, 1]. That is, $\rho_{k,n}$ is considered as the time-sharing factor for the kth

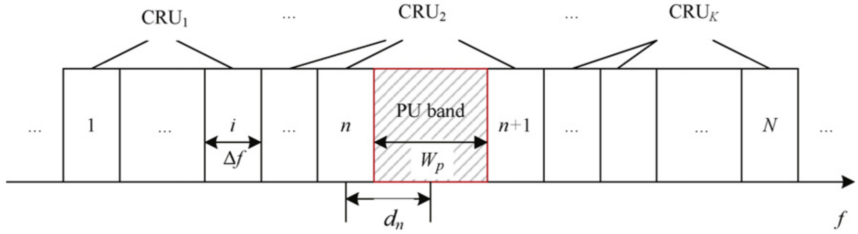

Fig. 1. Distribution of the PU and CRUs in frequency domain.

user of the nth subcarrier. This time-sharing relaxation has been frequently used in the context of subcarrier assignment in multiuser OFDM systems to convert a mixed integer programming problem into a convex optimization problem [14,27].

In addition, let $t_{k,n} = \rho_{k,n} p_{k,n}$ for all k and n. With the aid of time-sharing factors $\rho_{k,n}$, we can transform $OP1$ into:

$$OP2: \min_{\rho_{k,n}, t_{k,n}} \sum_{n=1}^{N}\sum_{k=1}^{K} t_{k,n} \tag{12}$$

$$s.t. \sum_{n=1}^{N} \rho_{k,n} \log_2(1+\alpha_{k,n}\frac{t_{k,n}}{\rho_{k,n}}) \geq R_k^{req}, \quad \forall k \tag{13}$$

$$E\left\{\sum_{n=1}^{N}\sum_{k=1}^{K} t_{k,n} S_{k,n}\right\} \leq I_{th} \tag{14}$$

$$\sum_{k=1}^{K} \rho_{k,n} \leq 1, \quad \forall n \tag{15}$$

$$t_{k,n} \geq 0, 0 \leq \rho_{k,n} \leq 1, \quad \forall k, n, \tag{16}$$

It is easy to see that $OP2$ is equivalent to $OP1$, except that the minimization is done over a larger set. As a result, the minimum power for $OP2$ is a lower bound to that for $OP1$.

By evaluating the Hessian matrix of the left side of the constraint (13) at $t_{k,n}$ and $\rho_{k,n}$, we can prove that the constraint (13) is concave [30]. Besides, since the constraints (14)–(16) are affine and the objective function (12) is linear, $OP2$ is a convex optimization problem and there exists a unique optimal solution.

3.1. Optimal solution

3.1.1. Optimal power allocation for given subcarrier assignment

In order to obtain the optimal power allocation, a subcarrier assignment strategy is assumed to be given. Introducing Lagrange multipliers $(\lambda_k, \mu, \beta_n) \geq 0$ and based on the Karush–Kuhn–Tucher (KKT) conditions [30], we can obtain the optimal power allocation as follows:

$$p_{k,n}^* = \frac{t_{k,n}^*}{\rho_{k,n}^*} = \left[L_{k,n} - \frac{1}{\alpha_{k,n}}\right]^+, \tag{17}$$

$$L_{k,n} = \frac{\lambda_k}{(1+\mu E\left\{S_{k,n}\right\})\ln 2}, \tag{18}$$

where $[x]^+ = \max(0, x)$ and $L_{k,n}$ is a modified water-filling level for the nth subcarrier of the kth CRU. It can be found that, for a given subcarrier assignment, $L_{k,n}$ varies with different subcarriers and users. It is related to λ_k and $S_{k,n}$, i.e., the interference to the PU caused by the nth subcarrier of the kth CRU.

3.1.2. Optimal subcarrier assignment

Assuming that the power allocation is optimized, the optimal strategy for subcarrier assignment can be given by:

$$\rho_{k,n}^* = \begin{cases} 1, & k = \arg\max_{1\leq k\leq K} A_{k,n} \\ 0, & \text{otherwise} \end{cases}, \quad \forall n \tag{19}$$

where $A_{k,n}$ is given by

$$A_{k,n} = \lambda_k\left((\log_2(L_{k,n}\alpha_{k,n}))^+ - \frac{1}{\ln 2}\left(1 - \frac{1}{L_{k,n}\alpha_{k,n}}\right)^+\right). \tag{20}$$

Based on (19) and (20), for each subcarrier n only the CRU with the largest $A_{k,n}$ can use that subcarrier if the value of $A_{k,n}$, for k = 1, 2, . . ., K, are all distinct.

In order to determine the optimal subcarrier and power allocation, λ_k and μ should be chosen to make the following equations hold:

$$\sum_{n=1}^{N} \rho_{k,n}^* \log_2\left(1+\alpha_{k,n}\frac{t_{k,n}^*}{\rho_{k,n}^*}\right) = R_k^{req}, \quad \text{for } k = 1, 2, \ldots, K \tag{21}$$

$$E\left\{\sum_{n=1}^{N}\sum_{k=1}^{K} t_{k,n}^* S_{k,n}\right\} = I_{th}. \tag{22}$$

Assume that $\alpha'_{k,1} \geq \alpha'_{k,2} \geq \cdots \geq \alpha'_{k,N}$ are the ordered CINRs of the kth CRU on each subcarrier. Solving (21), we can obtain

$$\lambda_k(\mu) = \ln 2\left(2^{R_k^{req}} \prod_{n\in\Omega_k} \frac{1+\mu E\{S_{k,n}\}}{\alpha'_{k,n}}\right)^{1/|\Omega_k|}. \tag{23}$$

where $\Omega_k = \{n \in A : \alpha'_{k,n} \geq 1/L_{k,n}\}$ is the set of subcarriers of the kth CRU, and $|\Omega_k| \leq N$ is the largest integer satisfying. $A = \{1, 2, \ldots, N\}$ is the set of all subcarriers. For any value of $\mu \geq 0$. Eq. (23) specifies a $\lambda_k(\mu)$, and hence the optimal subcarrier and power allocation is determined. We can obtain μ here by solving (22) using numerical methods such as subgradient methods [30].

3.2. Proposed algorithms

3.2.1. Optimal allocation algorithm

Through the above observations, we propose in this subsection an exhaustive iteration algorithm to obtain the optimal subcarrier and power allocation. The proposed algorithm outlines in Algorithm 1.

Algorithm 1. Optimal algorithm

1) Let $B = \{1, 2, \ldots, K\}$ and set $\mu(0)$
2) Calculate λ_k, $k \in B$ using (23)
3) Obtain $\rho_{k,n}$ using (19) and $p_{k,n}$ using (17)
4) Calculate $b_{k,n}$ using (5) and $R_k = \sum_{n=1}^{N} \rho_{k,n} b_{k,n}$, find $B_k = \{k \in B : R_k < R_k^{req}\}$
5) If $A \neq \emptyset$

- find k^* with $R_{k^*} - R_{k^*}^{req} < R_j - R_j^{req}$, for $j \in B_k$
- update $\lambda_{k^*} = \lambda_{k^*} + s_\lambda$
- goto step 3)

Else if $B_k \neq \emptyset$
- service outage occurs, and exit

EndIf

6) Calculate the actual interference to the PU: $I_t = E\left\{\sum_{k=1}^{K}\sum_{n=1}^{N}\rho_{k,n}p_{k,n}S_{k,n}\right\}$
7) If $I_t > I_{th}$
- update $\mu(0)$ using subgradient methods
- goto step 2)

EndIf

8) Output $(\rho_{k,n}, p_{k,n})$ and exit.

where s_λ is a step size

In fact, Algorithm 1 contains two nested loops. The outer loop varies μ to meet the interference constraint and the inner loop searches the optimal $(\rho_{k,n}, p_{k,n})$ for all k and n at a given μ to satisfy the basic rate requirement for each RT CRU. Thus, the total complexity of the optimal algorithm is $O(\Xi_1\Xi_2 KN^2\log N)$.

3.2.2. Suboptimal algorithm based on stochastic nature

Unfortunately, when the number of the system parameters (i.e., the number of subcarriers and CRUs) becomes large, such strategy appears to be impractical. In order to reduce the computational cost, a suboptimal algorithm based on stochastic nature is hence proposed. A similar strategy was applied in statistical mechanics [31] for determining the ground state of systems using a simulated annealing process.

The main idea of the suboptimal algorithm is carried out several times starting from different initial configurations. The outline of the suboptimal algorithm is described in Algorithm 2.

Algorithm 2. Suboptimal algorithm

1) Let $A = \{1, 2, \ldots, N\}$ and $B = \{1, 2, \ldots, K\}$, set the maximum number of iterations Ite_{max}, $s = 0$ and $\mu(0)$, $P_{tot,old} = \infty$
2) Generate a permutation of K CRUs: C_{perm}
3) For $i = 1 : K$
- select a CRU: $k = C_{perm}(i)$
- calculate λ_k, $k \in B$ using (23) and obtain Ω_k
- obtain $p_{k,n}$ using (17), update $A = A - \Omega_k$
- set $\rho_{k,n} \leftarrow \Omega_k$, $\forall n$
- update $B = B - k$
- if $A = \emptyset$ and $B \neq \emptyset$

  service outage occurs, and exit
- Endif

EndFor

4) Estimate the current total transmission power $P_{tot,new}$ using (6)
5) If $s \leq Ite_{max}$
- if $P_{tot,old} \geq P_{tot,new}$

  set $P_{tot,old} = P_{tot,new}$
- else

  set $P_{tot,old} = P_{tot,old}$
- Endif
- update $s = s + 1$, goto step 2)

EndIf

6) Calculate the actual interference to the PU: $I_t = E\left\{\sum_{k=1}^{K}\sum_{n=1}^{N}\rho_{k,n}p_{k,n}S_{k,n}\right\}$
7) If $I_t > I_{th}$
- update $\mu(0)$ using subgradient methods
- goto step 2)

EndIf

8) Output $(\rho_{k,n}, p_{k,n})$ and exit.

Table 1
Values of the system parameters in simulations.

Symbols	K	N	W (MHz)	I_{th} (W)	σ^2 (W)	s_λ
Value	8	32	10	10^{-5}	10^{-5}	10^{-3}

Algorithm 2 also has two nested loops. The outer loop is the same as that in Algorithm 1. But the inner loop only selects one CRU at each iteration to determine its optimal $\rho_{k,n}$ in the set of the remaining subcarrier at each fixed value of μ. In this way, exhaustive searching $\rho_{k,n}$ from all subcarriers among all CRUs is avoided. Therefore, the total complexity of the suboptimal algorithm is $O(\Xi_1 Ite_{max} KN)$.

4. Simulation results

In this section, the performance of the proposed optimal and suboptimal resource allocation algorithms in simulations is presented and compared with other existing algorithms.

For comparison purpose, two different methods are considered in the simulations. One is the Greedy-based method, denoted as "*Greedy*", where bits are assigned to the subcarriers Δb bit at a time, and in each assignment, the subcarrier that requires the least additional power among all CRUs is selected [14]. It requires $O(KN\log N/\Delta b)$ iterations to complete the bit allocation process. The other is called as "*OneIte*", which is the same as Algorithm 2, except that Ite_{max} is set to be one. Thus it requires $O(\Xi_1 KN)$ iterations to converge.

The system parameters are set as follows. The bandwidth of PU is $W_p = \Delta f$ Hz. The channels are six-tap Rayleigh fading ones and all channel power gains comply with an exponentially random distribution profile. The maximum path loss difference is 5 dB and the users are assumed to be equally distributed. The step size for updating μ and the accuracy requirement are 10^{-3} and 10^{-7}, respectively. For simplicity, each CRU's target bit rate requirement is assumed to be equal to R_{req}. It increases from 0.5 bps/Hz to 1.5 bps/Hz. The other parameters considered in our simulations are given in Table 1. We use 1000 Monte Carlo simulations to verify the performance of the proposed algorithms. The results are shown in Figs. 2, 3 and 4, 5, respectively.

Fig. 2 illustrates the total transmission power versus the number of the CRUs for different algorithm considerations under R_{req} = 0.5 bps/Hz. Clearly, it can be found that the total transmission

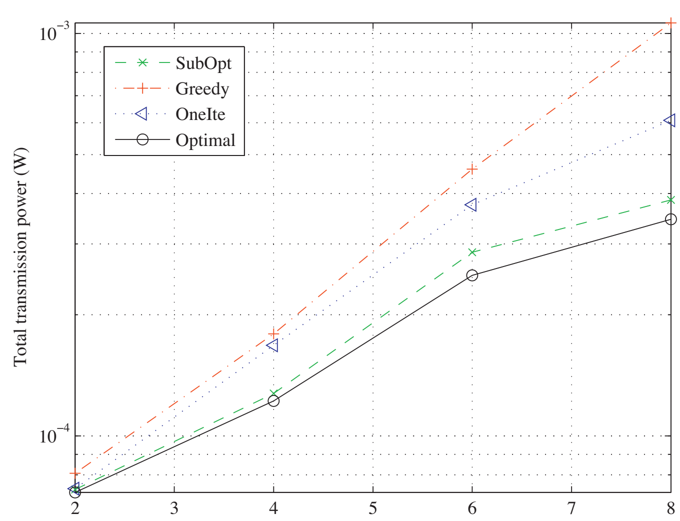

Fig. 2. Total transmission power versus the number of the CRUs for different algorithms consideration under R_{req} = 0.5 bps/Hz.

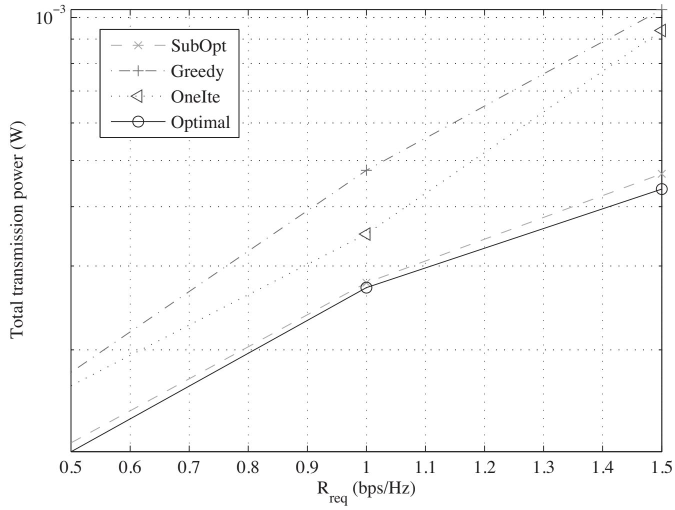

Fig. 3. Total transmission power versus different R_{req} under $K = 4$ CRUs.

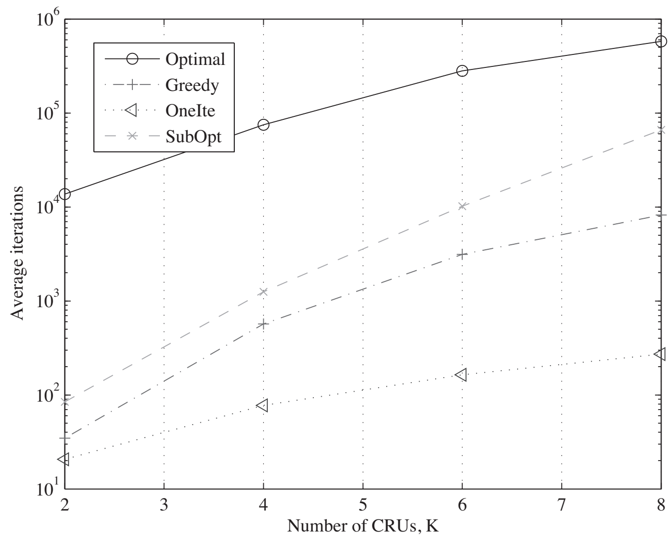

Fig. 4. Comparison of the number of iterations for different algorithms at $R_{req} = 1.0$ bps/Hz.

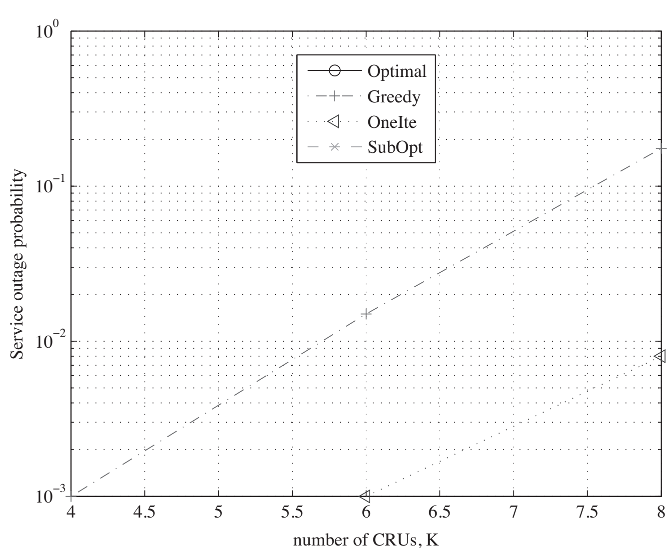

Fig. 5. Service outage probability under $R_{req} = 1.2$ bps/Hz.

power increases with the number of the CRUs. Besides, the optimal algorithm ("*Optimal*") has the lowest transmission power, and the suboptimal algorithm ("*SubOpt*") is somewhat higher than the "*Optimal*". However, both the "*Optimal*" and the "*SubOpt*" outperform the "*Greedy*" and the "*OneIte*". This is because the optimal and the suboptimal algorithms calculate the power allocation using (17) shown in Section 3.1 at each iteration. Moreover, the suboptimal algorithm can go through all states due to the stochastic nature of permutation.

Fig. 3 shows the effects of different R_{req} on the total transmission power under $K = 4$ CRUs. It can be seen that the transmission power increases with R_{req}. Increasing R_{req} means an increase of the basic rate requirement of each CRU, and hence leads to more required transmission power.

Fig. 4 depicts the comparison of the number of iterations for different algorithms at $R_{req} = 1.0$ bps/Hz. It can be found that the number of iterations of each algorithm increases with the number of the CRUs. The more the number of the CRUs, the higher complexity the algorithm has. Besides, the "*SubOpt*" has significantly less iterations than the "*Optimal*". Although the complexity of the "*Greedy*" and the "*OneIte*" is very low, both of them have poor system performance.

Fig. 5 shows the service outage probability for different algorithms under $R_{req} = 1.2$ bps/Hz. The service outage probabilities of the"*Greedy*" and the "*OneIte*" increase with the number of the CRUs. However, no service outage occurred in our proposed optimal and suboptimal algorithms.

5. Conclusions

This paper proposed the optimal subcarrier and power allocation algorithm with the aim of minimizing the total transmission power while satisfying the target rate requirements of all RT CRUs and keeping the interference to the PU under the given threshold. Due to the high complexity, the suboptimal algorithm was proposed. Numerical results showed that the proposed algorithms outperform other existing ones. Furthermore, the performance of the suboptimal algorithm is very close to that of the optimal one. However, the suboptimal algorithm could provide greatly lower complexity than the optimal one. The future work should investigate the effects of imperfect CSI estimation on power saving in multiuser OFDMA-based CR systems with heterogeneous traffic.

Acknowledgement

This work was supported in part by the National Natural Science Foundation of China under Grant No. 61071079.

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