INTERNATIONAL JOURNAL OF COMMUNICATION SYSTEMS
Int. J. Commun. Syst. 2014; **27**:3441–3459
Published online 25 April 2013 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/dac.2553

Cooperative bargaining solution for efficient and fair spectrum management in cognitive wireless networks

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SUMMARY

This paper studies the fairness among the primary users (PUs) and the secondary users (SUs) for resource allocation in cognitive radio systems. We propose a novel co-opetition strategy based on the Kalai–Smorodinsky bargaining solution to balance the system efficiency and the fairness among users. The strategy formulates the spectrum sharing problem as a nonlinear and integral sum utility maximization subject to a set of constraints describing the co-opetition among the PUs and the SUs. Then, we solve the maximization problem by proposing a heuristical method that consists of four steps: multi-PU competition, PU's subcarrier contribution, multi-SU competition, and SU's subcarrier contribution. Extensive simulation results are presented by comparing the co-opetition strategy with several conventional ones, including the Kalai–Smorodinsky bargaining solution, sum rate maximization as well as the Max–Min. Results indicate that the co-opetition strategy can jointly balance the system efficiency and fairness in multiuser resource allocation, as it is able to support more satisfied users and in the meanwhile improve the utility of those unsatisfied. Moreover, the co-opetition can help enable the coexistence of the PUs and the SUs in cognitive radio systems. Copyright © 2013 John Wiley & Sons, Ltd.

Received 29 August 2012; Revised 14 February 2013; Accepted 15 March 2013

KEY WORDS: cognitive radio (CR); cooperative bargaining solution; co-opetition strategy; dynamic spectrum management

1. INTRODUCTION

Cognitive radio (CR) has evolved to improve the spectrum utilization by enabling the unlicensed user (or secondary user, SU) to use the idle available spectrum band of the licensed user (or primary user, PU) [1]. During the past decade, CR has attracted extensive attention of researchers as the frequency shortage is increasingly critical with the development of wireless communications. In existing publications, one of the main objectives in CR is to maximize the sum rate of multiple SUs subject to the constraint that the interference of SUs to the PU is below the interference temperature [2–7]. For example, P. Wang *et al.* proposed an iterative partitioned water-filling method to maximize the capacity in OFDM-based CR systems [2]. In [3], the authors solved the problem of weighted sum rate maximization (SRM) for multiple SUs in orthogonal frequency division multiple access-based cognitive systems, by jointly adjusting their rate, frequency, and power. In our previous work [4], an optimal and distributed method was proposed on the basis of the geometric programming for power control in cellular cognitive networks. Most of these researches primarily focus on the system efficiency without explicitly considering the fairness among users.

Because the multicarrier technique such as OFDM [8] provides a promising physical (PHY) layer technique for future CR systems, much attention of research has been paid to multicarrier systems

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[9–20]. For instance, in [9, 10], the proportional rate constraint was introduced for fair subcarrier allocation in multiuser OFDM systems. In [11], the authors proposed an adaptive proportional rate constraint to take the priorities of users and the fairness into consideration in radio resource allocation in multiuser OFDM systems. In [12], the authors studied the weighted SRM for downlink OFDMA systems. The fairness based on the Nash bargaining solution, a notion from the cooperative game theory, was applied to multicarrier networks for fair subcarrier assignment and power allocation [13–15]. Most recently, OFDM has also been applied to cooperative communication networks [21], CR networks [22], and also the energy efficient wireless networks [23]. Readers are referred to [24, 25] and references therein for a good literature review in this area. Most of existing fairness policies are inherently competitive, for example, fairness with proportional rate constraint makes users compete for resources based on predefined rate ratios. The disadvantage of competitive fairness is that it is quite difficult to determine these rate ratios. To the best of our knowledge, so far, how to determine the rate ratios is still left open.

To alleviate the aforementioned disadvantages, the idea of co-opetition has been introduced to radio resource allocation. Co-opetition is a newly developed but rather popular concept from the game theory, and it suggests a judicious mixture of competition and cooperation in multiuser resource allocation [26]. The co-opetition is firstly applied to decentralized spectrum agile networks for multimedia resource allocation [27]. In our preliminary work, the co-opetition is applied to centralized multimedia resource allocation in error-free networks [28, 29] and wireless networks with AWGN channel [30]. It is shown that the co-opetition strategy can support more satisfied users compared with absolutely competitive fairness and in the meanwhile maintain the fairness among unsatisfied users. However, all these works focus on scalar access channel, and so far, to the best of our knowledge, there is no existing work applying the co-opetition to vector access channel [31], such as multicarrier system and multiple-antenna system.

The main contribution of this paper is that we develop the co-opetition strategy for spectrum sharing in multicarrier-based CR systems. Notice that, although the co-opetition has been applied to scalar access systems in our preliminary work, the application cannot be directly extended to vector access systems. This is because in vector access systems, the bijection between resource and utility domains does not exist any more, for example, to achieve certain rate, whereas in multicarrier systems, there exist multiple combinations of subcarrier assignment.[‡] As a result, the resource allocation in vector access systems becomes quite different and also more challenging. Moreover, developing the co-opetition strategy in CR networks is also left open in our preliminary work. In this paper, the KSBS is chosen as the competitive fairness [32], based on which we design the co-opetition strategy. Justification of choosing the KSBS is illustrated in Section 2. On one hand, we apply the co-opetition among multiple PUs and among multiple SUs, and on the other hand, we apply it between the PUs and the SUs. We illustrate the co-opetition strategy over multiuser uplink of multicarrier-based CR networks. First, the subcarrier allocation problem is formulated as maximizing the sum utility of all PUs and SUs subject to the constraint of the co-opetition fairness. Then, we propose a user-decomposition-based method to solve the constrained maximization problem. Finally, extensive numerical results are presented for performance evaluation. Complexity and convergence of the proposed method are also studied.

The rest of this paper is organized as follows. In Section 2, we review the basic definition of the KSBS. In Section 3, we formulate the resource allocation problem, and in Section 4, we describe the user-decomposition-based method. Numerical results are presented for performance evaluation in Section 5. Finally, we draw some conclusions for the whole paper in Section 6.

2. COMPETITION CRITERION: KSBS

Assume there are N users, and denote user n's utility function as $U_n(R_n)$ with R_n representing the rate of user n. Assume $U_n(R_n)$ is concavely increasing and twice differentiable with respect to R_n. Denote $\boldsymbol{R}$ as the feasible rate region of N users, that is, $\boldsymbol{R} = \{R_1, R_2, \dots, R_N\}$. Assume that $\boldsymbol{R}$ is

[‡]In our preliminary work, we assume that only power is allocated among multiple users, so the bijection exists between resource and utility domains.

DOI: 10.1002/dac

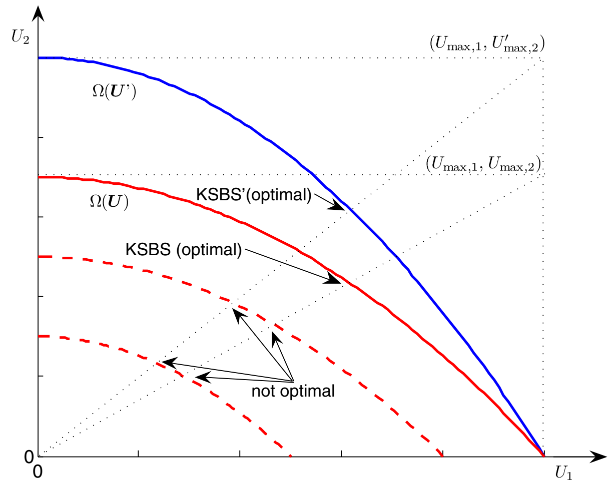

Figure 1. Illustration of Kalai–Smorodinsky bargaining solution (KSBS) in the case of two users. Keep user 1's utility unchanged. Increasing user 2's utility from $\Omega(\boldsymbol{U})$ to $\Omega(\boldsymbol{U}')$ can increase user 2's competence from $U_{\max,2}$ to $U'_{\max,2}$. Consequently, at KSBS$'$, the utility achieved by user 2 is improved compared with that of KSBS. At the inner part of $\boldsymbol{U}$ (dash lines), the intersections satisfy the constraint in (1) but are not optimal.

compact and convex. Here, by compact we mean that the total resource is limited, whereas convex implies that time sharing is enabled at the PHY layer. Denote $\Omega(\boldsymbol{R})$ as the boundary of $\boldsymbol{R}$. Let $R_{\max,n}$ represent the maximum rate achievable by user n; if we allocate all resources to it, then we have $\{0, \ldots, R_{\max,n}, \ldots, 0\} \in \Omega(\boldsymbol{R})$. Denote the resulted utility region and the corresponding boundary as $\boldsymbol{U}$ and $\Omega(\boldsymbol{U})$, respectively. Then, KSBS allocates resources such that the achieved utilities satisfy

$$\frac{U_n(R_n)}{U_{\max,n}} = \frac{U_m(R_m)}{U_{\max,m}}, \ \forall n, m \tag{1}$$

and

$$(U_1, U_2, \ldots, U_N) \in \Omega(\boldsymbol{U}). \tag{2}$$

From (1), we can see that KSBS makes the achieved utilities proportional to the achievable maximum utilities; (2) guarantees that the achieved utilities are Pareto optimal. The idea of KSBS is briefly illustrated in Figure 1 in the case of two users. According to the definition in economic area, we call $(U_{\max,1}, \ldots, U_{\max,N})$ the ideal point, then we observe that KSBS is namely the intersection of the utility boundary and the line connecting the original point and the ideal.

The maximum achievable utility in (1) is jointly determined by several factors, including the quality of the wireless channels and transmission strategies (e.g., channel coding scheme and modulation mode). Therefore, $U_{\max,n}$ can be viewed as an indication of how easy for user n to achieve high utility; for example, those users with better channel quality, and with more intelligent transmission strategies, are more likely to achieve high utilities. To this aspect, resource allocation using KSBS can be viewed as a process, in which users compete for resources based on their maximum achievable utilities. With the help of $U_{\max,n}$, KSBS takes all the aforementioned factors into account in resource allocation, and users are encouraged to optimize their transmission strategies to strengthen their competence. As shown in Figure 1, keep the maximum utility of user 1 $U_{\max,1}$ unchanged and increase the maximum utility of user 2 from $U_{\max,2}$ to $U'_{\max,2}$ with $U'_{\max,2} > U_{\max,2}$; consequently, the utility region expands from $\boldsymbol{U}$ to $\boldsymbol{U}'$. Denote the new solution associated to $\boldsymbol{U}'$ with KSBS$'$, and we can see that at KSBS$'$, the utility of user 2 is improved compared with that of KSBS.

Considering that in $\boldsymbol{U}$ (or $\boldsymbol{U}'$) there might exist multiple utility combinations satisfying the constraint in (1), it is desirable to make individual utility as high as possible through resource allocation. For example, as shown in Figure 1, assume that there are two dotted lines in $\boldsymbol{U}$ (or $\boldsymbol{U}'$) each consisting of multiple utility combinations. Here, the outer dotted line represents more efficient resource

DOI: 10.1002/dac

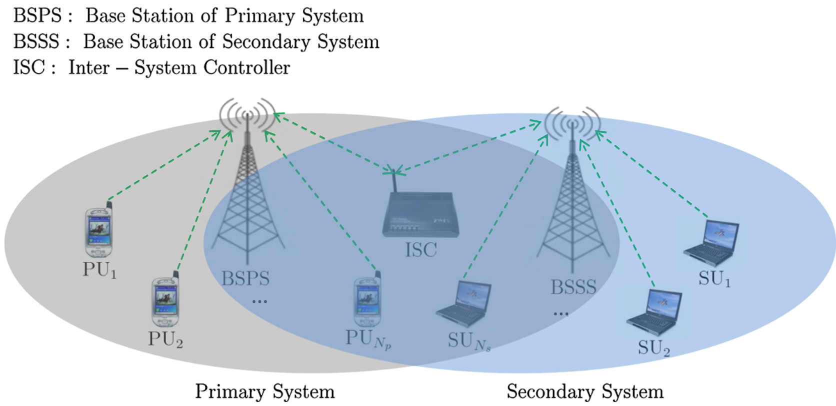

Figure 2. Brief illustration of the cognitive radio system. PU, primary user; SU, secondary user.

allocation than the inner. We can see that the intersections of the two dotted lines and the line connecting the original and ideal points of utility region $\boldsymbol{U}$ (or $\boldsymbol{U}'$) satisfy the constraint in (1), but they are not optimal, as they do not satisfy constraint (2).

3. PROBLEM FORMULATION

In this section, we formulate the subcarrier assignment problem in CR networks subject to the constraint of the co-opetition fairness, which is constructed on the basis of KSBS.

3.1. System model

We consider a system as illustrated in Figure 2. Assume that there are two cellular systems, the primary and secondary systems. The two systems are located close to each other, and they work on the same frequency band but different sub-bands. For simplicity, we further assume that both systems are multicarrier-based systems. There are N_p PUs in the primary system, and they communicate with each other via the base station of primary system (BSPS). There are N_s SUs in the secondary system, and they communicate with each other via the base station of the secondary station (BSSS).[§] Assume that there exists an inter-system controller (ISC) accommodating the communication protocols of the two systems. The ISC can also support information exchange between the BSPS and BSSS.[¶] Before transmission, each PU (SU) transmits its parameters, for example, maximum transmission power and channel state information, to the BSPS (BSSS) through a dedicated control channel. The BSPS (BSSS) then calculates the utility function for each PU (SU), decides the subcarrier assignment, and sends back the assignment result via the dedicated control channel. It is assumed that the BSPS is willing to support its timely subcarrier assignment state to the BSSS. On the basis of the assignment information, the BSSS can take or release subcarriers.

Assume there are K subcarriers and the CR network runs in the overlay mode. One subcarrier can only be occupied by one user at a time. Denote $\boldsymbol{\omega} = \left\{\boldsymbol{\omega}_1^\mathrm{p}, \ldots, \boldsymbol{\omega}_{N_\mathrm{p}}^\mathrm{p}, \boldsymbol{\omega}_1^\mathrm{s}, \ldots, \boldsymbol{\omega}_{N_\mathrm{s}}^\mathrm{s}\right\}$ as the subcarrier assignment vector of PUs and SUs, where $\boldsymbol{\omega}_n^\mathrm{p} = \left\{\omega_{n,1}^\mathrm{p}, \ldots, \omega_{n,K}^\mathrm{p}\right\}$, $n \in \{1, \ldots, N_\mathrm{p}\}$, and

[§]For the sake of clarity, we denote the users in the primary and secondary systems with cell phone and laptop, respectively. Actually, there can be different types of mobile stations in one system.

[¶]The assumption of the existence of inter-system controller (ISC) is acceptable if the primary system is cellular systems or wireless local area networks (LANs). In this case, it is possible for the primary and secondary systems, through amending their communication protocol stacks accordingly, to communicate with each other via the ISC for potential message exchanges. The ISC could also be a third-party device with powerful spectrum sensing ability, which senses the spectrum not being used by the primary users and records the sensed results in a database so the cognitive users could check with.

DOI: 10.1002/dac

$\boldsymbol{\omega}_n^{\mathrm{s}} = \left\{\omega_{n,1}^{\mathrm{s}}, \ldots, \omega_{n,K}^{\mathrm{s}}\right\}$, $n \in \{1, \ldots, N_{\mathrm{s}}\}$, then we have

$$\sum_{n=1}^{N_{\mathrm{p}}} \omega_{n,k}^{\mathrm{p}} + \sum_{n=1}^{N_{\mathrm{s}}} \omega_{n,k}^{\mathrm{s}} \leqslant 1, \text{ with } \omega_{n,k}^{\mathrm{p}}, \omega_{n,k}^{\mathrm{s}} \in \{0, 1\}, \ \forall k. \tag{3}$$

Denote $\boldsymbol{P} = \left\{P_1^{\mathrm{p}}, \ldots, P_{N_{\mathrm{p}}}^{\mathrm{p}}, P_1^{\mathrm{s}}, \ldots, P_{N_{\mathrm{s}}}^{\mathrm{s}}\right\}$ as the power budget vector, then each user can maximize its rate through water-filling. Denote the resulted rate vector with $\boldsymbol{R} = \left\{R_1^{\mathrm{p}}, \cdots, R_{N_{\mathrm{p}}}^{\mathrm{p}}, R_1^{\mathrm{s}}, \cdots, R_{N_{\mathrm{s}}}^{\mathrm{s}}\right\}$. The objective is to determine the optimal subcarrier assignment vector such that the achieved utilities satisfy the given fairness constraint. In this paper, we study two types of fairness, competition and co-opetition.

3.2. *Competition and co-opetition*

In CR networks, we should first guarantee the QoS of PUs. However, because of channel fading or limited power, not all PUs' QoS can be guaranteed. In the case of scarce resource, the fairness criteria are necessary. In this paper, we adopt the fairness of KSBS, under which multiple PUs compete for subcarriers fairly. Recall that in competition-based resource allocation, users who have weak competence might suffer very low rate. To alleviate this, the most straightforward way is to make those users with strong competence stop competing for more resources if their required QoS have already been achieved. To the extent of stopping competing, PUs also run in the cooperative manner, meaning that the proposed resource allocation considers both competition and cooperation, hence co-opetition for short.

Similarly, the co-opetition also can be applied to the SUs. Even in the case of scarce resources, according to the water-filling theorem, PUs do not necessarily occupy all subcarriers. SUs can compete with each other for unused subcarriers. SUs who have achieved the required QoS can stop competing such that the other SUs' QoS should be improved. Finally, the co-opetition is also applicable between PUs and SUs. Although the QoS of PUs needs to be guaranteed firstly, there still exists incentive for them to stop occupying more subcarriers to help the SUs. In future heterogenous communication networks, PUs in one subsystem might be SUs with respect to another subsystem. According to the mechanism design theory in economic area [33], users are encouraged to work in a proactive way to compete and cooperate with other users. To summarize, the co-opetition exists among PUs, among SUs, and between PUs and SUs.

3.3. *Mathematical formulation*

The resource allocation problem can be mathematically formulated as the sum utility maximization subject to the constraint of the co-opetition fairness as follows:

$$\text{Find: } \boldsymbol{\omega}$$

$$\text{maximize } \alpha \sum_{n=1}^{N_{\mathrm{p}}} U_n^{\mathrm{p}}(R_n^{\mathrm{p}}(\boldsymbol{\omega}, \boldsymbol{P})) + \sum_{n=1}^{N_{\mathrm{s}}} U_n^{\mathrm{s}}(R_n^{\mathrm{s}}(\boldsymbol{\omega}, \boldsymbol{P})) \tag{4}$$

$$\text{subject to: } \boldsymbol{R} \in \mathcal{R} \tag{5}$$

$$\mathcal{A}_{\mathrm{p}} = \left\{U_n^{\mathrm{p}} | U_n^{\mathrm{p}} > U_{\mathrm{req},n}^{\mathrm{p}}\right\} \tag{6}$$

$$\mathcal{A}_{\mathrm{s}} = \left\{U_n^{\mathrm{s}} | U_n^{\mathrm{s}} > U_{\mathrm{req},n}^{\mathrm{s}}\right\} \tag{7}$$

$$\mathcal{B}_{\mathrm{p}} = \left\{U_n^{\mathrm{p}} | U_n^{\mathrm{p}} < U_{\mathrm{req},n}^{\mathrm{p}}\right\} \tag{8}$$

$$\mathcal{B}_{\mathrm{s}} = \left\{U_n^{\mathrm{s}} | U_n^{\mathrm{s}} < U_{\mathrm{req},n}^{\mathrm{s}}\right\} \tag{9}$$

$$|\mathcal{A}_{\mathrm{p}}| \cdot |\mathcal{B}_{\mathrm{p}}| = 0 \tag{10}$$

$$|\mathcal{A}_{\mathrm{s}}| \cdot |\mathcal{B}_{\mathrm{s}}| = 0 \tag{11}$$

$$|\mathcal{A}_{\mathrm{p}}| \cdot |\mathcal{B}_{\mathrm{s}}| = 0 \tag{12}$$

$$\frac{U_n^{\mathrm{p}}}{U_{\max,n}^{\mathrm{p}}} \leqslant \frac{U_m^{\mathrm{p}}}{U_{\max,m}^{\mathrm{p}}},\ U_n^{\mathrm{p}} \in \mathcal{A}_{\mathrm{p}},\ U_m^{\mathrm{p}} \in \mathcal{B}_{\mathrm{p}} \tag{13}$$

$$\frac{U_n^{\mathrm{s}}}{U_{\max,n}^{\mathrm{s}}} \leqslant \frac{U_m^{\mathrm{s}}}{U_{\max,m}^{\mathrm{s}}},\ U_n^{\mathrm{s}} \in \mathcal{A}_{\mathrm{s}},\ U_m^{\mathrm{s}} \in \mathcal{B}_{\mathrm{s}} \tag{14}$$

$$\frac{U_n^{\mathrm{p}}}{U_{\max,n}^{\mathrm{p}}} = \frac{U_m^{\mathrm{p}}}{U_{\max,m}^{\mathrm{p}}},\ U_n^{\mathrm{p}}, U_m^{\mathrm{p}} \in \mathcal{B}_{\mathrm{p}} \tag{15}$$

$$\frac{U_n^{\mathrm{s}}}{U_{\max,n}^{\mathrm{s}}} = \frac{U_m^{\mathrm{s}}}{U_{\max,m}^{\mathrm{s}}},\ U_n^{\mathrm{s}}, U_m^{\mathrm{s}} \in \mathcal{B}_{\mathrm{s}}, \tag{16}$$

where $\mathcal{R}$ is the rate region consisting of all feasible rate combinations, $|\cdot|$ is the number of elements, and α is the coefficient that takes positive and large value.[‖]

In the aforementioned formulation, constraint (5) comes from the PHY layer, and the rate region $\mathcal{R}$ can be described through maximizing the weighted sum rate subject to the constraints of individual power and total subcarriers; $\mathcal{A}_{\mathrm{p}}, \mathcal{A}_{\mathrm{s}}, \mathcal{B}_{\mathrm{p}}, \mathcal{B}_{\mathrm{s}}$ defined in (6), (7), (8), and (9) represent the sets of PUs and of SUs whose achieved utilities are greater than the required utilities, and the sets of PUs and of SUs whose achieved utilities are smaller than the required utilities, respectively—we call users in $\mathcal{B}_{\mathrm{p}}$ and $\mathcal{B}_{\mathrm{s}}$ unsatisfied users; (10) implies that if there exist unsatisfied PUs, the maximum utilities of PUs are pegged at the corresponding required utilities; (13) indicates that the PUs who have strong competence stop competing, resulting in decreased utility ratios; (15) means that those unsatisfied PUs compete for resources based on KSBS; (10), (13), and (15) together describe the co-opetition among PUs. Similarly, (11), (14), and (16) describe the co-opetition among SUs; (12) implies that if all PUs have achieved their required utilities, they stop competing to improve the utilities of SUs. It is worth pointing out that this constraint also implies that the PUs should help the SUs by sacrificing their maximum utility, which seems contradictive to the fundamental concept of CR networks where the utility of the PUs cannot be affected. The motivation to make such a constraint lies in that, in future heterogenous wireless networks that may consist of multiple subsystems, each subsystem can be either primary subsystem or secondary subsystem in the same time. Therefore, by worrying about the secondary subsystems, the primary subsystem also expects to be helped in the case of scarce resources. Notice that, by making the value of α as large as possible, it can be ensured that the QoS of PUs is firstly guaranteed, so the utility of the PUs is still of higher priority, thus not contradicting to the principle of CR networks.

4. CO-OPETITION STRATEGY

The constrained maximization in the previous section belongs to nonlinear and integral programming (NLIP), whose optimal solution can only be obtained through exhaustive search. In the case of large user number and subcarrier number, the exhaustive search is computationally prohibitive. The most common way to solve it is to turn to the suboptimal solution with much lower computational complexity. In the following, we propose a suboptimal method to solve the NLIP.

The coefficient α in (4) indicates the NLIP can be solved by first maximizing the sum utility of PUs and then maximizing the sum utility of SUs through assigning unused subcarriers. Considering that the co-opetition strategy is the combination of competition and cooperation, we first examine the competition among PUs; then on the basis of the competition, we study the co-opetition among PUs and finally examine the co-opetition among PUs and SUs.

[‖]Here, we introduce α in (4) for easy formulation. We assume that the value of α is large enough to ensure that when maximizing the objective of (4), the primary users' (PUs') utility is firstly maximized. Therefore, as proposed in our method, if the utility of PUs is indeed firstly maximized, then it is not necessary for α to take any specific value.

DOI: 10.1002/dac

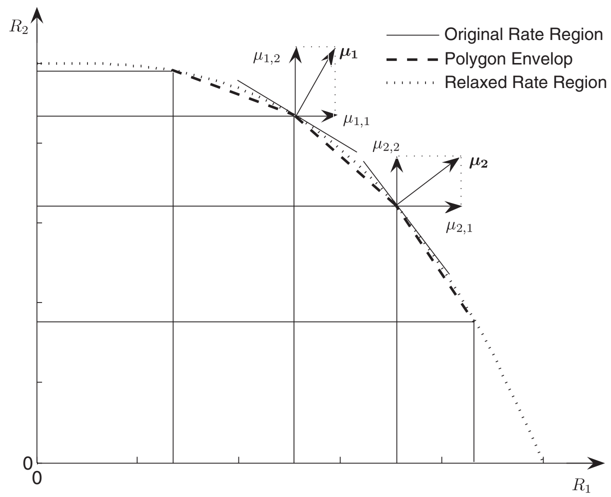

Figure 3. Illustration of the rate regions. The original region has a polygon envelop, whose vertexes are also vertexes of the relaxed region.

4.1. Competition among PUs

Assume that no PU can be satisfied through subcarrier assignment, that is, $|\mathcal{A}_{\mathrm{p}}| = 0, |\mathcal{B}_{\mathrm{p}}| = N_{\mathrm{p}}$, then the competition among PUs can be formulated as (4), (5), (8), and (15). Next, we first examine the simplest case of competition between two PUs to obtain some intuition.

4.1.1. Two-PU case. In the case of two PUs, the feasible rate region can be expressed as

$$\omega^{\mathrm{p}}_{1,k} + \omega^{\mathrm{p}}_{2,k} \leqslant 1,\ \omega^{\mathrm{p}}_{1,k}, \omega^{\mathrm{p}}_{2,k} \in \{0,1\},\ \forall k, \tag{17}$$

$$\sum_{k=1}^{K} P^{\mathrm{p}}_{n,k} \leqslant P^{\mathrm{p}}_{n},\ \forall n, \tag{18}$$

where $\boldsymbol{P}^{\mathrm{p}}_{n} = (P^{\mathrm{p}}_{n,1}, \ldots, P^{\mathrm{p}}_{n,K})$ represents the power allocation vector of PU n, constraint (18) is linear and continuous, and (17) is linear but discrete with total number 3^K of combinations of subcarrier assignment.[**] The resulted rate region has a convex polygon envelope. By relaxing the constraint that each subcarrier can be occupied by only one user simultaneously, (17) can be rewritten as

$$\omega^{\mathrm{p}}_{1,k} + \omega^{\mathrm{p}}_{2,k} \leqslant 1,\ \omega^{\mathrm{p}}_{1,k}, \omega^{\mathrm{p}}_{2,k} \in [0,1],\ \forall k, \tag{19}$$

then the new rate region becomes differentiable and convex, and the vertexes of the polygon region are also boundary points of the relaxed rate region. The rate regions are illustrated in Figure 3. The relaxed rate region can be described by maximizing the sum rate of two users for any weight coefficient, that is,

$$\begin{aligned} \text{Find:}\ & \boldsymbol{\omega} \\ \text{maximize}\ & \mu_1 R_1(\boldsymbol{\omega}, \boldsymbol{P}) + \mu_2 R_2(\boldsymbol{\omega}, \boldsymbol{P}),\ \forall\ \|\boldsymbol{\mu}\|_1 = 1, \\ \text{subject to:}\ & \omega^{\mathrm{p}}_{1,k} + \omega^{\mathrm{p}}_{2,k} \leqslant 1,\ \omega^{\mathrm{p}}_{1,k}, \omega^{\mathrm{p}}_{2,k} \in [0,1],\ \forall k, \\ & \sum_{k=1}^{K} P^{\mathrm{p}}_{n,k} \leqslant P^{\mathrm{p}}_{n},\ \forall n, \end{aligned} \tag{20}$$

[**]There are K subcarriers, and each subcarrier can be assigned to PU 1, or PU 2, or unused.

where $\boldsymbol{\mu} = (\mu_1, \mu_2)$, and $\|\cdot\|_1$ represents the one-norm operation. The Lagrange of (20) writes

$$\mathcal{L}(\upsilon_k, \eta_n, \boldsymbol{\omega}, \boldsymbol{P}) = \sum_{n=1}^{2} \mu_n R_n(\boldsymbol{\omega}, \boldsymbol{P}) + \sum_{k=1}^{K} \upsilon_k \left(1 - \sum_{n=1}^{2} \omega_{n,k}\right) + \sum_{n=1}^{2} \eta_n \left(P_n^{\mathrm{p}} - \sum_{k=1}^{K} P_{n,k}^{\mathrm{p}}\right), \tag{21}$$

where υ_k, η_n are Lagrange multipliers. Setting the first derivative of $\mathcal{L}$ with respect to $P_{n,k}^{\mathrm{p}}$ to 0 gives the Karush–Kuhn–Tucker condition of optimality of power distribution, that is, there exists $\eta_n > 0$ such that

$$\frac{\partial R_n}{\partial P_{n,k}^{\mathrm{p}}} = \frac{\eta_n}{\mu_n}, \ \forall n. \tag{22}$$

This indicates that for fixed subcarrier assignment, each user can maximize its rate through distributing its power via water-filling. Setting the first derivative of $\mathcal{L}$ with respect to $\omega_{n,k}$ gives the Karush–Kuhn–Tucker condition of optimality of subcarrier assignment; that is, there exists positive υ_k such that

$$\mu_n \frac{\partial R_n}{\partial \omega_{n,k}} = \upsilon_k, \ \forall k, n, \tag{23}$$

telling that the optimal subcarrier assignment ensures that all users have the same weighted marginal rate; (23) also implies that the larger the μ_n is, the smaller the marginal rate will be. Considering that R_n is usually concavely increasing with respect to resources, we have that R_n increases with μ_n, and hence, U_n is an increasing function of μ_n.

The aforementioned analysis enables us to implement the two-user competition strategy through bisection method. Denote $R_{\max,n}$ and $U_{\max,n}$ as user n's maximum rate and corresponding utility, respectively. The optimal value of $\boldsymbol{\mu}$ can be obtained iteratively, and the bisection method is summarized in Algorithm 1.

Algorithm 1: Two-user competition

1) Set $\mu_{\mathrm{upp},1} = 1, \mu_{\mathrm{low},1} = 0$, precision tolerance $\epsilon = 10^{-4}$.
2) Set $\mu_1 = (\mu_{\mathrm{upp},1} + \mu_{\mathrm{low},1})/2, \mu_2 = 1 - \mu_1$, and solve $\max(\mu_1 R_1 + \mu_2 R_2)$ and calculate $U_1(R_1), U_2(R_2)$.
3) If $\frac{U_1(R_1)}{U_{\max,1}} > \frac{U_2(R_2)}{U_{\max,2}}$, set $\mu_{\mathrm{upp},1} = \mu_1$. If $\frac{U_1(R_1)}{U_{\max,1}} < \frac{U_2(R_2)}{U_{\max,2}}$, set $\mu_{\mathrm{low},1} = \mu_1$. Go to 2). If $\frac{U_1(R_1)}{U_{\max,1}} = \frac{U_2(R_2)}{U_{\max,2}}$, stop iteration.
4) Stop iteration until $\mu_{\mathrm{upp},1} - \mu_{\mathrm{low},1} < \epsilon$.

4.1.2. Multiple-PU case. Competition strategy based on KSBS can be formulated as maximizing the sum utility subject to the constraint $U_1/U_{\max,1} = \cdots = U_N/U_{\max,N}$. If we define the variance among all $U_n/U_{\max,n}$, $n = 1, \ldots, N$, as

$$C\left(\frac{U}{U_{\max}}\right) \triangleq \frac{1}{N} \sum_{n=1}^{N} \left(\frac{U_n}{U_{\max,n}} - E\left(\frac{U}{U_{\max}}\right)\right)^2, \tag{24}$$

with $E\left(U/U_{\max}\right) = 1/N \sum\limits_{n=1}^{N} U_n/U_{\max,n}$ representing the mean of all $U_n/U_{\max,n}$, then the constraint can be exactly satisfied if the variance $C\left(U/U_{\max}\right)$ takes a value of zero, that is,

$$\frac{U_1}{U_{\max,1}} = \cdots = \frac{U_N}{U_{\max,N}} \Leftrightarrow C\left(\frac{U}{U_{\max}}\right) = 0. \tag{25}$$

DOI: 10.1002/dac

However, for the problem of subcarrier assignment that involves integral programming, the constraint might not be strictly satisfied. To address this challenge, in this paper, we propose to approximate the constraint by minimizing the variance $C\left(U/U_{\max}\right)$, that is, $Minimize\ C\left(U/U_{\max}\right)$.

The value of the variance can be minimized through iterative subcarrier exchange among PUs, and in each iteration, the exchange is only performed between two PUs. Similar to [34], we define **A** as the subcarrier exchange matrix as follows

$$\mathbf{A} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1N} \\ A_{21} & A_{22} & \cdots & A_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ A_{N1} & A_{N2} & \cdots & A_{NN} \end{bmatrix}, \tag{26}$$

where $A_{mn} = 0,\ m,n \in \{1,\ldots,N\}$, if the subcarrier exchange between user n and user m is required, and $A_{mn} = 1$ otherwise. To initiate, **A** is set to be a zero matrix. The subcarrier exchange can be performed as shown in Algorithm 2.

Algorithm 2: Multiple-user competition

1) Allocate subcarriers randomly. Each user allocates power based on water-filling strategy, and calculates its own utility. Set $C_{\min}$ to the corresponding variance of resulted utilities.
2) For $m = 1,\cdots,N$
   For $n = 1,\cdots,N$
   - If $m = n$ or $A_{mn} = 1$, skip this iteration, else, perform Algorithm 1 and calculate $C\left(\frac{U}{U_{\max}}\right)$.
   - If $C\left(\frac{U}{U_{\max}}\right) < C_{\min}$, save the subcarrier exchange.
     Set $A_{mm'} = 0, A_{n'n} = 0,\ \forall m', n', C_{\min} = C\left(\frac{U}{U_{\max}}\right), A_{mn} = 1, m = 1, n = 1$.
     Each user updates its power allocation based on water-filling strategy.
   - If $C\left(\frac{U}{U_{\max}}\right) \geqslant C_{\min}$, set $A_{mn} = 1$, give up the result.
3) Stop if $A_{mn} = 1,\ \forall m,n$.

4.1.3. Two-PU SRM. Recall that in Algorithm 1, we assume that it is known how to solve $\max(\mu_1 R_1 + \mu_2 R_2)$. The SRM has been extensively studied in previous research for different PHY layer setups, and the results can be applied directly to make our resource allocation easier and more applicable. In this paper, we employ the two-band searching algorithm proposed in [35] to obtain the nearly optimal subcarrier assignment.

4.2. Co-opetiton among PUs

Now, we will discuss how to design the co-opetition strategy based on it. The core idea of constructing the co-opetition strategy is to let those satisfied PUs contribute part of their subcarriers to help the unsatisfied. Because the optimal subcarrier contribution is an NP-hard problem, to solve it, we propose a suboptimal but simple contribution criterion. We call it contributing the worst subcarrier criterion. Assume PU n is satisfied and denote $\mathcal{S}_n^{\mathrm{p}}$ as the set of subcarriers assigned to it. Denote P_{nk}^{p} as the power that PU n allocates to its kth subcarrier. Then, PU n's rate can be maximized through distributing its power according to the water-filling theorem; that is, there exists a positive v such that, if $P_{nk}^{\mathrm{p}} > 0$, we have

$$P_{nk}^{\mathrm{p}} + \frac{BN_{nk}}{H_{nk}^2} = v, \tag{27}$$

and if $P_{nk}^{\mathrm{p}} = 0$, then we have

$$\frac{BN_{nk}}{H_{nk}^2} > v, \tag{28}$$

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where B is the bandwidth of each subcarrier, N_{nk} and H_{nk} are the noise power-spectral-density and the channel gain for user n on subcarrier k, respectively. The theorem tells that subcarriers with high channel gain are more likely to be allocated with power, and vice versa, that is,

$$\frac{1}{H_{nk}^2} < \frac{1}{H_{nj}^2}, P_{nj}^{\mathrm{p}} > 0 \Rightarrow P_{nk}^{\mathrm{p}} > 0. \tag{29}$$

Without loss of generality, assume that there are K_n subcarriers in $\mathcal{S}_n^{\mathrm{p}}$ and $H_{n1}^2 > H_{n2}^2 > \cdots > H_{nK_n}^2$. Then, the subcarrier contribution can be performed user-wisely as shown in Algorithm 3. It is worth mentioning that the bisection searching method can also be applied in subcarrier contribution to reduce the computational complexity.

Algorithm 3: Subcarrier contribution

For $k = 1, \cdots, K_n$
- Allocate power among subcarriers 1 to k based on water-filling strategy.
- If the resulted utility is above or equal to the target utility, then continue. Otherwise, stop iteration and contribute subcarriers k to K_n.

After subcarrier contribution, more subcarriers are available for those unsatisfied PUs. On the basis of the KSBS, the unsatisfied PUs compete with each other for these subcarriers. The competition can be finished by performing the multiuser competition described in Algorithm 2. The competition might make some unsatisfied PUs satisfied while keeping the others still unsatisfied. Consequently, the newly satisfied PUs contribute some subcarriers. The iteration of competition and contribution proceeds until all PUs are satisfied or no new PU becomes satisfied in competition. In the procedure of subcarrier assignment among PUs, the competition and contribution are performed iteratively. By viewing the contribution as a kind of cooperation, the procedure can be called as co-opetition.

4.3. Co-opetition among SUs

With the aforementioned co-opetition among PUs, it is possible that not all subcarriers are occupied by the PUs. Recall that the objective of resource allocation in CR system is to maximize the QoS of SUs while guaranteeing the QoS of PUs. Therefore, the unoccupied subcarriers will be assigned among SUs. The co-opetition among SUs is identical to that among PUs. Thus, Algorithms 1, 2, and 3 can be directly applied to the subcarrier assignment among SUs. An exception in the co-opetition among SUs is that, after all SUs are satisfied, they should proceed to assign those subcarriers that remain unused. In this case, the system efficiency of resource allocation among SUs is not so crucial, and we simply assign these subcarriers equally.

4.4. Co-opetition among PUs and SUs

The co-opetition not only exists among PUs but also among SUs. Notice that according to the co-opetition strategy among PUs, no PU could achieve utility above its target utility.[††] Taking the effect of the integral programming into consideration, each PU's utility only can be made as close to the target utility as possible. Hence, the PUs also contribute some subcarriers to the SUs in the last iteration of co-opetition.

The whole procedure of co-opetition among PUs and SUs is illustrated in Figure 4. We can see that the co-opetition consists of two main steps, co-opetition among PUs and co-opetition among SUs. Because the two steps have almost the same iterations, we take the co-opetition among PUs as an illustration to show how the constraints in Section 3.3 are satisfied either exactly or approximately.

(1) Minimizing the variance in Algorithm 2 ensures that all unsatisfied PUs have similar or the same utility ratio; that is, constraint in (15) can be satisfied.

[††] In this paper, we use the 'required utility' and 'target utility' interactively.

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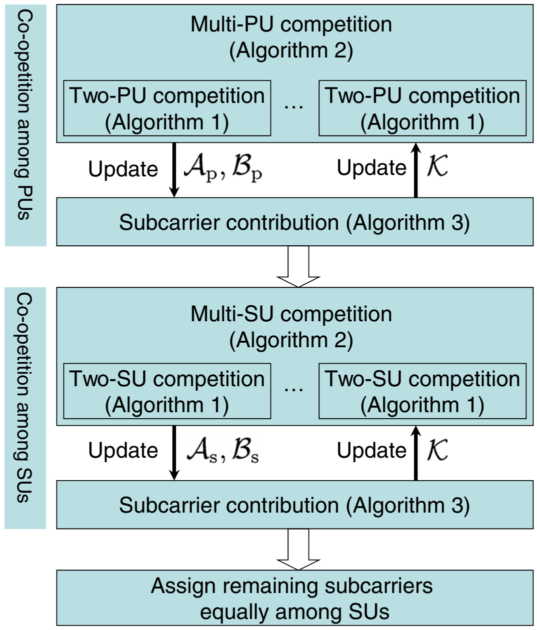

Figure 4. Illustration of the co-opetition strategy. First, assign subcarriers for the primary users (PUs) using the co-opetition, then assign subcarriers for the secondary users (SUs) using the co-opetition. The co-opetition consists of an iteration of multiuser competition and subcarrier contribution. $\mathcal{K}$ represents the set of available subcarriers.

(2) All satisfied PUs are made to contribute subcarriers such that their utility is as close to the corresponding target utility as possible. This implies that the constraints in (10) and (12) can be satisfied.
(3) The contribution decreases the utility ratios of those satisfied PUs to improve the utility ratios of unsatisfied PUs; therefore, the constraint of (13) can be satisfied.
(4) We observe in Figure 4 that the co-opetition among PUs consists of a series of two-PU competitions, each consisting of a series of two-user weighted SRM. So the multi-PU competition is optimal. Although the subcarrier contribution is suboptimal, high spectrum efficiency can be ensured because of the contribution criterion of 'the worst subcarrier the first contributed'.

4.5. Complexity analysis

Complexity of the proposed co-opetition strategy is affected by different factors, including the number of PUs and SUs, the number of subcarriers, and each user's channel state information. Hence, it is difficult to analyze its complexity precisely. We can only analyze the upper bound of the complexity and further study its complexity using some numerical results.

Complexity of the two-band searching algorithm for weighted SRM is $O(K \log K)$ with K being the number of subcarriers [35]. Each two-user competition requires to perform $\log_2 1/\varepsilon$ times of the weighted SRM with ε being the required precision on weight coefficients. The multi-PU competition requires at most N_{p}^3 two-user competitions. In each subcarrier contribution, there are at most N_{p} PUs, and each PU at most needs to perform K times of the water-filling algorithm with maximum complexity of $O(K)$. There are at most N_{p} iterations of multi-PU competition and subcarrier contribution. Therefore, the maximum complexity of the co-opetition among PUs is $N_{\mathrm{p}}(O(K^2) + N_{\mathrm{p}}^3 O(K \log K) \log_2 1/\varepsilon)$. Similarly, the maximum complexity of the co-opetition among SUs is $N_{\mathrm{s}}(O(K^2) + N_{\mathrm{s}}^3 O(K \log K) \log_2 1/\varepsilon)$. Thus, the co-opetition strategy has an upper bound of complexity of $(N_{\mathrm{p}} + N_{\mathrm{s}})O(K^2) + (N_{\mathrm{p}}^4 + N_{\mathrm{s}}^4)O(K \log K) \log_2 1/\varepsilon$ that is polynomial.

DOI: 10.1002/dac

5. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed co-opetition strategy. We first introduce the definition of the utility function and then present the numerical results.

5.1. Utility definition

The CR system is inherently a heterogenous communication system where users might come from different subsystems and hence might have different services and QoS metrics. The metrics of different media are hard to compare. Therefore, finding a common utility function that allows optimization and comparison across concurrent applications of different types would be a useful break to apply different resource management schemes to future CR systems [36]. However, this goes out of the scope of this paper.

Two types of traffics are considered in this paper. We assume that all PUs transmit video sequences, so they have the same service type of real-time polling service. Assume that the service type of SUs is the best effort (BE) service. Notice that we do not consider the case that different PUs (or SUs) have different service types. On one hand, common utility function for different services is so far still an open problem, and on the other hand, employing the same service type among different PUs (or SUs) can be helpful in highlighting the focus of this paper, that is, fairness among multiple users. The assumption of BE service for the SUs is acceptable because the QoS of SUs in CR system is not guaranteed, and hence, it is not suitable for SUs to transmit real-time polling service.

5.1.1. Utility function for video service. Several rate-distortion models have been proposed in previous work. In this paper, we employ the model in [37], as it suits well to the state of the art of the video encoders [38]. The rate-distortion model is given as

$$D = \frac{\theta}{R - R_0} + D_0, \tag{30}$$

where D is the distortion measured in mean square error, R is the rate achieved with resources allocated at the PHY layer, θ, D_0, R_0 are sequence dependent parameters, which are affected by the spatial and temporal resolution, delay constraints as well as the percentage of INTRA coded macro-blocks.[‡‡] Because (30) is an empirical model, the parameters need to be fitted to the curve of a set of measured data. The relation between the peak signal-to-noise ratio (PSNR) and the distortion is given as [37]

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{D}\right). \tag{31}$$

Then, the utility function can be defined as [39]

$$U_{\text{p}} = \frac{255^2}{D} = \frac{255^2(R - R_0)}{\theta + D_0(R - R_0)}, \tag{32}$$

where subscript p represents that the utility function is defined for the PUs, and R is a function of each PU's assigned subcarriers. In this paper, three sequences are employed, and their parameters are listed in Table I [39].

5.1.2. Utility function for BE service. For BE services, the utility function is usually used to capture user's feeling or satisfaction degree and can be estimated from subjective surveys. In [40], three kinds of utility functions were studied, that is, exponential, log, and power utility functions. It is shown that the utility is usually a concavely increasing function of the channel rate, or in other

[‡‡]INTRA is a video coding mode in the field of video signal processing. An INTRA coded macro-block is a macro-block that is coded using intra prediction from decoded samples in the same slice. INTRA coded macro-blocks can be used for preventing the propagation of decoding errors [42].

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Table I. Test video sequences (video ID, video type, temporal level (TL), and frame rate).

ID	Video sequence	μ	D_0	R_0
1	Foreman (CIF, TL=4, 30 Hz)	5,232,400	0	0
2	Coastguard (CIF, TL=4, 30 Hz)	6,329,700	4.3	0
3	Mobile (CIF, TL=4, 30 Hz)	38,230,000	1	44,040

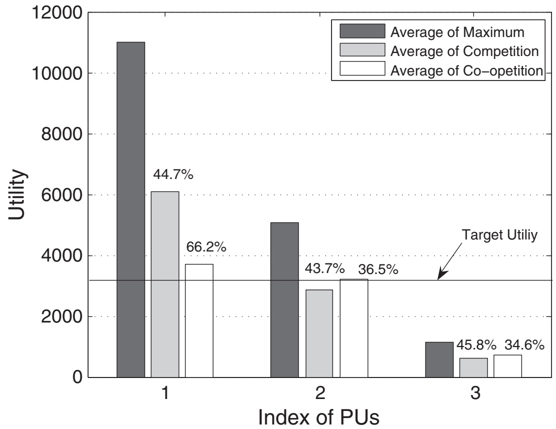

Figure 5. Average performance of the competition and co-opetition among primary users (PUs). 44.7%, 43.7%, and 45.8% are the percentage of utility decrease in the case of competition, with respect to the maximum utility for PU 1, PU 2, and PU 3, respectively. 66.2%, 36.5%, and 34.6% are the corresponding decrease percentage in the case of co-opetition.

words, user's satisfaction degree increases at a decreasing speed as the channel rate increases. In this paper, we borrow the utility function from [41], that is

$$U_{\mathrm{s}}(r) = 0.16 + \ln(R - 0.3), \tag{33}$$

where subscript s means that the utility function is defined for the SUs, and the channel rate R is a function of SU's individual power and the assigned subcarriers.

5.2. Competition and co-opetition among PUs

In this section, we study the performance of the competition and co-opetition among multiple PUs. For simplicity, we do not take the mobility of users into consideration. If users' mobility is incorporated, performance gain of the co-opetition strategy needs to be represented in different way, because the PUs may act as SUs, whereas the SUs may also act as PUs as they move. Numerical results are obtained by averaging over 10^4 independent channel realizations, each being assumed to be Rayleigh distributed for each user. There are three PUs transmitting the Foreman, Mobile, and Coastguard sequences, respectively. Assume that there are 16 subcarriers each with a bandwidth of 15 kHz. The power density of the AWGN noise at each subcarrier is assumed to be 1. Transmission power of the three PUs is set to be 95, 60, and 55, respectively.

Average utility achieved by the two strategies is shown in Figure 5. We can see that PU 1 has the highest maximum utility, whereas PU 3 has the lowest. Through competition, the average percentage of utility decrease of the three PUs with respect to the corresponding maximum utility is 44.7%, 43.7%, and 45.8%, respectively. We find that the decrease percentage is very close to each other, meaning that the fairness of KSBS can be well implemented using the proposed method. Assuming that the three PUs have the same target utility corresponding to a PSNR of 35 dB, we can see that only PU 1 can be satisfied through competition, and the PU 2's utility is close to but less than the target utility. Through co-opetition, the decrease percentage increases from 44.7% to 66.2% for PU 1, decreases from 43.7% to 36.5% for PU 2, and decreases from 45.8% to 34.6% for

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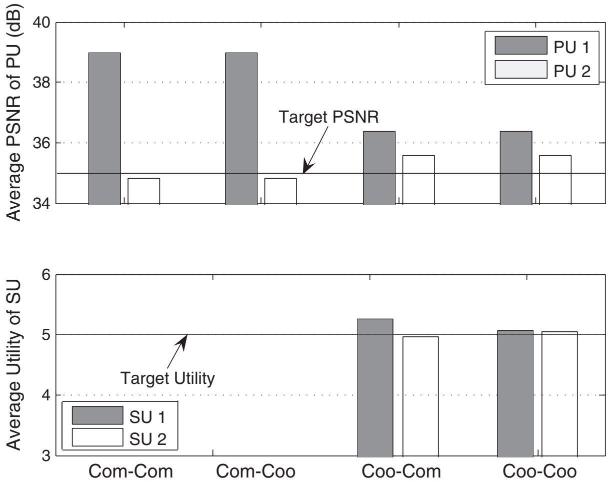

Figure 6. Average performance of the competition and co-opetition among the primary users (PUs) and secondary users (SUs). PSNR, peak signal-to-noise ratio.

PU 3. Consequently, PU 2 becomes satisfied, and the PU 3's utility is also increased. Notice that PU 1 still can be satisfied with co-opetition. Therefore, the KSBS provides a well-defined fairness criterion, as it employs the maximum utility as an indication of user's competence. Employing KSBS as a competition criterion encourages each user to optimize its transmission strategy to increase the competence.

5.3. Co-opetition among PUs and SUs

In the aforementioned experiment, we do not take the SUs into consideration in the subcarrier assignment. In practical communication systems, the number of subcarriers is always very large, and usually, not all subcarriers are used simultaneously. This enables the coexistence of PUs and SUs.

In this experiment, we assume that there are two PUs and two SUs. Denote the proposed co-opetition strategy with Coo-Coo, meaning that the co-opetition is applied to PUs and SUs. We compare the Coo-Coo with other three strategies: (i) Com-Com which means no co-opetition is applied to PUs or SUs; (ii) Com-Coo which means the co-opetition is applied only to SUs; and (iii) Coo-Com which means that the co-opetition is applied only to PUs. The parameters of the PUs are the same as in Section 5.2, and the target utility for the SUs is set to 5. Results are shown in Figure 6. We can see that, in the cases of Com-Com and Com-Coo, the SUs suffer from zero utility.[§§] Moreover, through competition, only PU 1 can be satisfied but not PU 2 because of low transmission power. This can be alleviated by applying the co-opetition to assign subcarriers for PUs. In the cases of Coo-Com and Coo-Coo, on one hand, PU 2 becomes satisfied with the help of subcarrier contribution of PU 1, and on the other hand, the PUs do not need to occupy all subcarriers any longer. Consequently, the coexistence of PUs and SUs becomes possible. Moreover, the co-opetition is more desirable than the competition for subcarrier assignment between the two SUs, as the co-opetition can make both of the two SUs satisfied whereas the competition cannot.

From this experiment, we can see that the proposed method, that is, Coo-Coo, is the most desirable for resource allocation among PUs and SUs. The advantages of the Coo-Coo are, first, it enables the coexistence of the PUs and SUs, and, second, it can make more satisfied PUs and SUs. These advantages can be extended to future heterogenous communication system, in which the PUs in one subsystem might become SUs in another subsystem. In such systems, the users can react to the changes of the network conditions proactively. In the case of rich resource, users can contribute

[§§]Here, we assume that the secondary users (SUs) have no other subcarriers that can be used for transmission.

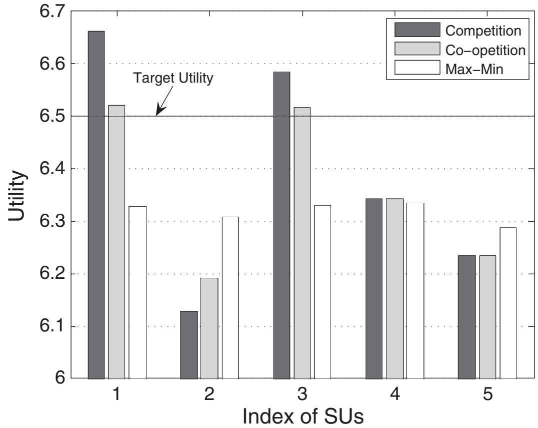

Figure 7. Comparison in terms of the average utility among the competition, co-opetition, and Max–Min. SUs, secondary users.

part of their resources to other users in the same or other subsystems. Conversely, in the case of scarce resources, the users can borrow resources from users in the same or other subsystems. The mechanism design theory [33] is helpful in enforcing users from different subsystems to contribute and borrow resources.

5.4. Comparison between the co-opetition and the Max–Min

Next, we compare the proposed co-opetition strategy to the absolute fairness, that is, the Max–Min. Assume that the co-opetition strategy is applied to subcarrier assignment among PUs. Further assume there are five SUs sharing 128 subcarriers contributed by the PUs. The individual power is set to 70, 30, 60, 50, and 40, respectively, and the target utility is set to 6.5 for all SUs. The Max–Min is implemented using the proposed method by assuming that all users have the same maximum utility. Hence, the Max–Min can be viewed as a special case of the proposed co-opetition strategy. We also include the KSBS in the comparison. Results are given in Figure 7 by averaging over 500 independent channel realizations.

We can see that, based on the Max–Min, the five SUs can achieve very similar utilities. However, the disadvantage of the Max–Min is that it may result in low system efficiency; for example, no SU could be satisfied in this experiment. The KSBS allows users, for example, who are experiencing good channel, to achieve high utility. This coincides to the common knowledge in social resource allocation; that is, the smarter person gains more. In this experiment, SUs 1 and 3 more easily achieve high utility, and they can be satisfied through competition. The co-opetition keeps them still satisfied but enforces them to contribute part of their subcarriers, and hence, the SU 2's utility gets improved. Therefore, the co-opetition strategy can be employed to jointly consider the system efficiency and fairness among users. Notice that the focus of this experiment is not to emphasize the utility gain that SU 2 can achieve but to highlight that the co-opetition considers more fairness than KSBS and is more efficient than the Max–Min.

5.5. Comparison between the co-opetition and the SRM

System setup is the same as that in the aforementioned experiment except that the target utility for the five SUs is set to 6.0, 6.1, 6.2, 6.3, and 6.4, respectively. Result is shown in Figure 8(a). We can see that the SRM can make three SUs satisfied, whereas the co-opetition strategy can satisfy all. Therefore, the co-opetition strategy is more efficient than the SRM in terms of the number of satisfied users. In fact, the SRM can also be viewed as a competition criterion, under which users

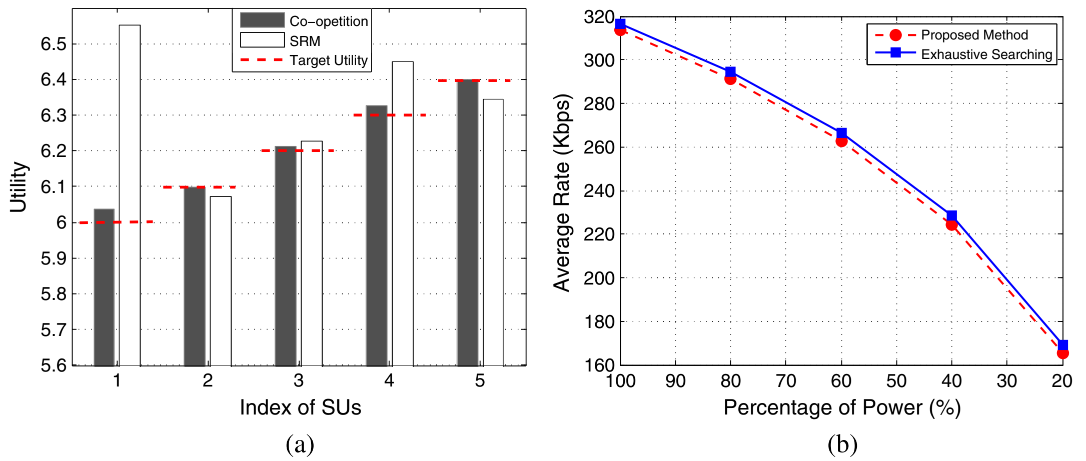

Figure 8. (a)Comparison in terms of the average utility between the co-opetition and sum rate maximization (SRM) and (b) optimality verification for the two-user competition algorithm. SUs, secondary users.

compete with each other on the basis of the marginal rate.[¶¶] Hence, the SRM is inherently competitive, and it does not take the fairness into consideration in resource allocation. It is worth mentioning that we can also construct the co-opetition based on the SRM; that is, let SUs 1, 3, and 4 contribute subcarriers. However, the marginal rate is usually a nonlinear function of the allocated resource, and there is no simple mathematical formulation for the SRM-based co-opetition. The SRM-based co-opetition and the comparison between it, and KSBS-based co-opetition will be studied in our future work.

5.6. *Optimality and convergence*

The co-opetition itself can only guarantee that satisfied users contribute resources to those unsatisfied users. We also need to maximize the sum utility to ensure the resource efficiency. Recall that the proposed method decomposes the multiuser competition into a series of two-user competition, which is further decomposed into a series of two-user SRM. For simplicity of exhaustive searching, we employ two users. Their initial power is set to 60 and 40, respectively. Considering that the subcarrier assignment belongs to integral programming, we exhaustively search the subcarrier assignment that maximizes the sum rate subject to the constraint that the difference between two utility ratios is less than that achieved by the proposed method. Performance of the decomposition-based method is shown in Figure 8(b). We can see that the average rate achievable by the proposed method is very close to the optimum, and greater than 98% in average of the optimal rate can be achieved. The slight performance degradation is because the two-band searching algorithm for solving the two-user SRM becomes suboptimal in the case of low SNR.

Complexity and convergence of the proposed method are illustrated in Figure 9(a) and (b), respectively. Assume that there are six potential PUs transmitting sequences 1, 2, 3, 1, 2, and 3, respectively. Their power is set to 30, 50, 100, 30, 50, and 100, respectively. The target utility is set corresponding to a PSNR of 33 dB. In Figure 9(a), we show the average number of resource exchanges by varying the number of users and of the subcarriers. When we say there are three active PUs, it means that PUs 1, 2, and 3 are active, whereas 4, 5, and 6 are silent. We can see that the number of resource exchanges is only slightly affected by the number of subcarriers. Moreover, the proposed method requires no more than N^3 resource exchanges with N being the number of users. Figure 9(b) gives an example of the resource exchange with six PUs and 64 subcarriers. To emphasize the convergence of the resource exchange, we omit those resource exchanges whose

[¶¶]Marginal rate refers to the slope of the rate-resource curve. Given resource, the greater the marginal rate is, the higher rate can be achieved.

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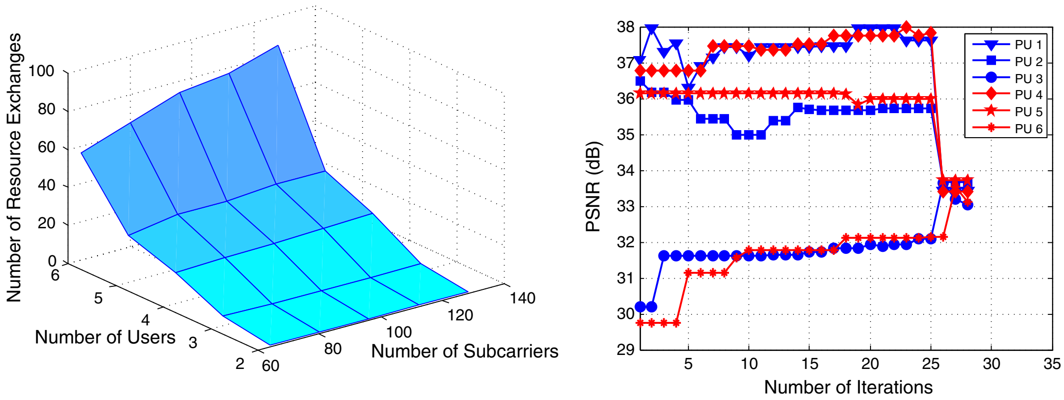

(a) (b)

Figure 9. (a) Average number of the required resource exchanges in the multiuser competition and an (b) example to show the convergence of the multiuser competition. PSNR, peak signal-to-noise ratio; PU, primary user.

result is not saved. We can see that the multiuser competition can be finished within 25 iterations. The subcarrier contribution only needs to be performed once.

6. CONCLUSION

In this paper, we studied the fairness in the multiuser resource allocation in CR systems and proposed a novel co-opetition strategy based on the KSBS for subcarrier assignment among multiple PUs and SUs over multicarrier uplinks. We formulated the resource allocation as an NLIP problem, then proposed a heuristic method. Extensive numerical results have also been presented. It was shown that the conventional competitive strategies, such as KSBS and SRM, are not suitable for resource allocation in CR systems. The proposed co-opetition strategy is more desirable as it can (i) result in more satisfied PUs or SUs with given resource and (ii) enable the coexistence of PUs and SUs. Moreover, the co-opetition strategy implies that, in future heterogenous (e.g., cognitive) networks, it is more reasonable for users from different subsystems to work in a hybrid competitive and cooperative way, through proactively predicting their transmission environments.

ACKNOWLEDGEMENTS

This paper is based upon the work supported in part by the NSFC (61101120), the PhD Programs Foundation of Ministry of Education of China (20110131120028), the China Postdoctoral Science Foundation (2012M521332), the Shandong Doctoral Foundation (2012BSE27052), and the Independent Innovation Foundation of Shandong University (2011GN059).

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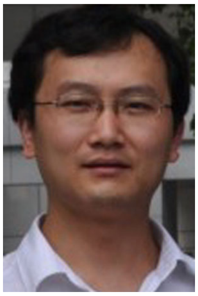

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DOI: 10.1002/dac