Spectrum Sharing in Cognitive Radio Networks – An Auction based Approach

Xinbing Wang, Zheng Li, Pengchao Xu, Youyun Xu, Xinbo Gao, and Hsiao-Hwa Chen

***Abstract*—Cognitive radio is emerging as a promising technique to improve the utilization of radio frequency spectrum. In this paper, we consider the problem of spectrum sharing among primary (or "licensed") and secondary (or "unlicensed") users. We formulate the problem based on bandwidth auction in which each secondary user makes a bid for the amount of spectrum and each primary user may assign the spectrum among secondary users by itself according to the information from secondary users without degrading its own performance. We show that the auction is a non-cooperative game and Nash equilibrium can be its solution. We first consider a single-primary-user network to investigate the existence and uniqueness of Nash equilibrium, and further discuss the fairness among secondary users under given conditions. Then, we present a dynamic updating algorithm in which each secondary user achieves Nash equilibrium in a distributed manner. The stability condition of the dynamic behavior for this spectrum sharing scheme is studied. The discussion is generalized to the case in which there are multiple primary users in the network, where the properties of Nash equilibrium are shown under appropriate conditions. Simulations were used to evaluate the system performance and verify the effectiveness of the proposed algorithm.**

***Index Terms*—Cognitive radio, spectrum sensing, spectrum sharing, game theory, Nash equilibrium.**

I. Introduction

THE current static spectrum allocation policies cause under-utilization of radio frequency spectrum. According to Federal Communications Commission (FCC) [1], the limited spectrum and inefficiency in spectrum usage necessitate a new communication paradigm to exploit the existing spectrum opportunistically. The concepts of software defined radio and cognitive radio (CR) were introduced to enhance the efficiency of spectrum usage [2]. Software radio provides a programmable and scalable software platform for a wireless radio transceiver and enables the radio receiver to operate in multiple frequency bands by using multiple transmission protocols. Cognitive radio is an extension of software radio, which is able to change its transmission parameters and adapt itself intelligently to the wireless environment. With this agility and cognitive ability of the radio transceiver, frequency spectrum can be shared among primary (i.e., licensed) and secondary (i.e., unlicensed) users to improve spectrum utilization.

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Meanwhile, dynamic spectrum sharing mechanism requires that the performance of primary users should not be negatively affected by the opportunistic behavior of secondary users (or at least the negative impacts should be minimized). Therefore, a well-designed spectrum sharing scheme which can guarantee a "peaceful" coexistence of primary and secondary users plays an important role.

In this paper, we propose a novel auction-based model to characterize and analyze some inherent features (e.g., competition among secondary users and uncertainty about the wireless environment for secondary users) in the problem of dynamic spectrum sharing for cognitive radio networks. Based on this model, we analyze how each primary user takes "precautions" to avoid the degradation of its own performance. We assume that secondary users are in general selfish, and we show that this auction is a non-cooperative game in which each secondary user behaves rationally to maximize its own utility (i.e., payoff). In this non-cooperative game, we present Nash equilibrium as a desirable outcome and investigate the properties of this outcome. Our analysis concentrates on a simple network with one primary user and multiple secondary users, and an extension to a network with multiple primary users is discussed in the text followed.

The rest of this paper is outlined as follows. We will discuss the background and related works in II. We present the system model in Section III, and we will further describe the bandwidth auction scheme and investigate the properties of its solution (i.e., Nash equilibrium) in Section IV. We also present a distributed algorithm to achieve the Nash equilibrium and study its stability. We provide extensive simulation results to evaluate system performance and verify the effectiveness of proposed algorithm in Section V, followed by the conclusions of this work in Section VI.

II. Background And Related Works

An introduction to cognitive radio was provided in [3] where cognitive radio was defined as an intelligent wireless system and the fundamental cognitive tasks as well as the behaviors of cognitive radio were discussed. In [4], a comprehensive survey of the functionalities and research challenges in cognitive radio networks (also referred to as NeXt Generation (xG) networks) was presented. The key functions and implementation aspects for this cognitive radio network, including spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing, were discussed. The categorization of different spectrum sharing models in cognitive radio networks, namely, open sharing, hierarchical access, and dynamic exclusive usage models, was provided in [5] and the major issues related to primary user detection and spectrum sensing were discussed.

In the literature, extensive researches have been done on the traditional problem of channel allocation, particularly on base station frequency/channel assignment in cellular networks [6]. The channel assignment in cellular networks is driven by call requests to reduce the probability of call blocking. In the channel/slot assignment problems, a graph coloring algorithm was used in [7] to produce an allocation that avoids all possible collisions for a given network topology. The objective is to minimize the color usage where each vertex is assigned with one color. Distributed channel assignment for OFDM based systems was studied in [8] but it was limited to fully-connected networks, where different flows may interfere with each other. Apart from analytical frameworks, practical strategies were proposed for sharing a single channel. For instance, contention based schemes invoke a random access protocol such as ALOHA and CSMA, where users contend in time to share a common channel [9] [10] [11]. Although spectrum sharing for cognitive radio networks is similar to traditional channel allocation problem in a sense that they both belong to a general problem of spectrum allocation. But traditional spectrum/channel allocation scheme was demand-based and fixed, while in cognitive radio networks it requires that secondary users dynamically and opportunistically utilize unused licensed spectrum on a non-interfering or leasing basis.

Dynamic spectrum sharing is one of the main challenges in the design of cognitive radio networks due to the requirement of ”peaceful” coexistence of both primary (i.e., licensed) and secondary (i.e., unlicensed) users as well as the availability of wide range of radio spectrum. Various techniques were used to model the spectrum sharing problems for cognitive radio networks. Graph theory was used to analyze spectrum allocation schemes among secondary users. In [12], spatial opportunistic spectrum assignment was reduced to a graph-coloring problem and fairness issue was also considered. Game theory [21] has been identified as one of the key techniques to characterize the competitiveness and cooperation among secondary users. In [13], the game theory was used to carry out spatial spectrum allocation and an interesting connection between the resultant colored graph and the Nash equilibria of the corresponding games was provided. A game-theoretic Cournot model was presented in [14], where secondary users (i.e., the oligopolists) compete to share the bandwidth offered by the primary user (i.e., the market). Also, a Bertrand model was presented in [15] where a joint consideration of competitive pricing among primary users and spectrum sharing among secondary users was addressed. Furthermore, auction theory [22] has been introduced recently to several types of resource allocation problems (e.g., time slot allocation [16], power allocation [17] and cooperative communications [18]). In the context of spectrum allocation, power allocation subject to a constraint on the interference temperature at a measurement point was addressed in [19]. However, the interaction between primary and secondary users was not considered there and the bid of one secondary user was unbounded which is unrealistic.

In this paper we are motivated to propose an auction-based model to characterize how primary and secondary users behave to share the common spectrum and how they interact with each other in real situations, and we will present analysis based on this model. To the best of our knowledge, this paper is the first that applies the auction theory in designing spectrum sharing scheme among primary and secondary users for cognitive radio networks.

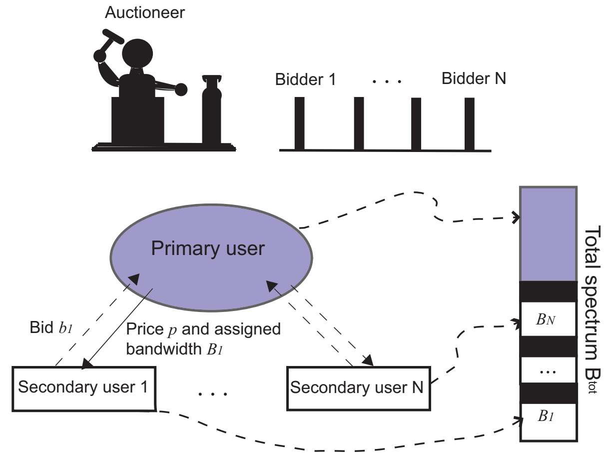

Fig. 1. System model for spectrum sharing.

III. System Model

A. Primary and Secondary Users

Let us consider a simple system where there are only one primary user (PU) and a group $\mathcal{I} = (1, \ldots, I)$ of secondary users (SUs) who want to share the spectrum allocated to the primary user B_{tot} (as shown in Figure 1). In this system, we assume that the primary user can enhance the efficiency of spectrum usage by sharing some portion of the bandwidth B_i ($B_i \leq B_{tot}$) with secondary user i ($i \in \mathcal{I}$). However, the primary user should retain a given amount of bandwidth B_{rem} to guarantee its own performance. The constraint on the remaining bandwidth held by the primary user is given as follows:

$$B_{rem} = B_{tot} - \sum_{i \in \mathcal{I}} B_i \geq B_{req}, \tag{1}$$

where B_{req} is the required bandwidth for the primary user to provide a particular quality of service requirement. It is noted that this requirement may be time-varying. The primary user charges secondary users for the spectrum at a price of p per unit bandwidth. After the allocation, the secondary users may transmit in the allocated spectrum using adaptive modulation to enhance the transmission performance. The revenue of the secondary user i is denoted by r_i per unit of achievable transmission rate.

B. Wireless Transmission

By using adaptive modulation, the secondary users can dynamically adjust transmission rate based on channel quality. For modulation schemes such as uncoded quadrature amplitude modulation (QAM) with square constellation (e.g., 4-QAM and 16-QAM) the bit-error-rate (BER) in single-inputsingle-output Gaussian noise channel can be well approximated as follows [20]:

$$BER \approx 0.2 \exp\left(\frac{-1.5\gamma}{2^k - 1}\right), \tag{2}$$

where γ is the SNR (signal to noise radio) at the receiver and k is the spectral efficiency of the modulation scheme used. Without loss of generality, let us assume that the spectral efficiency is a non-negative real number. To meet the requirement of a specific application, BER must be maintained at a target level (i.e., BER_i^{tar}). The spectral efficiency of the transmission for the secondary user i can be expressed as follows:

$$k_i = \log_2\Big(1 + K\gamma_i\Big), \tag{3}$$

where

$$K = \frac{1.5}{\ln 0.2/BER_i^{tar}}. \tag{4}$$

We assume that through channel estimation, the secondary users can obtain the received SNR of the channel. In summary, for the secondary user i, given the received SNR γ, target BER_i^{tar}, and assigned spectrum B_i, the transmission rate (in bits per second) can be obtained.

IV. Spectrum Sharing Schemes

A. Bandwidth Auction

We formulate the problem of spectrum sharing as an auction in which the secondary users (SUs) make bids for the bandwidth allocated to the primary user (PU). An auction is a decentralized market mechanism for allocating resources in an economy. Based on the assumption about rational behavior, an auction is essentially a non-cooperative game, where the players are the bidders, the strategies are the bids, and both allocations and payments are functions of the bids. A well known auction scheme is the Vickrey-Clarke-Groves (VCG) auction [22], which requires to gather global information from the network and perform centralized computations. However, the communication overhead and computational complexity make VCG auction unsuitable to this scenario. To characterize the behaviors of the interaction between the primary user and multiple secondary users, we propose an auction which has relatively simple rules as described below.

1) *Information*: Each SU i knows its revenue r_i per unit of achievable transmission rate, and it also knows its spectral efficiency k_i of transmission through channel estimation. r_i relates to the QoS in a real network. In other words, the higher the QoS required by the SU i is, the greater the revenue r_i will be. As for the precise relationship between QoS levels required by SU i and r_i, it is not our focus in this paper. And k_i can be obtained from (3). The PU announces a positive reserve bid $\beta > 0$ and the price $p > 0$ to all SUs before the auction starts.
2) *Bids*: The SU i submits a bid b_i ($0 \le b_i \le B_{tot}$) which generally represents the maximum bandwidth that SU desires for data transmission.
3) *Allocation*: The PU allocates bandwidth according to (here we only consider the FDM scheme, and OFDM scheme is more applicable. Once the bandwidth is allocated by PU, there is no contention among SUs. Thus, MAC layer or DLL layer is not involved here.)

$$B_i = \frac{b_i}{\sum_{j \in \mathcal{I}} b_j + \beta} B_{tot}. \tag{5}$$

4) *Payments*: SU i pays the PU

$$C_i = p\ \theta_i b_i, \tag{6}$$

where θ_i is a user-dependent priority parameter (i.e., this payment differentiation is in a spirit similar to the ”price discrimination” in an economical market). In this auction, we adopt a ”prepay” mechanism that each SU pays for the bandwidth it bids instead of that it is assigned by the PU.

A bidding profile is defined as the vector containing the SUs' bids, $\mathbf{b} = (b_1, \dots, b_I)$. The bidding profile of SU i's opponents is defined as $\mathbf{b_{-i}} = (b_1, \dots, b_{i-1}, b_{i+1}, \dots, b_I)$, such that $\mathbf{b} = (b_i; \mathbf{b_{-i}})$. Under the rule of this auction, we notice that $b_i \in \mathrm{b_r} \triangleq [0, B_{tot}]$ and the bidding profile $\mathbf{b}$ is constrained by

$$\mathbf{b} \in \mathbf{b_R} \triangleq \Big\{\mathbf{b} \;\Big|\; 0 \le b_i \le B_{tot},\ \forall i \in \mathcal{I}\Big\}. \tag{7}$$

In this auction, a positive reserve bid β is used by the PU to control the remaining portion of the spectrum for its own usage. The PU sets β such that (1) is satisfied. The minimum bandwidth that the PU could possibly hold after allocation is given as follows:

$$\min_{\mathbf{b} \in \mathbf{b_R}} B_{rem} = \frac{\beta B_{tot}}{I B_{tot} + \beta} > 0. \tag{8}$$

The PU can obtain the total number of SUs (i.e., I) by broadcasting a pilot signal before the auction starts, and the safest strategy for the PU is to set the reserve bid β such that $\min_{\mathbf{b} \in \mathbf{b_R}} B_{rem} \ge B_{req}$, and from (8) we obtain the required β for this strategy as follows:

$$\widetilde{\beta} = \frac{B_{req} I B_{tot}}{B_{tot} - B_{req}}. \tag{9}$$

If the PU sets the reserve bid $\beta = \widetilde{\beta}$, it always hold enough bandwidth for its own usage, given the requirement of a particular type of quality of service. If $\beta > \widetilde{\beta}$, some bandwidth would be wasted.

The ”prepay” mechanism is a crucial part of the auction rules and we can explain this mechanism as follows. By regulating that each SU pays for its own bid, the PU prohibits SUs from over-bidding the bandwidth, which is limited in this situation. Under this regulation, each SU takes risks in bidding the bandwidth which represents the maximum bandwidth it desires, since the SU makes profit (i.e., payoff is positive) when there are few other SUs competing for the bandwidth, and the SU loses profit (i.e., payoff is negative) otherwise. Based on this mechanism, the risks reflect one SU's uncertainty of the changing wireless environment.

Given the allocated bandwidth, the SU i's revenue is

$$R_i = r_i k_i B_i \tag{10}$$

The SU i chooses the bid b_i to maximize its payoff

$$U_i(b_i;\mathbf{b_{-i}},p) = R_i\Big[B_i(b_i;\mathbf{b_{-i}})\Big] - C_i(b_i,p). \qquad (11)$$

The desirable outcome of an auction (non-cooperative game) is Nash equilibrium (NE), which is a bidding profile $\mathbf{b}^*$ such that no SU wants to deviate unilaterally, i.e.,

$$U_i(b_i^*;\mathbf{b}^*_{-\mathbf{i}},p) \geq U(b_i;\mathbf{b}^*_{-\mathbf{i}},p), \qquad \forall i \in \mathcal{I}, b_i \in \mathbf{b_R}. \qquad (12)$$

We define SU i's best response as

$$\mathcal{B}(\mathbf{b_{-i}},p) = \left\{ b_i \;\Big|\; b_i = \arg\max_{\mathbf{b}\in \mathrm{b_R}} U_i(b_i;\mathbf{b_{-i}},p) \right\}, \qquad (13)$$

which in general could be a set. A NE is also a fixed point solution of all SUs' best responses. In the following part, we would like to investigate the properties of the NE, and we would like also to present a dynamic updating algorithm to reach the NE in a distributed fashion. First, we have the theorem given as follows.

Theorem 1: There are two extreme prices, $\underline{p_i}$ and $\overline{p_i}$, which are defined as

$$\underline{p_i} = \frac{r_i k_i B_{tot}\Big\{(I-1)B_{tot}+\beta\Big\}}{\theta_i (IB_{tot}+\beta)^2}, \qquad (14)$$

$$\overline{p_i} = \frac{r_i k_i B_{tot}}{\theta_i \beta}. \qquad (15)$$

If $p < \underline{p_i}$, all SUs would bid the maximum bandwidth allocated to the PU (i.e., $b_i = B_{tot},\ \forall i \in \mathcal{I}$); if $p > \overline{p_i}$, no SU would be willing to use any of the spectrum provided by the PU (i.e., $b_i = 0,\ \forall i \in \mathcal{I}$).

Proof: From the equation given below

$$\frac{\partial U_i}{\partial b_i} = \frac{r_i k_i B_{tot}\Big(\sum_{j\neq i} b_j + \beta\Big)}{\Big(\sum_{j\in\mathcal{I}} b_j + \beta\Big)^2} - p\,\theta_i, \qquad (16)$$

we observe that the first derivative of U_i in terms of b_i is a decreasing function of both b_i and $\sum_{j\neq i} b_j$, and we define $\underline{p_i}$ and $\overline{p_i}$ as

$$\begin{cases} \underline{p_i} \triangleq \dfrac{\min_{\mathbf{b}\in\mathbf{b_R}} \dfrac{\partial U_i}{\partial b_i}}{\theta_i} = \dfrac{r_i k_i B_{tot}\Big\{(I-1)B_{tot}+\beta\Big\}}{\theta_i (IB_{tot}+\beta)^2}, \\ \qquad\qquad \text{for } b_i = B_{tot},\ \forall i\in\mathcal{I} \\ \overline{p_i} \triangleq \dfrac{\max_{\mathbf{b}\in\mathbf{b_R}} \dfrac{\partial U_i}{\partial b_i}}{\theta_i} = \dfrac{r_i k_i B_{tot}}{\theta_i\beta},\ \text{for } b_i = 0,\ \forall i\in\mathcal{I} \end{cases} \qquad (17)$$

respectively. We observe that if $p < \underline{p_i}$, then $\frac{\partial U_i}{\partial b_i} > 0$, when $b_i \in \mathrm{b_r},\ \forall i \in \mathcal{I}$, and therefore $b_i^* = B_{tot}$; if $p > \overline{p_i}$, $\frac{\partial U_i}{\partial b_i} < 0$, when $b_i \in \mathrm{b_r},\ \forall i \in \mathcal{I}$, and therefore we have $b_i^* = 0$. ■

In the price-setting process, the PU could gather the information (i.e., r_i, k_i, θ_i, I) from SUs to calculate both $\underline{p_i}$ and $\overline{p_i}$. We also note $\underline{p_i} < \overline{p_i}$ and that a reasonable price (at least one SU can achieve its best response) must lie between $\underline{p_i}$ and $\overline{p_i}$.

Theorem 2: There is a unique Nash equilibrium for the bids of the SUs. And if $p \in (\underline{p_i}, \overline{p_i})$, the SU i's unique best response function is given as follows:

$$\mathcal{B}(\mathbf{b_{-i}},p) = \left[\sqrt{\frac{r_i k_i B_{tot}\left(\sum_{j\neq i} b_j + \beta\right)}{p\,\theta_i}} - \left(\sum_{j\neq i} b_j + \beta\right) \right]_0^{B_{tot}} \qquad (18)$$

where $[x]_a^b$ is defined as $[x]_a^b = \max\{\min\{x,b\},a\}$.

Proof: Let us first consider the existence of the Nash equilibrium. The equilibrium point exists for every concave n-person game [23]. In this case, it can be shown that the payoff function of each SU is continuous in all SUs' bids and concave with respect to that SU's bid (i.e., b_i). Using (16), this concavity can be shown by observing

$$\frac{\partial^2 U_i(b_i;\mathbf{b_{-i}},p)}{\partial b_i^2} < 0.$$

It is observed that this auction is a concave n-person game with orthogonal constraints and we use *Theorem 2* in [23] to prove the uniqueness of the Nash equilibrium. First, we show that the payoff of each SU is convex with respect to the bids of other SUs. That is,

$$\left.\frac{\partial^2 U_i(b_i;\mathbf{b_{-i}},p)}{\partial b_j^2}\right|_{j\neq i} \geq 0. \qquad (19)$$

Then, a nonnegative weighted sum of the payoff functions can be obtained as follows: $\mathscr{S}(\mathbf{b},\mathbf{x}) = \sum_{i=1}^{I} x_i U_i(b_i;\mathbf{b_{-i}},p)$. The pseudo gradient of $\mathscr{S}(\mathbf{b},\mathbf{x})$ is given by

$$\mathscr{F}(\mathbf{b},\mathbf{x}) = \begin{bmatrix} x_1\nabla_1 U_i(b_1;\mathbf{b_{-1}},p) \\ \vdots \\ x_I\nabla_I U_I(b_I;\mathbf{b_{-I}},p) \end{bmatrix}. \qquad (20)$$

Using (16) and (19), we can show that $\mathscr{S}(\mathbf{b},\mathbf{x})$ is concave in b_i based on the observation

$$\frac{\partial^2 \mathscr{S}(\mathbf{b},\mathbf{x})}{\partial b_i^2} < 0. \qquad (21)$$

Let the Jacobian of the pseudo-gradient of $\mathscr{F}(\mathbf{b},\mathbf{x})$ with respect to b_i be denoted as $\mathbf{J}$. Based on (19) and (21), we observe that $(\mathbf{J}+\mathbf{J^T})$ is negative definite. Therefore, $\mathscr{S}(\mathbf{b},\mathbf{x})$ is diagonally strictly concave, and the Nash equilibrium of the bids is unique.

Using the first order condition in (16), we can obtain the best response function taking the constraint on the amount of bid (i.e., $b_i \in \mathrm{b_r}$) into account. This completes the proof. ■

Given the existence of a unique NE, next we characterize the resulting bid profile. We consider a fair bandwidth allocation, which solves the following problem:

$$\min_{\mathbf{b}\in\mathbf{b_R}} \ c, \tag{22}$$

subject to

$$\frac{\partial R_i(b_i;\mathbf{b_{-i}})}{\partial b_i} = c\ \theta_i\ \mathbf{1}_{\{b_i>0\}}, \qquad \forall i \in \mathcal{I}$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function, and θ_i is the priority parameter defined above in the payment of SUs. When $\theta_i = 1$ for each SU i, all SUs who use the spectrum offered by the PU will have the same marginal revenue, which leads to strict fairness among SUs (i.e., all SUs have equal rights to bid the maximum bandwidth they desire). [1] It is possible to assign different weights to different SUs to achieve different QoS requirements. One such example is to let

$$\theta_i = \frac{r_i k_i B_{tot}}{\beta} = \frac{\partial R_i}{\partial b_i}\bigg|_{b_i=0,\ b_j=0,\ \forall j\neq i} \tag{23}$$

i.e., θ_i represents SU i's eagerness to bid extra bandwidth offered by the PU before the auction starts. The intuition behind the problem (22) is that for all SUs that choose to use the spectrum provided by the PU, the corresponding b_i should be maximized subject to the "weighted marginal revenue equalization" condition. This can be transformed into the minimization of the common coefficient c due to the concavity of R_i in terms of b_i.

It is noted that a fair bandwidth allocation is the Pareto optimal, i.e, no SU's revenue (i.e., R_i) can be further increased without decreasing the revenue of another SU.

Theorem 3: If the unique Nash equilibrium is interior [2], then the bandwidth allocation is fair.

Proof: If the first order conditions in (16) hold for each SU i, then we prove that the "weighted marginal revenue equalization" property of a fair bandwidth allocation (i.e., the constraint in the problem (22)) is satisfied at the NE of the auction. ■

We notice that a properly-set price p^* ($\underline{p_i} \leq p^* \leq \overline{p_i}$) such that the NE is interior can lead to a fair bandwidth allocation. However, it is difficult to find p^* analytically. Since SUs' best responses in (18) are monotonically non-increasing in price, here we propose a simple search algorithm for seeking the best price p^* as shown in Figure 2. In the text followed, we would investigate how each SU achieves the Nash equilibrium in a distributed manner. For notational simplicity, the dependence on p is omitted.

[1]This is one type of fairness. The other types of fairness, including max-min fairness and proportional fairness, are also commonly used in the literature.

[2]Interior equilibrium is the one in which the first order conditions hold for each player. The alternative is the boundary equilibrium in which at least one of the players selects the strategy on the boundary of his strategy space.

Algorithm: Seeking the best price p^*
1. **Set** $p = \underline{p}$, announce p to all SUs.
2. SU i calculates its best response $b_i^*,\ \forall i \in \mathcal{I}$.
3. **if** $b_i^* \leq B_{tot}, \forall i \in \mathcal{I}$,
   then go to step 5.
4. PU increments $p = p + \triangle p$ and updates p to all SUs,
   then go to step 2.
5. **Stop**, and declares the best price $p^* = p$.

Fig. 2. The price-seeking algorithm.

B. Dynamic Updating Algorithm

In a practical cognitive radio network, the secondary users (SUs) may only be able to observe the pricing and assignment information from the primary user (PU), but not the strategies and payoffs of other secondary users. Therefore, we should investigate a distributed algorithm for each SU to achieve Nash equilibrium based on its own interaction with the PU only. In this case, each SU communicates with the PU to obtain the price and different assignment functions for different bids. Then, each SU updates its bid according to its marginal payoff function as follows:

$$b_i(t+1) = b_i(t) + \alpha_i\ b_i(t)\frac{\partial U_i(\mathbf{b})}{\partial b_i(t)}, \tag{24}$$

where $b_i(t+1)$ is the bid in terms of bandwidth at time t, and α_i is the speed adjustment parameter (i.e., learning speed) of SU i. The dynamic updating process for each SU can be expressed as

$$b_i(t+1) = b_i(t)+\alpha_i b_i(t)\left\{ r_i k_i B_{tot}\left[\frac{\sum_{j\neq i} b_j + \beta}{\left(\sum_{j\in\mathcal{I}} b_j\right)^2}\right] - p\ \theta_i \right\}. \tag{25}$$

C. Local Stability Analysis

We can write the dynamic updating function in a matrix form as follows: [24]:

$$\mathbf{b}(t+1) = \mathbf{S}\Big\{\mathbf{b}(t)\Big\}. \tag{26}$$

At the equilibrium, we have $\mathbf{b}(t+1) = \mathbf{b}(t) = \mathbf{b}$, namely $\mathbf{b} = \mathbf{S}(\mathbf{b})$, where $\mathbf{S}$ is the self-mapping function of the fixed point $\mathbf{b}$. With the payoff function in this auction, the fixed point can be obtained by solving the set of equations as follows:

$$\alpha_i b_i(t)\left\{ r_i k_i B_{tot}\left[\frac{\sum_{j\neq i} b_i + \beta}{\left(\sum_{j\in\mathcal{I}} b_j\right)^2}\right] - p\ \theta_i \right\} = 0, \qquad \forall i \in \mathcal{I} \tag{27}$$

With two SUs in a cognitive radio network, we have fixed points b_0, b_1, b_2, and b_3 which can be expressed as

$$\begin{aligned}
\mathbf{b_0} &= (0,\ 0)\,, \\
\mathbf{b_1} &= \left(\sqrt{\frac{r_1 k_1 B_{tot}\beta}{p\ \theta_1}} - \beta,\ 0\right), \\
\mathbf{b_2} &= \left(0,\ \sqrt{\frac{r_2 k_2 B_{tot}\beta}{p\ \theta_2}} - \beta\right), \\
\mathbf{b_3} &= \left(\sqrt{\frac{r_1 k_1 B_{tot}(b_2+\beta)}{p\ \theta_1}} - (b_2+\beta),\right. \\
&\qquad \left.\sqrt{\frac{r_2 k_2 B_{tot}(b_1+\beta)}{p\ \theta_2}} - (b_1+\beta)\right),
\end{aligned} \tag{28}$$

where $\mathbf{b_3}$ is the Nash equilibrium.

We analyze the local stability of this spectrum sharing auction scheme based on localization by considering the eigenvalues of the Jacobian matrix of the mapping. By definition, the fixed point is stable if and only if the eigenvalues are all inside the unit circle of the complex plane (i.e., $|\lambda_i| < 1$ for $i = 1 \in \mathcal{I}$) [24]. With two SUs, there are two eigenvalues, and the Jacobian matrix can be expressed as

$$\mathbf{J}(b_1, b_2) = \begin{bmatrix} \xi_1 & \zeta_1 \\ \eta_1 & \kappa_1 \end{bmatrix}, \tag{29}$$

where ξ_1, ζ_1, η_1 and κ_1 are defined as follows:

$$\xi_1 = 1 + \alpha_1 \left\{ r_1 k_1 B_{tot}\left(1 - \frac{2b_1}{b_1+b_2+\beta}\right)\frac{b_2+\beta}{(b_1+b_2+\beta)^2} - p\ \theta_1 \right\}, \tag{30}$$

$$\zeta_1 = \frac{\alpha_1 b_1 r_1 k_1 B_{tot}(b_1 - b_2 - \beta)}{(b_1+b_2+\beta)^3}, \tag{31}$$

$$\eta_1 = \frac{\alpha_2 b_2 r_2 k_2 B_{tot}(b_2 - b_1 - \beta)}{(b_1+b_2+\beta)^3}, \tag{32}$$

$$\kappa_1 = 1 + \alpha_2 \left\{ r_2 k_2 B_{tot}\left(1 - \frac{2b_2}{b_1+b_2+\beta}\right)\frac{b_1+\beta}{(b_1+b_2+\beta)^2} - p\ \theta_2 \right\}. \tag{33}$$

We investigate the stability condition at each fixed point. For $\mathbf{b_0}$, we have

$$\mathbf{J}(0,0) = \begin{bmatrix} 1+\alpha_1\left(\frac{r_1 k_1 B_{tot}}{\beta} - p\ \theta_1\right), & 0 \\ 0, & 1+\alpha_2\left(\frac{r_2 k_2 B_{tot}}{\beta} - p\ \theta_2\right) \end{bmatrix}. \tag{34}$$

It is noted that the eigenvalues are given by the diagonal elements of $\mathbf{J}(\cdot)$ if matrix $\mathbf{J}(\cdot)$ is diagonal or triangular. The coordinate $(0,0)$ would be stable if

$$\left|1 + \alpha_1\left(\frac{r_1 k_1 B_{tot}}{\beta} - p\ \theta_1\right)\right| \le 1, \tag{35}$$

and

$$\left|1 + \alpha_2\left(\frac{r_2 k_2 B_{tot}}{\beta} - p\ \theta_2\right)\right| \le 1. \tag{36}$$

However, with a properly set price or

$$p < \overline{p_i} = \frac{r_i k_i B_{tot}}{\theta_i \beta}, \tag{37}$$

the cognitive system with two SUs is not stable. This agrees with *Theorem 1* that when the PU sets a proper price, SUs would like to use some spectrum provided by the PU and then $\mathbf{b_0} = (0,0)$ is not stable. On the other hand, if the price is higher than $\overline{p_i}$, all SUs will stay out of the auction.

For the fixed point $\mathbf{b}_1$, we have the Jacobian matrix expressed as

$$\mathbf{J}\left(\sqrt{\frac{r_1 k_1 B_{tot}\beta}{p\ \theta_1}} - \beta,\ 0\right) = \begin{bmatrix} \xi_2 & \zeta_2 \\ \eta_2 & \kappa_2 \end{bmatrix}, \tag{38}$$

where ξ_2, ζ_2, η_2 and κ_2 are defined as

$$\xi_2 = 1 - 2\alpha_1 p\ \theta_1\left(1 - \sqrt{\frac{p\ \theta_1\beta}{r_1 k_1 B_{tot}}}\right), \tag{39}$$

$$\zeta_2 = \frac{\alpha_1 p\ \theta_1}{\beta}\left(1 - \sqrt{\frac{p\ \theta_1\beta}{r_1 k_1 B_{tot}}}\right)\left(1 - 2\sqrt{\frac{p\ \theta_1\beta}{r_1 k_1 B_{tot}}}\right), \tag{40}$$

$$\eta_2 = 0, \tag{41}$$

$$\kappa_2 = 1 + \alpha_2\left(\sqrt{\frac{r_2^2 k_2^2 p\ \theta_1}{r_1 k_1 \beta}} - p\ \theta_2\right). \tag{42}$$

We observe that whether a system is stable for $\mathbf{b_1}$ is not straightforwardly seen and it depends on system parameters (i.e., r_i, k_i, θ_i, β, p). It would be stable if

$$\left|1 - 2\alpha_1 p\ \theta_1\left(1 - \sqrt{\frac{p\ \theta_1\beta}{r_1 k_1 B_{tot}}}\right)\right| \le 1, \tag{43}$$

and

$$\left|1 + \alpha_2\left(\sqrt{\frac{r_2^2 k_2^2 p\ \theta_1}{r_1 k_1 \beta}} - p\ \theta_2\right)\right| \le 1. \tag{44}$$

Detail discussions are omitted here due to space limitation. We only verify that in our simulation settings used in Section V the fixed point $\mathbf{b_1}$ is not stable. Similarly, the fixed point $\mathbf{b_2}$, depending on system parameters, is not stable in our simulation settings given in Section V. For the fixed point $\mathbf{b_3}$, which is the Nash equilibrium, the Jacobian matrix can be expressed as

$$\mathbf{J}(b_1^*, b_2^*) = \begin{bmatrix} j_{i,j} \end{bmatrix}, \tag{45}$$

where

$$\begin{aligned}
j_{1,1} &= 1 - \alpha_1 p\ \theta_1 \frac{2b_1^*}{b_1^* + b_2^* + \beta}, \\
j_{1,2} &= \frac{\alpha_1 b_1^*(b_1^* - b_2^* - \beta)}{(b_2^*+\beta)(b_1^*+b_2^*+\beta)}, \\
j_{2,1} &= \frac{\alpha_2 b_2^*(b_2^* - b_1^* - \beta)}{(b_1^*+\beta)(b_1^*+b_2^*+\beta)}, \\
j_{2,2} &= 1 - \alpha_2 p\ \theta_2 \frac{2b_2^*}{b_1^* + b_2^* + \beta},
\end{aligned}$$

and (b_1^*,b_2^*) is the Nash equilibrium of the auction. If the NE is interior, we can obtain b_1^*,b_2^* by solving the following equations

$$b_1^* = \sqrt{\frac{r_1 k_1 B_{tot}(b_2^* + \beta)}{p\ \theta_1}} - (b_2^* + \beta),$$

$$b_2^* = \sqrt{\frac{r_2 k_2 B_{tot}(b_1^* + \beta)}{p\ \theta_2}} - (b_1^* + \beta).$$

It is observed that this Jacobian matrix is neither diagonal nor triangular, and therefore the characteristic equation to obtain the eigenvalues is given as follows:

$$\lambda^2 - \lambda(j_{1,1} + j_{2,2}) + (j_{1,1}j_{2,2} - j_{1,2}j_{2,1}) = 0. \quad (46)$$

We can solve this by using the standard formula

$$\lambda_1, \lambda_2 = \frac{(j_{1,1} + j_{2,2}) \pm \sqrt{4j_{1,2}j_{2,1} + (j_{1,1} - j_{2,2})^2}}{2}. \quad (47)$$

Basically, given r_1, r_2, k_1, k_2, B_{tot} and β, p (announced by the PU to all SUs before the auction starts), we can obtain the relationship between α_1 and α_2 in the auction such that the fixed point of Nash equilibrium is stable. When the Nash equilibrium is stable, the payoff of the SUs can not be increased by altering the spectrum bandwidth bids (i.e., marginal payoff is zero).

D. Extension To Multiple Primary User Networks

The proposed auction-based spectrum sharing scheme can be generalized to cognitive radio networks with multiple primary users (PU). We define the set of primary users as $\mathcal{L} = 1, \ldots, L$. Each primary user $l \in \mathcal{L}$ announces a price p_l and a reserved bid β_l without knowing the prices and reserved bids of other primary users. To maximize its own revenue, the secondary user (SU) i would submit its bid to the optimal PU for the channel that the SU i achieves the highest spectral efficiency in transmission. Based on the bids, PU l allocates the secondary user i with bandwidth given by

$$B_{il} = \frac{b_{il}}{\sum_{j \in \mathcal{I}_l} b_{jl} + \beta_l} B_{tot}^l, \quad (48)$$

where B_{tot}^l is the total bandwidth allocated to PU l and the set of SUs who choose PU l is denoted by $\mathcal{I}_l$.

The revenue and the payment of SU i can be expressed as

$$R_i = r_i k_{il} B_{il}, \quad (49)$$

$$C_i = p_l \theta_i b_{il}, \quad (50)$$

respectively. After choosing its optimal PU, each SU competes with other SUs which choose the same PU for the bandwidth allocated to that PU. This implies that we can divide a multiple-primary-user network into L clusters of nodes: each of the L clusters contains one PU and the SUs which use the bandwidth allocated to this PU. Then we can analyze each cluster independently as a single-primary-user network as we did in Section IV-A. Similar to a single-primary-user network, a unique Nash equilibrium exists for each cluster. Therefore, there is a NE for the whole network and using the dynamic updating algorithm all SUs can globally converge to that NE. Also, if a PU sets a proper price, a fair bandwidth allocation among SUs can be achieved for the cluster in which that PU lies.

Each SU's choice of PU increases the risks it takes in bidding, and the risks again reflect the uncertainty of the wireless environment for one particular SU with an increased complexity. The intuition behind is that each SU i has no information about other SU's choices and how many other SUs it competes with for the bandwidth offered by the PU l, and it risks in choosing the optimal PU for its channel in which the SU achieves the best spectral efficiency. There is a case in which SU i gains lower revenue by choosing its optimal PU due to fierce competition (i.e., many SU's choose the same PU to bid), whereas SU i can gain an higher revenue even though it chooses the PU which is not the best. Numerical examples are shown in Section V. In this case, cooperation is likely to be beneficial to competing secondary users. System performance can be improved when a well-designed cooperation mechanism is used. However, this is beyond the scope of this paper and left for our future research.

V. Performance Evaluation

A. Parameter Setting

Let us first consider a cognitive radio environment with one primary user (PU) and two secondary users (SUs) sharing a frequency spectrum of size $B_{tot} = 10$ MHz. The target BER for both SUs is $BER_i^{tar} = 10^{-4}$. The revenue of a SU per unit transmission rate is $r_i = 10, \forall i \in \mathcal{I}$. First, let us assume that SNR information γ_i is already available to SUs by channel estimation, and later in the case of multiple primary users network we will adopt a location-based model in which SNR γ_i is determined by distances. In this case, the PU sets the price $p = 10$ per unit bandwidth and reserves bid $\beta = 0.2$ (i.e., the PU is idle at a given time and uses only a tiny amount of bandwidth to transmit control signals).

B. Numerical Results

We first set $\theta_1 = \theta_2 = 1$, which leads to a strict fairness among SUs. Figure 3 shows the best response of both SUs in this auction. The best response of each SU is a nonlinear function of the other user's strategy (i.e., bid). The Nash equilibrium is located at the point at which the best responses of both the SUs intersect. It is observed that under different channel qualities, the Nash equilibrium is located at the different places. Since the SU can achieve an higher transmission rate from the same spectrum size due to adaptive modulation, an SU with a better channel quality (or spectral efficiency) prefers to bid a larger spectrum size. Also, the trajectory of spectrum sharing in the dynamic updating process is shown for the case of $\alpha_1 = \alpha_2 = 0.14$. Again, we observe that with the same speed adjustment parameter, a better channel quality results in more fluctuations in the trajectory leading to the Nash equilibrium.

Based on the eigenvalues of the Jacobian matrix derived in (45), the relationship between α_1 and α_2 to provide stable spectrum sharing can be obtained. In particular, the stability

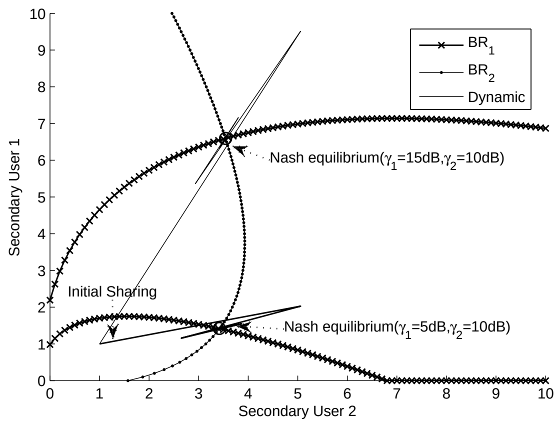

Fig. 3. The best response and trajectories to Nash equilibrium.

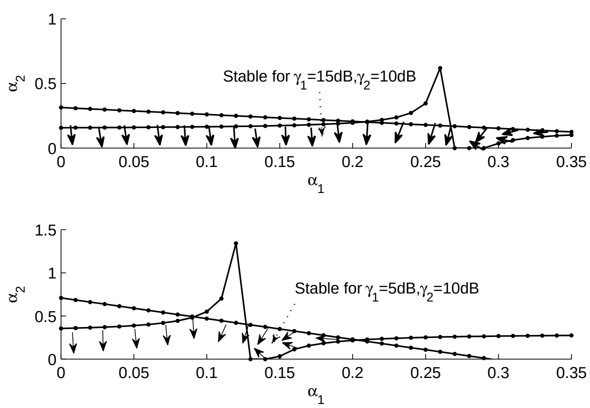

Fig. 4. Region of values for stable Nash equilibrium.

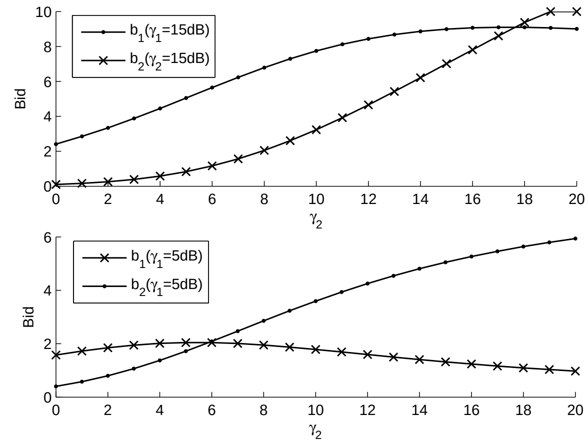

Fig. 5. The Nash equilibrium of bid under different channel qualities.

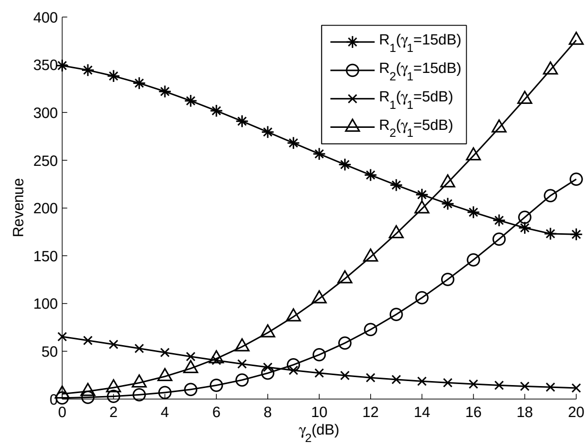

Fig. 6. The Nash equilibrium of revenue under different channel qualities.

regions in (α_1, α_2) plane for different channel qualities are shown in Figure 4. If α_1 and α_2 are set with the values in this region (i.e., region indicated by arrows in Figure 4), the spectrum sharing is stable and the Nash equilibrium would be reached. Otherwise, the sharing would be unstable, and fluctuations would occur.

The adaption of SU's bids under different channel qualities is presented in Figure 5 and then the variation of revenues is presented in Figure 6. As expected, the SU 2 bids more bandwidth and achieves an higher revenue when its channel quality becomes better. Also, we observe that the channel quality of one secondary user affects the bid and the revenues of the other secondary users. We observe that one SU's reaction to the improvement of its opponent's channel quality is divided into two cases. In Figure 5, when SU 2's channel quality becomes better, a) SU 1 would increase its bid as long as it maintains the superiority in channel quality to SU 2; b) otherwise, it decreases its bid. In any case, the revenue of the SU 1 decreases as its opponent's channel quality improves. This reflects the impact of competitiveness among SUs on each SU's strategy (i.e., bid) and also the risks that SU takes in bidding bandwidth.

In Figure 7, it is observed that the revenues of SUs scale linearly with the total bandwidth allocated to the PU. It is obvious that all the SUs can obtain more bandwidth and therefore gain higher revenues when the PU has more bandwidth to share. For comparison between SUs with different weights, we set $\theta_1 = 2, \theta_2 = 1$ in this case. Considering the payment of each SU, we note that the "price discrimination" mechanism can be well implemented. It is seen that the SU with a higher priority gains a higher revenue as expected. Furthermore, marginal revenues (i.e., the slope of the lines) of SUs are proportional to the weights and by our definition it is a fair bandwidth allocation among all SUs.

To extend the problem to a multiple-primary-user case, Let us consider a network with two PUs and two SUs. We still set $\theta_1 = \theta_2 = 1$. For illustration purpose, we use a location-based model here. As shown in Figure 8, the locations of two PUs (P_1 and P_2) and two SUs (S_1 and S_2) are fixed at (0,0), (50,0), (0,100), and (0,−100). In the simulations, the propagation loss factor α is set to four, and the channel gains are distance based (i.e., time-varying fading is not considered here). The transmit power of an SU is $P_i = 0.01$ W, the noise level is $\sigma^2 = 10^{-11}$ W. For the SU i, its SNR γ_i can be calculated from $\gamma_i = P_i d^{-\alpha}/\sigma^2$.

In Figure 9, we show that if two SUs both choose their optimal PU (in this case P_1 is optimal for both the SUs) for the channel in which both of the SUs achieve the best spectral

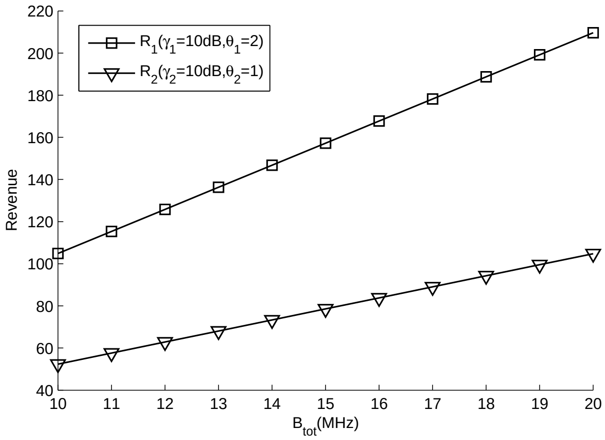

Fig. 7. The Nash equilibrium of revenue for secondary users with different weights.

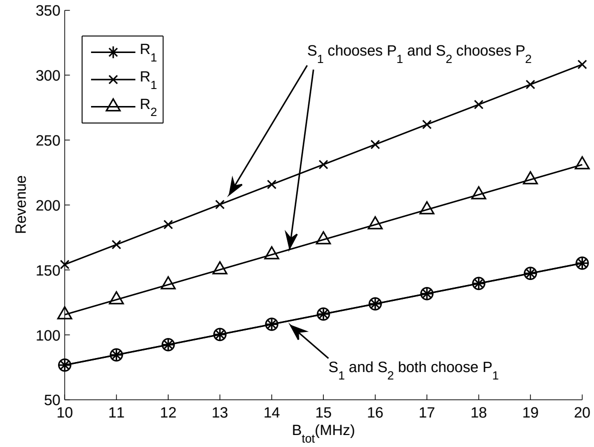

Fig. 9. The Nash equilibrium of revenue in a multiple-primary-user network.

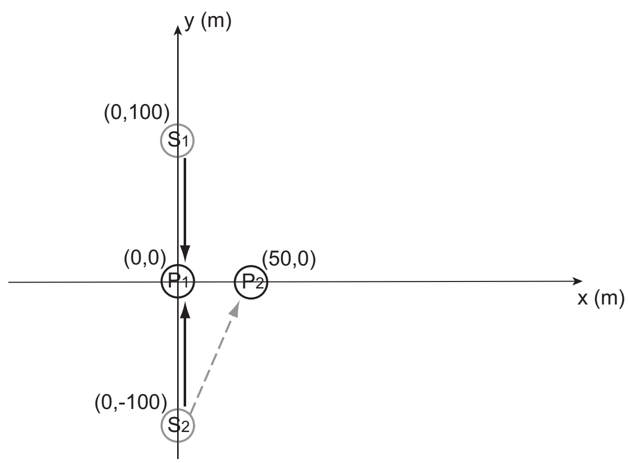

Fig. 8. A cognitive radio network with two primary users and two secondary users.

efficiency in transmission, they compete for the bandwidth possessed by that PU. In this case, P_1 and P_2 achieve the same revenue since they have the same spectral efficiency in transmission using that channel. However, if they can cooperate somehow with each other such that S_2 is willing to choose P_2 which is not optimal and S_1 still chooses P_1. Both of S_1 and S_2 can achieve higher revenues. Based on this observation, we know that an appropriate cooperation mechanism is sometimes beneficial to all competing SUs. And the design of this cooperation mechanism is our future work.

For more information about our works in this area, please refer to the references [28]- [34].

VI. Conclusion

Dynamic spectrum sharing is one of the key functions for CR networks. In this paper, we proposed a competitive spectrum sharing scheme based on the auction theory. For a CR network consisting of one primary user and multiple secondary users sharing the same frequency spectrum, we introduced this auction scheme and investigated the properties of Nash equilibrium in terms of bids, followed by a discussion on fairness among secondary users. We presented a dynamic updating algorithm for secondary users to achieve the Nash equilibrium in a distributed fashion. We analytically investigated the stability of this dynamic updating behavior using local stability theory. We have also shown that a similar analysis is applicable for CR networks with multiple primary users. This spectrum sharing scheme characterizes the inherent properties of a CR system and will be useful for design of CR networks.

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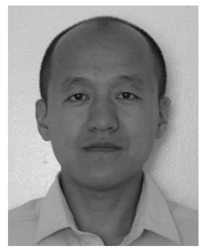

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