Pricing for Past Channel State Information in Multi-Channel Cognitive Radio Networks

Sunjung Kang*, Changhee Joo*, Joohyun Lee†

***Abstract*—Cognitive Radio (CR) networks have received much attention as a solution to the spectrum inefficiency problem of current license-based regulatory management. In CR networks, Secondary User (SU) can use a spectrum vacancy that can be detected by either sensing-before-transmission or database access. However, sensing inaccuracy or long access time to database often becomes a major obstacle to timely detect the spectrum vacancy. In this paper, we develop a hybrid detection framework in multi-channel CR networks, where an SU can selectively sense a channel for spectrum vacancy by accessing the spectrum history of Markovian channels. We focus on the value of the channel history information offered by the Primary Provider (PP) of each channel, and consider a market for the information between multiple PPs and SU. We investigate the interplay between of the PPs and the SU through their pricing and buying decisions for the information, in the presence of sensing inaccuracy, i.e., false alarm and miss detection.**

I. Introduction

In current spectrum management, centralized authorities, e.g., the Federal Communications Commission, regulate the usage of frequency spectrum and license spectrum bandwidth to service providers. It has been observed that this command-and-control spectrum management approach has suffered from very low spectrum utilization in both time and space [1]. As an alternative, cognitive radio (CR) networks have received much attention as a solution to the problem of inefficient spectrum usage [2]. In CR networks, license holders (*Primary Providers* (PPs)) have the right to use their assigned spectrum to serve *Primary Users* (PUs), and unlicensed users[1] (*Secondary Users* (SUs) or *Secondary Providers* (SPs)) can access to unused spectrum with responsibility of managing interference to PUs.

One of the key technologies that enable CR networks is Dynamic Spectrum Access (DSA) that allows SU to identify space-time-frequency vacancies and to opportunistically use the holes, achieving high spectrum efficiency [3]. In large, there have been two classes of schemes to address *uncertainty* of the spectrum availability: *sensing-before-transmission* [4] and *database access* [5]. In the former approach, the network performance highly depends on the rate of sensing errors, i.e., *false alarm* and *miss detection*. Although recent advances in radio technologies have improved the sensing accuracy from many different angles of circuit design, radio signal detection, and collaborative sensing [6], non-negligible sensing errors will still remain in the near future [7]. In the latter approach, the information of the spectrum availability can be accessed directly through database. A weakness of this approach is that it takes time to access (write and read) the database, which is often much longer than the time for scheduling transmissions. Thus, the database access would be suitable for long-term channel statistics or the history of spectrum usage, and it is unlikely to provide SUs immediate availability of the spectrum within a few micro seconds.

Spectrum access controls in cognitive radio networks have been also studied in the perspective of a spectrum market, where the access control can be managed through auction-based [8] or pricing-based mechanisms [9]. In auction-based mechanisms, SUs bid for spectrum as a function of their own desires, and each PP chooses a set of SUs in order to maximize its own revenue. In pricing-based mechanisms, PPs set a price for their spectrum and SUs buy the spectrum on the market.

In this work, we develop the framework of hybrid DSA using both the sensing and the database access in multi-channel CR networks, where the database information assists the decision for sensing. As a first step, we consider a CR network with one SU (or SP) and two PPs, where each PP uses a separate spectrum band. The SU can sense only one of the spectrum bands before transmission due to long sensing delay. When an SU has data to send, it wakes up its communication module and selectively senses one of primary spectrum bands before transmission. If the SU senses the spectrum band as idle and successfully transmits data, it returns to sleep the communication module until it has data again. Many applications of Internet-of-Things such as metering [10] and event detection monitoring [11] fit well with this scenario. We assume that the SU has no history information[2] about the activity of PPs except long-term characteristics of channels (e.g., stationary distribution of the Markov channel model).

To make the PPs to participate in and voluntarily provide their activity information, we introduce a pricing-based mechanism. Each PP with an assigned spectrum band can set the price of its information about its previous activities. For each channel, the SU can buy the information, and use it to figure out the most-likely vacant channel. Thus the gain from the channel information can be distributed to the PPs and the SU through the market.

This work is supported in part by Basic Science Research Program through the National Research Foundation of Korea (NRF), funded by the Ministry of Science, ICT Future Planning (No. NRF-2014R1A1A1A05002557)

* School of ECE, Ulsan National Institute of Science and Technology (e-mails: {sky12382, cjoo}@unist.ac.kr). † Department of ECE, The Ohio State University (e-mail: lee.7119@osu.edu).

[1]An unlicensed user can be either the Secondary Provider (SP) or the Secondary User (SU), depending on the entity that decides transmission. We interchangeably use the terms of SP and SU.

[2]When the transmission of the SU fails, it can learn the activity of the spectrum band and can utilize the information for the access in the next time. In this work, we ignore the impact of the learning, which is beyond the scope of this paper and remains as an interesting open problem.

To the best knowledge of the authors, it is the first work that considers CR networks with both the sensing and the database access, and that investigates the pricing of the information (rather than commodity) in CR networks. Our contribution can be summarized as follows.

- We develop the framework of hybrid DSA schemes with spectrum sensing and database access in multi-channel CR networks.
- Using two-stage sequential game (i.e., Stackelberg game [12]), we investigate the pricing behavior of the PPs for their channel activity information, and the decisions of the SU.
- We clarify the impact of competition and cooperation between the PPs on the performance (i.e., the revenue of the PPs, the payoff of the SU, and the social welfare).

The rest of paper is organized as follows: In Section II, we describe the network model and two-stage game model. We investigate the behavior of the SU to maximize its reward in Section III. Then we study the responses of the PPs under competition and cooperation, and show how the prices can be determined in Section IV. In Section V, we verify our results through simulations. Finally, we conclude the paper in Section VI.

II. System Model

We consider a cognitive radio network with two primary providers (PPs) and a secondary user (SU). There are two non-interfering frequency channels (or spectrum bands), each of which is assigned to one of the PPs, and can be used opportunistically by SU when idle. The channels need not be adjacent and it may take substantial time for the SU to switch the operating channel. We assume a time-slotted system, where the SU can sense/use one of the two frequency channels in a time slot, due to delay of switching the channel [13].

We denote the two channels by channel A and channel B. For each channel $i \in \{A, B\}$, let PP i denote the primary provider that the channel is assigned to, and let $d^i(t)$ denote the state of channel i (or the activity of PP i) at time slot t. Channel i is either *busy* ($d^i(t) = 1$) if the channel is in use at time slot t by PP i, or *idle* ($d^i(t) = 0$), otherwise. We interchangeably use the state of channel i and the activity of PP i throughout the paper. We assume that the state of channel i is independent from the other, and changes across time following an independent Markov process with transition probability matrix $P^i = \{p^i_{jk}\}$, where $p^i_{jk} := \text{Prob}\{d^i(t) = k \mid d^i(t-1) = j\}$. Clearly, we have $p^i_{00} + p^i_{01} = 1$ and $p^i_{10} + p^i_{11} = 1$. We assume that the transition matrices (i.e., P^A and P^B) are known to all the PPs and the SU. Let π^i_j denote the steady-state probability distribution of channel i in state j. From the balance equations, it can be easily obtained as $\vec{\pi}^i = (\pi^i_0, \pi^i_1)$ where $\pi^i_0 = \frac{p^i_{10}}{p^i_{10}+p^i_{01}}$, and $\pi^i_1 = \frac{p^i_{01}}{p^i_{10}+p^i_{01}}$. Although our result has been developed under the binary channel state model, it can be extended to more fine-grained channel model with multiple states with different transmission rates.

When the SU has data to send, the SU chooses one of the channels, senses the channel, and uses the channel if it senses the channel as idle. Let $x^i(t) \in \{0, 1\}$ be the sensing decision of the SU: $x^i(t) = 1$ if the SU decides to sense channel i, and $x^i(t) = 0$, otherwise. We assume that the SU can sense only one channel at a time slot, i.e., $x^A(t) + x^B(t) \leq 1$. Suppose that the SU senses channel i at time slot t. The sensing result is denoted by $\tilde{d}^i(t) \in \{0, 1\}$: $\tilde{d}^i(t) = 0$ if the SU senses channel i as idle, in which case the SU transmits data on channel i during time slot t, $\tilde{d}^i(t) = 1$ if the SU senses channel i as busy, in which case the SU remains silent on channel i. There is possibility that the SU senses busy but the channel is indeed idle, in which case the time slot is wasted. This is called as *false alarm*, and we denote the false alarm probability by $p^i_f := \text{Prob}\{\tilde{d}^i = 1 \mid d^i = 0\}$. Similarly, it is possible that the SU senses idle but the channel is indeed busy. In this case, a collision occurs and both transmission from the PP and the SU fail. This is called as *miss detection*, and we denote the miss detection probability by $p^i_m := \text{Prob}\{\tilde{d}^i = 0 \mid d^i = 1\}$. Further, we assume no channel error, i.e., a packet transmission is successful if there is no collision. The SU who transmits on channel i receives reward $r^i > 0$ for its successful transmission, and pays penalty $a^i > 0$ (to the PP) for a collision caused by miss detection. The reward and penalty are inclusive of the payment from the users, the fee of using the channels, the cost of collision, etc. Algorithm 1 (line 4-8) shows the decisions of the SU for sensing and transmitting data.

Algorithm 1 Operation of the SU.

1: Collect the price of information α^A and α^B
2: Calculate payoffs U_{ij} for each $(i, j) \in \{0, 1\}^2$
3: Find $\left(w^A, w^B\right) = \arg\max_{(i,j)\in\{0,1\}^2} U_{ij}$
4: Find $\left(x^A, x^B\right)$ as in (5)
5: Sense channel i if $x^i = 1$, store the sensing result in $\tilde{d}^i$
6: **if** senses idle channel, i.e., $\tilde{d}^i = 0$ **then**
7:     Make a transmission on channel i
8: **end if**
9: Earn reward r^i or pay penalty a^i depending on the result of the transmission

We now consider a market for the channel information, where the PPs try to sell their information to the SU. At the beginning of given time slot t, the SU has the statistical information of both the channels but has no knowledge about the actual channel states $d^i(k)$ for all $k \leq t-1$. In contrast, PU i has the history of its activity, i.e., channel states $d^i(k)$ for $k \leq t-1$.

At the beginning of time slot t, PPs send their current activity information to a common storage (or database) via a control channel which, we assume, takes less than a half time slot. The SU makes the buying decision for the information. In other words, in the middle of the time slot t, the SU decides whether it buys the information or not. If it decides to buy, it should be able to retrieve the information within the second half of time slot t, such that the SU can make use of the information to determine the channel to sense at time slot $t+1$. Note that considering the Markovian property of the channel, the channel state information at t is sufficient for the SU to make the best prediction on the channel state at $t+1$. Thus,

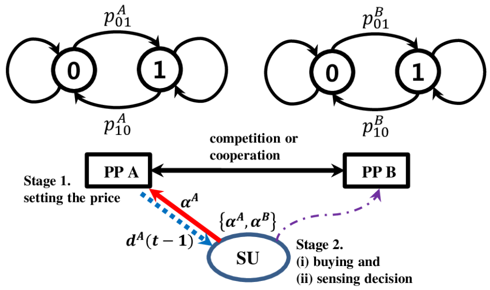


Fig. 1: Channel and game models. PP i sets price α^i for the channel information $d^i(t-1)$. The SU decides to buy the information, and then, selects the channel to sense. Depending on the sensing result, the SU transmits on the channel that it sensed.

we assume that each half time slot, which is supposed to be tens of milli seconds, for storing or retrieving the information is sufficiently large for accessing through the control channel: for example, a careful time coordination can let the PP store its information through a short signal tone, and radio-tuning time for channel switching can be also minimized by exploring new radio techniques, e.g., OFDM subcarrier nulling [14].

Since the channel information is beneficial to the SU, the PPs may sell the information to the SU at a reasonable price. we model the behaviors of the PPs and the SU as a two-stage sequential game with known strategy, i.e., a Stackelberg game [12]. At the first stage of the game, PP i decides on price α^i for its state information as a *leader*, and at the second stage, the SU as a *follower* determines (i) whether it buys the information, and (ii) which channel to sense. Fig. 1 illustrates the interactions. for example, PP i determines price α^i (independently or in a cooperative manner) in the stage 1. Then, in stage 2(i) the SU decides to buy the information of each channel i, and in stage 2(ii), decides which channel it senses. In Fig. 1, the SU bought the information $d^A(t-1)$ of channel A at price α^A, and sensed channel B. Let $w^i(t)$ denote the buying decision of the SU: $w^i(t) = 1$ if the SU decides to buy the information of channel i, and $w^i(t) = 0$ otherwise.

Under our model, we assume that the strategy of the SU is known a priori, and the PPs will choose the prices that maximize their revenue. To elaborate, given the buying decision $(w^A, w^B) \in \{0,1\}^2$, the expected payoff of the SU is known as

$$U_{w^A w^B} = V_{w^A w^B} - w^A\alpha^A - w^B\alpha^B, \tag{1}$$

where $V_{w^A w^B}$ denotes the expected reward of the SU provided the buying decision (w^A, w^B).

In this work, we investigate the interplay between the optimal decisions of the SU and the pricing of the PPs. We first study the decisions of the SU and then focus on the pricing of the PPs under two different scenarios of competition and cooperation.

III. Optimal decisions of Secondary User

At the beginning of time slot t, when the SU has data to send, it would sense the channel with the highest expected reward if it can sense only one channel. Since the state of channel i follows the on-off Markov model (i.e., Gilbert-Elliott channel), the SU can make more precise estimation on the expected reward for channel i with the channel state information at $t-1$. In this section, we formulate the reward estimation of the SU, and investigate the value of the channel information by comparing the performance of the SU with and without the information. We omit subscript if there is no confusion.

(1) Expected reward of the SU without previous channel state information: We first consider when the previous channel state information ($\{d^i(t-1)\}$) is not available, i.e., when $w^A = w^B = 0$. Since no channel state information is available, the SU will make its sensing decision based on long-term characteristics of the channels. Given the steady-state probability π_j^i that channel i is in state $j \in \{0(idle), 1(busy)\}$, we define the gain G^i of sensing channel i as

$$G^i = \pi_0^i(1-p_f^i)r^i - \pi_1^i p_m^i a^i,$$

where p_f^i and p_m^i denote the false alarm probability and miss detection probability of channel i, respectively, and r^i and a^i denote the reward upon a successful transmission and the penalty upon a collision for transmitting on channel i, respectively. The first term is the expected reward when the channel is idle and the SU's sensing is correct (i.e., no false alarm), and the second term is the expected penalty when the channel is busy and the sensing result is wrong (i.e., miss detection).

Since the SU makes a sensing decision by comparing G^A and G^B, the expected reward of the SU can be written as

$$V_{00} = \max\{G^A, G^B, 0\}. \tag{2}$$

From (1), we can obtain the payoff of the SU as $U_{00} = V_{00}$.

(2) Expected reward of the SU with previous channel state information: We next consider the case that the SU makes the buying decision $(w^A, w^B) = (1,1)$ and obtains the channel state information of both the channels, i.e., $d^A(t-1)$ and $d^B(t-1)$. Letting $\gamma_i = d^i(t-1)$ and from the channel state transition matrix P^i, the SU can estimate the expected channel gain $G_{\gamma_i}^i$ at time slot t given the previous channel state γ_i as

$$G_{\gamma_i}^i = p_{\gamma_i 0}^i(1-p_f^i)r^i - p_{\gamma_i 1}^i p_m^i a^i,$$

where $p_{\gamma_i 0}^i$ and $p_{\gamma_i 1}^i$ denote the transition probability from γ_i to 0 (idle) and to 1 (busy), respectively. The SU will make the sensing decision by comparing $G_{\gamma_A}^A$ and $G_{\gamma_B}^B$.

At a given time slot t, the channel state at time $t-1$ is one of the four cases, i.e., $\big(d^A(t-1), d^B(t-1)\big) \in \{(0,0),(0,1),(1,0),(1,1)\}$. Since the channels are independent, we can obtain the expected reward as

$$V_{11} = \sum_{\gamma_A=0}^{1}\sum_{\gamma_B=0}^{1}\pi_{\gamma_A}^A\pi_{\gamma_B}^B \max\{G_{\gamma_A}^A, G_{\gamma_B}^B, 0\},$$

where $\pi_{\gamma_A}^A\pi_{\gamma_B}^B$ denotes the probability of state (γ_A, γ_B) at time slot $t-1$. From (1), the payoff of the SU will be $U_{11} = V_{11} - \alpha^A - \alpha^B$.

Similarly, when the SU has the previous state information of only one channel, the expected reward and the payoff of the SU can be calculated as follows:

- When $\gamma_A = d^A(t-1)$ is known with $(w^A, w^B) = (1, 0)$, $V_{10} = \sum_{\gamma_A=0}^{1} \pi^A_{\gamma_A} \max\{G^A_{\gamma_A}, G^B, 0\},\ U_{10} = V_{10} - \alpha^A$.
- When $\gamma_B = d^B(t-1)$ is known with $(w^A, w^B) = (0, 1)$, $V_{01} = \sum_{\gamma_B=0}^{1} \pi^B_{\gamma_B} \max\{G^A, G^B_{\gamma_B}, 0\},\ U_{01} = V_{01} - \alpha^B$. (3)

We expect that the reward will be higher with the channel information. The following proposition shows non-negative property of the reward with additional information.

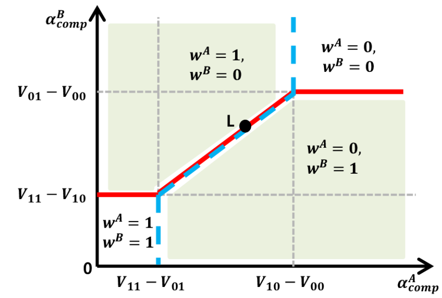
Proposition 3.1 (Non-negative gain of information): The expected gains satisfy (i) $V_{00} \leq V_{10} \leq V_{11}$, and (ii) $V_{00} \leq V_{01} \leq V_{11}$.

We refer [15] for the proof. We now can specify the buying decision of the SU that maximizes its payoffs as

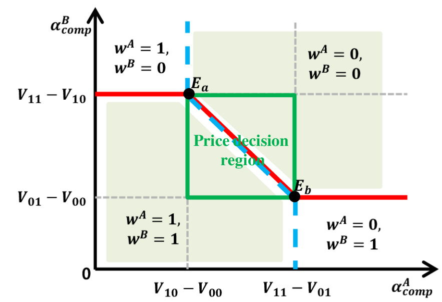
$$\big(w^A(t), w^B(t)\big) = \arg\max_{(j,k)\in\{0,1\}^2} U_{jk}, \quad (4)$$

where $U_{ij} = V_{ij} - w^i \cdot \alpha^A - w^j \cdot \alpha^B$. With the buying decision w^i of channel i, the expected gain $(1 - w^i) \cdot G^i + w^i \cdot G^i_{\gamma_i}$ will change according to the previous channel state γ_i. The SU will sense the channel with the highest expected gain, i.e.,

$$\begin{aligned} &\big(x^A(t), x^B(t)\big) \\ &= \arg\max_{\{(0,1),(1,0),(0,0)\}} \{x^A \cdot [(1 - w^A) \cdot G^A + w^A \cdot G^A_{\gamma_A}] \quad (5) \\ &\qquad + x^B \cdot [(1 - w^B) \cdot G^B + w^B \cdot G^B_{\gamma_B}]\}. \end{aligned}$$



(a) When the single-info gain of the SU is greater than the marginal-info, i.e., when $V_{10} - V_{00} \geq V_{11} - V_{01}$.



(b) When the marginal-info gain of the SU is greater than the single-info gain, i.e., when $V_{11} - V_{01} > V_{10} - V_{00}$.

Fig. 2: Pricing of the PPs and the corresponding buying decisions of the SU.

IV. Pricing Game of Primary Providers

Based on the optimal decisions of the SU in Section III, we consider the behaviors of the PPs. In our model, we assume that the gain of the PPs from leasing the channel is constant (e.g., flat fee) and the loss from collision is perfectly compensated by the penalty of the SU. The PPs can earn additional revenue by selling their channel state information, and thus they will try to maximize their revenue by setting the price to the highest value as long as the SU buys the information. We assume that the price is non-negative, and investigate the pricing of the PPs in two different scenarios of competition and cooperation between the PPs.

A. Competitive scenario

In a competitive scenario, the two PPs do not share their price information with other, while the SU knows both the prices. As a result, each PP will lower its price to attract the buying decision of the SU. We show that there are Nash equilibria where both the PPs do not change their prices.

Let α^i_{comp} be the price of previous channel state information of PP i in the competitive scenario. Once α^A_{comp} and α^B_{comp} are decided, the SU will make the buying decision as specified in (4). For example, if $\arg\max U_{jk} = (1, 0)$, the SU will buy only the previous state information of channel A. In the following lemma, we consider the price setting of PP A assuming that the price of PP B is known to PP A, and vice versa. This will be used later to estimate the pricing behavior of the other PP. Recall that V_{jk} is the expected reward of the SU with and without the previous state information of the two channels. For channel A, we denote $V_{10} - V_{00}$ by *single-info* gain, and $V_{11} - V_{01}$ by *marginal-info* gain. Similarly, for channel B, we denote $V_{01} - V_{00}$ and $V_{11} - V_{10}$ by single-info gain and by marginal-info gain, respectively.

Lemma 4.1: Under the competition, the price of one PP can be written as a function of the price of the other PP. For example, if PP A knows α^B_{comp} (fixed), the price α^A_{comp} of PP A can be shown as in Fig. 3(a). Similarly, if PP B knows α^A_{comp} (fixed), the price α^B_{comp} of PP B can be shown as in Fig. 3(b).

For the proof, we refer to [15]. Fig. 2 shows the pricing of PP i given the other PP's price and the corresponding buying decision of the SU. The buying decision of the SU is classified into four different regions according to PPs' prices. In Fig. 2(a), the dashed line represents PP A's price $\alpha^A_{\text{comp}}(\alpha^B_{\text{comp}})$ when PP B's price α^B_{comp} is fixed and known, and the solid line represents PP B's price $\alpha^B_{\text{comp}}(\alpha^A_{\text{comp}})$ when PP A's price α^A_{comp} is fixed and known. Let us consider a price point $(\alpha^A_{\text{comp}}, \alpha^B_{\text{comp}})$ where the two lines overlap (e.g., Point L in Fig. 2(a)). At this point, if PP A slightly decreases its price and PP B keeps α^B_{comp} (i.e., if the point moves to the left), then the SU will buy the information of PP A only. Similarly, if PP B slightly decreases its price and PP A keeps α^A_{comp} (i.e., if the point moves to the bottom), then the SU will buy the information of PP B only. Since each PP does not know the price of the other, they will lower the price to sell their information to the SU. We claim that there are the price points where the PPs no longer change their prices, i.e., Nash equilibrium points, in the following proposition. We first define $\alpha^A_m = V_{11} - V_{01}$,

(i) If the single-info gain of the SU is greater than the marginal-info gain, i.e., if $V_{10} - V_{00} \geq V_{11} - V_{01}$, then

$$\alpha_{\text{comp}}^{A}\left(\alpha_{\text{comp}}^{B}\right) = \begin{cases} V_{11} - V_{01} & \text{if } \alpha_{\text{comp}}^{B} \in [0, V_{11} - V_{10}) \\ \alpha_{\text{comp}}^{B} + V_{10} - V_{01} & \text{if } \alpha_{\text{comp}}^{B} \in [V_{11} - V_{10}, V_{01} - V_{00}] \\ V_{10} - V_{00} & \text{if } \alpha_{\text{comp}}^{B} \in (V_{01} - V_{00}, \infty) . \end{cases} \tag{6}$$

(ii) If the marginal-info gain of the SU is greater than the single-info gain, i.e., if $V_{10} - V_{00} \leq V_{11} - V_{01}$, then

$$\alpha_{\text{comp}}^{A}\left(\alpha_{\text{comp}}^{B}\right) = \begin{cases} V_{11} - V_{10} & \text{if } \alpha_{\text{comp}}^{B} \in [0, V_{10} - V_{00}) \\ -\alpha_{\text{comp}}^{B} + V_{11} - V_{00} & \text{if } \alpha_{\text{comp}}^{B} \in [V_{10} - V_{00}, V_{11} - V_{01}] \\ V_{01} - V_{00} & \text{if } \ (V_{11} - V_{01}, \infty) . \end{cases} \tag{7}$$

(a) The price α_{comp}^{A} of PP A as a function of α_{comp}^{B}.

(i) If the single-info gain of the SU is greater than the marginal-info gain, i.e., if $V_{01} - V_{00} \geq V_{11} - V_{10}$, then

$$\alpha_{\text{comp}}^{B}\left(\alpha_{\text{comp}}^{A}\right) = \begin{cases} V_{11} - V_{10} & \text{if } \alpha_{\text{comp}}^{A} \in [0, V_{11} - V_{01}) \\ \alpha_{\text{comp}}^{A} + V_{01} - V_{10} & \text{if } \alpha_{\text{comp}}^{A} \in [V_{11} - V_{01}, V_{10} - V_{00}] \\ V_{01} - V_{00} & \text{if } \alpha_{\text{comp}}^{A} \in (V_{10} - V_{00}, \infty) . \end{cases} \tag{8}$$

(ii) If the marginal-info gain of the SU is greater than the single-info gain, i.e., if $V_{01} - V_{00} \leq V_{11} - V_{10}$, then

$$\alpha_{\text{comp}}^{B}\left(\alpha_{\text{comp}}^{A}\right) = \begin{cases} V_{11} - V_{01} & \text{if } \alpha_{\text{comp}}^{A} \in [0, V_{01} - V_{00}) \\ -\alpha_{\text{comp}}^{A} + V_{11} - V_{00} & \text{if } \alpha_{\text{comp}}^{A} \in [V_{01} - V_{00}, V_{11} - V_{10}] \\ V_{10} - V_{00} & \text{if } \ (V_{11} - V_{10}, \infty) . \end{cases} \tag{9}$$

(b) The price α_{comp}^{B} of PP B as a function of α_{comp}^{A}.

Fig. 3: Price of PP i when the fixed price of the other PP is known.

$\alpha_s^A = V_{10} - V_{00}$, $\alpha_m^B = V_{11} - V_{10}$, and $\alpha_s^B = V_{01} - V_{00}$.

Proposition 4.1 (Nash equilibrium): Under competition, the Nash equilibria of channel state information prices are as follows:

(i) If $V_{10} - V_{00} \geq V_{11} - V_{01}$, then $(\alpha_{\text{comp}}^{A}, \alpha_{\text{comp}}^{B}) = (V_{11} - V_{01}, V_{11} - V_{10})$.

(ii) If $V_{10} - V_{00} \leq V_{11} - V_{01}$, then $(\alpha_{\text{comp}}^{A}, \alpha_{\text{comp}}^{B}) = \{(\alpha^A, \alpha^B) \mid \alpha^A + \alpha^B = V_{11} - V_{00}\}$.

We refer to [15] for the proof. As shown in Proposition 4.1, if $V_{11} - V_{01} \geq V_{10} - V_{00}$, multiple Nash equilibria exist. Since our problem is a one-shot game, it is difficult for one PP to decide its price without knowledge about the price of the other PP. Since each PP i sets its price between α_s^i and α_m^i, the prices will be some point within the green square box shown in Fig. 2(b). It is not very clear exactly what point the prices will be. To avoid such uncertainty, we assume that the PPs behave conservatively, i.e., they prefer a smaller guaranteed profit than a large uncertain profit. Under the assumption, the PPs want to secure its revenue regardless of the other's price, and then their prices will be settled down at $(V_{10} - V_{00}, V_{01} - V_{00})$, since below which each PP can sell its information. The price point is not a Nash equilibrium and the players will change their behavior if they know the other's a priori price. Also, at the price, the PPs will have no greater revenue than any those at Nash equilibrium points.

B. Cooperative scenario

In a cooperative scenario, the two PPs share their information and cooperate with each other as long as they achieve a higher individual revenue than their revenues under competition. In this case, it is necessary to predetermine how to share the total revenue between the PPs. In this work, we use the Shapley value [12] due to its desirable properties of efficiency, symmetry, linearity, etc. The Shapley value solves the distribution problem of the total surplus revenue produced under cooperation. Specifically, the total revenue is distributed among the users participating on cooperation depending on the level of contribution to the cooperation. Let ϕ^i denote the revenue of PP i when they cooperate. Let $N = \{A, B\}$, and let $\Pi^A = \{\{A, B\}, \{A\}\}$ and $\Pi^B = \{\{A, B\}, \{B\}\}$ be the set of all cooperation combinations containing, A and B, respectively. Further, let $v(S)$ be the revenue that can be earned by cooperation combination S. In the following paragraphs, we calculate the revenues of the PPs by the Shapley value in two distinct cases.

(1) When the single-info gain is greater than the marginal-info gain (when $V_{10} - V_{00} \geq V_{11} - V_{01}$):

We can obtain $v(\{A\}) = V_{11} - V_{01}$, $v(\{B\}) = V_{11} - V_{10}$, and $v(\{A, B\}) = \max\{2V_{11} - V_{10} - V_{01}, V_{10} - V_{00}, V_{01} - V_{00}\}$. It can be shown that $v(\{A, B\})$ is the maximum sum of revenues that the PPs can earn under cooperation. Note that under competition, the total revenue of the PPs at Nash equilibrium points is $2V_{11} - V_{10} - V_{01}$ with the buying decision of $(w^A, w^B) = (1, 1)$, $V_{10} - V_{00}$ with the buying decision of $(w^A, w^B) = (1, 0)$, or $V_{01} - V_{00}$ with $(w^A, w^B) = (0, 1)$. Under cooperation, the PPs will maximize their total revenue by selecting the prices such that $\max\{2V_{11} - V_{10} - V_{01}, V_{10} - V_{00}, V_{01} - V_{00}\}$. Hence, letting $\theta = \max\{2V_{11} - V_{10} - V_{01}, V_{10} - V_{00}, V_{01} - V_{00}\}$, we can obtain the Shapley value of PP A as $\phi^A = \sum_{S\in\Pi^A} [v(S) - v(S-A)] \frac{(|S|-1)!(|N|-|S|)!}{|N|!} = \frac{\theta+V_{10}-V_{01}}{2}$. The first line is from the definition of Shapley value. Similarly, we can calculate the Shapley value ϕ^B of PP B as $\phi^B = \frac{\theta+V_{01}-V_{10}}{2}$.

(2) When the marginal-info gain is greater than the single-info gain (when $V_{11} - V_{01} \geq V_{10} - V_{00}$):

Now, under the conservative-behavior assumption of the PPs, we have $v(\{A\}) = V_{10} - V_{00}$, $v(\{B\}) = V_{01} - V_{00}$, and $v(\{A, B\}) = V_{11} - V_{00}$, where $v(\{A, B\})$ is a point on the tilted line (E_a, E_b) in Fig. 2(b). Clearly, $v(\{A, B\})$ is the largest revenue that the PPs can achieve. Then the Shapley values can be calculated as

$$\phi^A = \frac{V_{11}+V_{10}-V_{01}-V_{00}}{2},\ \phi^B = \frac{V_{11}+V_{01}-V_{10}-V_{00}}{2}.$$

Interestingly, although the PPs achieve a larger revenue by cooperating with each other, the social welfare of the system, defined as the sum of all the revenues and the payoff of the SU, may decrease as described in Proposition 4.2.

Proposition 4.2 (Non-increasing social welfare): The social welfare under cooperation is no greater than the social welfare under (conservative) competition.

We refer to [15] for the proof. Proposition 4.2 implies that cooperation between the PPs may decrease the social welfare by excessively reducing the payoff of the SU. In order to prevent substantial loss of the social welfare, it may need an authority (e.g., government) to regulate cooperation between the PPs.

V. SIMULATION RESULTS

We have shown that the previous state information of the channels is valuable to the SU, and studied the buying and the sensing decision of the SU and the pricing decision of the PPs under competition and under cooperation. In this section, we simulate the behaviors of the PPs and the SU, and observe their performance: the revenues of the PPs, the payoff of the SU, and the social welfare. We assume that the PPs behave conservatively, and under an equal payoff, the SU makes a choice that maximizes the social welfare. For example, if $U_{11} = U_{10}$, the SU decides $(w^A, w^B) = (1, 1)$ since $V_{11} \geq V_{10}$.

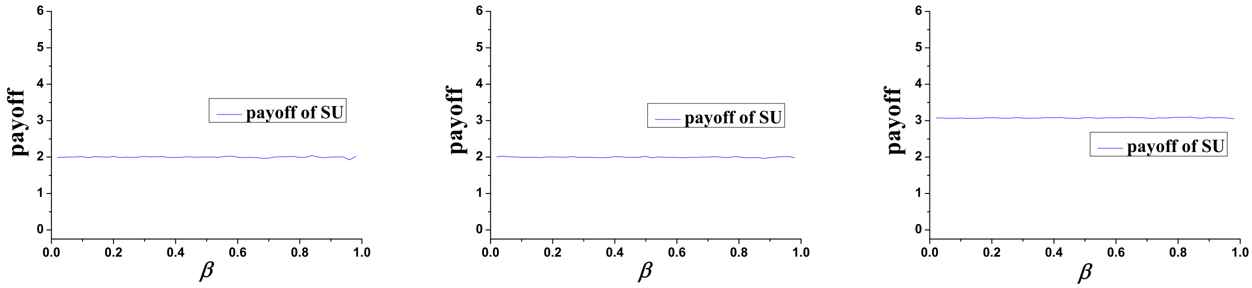
We consider a Markov chain channel model as shown in Fig. 1. We consider a special case that the channel behavior of PP A is symmetric, i.e., $p^A_{01} = p^A_{10} = \beta$, for ease of exposition. Changing β, we measure the revenues of the PPs, the payoff of the SU, and the social welfare in different scenarios: i) when the channel information is not provided, ii) when the PPs compete with each other, and iii) when the PPs cooperate with each other. We fix all the probabilities of the miss detection and the false alarm to 0.1 (i.e., $p^A_f = p^B_f = p^A_m = p^B_m = 0.1$), unless otherwise specified. The reward per a successful transmission and the penalty per a collision are set to 10 and 50, respectively (i.e., $r^A = r^B = 10$ and $a^A = a^B = 50$). We first evaluate the accuracy of our analysis through simulations, by measuring the revenues of the PPs, the payoff of the SU, and the social welfare. The results show that they are the same except some fluctuations in the simulation results caused by the randomness of the channel states and the sensing uncertainty. We omit these results due to the limited space.

(1) Payoff when the channel information is not provided: We observe the performance of the PPs and the SU when the channel information is not provided. We consider three different types of channel B: Case 1) $(p^B_{01}, p^B_{10}) = (0.5, 0.5)$ for the case when the previous state information (of channel B) is not helpful to predict the current channel state (of channel B), Case 2) $(p^B_{01}, p^B_{10}) = (0.85, 0.85)$, for the case when the previous state information (of channel B) is very helpful to predict the current channel state (of channel B), and Case 3) $(p^B_{01}, p^B_{10}) = (0.55, 0.75)$, for a more general case with asymmetric transition probability. Fig. 4 shows the payoff of the SU, and the social welfare (the sum of the revenues of the PPs and the payoff of the SU). Since the PPs do not provide the channel information, they achieve zero revenue and the social welfare is the same as the payoff of the SU.

(2) Revenue, payoff, welfare under competition: With the channel information, the SU will better predict the channel state, which in turn increases the social welfare as well as the PP's revenue when the SU buys any channel information. We run simulation to see the behavior of the PPs and the SU in two scenarios of competition and cooperation between the PPs. Fig. 5 demonstrates the results under the competition. Comparing Fig. 4 with Fig. 5, the payoff of the SU increases, and the PPs earn non-zero revenues by selling their information, and thus the social welfare also increases. Note that when $(p^B_{01}, p^B_{10}) = (0.5, 0.5)$, the channel information of PP B is not helpful because the current channel state is independent from the previous channel state, and thus the revenue of PP B remains zero (because the SU will not buy the information). In particularly, when $\beta = 0.5$, all the channel information is not beneficial and the social welfare is equal to the value achieved without channel information.

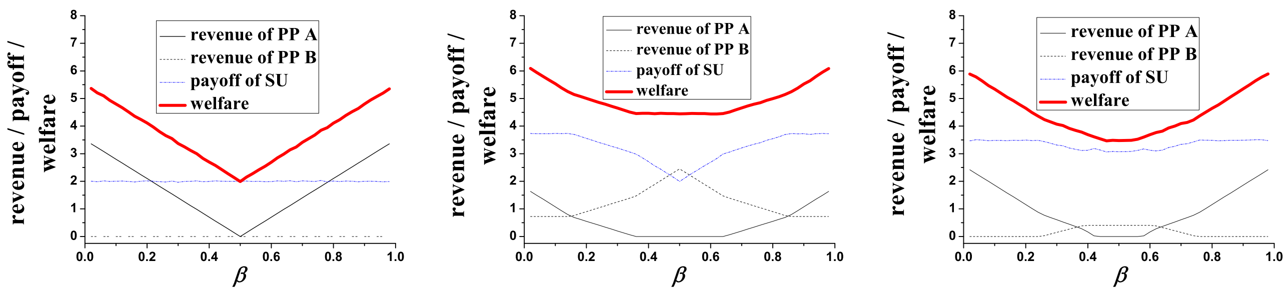
(3) Revenue, payoff, welfare under cooperation: When the PPs cooperate with each other, it is expected that the revenues of the PPs increase. Fig. 6 shows such results. In all the cases, the revenues of each PP are higher than those under competition, which also confirms that the Shapley value provides a fair distribution of the obtained gain to the PPs. However, the cooperation does not always lead to an increase of the social welfare. To elaborate, the social welfares are smaller than the values under competition for Case 2 when $\beta \in [0, 0.34]$ in Fig. 6(b), and for Case 3 when $\beta \in [0.22, 0.32]$ in Fig. 6(c). This is because, when $V_{10} > V_{11} - \alpha^B$ (or when $V_{01} > V_{11} - \alpha^A$), the pricing of the PPs under competition leads to social welfare V_{11}, and the pricing under cooperation leads to social welfare V_{10}.

We now provide direct comparison of different pricings: no pricing (no channel information), pricing of channel information under competition, and pricing of channel information under cooperation. Fig. 7 demonstrates the performance when $(p^B_{01}, p^B_{10}) = (0.85, 0.85)$. It shows that *the channel information improves the payoff of the SU.* Further, it shows that the cooperation increases the revenues of the PPs, but decreases the payoff of the SU and the social welfare as we showed in



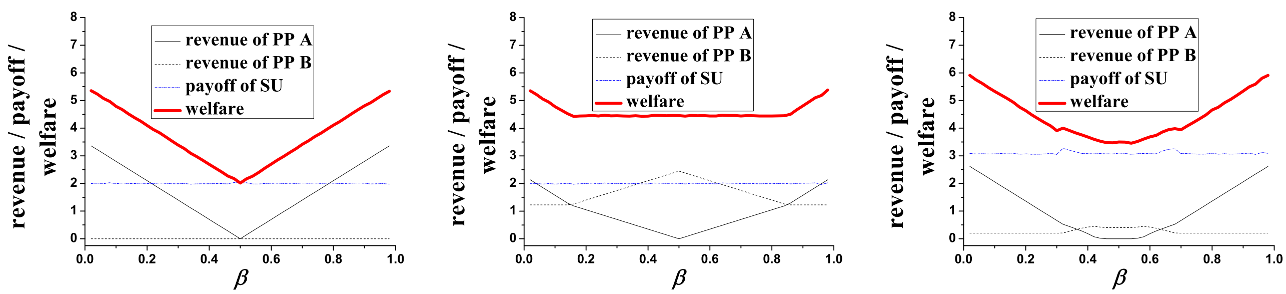
(a) When $(p_{01}^B, p_{10}^B) = (0.5, 0.5)$ (b) When $(p_{01}^B, p_{10}^B) = (0.85, 0.85)$ (c) When $(p_{01}^B, p_{10}^B) = (0.55, 0.75)$

Fig. 4: SU's payoff when β varies with no information.



(a) When $(p_{01}^B, p_{10}^B) = (0.5, 0.5)$ (b) When $(p_{01}^B, p_{10}^B) = (0.85, 0.85)$ (c) When $(p_{01}^B, p_{10}^B) = (0.55, 0.75)$

Fig. 5: PPs' revenues, SU's payoff, and social welfare when β varies under competition.



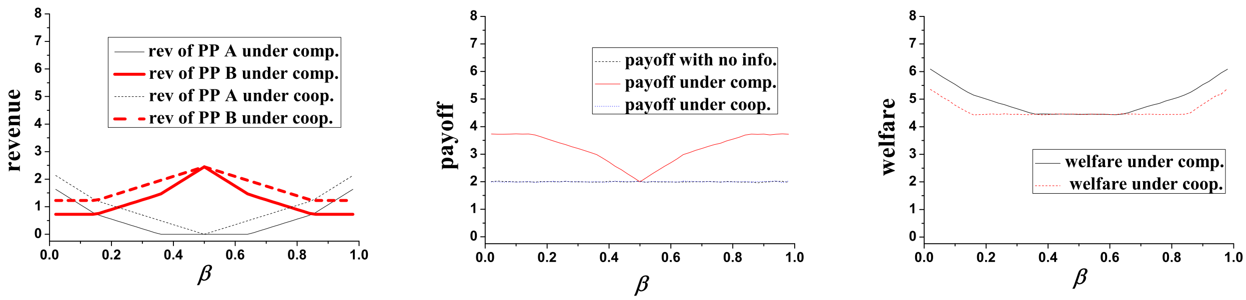
(a) When $(p_{01}^B, p_{10}^B) = (0.5, 0.5)$ (b) When $(p_{01}^B, p_{10}^B) = (0.85, 0.85)$ (c) When $(p_{01}^B, p_{10}^B) = (0.55, 0.75)$

Fig. 6: PPs' revenues, SU's payoff, and social welfare when β varies under cooperation.

Proposition 4.2.

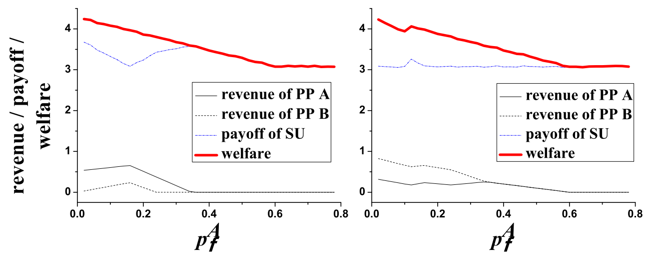
(4) The impact of the false alarm probability: We examine the performance changes with different levels of sensing uncertainty. Changing the probability of false alarm for channel A, we measure the revenues, the payoff, and the social welfare. The other probabilities of miss detection for both channels and false alarm for channel B are fixed as before. Fig. 8 shows the results when $(p_{01}^A, p_{10}^A) = (0.7, 0.7)$ and $(p_{01}^B, p_{10}^B) = (0.55, 0.75)$. Overall, the social welfare decreases as the false alarm probability increases in both cases of competition and cooperation. It is because the SU misses more opportunities with a higher probability of false alarm. On the other hand, the revenues of the PPs does not decrease monotonically, and there is a small interval that they increase. For example, under competition, the revenue of the PP increases until $p_f^A = 0.16$. In the interval of $p_f^A \in [0, 0.16]$, it turns out that the single-info gain is greater than the marginal-info gain, and thus the PPs have the price that is equal to their marginal-info gain from (i) of Proposition 4.1. In the interval, as the probability of false alarm increases, the gain of buying one-channel information decreases faster than the gain of buying two-channel information, which results in the increase of the marginal-info gains ($V_{11} - V_{10}$ and $V_{11} - V_{01}$). Hence, the revenues of the PPs increase in the interval. For $p_f^A > 0.16$, the marginal-info gain is greater than the single-info gain, and the prices are set to the single-info gain under the conservative-behavior assumption. Since the single-info gain monotonically decreases as the false-alarm probability increases, the prices (i.e., the revenues of the PPs) also decrease.

Under cooperation, the revenues of the PPs also increase in the interval of $p_f^A \in [0.12, 0.16]$, which can be explained similarly as in the competition case: (i) when $p_f^A \in [0, 0.12)$, the single-info gain is greater than the marginal-info gain and $V_{10} - V_{00} \geq 2V_{11} - V_{10} - V_{01}$. Thus, the total revenue of the PPs is $\theta = V_{10} - V_{00}$, which decreases as the false-alarm probability increases. (ii) when $p_f^A \in [0.12, 0.16)$, the



(a) Revenues of the PPs (b) Payoff of the SU (c) Social welfare

Fig. 7: Revenues of the PPs, payoff of the SU, and the social welfare under differenet pricing scenarios



(a) Competitive scenario. (b) Cooperative scenario.

Fig. 8: Revenues of the PPs, payoff of the SU, and the social welfare when changing the false-alarm probability of PP A.

single-info gain is greater than the marginal-info gain and $V_{10} - V_{00} \leq 2V_{11} - V_{10} - V_{01}$. Thus, the total revenue of the PPs is $\theta = 2V_{11} - V_{10} - V_{01}$, which increases with the false-alarm probability due to the difference of their decreasing rates. (iii) when $p_f^A \geq 0.16$, the single-info gain is smaller than the marginal-info gain, the total revenue of the PPs is $V_{11} - V_{00}$, which decreases as the false-alarm probability increases. Due to the changes of the PPs' pricing across the boundaries, the social welfare of the system increases in the interval of $p_f^A \in [0.12, 0.16]$ as shown in Fig. 8(b).

Finally, we note that the social welfares under cooperation are smaller than those under competition for $p_f^A \in [0, 0.12]$, and they are equal for all $p_f^A > 0.12$.

VI. Conclusion

In this paper, we develop the framework of hybrid DSA schemes of spectrum sensing and database access, and show that the previous channel state information can benefit both the PPs and the SU under a game-theoretic market model. We investigate how the PPs make the pricing decision of the channel information in order to maximize their revenues under competition and under cooperation, and how the SU responds through the buying decision of the channel information and the sensing decision. We characterize Nash equilibria in both competitive and cooperative scenarios, and show that the cooperation between the PPs may decrease the social welfare (though it improves the revenues of the PPs). We verify our results through numerical simulation with various parameters. Although we consider a small network that consists of two PPs and a single SU, our results based on the game-theoretic analysis provide insight into the information market in CR networks. Extension of our model to multiple PPs and multiple SUs will clarify the effect of heterogeneity (in terms of channel conditions, reward from successful transmission) in the channel information market, and remains as an interesting open problem.

References

[1] P. Kolodzy, "Spectrum Policy Task Force," *Federal Commun. Comm., Washington, DC, Rep. ET Docket*, no. 02-135, 2002.

[2] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006.

[3] M. M. Buddhikot, "Understanding dynamic spectrum access: Models, taxonomy and challenges," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, DySPAN*, 2007.

[4] H. Kim and K. G. Shin, "Efficient discovery of spectrum opportunities with mac-layer sensing in cognitive radio networks," *IEEE Transactions onMobile Computing*, vol. 7, no. 5, pp. 533–545, 2008.

[5] Z. Gao, H. Zhu, Y. Liu, M. Li, and Z. Cao, "Location privacy in database-driven cognitive radio networks: Attacks and countermeasures," in *IEEE INFOCOM*, 2013.

[6] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical communication*, vol. 4, no. 1, pp. 40–62, 2011.

[7] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 116–130, Mar 2009.

[8] X. Wang, Z. Li, P. Xu, Y. Xu, X. Gao, and H.-H. Chen, "Spectrum sharing in cognitive radio networksan auction-based approach," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics focuses on cybernetics*, vol. 40, no. 3, pp. 587–596, 2010.

[9] D. Niyato and E. Hossain, "Competitive pricing for spectrum sharing in cognitive radio networks: Dynamic game, inefficiency of nash equilibrium, and collusion," *IEEE Journal on Selected Areas in Communications*, vol. 26, no. 1, pp. 192–202, 2008.

[10] H. Li, R. Mao, L. Lai, and R. C. Qiu, "Compressed meter reading for delay-sensitive and secure load report in smart grid," in *IEEE SmartGridGomm*, 2010.

[11] D. L. Tennenhouse, J. M. Smith, W. D. Sincoskie, D. J. Wetherall, and G. J. Minden, "A survey of active network research," *IEEE Communications Magazine*, vol. 35, no. 1, pp. 80–86, 1997.

[12] E. Barron, *Game Theory: An Introduction, 2nd Edition*. Wiley, 2013.

[13] G. Cheng, W. Liu, Y. Li, and W. Cheng, "Joint on-demand routing and spectrum assignment in cognitive radio networks," in *IEEE ICC*, 2007, pp. 6499–6503.

[14] D. Kang, S. Park, C. Joo, and S. Bahk, "Address-free contention in wireless access networks with common control channel for throughput improvement," *Computer Networks*, vol. 64, pp. 112–124, 2014.

[15] S. Kang, C. Joo, and J. Lee, "Pricing for Past Channel State Information in Multi-Channel Cognitive Radio Networks," Ulsan National Institute of Science and Technology, Tech. Rep., 2016. [Online]. Available: https://www.dropbox.com/s/wzy6r3v065lts56/CRpricingTR.pdf