Hedonic Coalition Formation Game for Cooperative Spectrum Sensing and Channel Access in Cognitive Radio Networks

Xiaolei Hao, Man Hon Cheung, Vincent W.S. Wong, *Senior Member, IEEE,* and Victor C.M. Leung, *Fellow, IEEE*

***Abstract*—*Cooperative spectrum sensing* is an effective technique to improve the sensing performance and increase the spectrum efficiency in cognitive radio networks (CRNs). In this paper, we consider a CRN with multiple primary users (PUs) and multiple secondary users (SUs). We first propose a cooperative spectrum sensing and access (CSSA) scheme for all the SUs, where the SUs cooperatively sense the licensed channels of the PUs in the sensing subframe. If a channel is determined to be idle, the SUs which have sensed that channel will have a chance to transmit packets in the data transmission subframe. We then formulate this multi-channel spectrum sensing and channel access problem as a *hedonic coalition formation game*, where a coalition corresponds to the SUs that have chosen to sense and access a particular channel. The value function of each coalition and the utility function of each SU take into account both the sensing accuracy and the energy consumption. We propose an algorithm for decision node selection in a coalition. Moreover, we propose an algorithm based on the switch rule to allow the SUs to make decisions on whether to join or leave a coalition. We prove analytically that the set with all the SUs converges to a final network partition, which is both Nash-stable and individually stable. Besides, the proposed algorithms are adaptive to changes in network conditions. Simulation results show that our proposed CSSA scheme achieves a better performance than the closest PU (CPU) scheme and the noncooperative spectrum sensing and access (NSSA) scheme in terms of the average utility of the SUs.**

***Index Terms*—Cognitive radio networks, coalitional game theory, hedonic coalition formation, cooperative spectrum sensing.**

I. Introduction

SPECTRUM resources are scarce and fixed spectrum allocation may not always be efficient [2]. This motivates the concept of *cognitive radio* [3], which allows unlicensed users (secondary users) to *dynamically* and *opportunistically* access the licensed bands allocated to the legacy spectrum holders (primary users) when the spectrum is not being utilized temporarily. Cooperation techniques, such as cooperative communication [4], [5], can be used in cognitive radio networks (CRNs). In order to enable dynamic spectrum access in CRNs, *spectrum sensing* [6] is performed. In *local spectrum sensing*, the secondary users (SUs) are required to sense the radio environment within their operating range to find the spectrum which is not occupied by the primary users (PUs). However, it can be susceptible to sensing problems due to multipath fading, shadowing, and receiver uncertainty [6]. To enhance the sensing performance of local spectrum sensing, the idea of *cooperative spectrum sensing* was proposed that exploits the *spatial diversity* in the observations of spatially located SUs [6]–[8]. In [9], Liang *et al.* studied cooperative sensing by formulating the sensing-throughput tradeoff problem as an optimization problem. In [10], Saad *et al.* introduced a distributed model for cooperative spectrum sensing in CRNs. The cooperative sensing problem was modeled as a coalitional game, and distributed algorithms were proposed for coalition formation. In [11], Lee *et al.* proposed an adaptive and cooperative spectrum sensing method, and investigated how the cooperative sensing affects the performance of the proposed optimal spectrum sensing scheme. In [12], Wang *et al.* proposed a distributed scheme for cooperative multi-channel spectrum sensing based on coalitional game theory. A coalition selection scheme was proposed, where each channel is sensed by one coalition. In [13], Song *et al.* studied the theoretical improvement of the multi-channel coordination in cooperative spectrum sensing. They proposed practical centralized algorithm and distributed algorithms to find the solutions for the formulated integer programming problem. Channel utilization and energy consumption are considered in spectrum sensing. In [14], Zhao *et al.* proposed a periodic sensing opportunistic spectrum access scheme. The constrained Markov decision processes were used to maximize channel utilization while limiting the interference with the PUs. In [15], Su *et al.* proposed a spectrum sensing scheme for CRNs to save the sensing energy consumption, and guarantee the priority of the PUs and the spectrum opportunity for SUs.

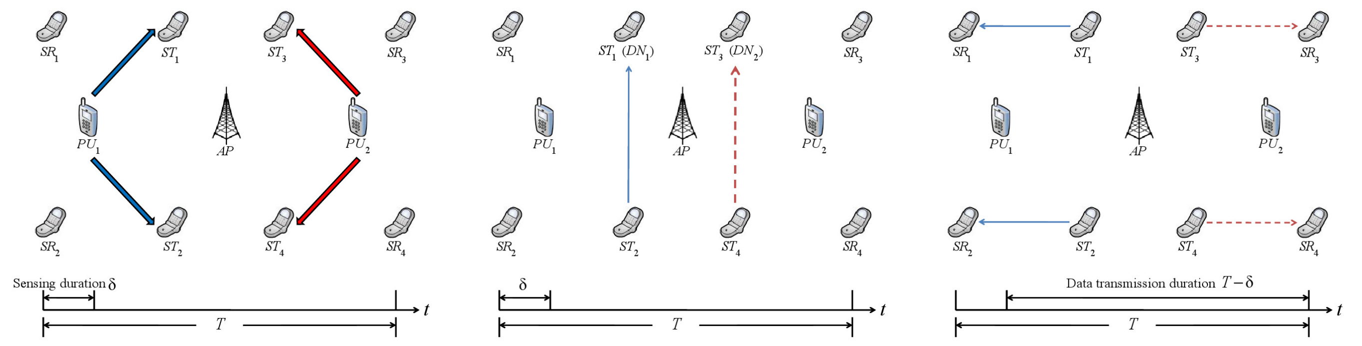
In general, there are multiple PUs (i.e., multiple licensed channels) and multiple SUs in a CRN. It is important to determine which channel each SU should sense and access by taking into account the *sensing accuracy* [16], [17] and *energy consumption* [18]. Moreover, it is more practical if we also

Manuscript received on October 8, 2011; revised on April 6, 2012 and June 29, 2012; and accepted on August 6, 2012. This work was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada. Part of this paper was presented at the *IEEE Global Communications Conference* (*Globecom'11*), Houston, TX, Dec. 2011 [1]. The review of this paper was coordinated by Prof. Natasha Devroye.

X. Hao is with TELUS Mobility, Vancouver, Canada, e-mail: xiaoleih@ece.ubc.ca.

M. H. Cheung is with the Department of Information Engineering, the Chinese University of Hong Kong, Hong Kong, China, e-mail: mhcheung@ie.cuhk.edu.hk. This work was completed when X. Hao and M. H. Cheung were with the Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, BC, Canada, V6T 1Z4.

V. W. S. Wong and V. C. M. Leung are with the Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, BC, Canada, V6T 1Z4, e-mail: {vincentw, vleung}@ece.ubc.ca.



(a) Sensing subframe with duration δ (b) Sensing decision (c) Data transmission subframe with duration $T-\delta$

Fig. 1. An example of our system model and the proposed CSSA scheme with $M = 2$ and $N = 4$, where the blue and red colours denote the operations in channels 1 and 2, respectively. (a) Each ST senses one licensed channel during the sensing subframe. (b) When the sensing time δ expires, each ST sends its sensing result to one of the STs in that channel that acts as a DN. (c) If the channel is determined to be idle by the DN, one of the STs in that channel can transmit data to the corresponding secondary receiver in the data transmission subframe.

consider *channel access* after spectrum sensing. Therefore, we consider a framework in CRNs that considers spectrum sensing accuracy, energy consumption, and channel access for the SUs. Algorithms are proposed which allow each SU to make its own decision on which channel to sense and access. Also, they enable the SUs to adapt to different changes in network conditions, such as the deployment of new PUs and SUs, the removal of existing PUs and SUs, and the change in wireless channel conditions.

In this paper, we study cooperative spectrum sensing and channel access in CRNs with multiple channels. We assume that a SU first chooses a channel to sense *locally* in the sensing subframe. Then, all the SUs that choose to sense the same channel *cooperatively* determine the channel status. If it is determined to be idle, one of the SUs which has sensed that channel can access it during the data transmission subframe. We consider both the spectrum sensing accuracy and energy consumption in our model, and analyze the behavior of the SUs by using *hedonic coalition formation game* [19]–[21]. The main contributions of this paper are summarized as follows:

- We propose a cooperative spectrum sensing and access (CSSA) scheme for the SUs in a CRN, where there are multiple licensed frequency channels.
- We formulate the cooperative multi-channel spectrum sensing and access problem as a hedonic coalition formation game, where the value function of each coalition and the utility function of each SU take into account both the sensing accuracy and energy consumption.
- In order for the SUs to make decisions to join or leave a coalition, we propose algorithms for the CSSA scheme. We prove analytically that the final partition is Nash-stable, where no SU has an incentive to move from its current coalition to another coalition.
- Simulation results show that our CSSA scheme achieves a better performance than the closest PU (CPU) scheme and the noncooperative spectrum sensing and access (NSSA) scheme. The proposed algorithms are adaptive to changes in network settings.

Our proposed framework is more practical as compared with some of the previous works in spectrum sensing. In the system model, we consider the general case where there are *multiple* licensed channels in the CRN, while the works in [9], [10], [15] only analyzed the scenario with only one channel in the network. Besides, the energy efficiency is always a concern in practice. Therefore, we take *energy consumption* into consideration for spectrum sensing and channel access in CRNs. However, the works in [9]–[14] did not consider energy consumption. In terms of spectrum sensing accuracy, we apply *cooperative* spectrum sensing in our proposed CSSA scheme. Compared to the work in [14], [15] which only considered local spectrum sensing, our CSSA scheme can further improve the sensing performance. Moreover, while previous works only focused on spectrum sensing and ignored *channel access* (e.g., [10], [12]), we consider both spectrum sensing and channel access in our CSSA scheme, and analyze the performance of the system by using hedonic coalition formation game, which has not been applied to study the cooperative spectrum sensing and channel access in CRNs. We present a complete framework for the CRN, and propose algorithms for our CSSA scheme.

The remainder of this paper is organized as follows. Section II describes the system model and the CSSA scheme. The proposed cooperative multi-channel spectrum sensing and channel access problem is modeled as a hedonic coalition formation game in Section III. In Section IV, we present the algorithms for coalition formation. In Section V, we discuss the nontransferable utility (NTU) approach for the coalitional formation game. Section VI presents the simulation results. Conclusions are given in Section VII.

II. System Model and CSSA Scheme

As shown in Fig. 1(a), we consider a CRN with one access point (AP), M PUs, and N secondary transmitter-receiver (ST-SR) pairs. In this paper, since the secondary transmitter (ST) is responsible for spectrum sensing and data transmission, we use the term ST and SU interchangeably. Let $\mathcal{M} = \{1, \ldots, M\}$ be the set of PUs and $\mathcal{N} = \{1, \ldots, N\}$ be the set of STs. Each $PU_i, i \in \mathcal{M}$ has its own licensed channel with bandwidth B_i. Thus, there are M non-overlapped channels in total. The M PUs are sending data to the AP. The N ST-SR pairs are located in the same area as the PUs, where each $ST_j, j \in \mathcal{N}$ seeks to exploit possible transmission opportunities in one of the M channels of the PUs. We assume that each ST_j always has data to send and no traffic requirement is imposed on the STs. In other words, each ST_j transmits data in a best-effort manner.

We consider a frame structure for *periodic* spectrum sensing, where each time frame consists of one sensing subframe[1] and one data transmission subframe[2] as shown in the bottom part in Fig. 1(a)-(c). We use T to denote the frame duration. All SUs have the same spectrum sensing duration, and we use δ, where $0 < \delta \leq T$, to denote the spectrum sensing time of the SUs. Therefore, the data transmission duration is $T - \delta$. Notice that in a practical system, a short duration between the sensing and data transmission subframes is required for the collection of the sensing results and the data fusion. However, its duration is much shorter than the time required for sensing and transmission. The received signal of the PUs is sampled at sampling frequency f_s at ST_j, $\forall\, j \in \mathcal{N}$. In addition, δ is a multiple of $1/f_s$. Thus, the number of samples is δf_s, which is an integer. We also assume that T is a multiple of $1/f_s$.

We consider *narrowband sensing*, where each SU chooses to sense one channel in each time frame. Let $\mathcal{H}_{1,i}$ and $\mathcal{H}_{0,i}$ be the hypothesis that PU_i, $i \in \mathcal{M}$ is active and inactive, respectively. For $j \in \mathcal{N}$, ST_j performs spectrum sensing in the channel of PU_i and determines the probabilities of detection and false alarm. The *probability of detection* is the probability of correctly detecting the appearance of PU_i under hypothesis $\mathcal{H}_{1,i}$ (i.e., a busy channel is determined to be busy correctly). The *probability of false alarm* is the probability of falsely declaring the appearance of the primary signal under hypothesis $\mathcal{H}_{0,i}$ (i.e., an idle channel is determined to be busy).

We assume the noise in the channel of $PU_i, i \in \mathcal{M}$ is an independent and identically distributed (iid) random process with zero mean and variance $\sigma^2_{n,i}$. Given the power spectral density N_0, we have $\sigma^2_{n,i} = N_0 B_i$. The primary signal of PU_i is an iid random process with zero mean and variance $\sigma^2_{s,i}$. The primary signal of PU_i is independent of other primary signals and the noise. We denote $\gamma_{i,j} = |g_{i,j}|^2 \sigma^2_{s,i} / \sigma^2_{n,i}$ as the received signal-to-noise ratio (SNR) of PU_i, $i \in \mathcal{M}$ measured at ST_j, $j \in \mathcal{N}$ under the hypothesis $\mathcal{H}_{1,i}$, where $|g_{i,j}|$ is the average channel gain of the link between PU_i and ST_j in channel i. We use ε to denote the detection threshold for all the STs. We consider the circularly symmetric complex Gaussian (CSCG) noise case. We also assume that the primary signal is complex phase shift keying (PSK) modulated signal. With the use of energy detection [6], [23], under hypothesis $\mathcal{H}_{0,i}$, the probability of false alarm [9] in channel $i \in \mathcal{M}$ by ST_j is

$$P_{f,i,j}(\varepsilon,\, \delta,\, \sigma^2_{n,i}) = Pr(y_{j,i} > \varepsilon \,|\, \mathcal{H}_{0,i}) = Q\left(\left(\frac{\varepsilon}{\sigma^2_{n,i}} - 1\right)\sqrt{\delta f_s}\right), \quad (1)$$

[1]The duration of the sensing subframe δ is less than 15 ms when the duration of each frame T is 100 ms [9], [22].

[2]During the data transmission subframe, the SU can transmit multiple packets. When T is equal to 100 ms and δ is equal to 2.5 ms, the data transmitted in the data transmission subframe is about 600 kbits [9].

where $y_{j,i}$ is the test statistic for energy detector of ST_j in channel i, and Q is the complementary distribution function of the standard Gaussian. If ε and δ are the same for all the SUs, and the bandwidth B_i are the same for all the PUs, then $P_{f,i,j}(\varepsilon,\, \delta,\, \sigma^2_{n,i})$ are the same $\forall\, i \in \mathcal{M}$, $\forall\, j \in \mathcal{N}$. Moreover, under hypothesis $\mathcal{H}_{1,i}$, the probability of detection in channel $i \in \mathcal{M}$ by ST_j, $j \in \mathcal{N}$ is

$$P_{d,i,j}(\varepsilon,\, \delta,\, \sigma^2_{n,i},\, \gamma_{i,j}) = Pr(y_{j,i} > \varepsilon \,|\, \mathcal{H}_{1,i}) = Q\left(\left(\frac{\varepsilon}{\sigma^2_{n,i}} - \gamma_{i,j} - 1\right)\sqrt{\frac{\delta f_s}{2\gamma_{i,j} + 1}}\right). \quad (2)$$

It has been reported that the hidden node problem, deep fading and shadowing can degrade the performance of local spectrum sensing of individual SU [6], [24]. To overcome this problem, *cooperative spectrum sensing* was proposed, where the SUs combine their local sensing results. In our system model, each SU first chooses to sense the channel independently, and then sends its spectrum sensing result to the *decision node* (DN) for that channel when the sensing time δ expires. Among those ST_j, $j \in \mathcal{N}$ which choose to sense channel $i \in \mathcal{M}$, DN_i is selected according to Algorithm 1, which will be presented in Section IV. The DN_i will combine the sensing results of the SUs which choose to sense channel i, and determine the status (i.e., busy or idle) of channel i. We consider an example shown in Fig. 1, where there are two channels and four ST-SR pairs. At the beginning of each frame, as shown in Fig. 1(a), ST_1 and ST_2 start sensing the channel of PU_1 in channel 1, and ST_3 and ST_4 start sensing the channel of PU_2 in channel 2. In Fig. 1(b), ST_1 and ST_3 serve as the DN_1 and DN_2, respectively. Each SU will send its spectrum sensing decision to the corresponding DN_i when its sensing time δ expires. The DN_i makes the final spectrum sensing decision for the channel $i \in \mathcal{M}$.

The decision node decides on the channel status based on a *decision fusion rule* to combine the sensing results of the SUs [9]. We consider *k-out-of-n* rule [25], where DN decides the presence of primary activity if there are k or more SUs that individually detect the presence of primary activity. For $k = 1$, $k = n$, and $k \geq n/2$, k-out-of-n rule becomes the OR rule, AND rule, and majority rule, respectively [6]. We assume that the local decisions made by the SUs in the same channel are independent. Let $\mathcal{S}_i$ be the set of SUs that choose to sense and access channel i. We have $\mathcal{S}_i \subseteq \mathcal{N}$, $\forall\, i \in \mathcal{M}$ and $\bigcup_{i \in \mathcal{M}} \mathcal{S}_i = \mathcal{N}$. Since we assume that ST_j, $\forall\, j \in \mathcal{N}$ can choose to sense only one channel in each frame, we have $\mathcal{S}_i \cap \mathcal{S}_l = \emptyset$, $\forall\, i, l \in \mathcal{M}, i \neq l$. Let $P_{f,i}$ be the probability of false alarm under the hypothesis $\mathcal{H}_{0,i}$, and let $P_{d,i}$ be the probability of detection under the hypothesis $\mathcal{H}_{1,i}$ in channel $i \in \mathcal{M}$. As an example, when the OR rule (i.e., $k = 1$) is used, they are given by

$$P_{f,i} = 1 - \prod_{j \in \mathcal{S}_i} \left(1 - P_{f,i,j}(\varepsilon,\, \delta,\, \sigma^2_{n,i})\right), \quad (3)$$

$$P_{d,i} = 1 - \prod_{j \in \mathcal{S}_i} \left(1 - P_{d,i,j}(\varepsilon,\, \delta,\, \sigma^2_{n,i},\, \gamma_{i,j})\right). \quad (4)$$

For the channel $i \in \mathcal{M}$, we denote $P_{\mathcal{H}_{1,i}}$ as the probability that PU_i is active, and $P_{\mathcal{H}_{0,i}}$ as the probability that PU_i

is silent. Therefore, we have $P_{\mathcal{H}_{1,i}} + P_{\mathcal{H}_{0,i}} = 1$. If DN_i declares that PU_i is active, then ST_j, $\forall j \in \mathcal{S}_i$ cannot transmit data during the data transmission subframe. However, if DN_i declares that channel i is idle, then each ST_j, $j \in \mathcal{S}_i$ has a chance to access the channel i with equal probability. In this way, the transmissions of the SUs do not interfere with each other. Therefore, under the decision that channel i is idle, one SU is chosen to transmit data among all the SUs in $\mathcal{S}_i$. The transmission probability of ST_j, $j \in \mathcal{S}_i$ is $1/|\mathcal{S}_i|$, and the transmission time is $T - \delta$. As an example shown in Fig. 1(c), ST_1 and ST_2 seek to access the channel of PU_1 (solid arrows), and ST_3 and ST_4 seek to access the channel of PU_2 (dash arrows). If DN_i declares that channel i is idle and PU_i is actually silent, then the secondary data transmission in channel i will be successful. However, if DN_i determines that channel i is idle but PU_i is actually active (i.e., a missed detection), then the secondary data transmission in channel i will interfere with PU_i's transmission. In this case, when the collision of PU_i's packets is detected at the AP, we assume that the SUs will be charged $D_0 > 0$ by the AP at the end of the data transmission subframe as a penalty for the interference, where D_0 can be chosen to map the level of the performance degradation of the PU to the penalty value of the SUs.

Given the system model and the CSSA scheme described above, when the sensing duration δ is fixed, it is important to determine which channel each SU should choose to sense and access in order to achieve the optimal performance. In the following sections, we will propose algorithms to solve this spectrum sensing and access problem by using coalitional game theory. Note that our algorithms can be applied directly to a more general system model, which is not restricted to the use of PSK modulated signal for transmission and the OR rule for data fusion.

III. Hedonic Coalition Formation Game

In this section, we formulate the problem of multi-channel energy-efficient cooperative spectrum sensing and access as a hedonic coalition formation game. We apply the switch rule for the SUs to make decisions on whether to join or leave a coalition. We prove that the hedonic coalition formation game always terminates at the final partition that is both Nash-stable and individually stable.

A. Value Function and Utility Function

In our system model, there are M non-overlapped channels and N SUs in the CRN. In order to exploit the possible transmission opportunities in the M channels with different channel conditions, each SU should carefully make its own decision on which channel it should sense and access during each time frame by taking into account both the sensing accuracy and energy consumption. For the sensing accuracy, it affects the amount of data transmitted by the SUs during the data transmission subframe and the penalty charged by the PUs for interfering with their transmission. For the energy consumption of the SUs, it is an important design criterion for spectrum sensing and data transmission in practice.

According to the CSSA scheme presented in Section II, there are four different scenarios related to the activity of the PU_i and the decision of DN_i in channel $i \in \mathcal{M}$. We present the payoff, energy consumption, and the probability that each scenario occurs as follows:

Scenario 1: PU_i is silent and the decision made by DN_i is not a false alarm. In this scenario, ST_j, $\forall j \in \mathcal{S}_i$ transmits data during the data transmission subframe successfully. Given the signal transmit power P_t, the noise power $\sigma^2_{n,i}$ in channel i, and the average channel gain $|h_{j,i}|$ of the link between the ST-SR pair j in channel i, the transmission rate $R_{j,i}$ of ST_j can be modeled as [26]:

$$R_{j,i} = B_i \log_2 \left(1 + |h_{j,i}|^2 \frac{P_t}{\sigma^2_{n,i}} \right). \tag{5}$$

The *payoff* of set $\mathcal{S}_i$ is defined as the *reward* (i.e., the amount of data transmitted by the SUs in $\mathcal{S}_i$) minus the *penalty* (i.e., the payment required by the SUs in $\mathcal{S}_i$ for interfering with PU_i's transmission) in the data transmission subframe. Since the transmission of the SUs is successful and the penalty is zero, the payoff of set $\mathcal{S}_i$ is given by $v_{0|0,D}(\mathcal{S}_i) = \frac{\sum_{j \in \mathcal{S}_i} R_{j,i}}{|\mathcal{S}_i|}(T - \delta)$. The energy consumption of set $\mathcal{S}_i$ is given by $v_{0|0,E}(\mathcal{S}_i) = P_s|\mathcal{S}_i|\delta + P_t(T - \delta)$, where P_s is the sensing power of ST_j, $\forall j \in \mathcal{N}$. The terms $P_s|\mathcal{S}_i|\delta$ and $P_t(T - \delta)$ represent the energy consumption for spectrum sensing and data transmission, respectively. The probability that scenario 1 will occur is $P_{0|0,i} = P_{\mathcal{H}_{0,i}}(1 - P_{f,i})$.

Scenario 2: PU_i is silent and the decision made by DN_i is a false alarm. In this scenario, since ST_j, $\forall j \in \mathcal{S}_i$ does not transmit during the idle data transmission subframe, and there is no interference with the PU, the payoff of set $\mathcal{S}_i$ is $v_{1|0,D}(\mathcal{S}_i) = 0$, and the energy consumption of set $\mathcal{S}_i$ is $v_{1|0,E}(\mathcal{S}_i) = P_s|\mathcal{S}_i|\delta$. The probability that this scenario will occur is $P_{1|0,i} = P_{\mathcal{H}_{0,i}} P_{f,i}$.

Scenario 3: PU_i is active and DN_i fails to detect the presence of the primary signal. In this scenario, both PU_i and $ST_j, j \in \mathcal{S}_i$ transmit data during the data transmission subframe, so they interfere with each other. We assume that their transmitted packets are corrupted, so the reward is zero. Thus, the payoff of set $\mathcal{S}_i$ is $v_{0|1,D}(\mathcal{S}_i) = -D_0(T - \delta)$, where $D_0 > 0$ is the unit penalty per second for interfering with the PU's data transmission. Notice that the penalty term $D_0(T - \delta)$ is decreasing with the duration of the sensing subframe δ. Besides, the energy consumption of set $\mathcal{S}_i$ is $v_{0|1,E}(\mathcal{S}_i) = P_s|\mathcal{S}_i|\delta + P_t(T - \delta)$, which is the same as that in scenario 1. The probability that scenario 3 will occur is $P_{0|1,i} = P_{\mathcal{H}_{1,i}}(1 - P_{d,i})$.

Scenario 4: PU_i is active and DN_i detects the presence of the primary signal. In this scenario, ST_j, $\forall j \in \mathcal{S}_i$ does not transmit data during the data transmission subframe. Since the reward and penalty are both zero, the payoff of set $\mathcal{S}_i$ is $v_{1|1,D}(\mathcal{S}_i) = 0$, and the energy consumption of set $\mathcal{S}_i$ is $v_{1|1,E}(\mathcal{S}_i) = P_s|\mathcal{S}_i|\delta$. The probability that scenario 4 will occur is given by $P_{1|1,i} = P_{\mathcal{H}_{1,i}} P_{d,i}$.

According to the above analysis for the four scenarios, the *expected* payoff for set $\mathcal{S}_i$ in each frame of duration T is

$$\begin{aligned} v_D(\mathcal{S}_i) &= \sum_{a=0}^{1}\sum_{b=0}^{1} P_{a|b,i} v_{a|b,D}(\mathcal{S}_i) \\ &= P_{0|0,i}\frac{\sum\limits_{j\in\mathcal{S}_i} R_{j,i}}{|\mathcal{S}_i|}(T-\delta) - P_{0|1,i}D_0(T-\delta). \end{aligned} \quad (6)$$

The expected energy consumption in set $\mathcal{S}_i$ in each frame of duration T is

$$\begin{aligned} v_E(\mathcal{S}_i) &= \sum_{a=0}^{1}\sum_{b=0}^{1} P_{a|b,i} v_{a|b,E}(\mathcal{S}_i) \\ &= P_s|\mathcal{S}_i|\delta + (P_{0|0,i} + P_{0|1,i})P_t(T-\delta). \end{aligned} \quad (7)$$

We define the *value function* of set $\mathcal{S}_i$ as the ratio of $v_D(\mathcal{S}_i)$ to $v_E(\mathcal{S}_i)$, which represents the expected payoff achieved per unit of energy consumed in set $\mathcal{S}_i$:

$$\begin{aligned} v(\mathcal{S}_i) &\triangleq \frac{v_D(\mathcal{S}_i)}{v_E(\mathcal{S}_i)} \\ &= \frac{P_{0|0,i}\sum\limits_{j\in\mathcal{S}_i} R_{j,i}(T-\delta) - |\mathcal{S}_i|P_{0|1,i}D_0(T-\delta)}{|\mathcal{S}_i|\big(P_s|\mathcal{S}_i|\delta + (P_{0|0,i}+P_{0|1,i})P_t(T-\delta)\big)}. \end{aligned} \quad (8)$$

In fact, by tuning the value D_0 in the value function, different degrees of *tradeoff* between the energy efficiency of the CSSA scheme and the protection of the PU's transmission can be achieved. Specifically, when $D_0 = 0$, $v(\mathcal{S}_i)$ is equal to the *energy efficiency* (i.e., the expected amount of data transmitted by the SUs divided by the expected energy consumption) of the CSSA scheme. On the other hand, when D_0 is large, more importance is placed on protecting the PU from the interference of the SUs. Moreover, from (8), the value function takes into account the *sensing accuracy* by considering the sensing results related to false alarm (i.e., $P_{0|0,i}$ is related to $P_{f,i}$) and detection (i.e., $P_{0|1,i}$ is related to $P_{d,i}$). The value of $v(\emptyset)$ is chosen such that $v(\mathcal{S}_i) > v(\emptyset)$, $\forall\, \mathcal{S}_i \subseteq \mathcal{N}$ and $\mathcal{S}_i \neq \emptyset$.

Since all the SUs in set $\mathcal{S}_i$ perform spectrum sensing and access channel i with equal probability, they should receive the same utility. The *utility function* of ST_j, $\forall\, j \in \mathcal{S}_i$ is thus given by

$$x_j^{\mathcal{S}_i} = \frac{v(\mathcal{S}_i)}{|\mathcal{S}_i|}. \quad (9)$$

Given the M non-overlapped channels and N SUs in our system model, each SU will make its own decision on which channel it should sense and access during each time frame so that it can achieve the best performance in terms of the utility defined in (9). Notice that the utility of each player does not correspond to a physical quantity that can be divided among the players in a coalition. Rather, it represents a performance metric that each player aims to optimize as in [21].

B. Hedonic Coalition Formation Analysis

Given the value function of set $\mathcal{S}_i$ defined in (8) and the utility function of each SU defined in (9), we formulate the problem of multi-channel cooperative spectrum sensing and channel access as a coalition formation game with *transferable utility* (TU) [20] with the following basic elements:

- *Players*: The players of the coalition formation game are the N SUs (i.e., ST_j, $\forall\, j \in \mathcal{N}$).
- *Strategies*: The strategy of each SU is the licensed channel it chooses to sense and access (i.e., ST_j chooses a licensed channel $i \in \mathcal{M}$).
- *Utilities*: The utility of each SU depends on which coalition it belongs to, and it is defined in (9) (i.e., the utility of ST_j in coalition $\mathcal{S}_i$ is $x_j^{\mathcal{S}_i}$).

Using the terminology of coalitional game theory, we refer to set $\mathcal{S}_i$ as *coalition* i. Since there are M channels in the CRN, there are M coalitions in the system, where each SU joins one of the M coalitions. Since we consider that there can only be *one* coalition in each channel, the coalitions are in fact operating in different orthogonal channels. Thus, there is no interference for SUs belonging to different coalitions. The SUs are allowed to autonomously form coalitions in the M channels in order to achieve higher utilities. Moreover, we can show that this game is a *hedonic coalition formation game* [27]. Before presenting its definition, we first introduce some basic definitions which are commonly used in the coalition formation games.

Definition 1: The set $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_M\}$ is a *partition* of $\mathcal{N}$ if $\mathcal{S}_i \cap \mathcal{S}_l = \emptyset$, $\forall\, i, l \in \mathcal{M}, i \neq l$ and $\bigcup_{i\in\mathcal{M}} \mathcal{S}_i = \mathcal{N}$.

A partition is also referred to as a *coalition structure* [20]. An example of a partition $\mathcal{S}$ is shown in Fig. 1, where $\mathcal{N} = \{1, 2, 3, 4\}$, $\mathcal{S}_1 = \{1, 2\}$, and $\mathcal{S}_2 = \{3, 4\}$. Therefore, the set $\mathcal{S} = \{\{1, 2\}, \{3, 4\}\}$ is a partition of $\mathcal{N}$.

Definition 2: For any player $j \in \mathcal{N}$, a preference relation $\succeq_j$ is defined as a complete, reflexive and transitive binary relation over the set of all coalitions that player j can possibly form [27].

Since the SUs are allowed to autonomously form the coalitions in the M channels, the above definition is used to compare the preference of player j over different coalitions, where player j is a member. Consequently, for player $j \in \mathcal{N}$, given two coalitions $\mathcal{S}_1 \subseteq \mathcal{N}$ and $\mathcal{S}_2 \subseteq \mathcal{N}$, $\mathcal{S}_1 \succeq_j \mathcal{S}_2$ indicates that player j prefers to be a member of coalition $\mathcal{S}_1$ over to be a member of coalition $\mathcal{S}_2$, or at least, player j prefers both coalitions equally. Furthermore, $\mathcal{S}_1 \succ_j \mathcal{S}_2$ indicates that player j *strictly* prefers being a member of coalition $\mathcal{S}_1$ over being a member of coalition $\mathcal{S}_2$. For evaluating the preferences of ST_j, $\forall\, j \in \mathcal{N}$, we define the following operation

$$\mathcal{S}_1 \succ_j \mathcal{S}_2 \Leftrightarrow U_j(\mathcal{S}_1) > U_j(\mathcal{S}_2), \quad (10)$$

where $\mathcal{S}_1 \subseteq \mathcal{N}$ and $\mathcal{S}_2 \subseteq \mathcal{N}$ are any two coalitions that contains ST_j. The preference function $U_j(\mathcal{S}_i)$, $j \in \mathcal{S}_i$ is defined as

$$U_j(\mathcal{S}_i) = \begin{cases} x_j^{\mathcal{S}_i}, & \mathcal{S}_i \notin h(j), \\ -\infty, & \text{otherwise}, \end{cases} \quad (11)$$

where $x_j^{\mathcal{S}_i}$ is defined in (9). $h(j)$ is the *history set* of ST_j, which will be defined in Definition 5. According to the preference function defined in (11), the preference over different coalitions for ST_j, $\forall\, j \in \mathcal{N}$ is related to its utility function defined in (9).

Given the set of players $\mathcal{N}$ and a preference relation $\succ_j$ for every player $j \in \mathcal{N}$, a hedonic coalition formation game is defined as follows:

Definition 3: A *hedonic coalition formation game* is a coalitional game that satisfies the following two conditions: 1) The utility of any player depends *solely* on the members of the coalition to which the player belongs; 2) The coalitions form as a result of the preferences of the players over their possible coalition set. Therefore, a hedonic coalition formation game is defined by the pair $(\mathcal{N}, \succ)$ where $\mathcal{N}$ is the set of players and $\succ$ is a profile of preferences defined for every player in $\mathcal{N}$.

The formulated game is a hedonic coalition formation game as it satisfies the above conditions. First, from (9), the utility function of ST_j, $\forall\, j \in \mathcal{S}_i$ depends only on the SUs in coalition $\mathcal{S}_i$, $i \in \mathcal{M}$. Second, the preference function of each SU is defined in (11).

From the definitions of the preference relations of the SUs in (10) and the preference function in (11), it is clear that ST_j, $\forall\, j \in \mathcal{N}$ would like to join a new coalition, which ST_j has never been a member of, if and only if ST_j can obtain a higher utility in this new coalition than ever before. Therefore, we present the *switch rule* for coalition formation.

Definition 4: (Switch Rule) Given a partition $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_M\}$, ST_j, $j \in \mathcal{S}_i$ decides to leave its current coalition $\mathcal{S}_i$ and join another coalition $\mathcal{S}_l$ where $i \neq l$, if and only if $\mathcal{S}_l \bigcup \{j\} \succ_j \mathcal{S}_i$.

The switch rule provides a mechanism through which a SU can leave its current coalition and join another coalition, given that the new coalition is strictly preferred over the current coalition. The switch rule can be viewed as a selfish decision made by a player to move from its current coalition to a new coalition, regardless of the effect of its move on the other players. According to the switch rule, all the N SUs can make decisions to automatically form coalitions in the system. Thus, the partition of the $(\mathcal{N}, \succ)$ hedonic coalition formation game may change in each time frame. We define the initial partition of the hedonic coalition formation game as $\mathcal{S}^{(0)} = \{\mathcal{S}_1^{(0)}, \ldots, \mathcal{S}_M^{(0)}\}$, and the partition at the r-th time frame as $\mathcal{S}^{(r)} = \{\mathcal{S}_1^{(r)}, \ldots, \mathcal{S}_M^{(r)}\}$. After each time frame of duration T, the partition may change according to our proposed switch rule. If $\mathcal{S}^{(r)} = \mathcal{S}^{(r-1)}$, then there is no switch operation during the r-th time frame. Otherwise, one SU should move from its current coalition to another coalition in the r-th time frame. Now, we present the definition of history set $h(j)$ of ST_j, which appeared in (11).

Definition 5: At the r-th time frame, the *history set* for $ST_j, j \in \mathcal{N}$ is $h(j) = \{\mathcal{S}_{i_0}^{(0)}, \ldots, \mathcal{S}_{i_{r-1}}^{(r-1)}\}$, where we have $i_z \in \mathcal{M}$ and $j \in \mathcal{S}_{i_z}$ at any time frame index $z \in \{0, 1, \ldots, r-1\}$. At the end of the r-th time frame, ST_j will update its history set $h(j)$ by including a new element $\mathcal{S}_{i_r}^{(r)}$, where $i_r \in \mathcal{M}$ and $j \in \mathcal{S}_{i_r}$.

Proposition 1: If ST_j performs the switch rule in the r-th time frame, which it leaves its previous coalition $\mathcal{S}_i$ (denoted as $\mathcal{S}_{i_{r-1}}^{(r-1)}$) and joins another coalition $\mathcal{S}_l$ with $i \neq l$, the newly formed coalition $\mathcal{S}_l \bigcup \{j\}$ (denoted as $\mathcal{S}_{i_r}^{(r)}$) cannot be the same with the previous coalition members in the history set $h(j)$. That is, we have $\mathcal{S}_l \bigcup \{j\} \notin h(j)$ before the update of $h(j)$ at the end of the r-th time frame.

Proof: Suppose that we can find $\mathcal{S}_{i_r}^{(r)} = \mathcal{S}_{i_z}^{(z)}$, where $z \in \{0, 1, \ldots, r-1\}$ and $\mathcal{S}_{i_z}^{(z)} \in h(j)$. Then, we have $x_j^{\mathcal{S}_{i_r}^{(r)}} = x_j^{\mathcal{S}_{i_z}^{(z)}}$ according to (9). However, according to the definition of the switch rule, ST_j will perform the switch operation if and only if the new coalition is strictly preferred by ST_j over the previous coalition. Therefore, we have $x_j^{\mathcal{S}_{i_r}^{(r)}} > x_j^{\mathcal{S}_{i_z}^{(z)}}$, which contradicts with our assumption. Thus, the newly formed coalition $\mathcal{S}_{i_r}^{(r)}$ cannot be the same with any of the previous coalitions $\mathcal{S}_{i_z}^{(z)}$ in the history set $h(j)$. ■

Next, we will prove that there exists a stable partition in our hedonic coalition formation game. Before presenting the proof, we first define two types of stable partitions [19].

Definition 6: A partition $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_M\}$ is *Nash-stable* if $\forall\, j \in \mathcal{S}_i$ with $\forall\, i \in \mathcal{M}$, $\mathcal{S}_i \succeq_j \mathcal{S}_l \bigcup \{j\}$, $\forall\, l \in \mathcal{M}$.

In other words, a coalition partition $\mathcal{S}$ is Nash-stable if no player has an incentive to move from its current coalition to another coalition. Therefore, no player can obtain a higher utility by performing the switch rule when the current partition is Nash-stable. When a partition is Nash-stable, it implies that it is individually stable [19] that there does not exist any coalition, where a player strictly prefers to join, while the other players in that coalition do not get hurt by the formation of this new coalition.

Definition 7: A partition $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_M\}$ is *individually stable* if there does not exist $j \in \mathcal{S}_i$ with $i \in \mathcal{M}$, and a coalition $\mathcal{S}_l$ $(l \neq i)$ such that $\mathcal{S}_l \bigcup \{j\} \succ_j \mathcal{S}_i$, and $\mathcal{S}_l \bigcup \{j\} \succeq_k \mathcal{S}_l$ for all $k \in \mathcal{S}_l$.

Theorem 1: Starting from any initial partition $\mathcal{S}^{(0)}$, all the SUs will always converge to a final partition $\mathcal{S}^* = \{\mathcal{S}_1^*, \ldots, \mathcal{S}_M^*\}$, which is both Nash-stable and individually stable.

Proof: Given any initial partition $\mathcal{S}^{(0)}$, the hedonic coalition formation consists of a sequence of switch operations. Therefore, there is a sequence of network partitions $\{\mathcal{S}^{(0)}, \mathcal{S}^{(1)}, \mathcal{S}^{(2)}, \ldots, \mathcal{S}^{(r)}\}$ after r iterations. According to Definition 4, a SU will achieve a higher utility in its new coalition after each switch operation. From Proposition 1, we know that each switch operation leads to a new partition which has not been visited before. Given the number of channels M and the number of SUs N in the CRN, the total number of different partitions is M^N, which is a finite number. Thus, from any $\mathcal{S}^{(0)}$, the switch operations will always terminate at a point after a finite number of iterations, where the coalition structure converges to the final partition $\mathcal{S}^*$.

Suppose $\mathcal{S}^*$ is not Nash-stable. According to Definition 6, there exist some switch operations which can increase the utility of one SU by moving this SU from its current coalition to another coalition. The partition will be updated that $\mathcal{S}^*$ is not the final partition, which contradicts with our assumption. Thus, the final partition $\mathcal{S}^*$ must be Nash-stable. According to [19], a Nash-stable partition is individually stable. ■

It should be noted that when the history sets are not used, the partition still converges to stability, but at the expense of a longer convergence time. In the next section, we will present the coalition formation algorithms.

Algorithm 1 Decision node DN_i selection algorithm in channel $i \in \mathcal{M}$. The algorithm is executed by ST_j, $\forall\, j \in \mathcal{S}_i$.

1: **for** iteration $r := 1$ to MAX **do**
2: ST_j broadcasts its measured SNR information $\gamma_{i,j}^{(r)}$ and transmission rate $R_{j,i}$ to other secondary transmitters ST_k, $\forall\, k \in \mathcal{S}_i^{(r)} \backslash \{j\}$
3: ST_j receives the measured SNR information $\gamma_{i,k}^{(r)}$ and transmission rate $R_{k,i}$ from other ST_k, $\forall\, k \in \mathcal{S}_i^{(r)} \backslash \{j\}$
4: $q := \arg\max_{p \in \mathcal{S}_i^{(r)}} \gamma_{i,p}^{(r)}$
5: $DN_i^{(r)} := ST_q$
6: **end for**

Algorithm 2 Coalition formation algorithm based on the switch rule. It is executed by ST_j, $\forall\, j \in \mathcal{N}$.

1: **Initialization**: $\mathcal{S}_1^{(0)} := \mathcal{N}$; $\mathcal{S}_l^{(0)} := \emptyset$, $\forall\, l \in \mathcal{M}\backslash\{1\}$
2: **for** iteration $r := 1$ to MAX **do**
3: $\mathcal{S}_i^{(r)} := \mathcal{S}_i^{(r-1)}$, where $i \in \mathcal{M}$ and $j \in \mathcal{S}_i^{(r)}$
4: ST_j generates θ_j, which is a Gaussian random variable with mean 0 and variance 1
5: ST_j randomly selects another licensed channel α_j such that $\alpha_j \in \mathcal{M}$, $\alpha_j \neq i$
6: ST_j broadcasts the information of θ_j to other ST_k, $\forall\, k \in \mathcal{N}$, $k \neq j$
7: ST_j receives the information of θ_k from other ST_k, $\forall\, k \in \mathcal{N}$, $k \neq j$
8: $m := \arg\max_w \theta_w$, $\forall\, w \in \mathcal{N}$
9: **if** $ST_j = ST_m$ **then**
10: ST_j computes $x_j^{\mathcal{S}_i^{(r)}} := v(\mathcal{S}_i^{(r)})/|\mathcal{S}_i^{(r)}|$
11: $\mathcal{S}_i^{(r)} := \mathcal{S}_i^{(r)} \backslash \{j\}$
12: ST_j requests and obtains the information of $\mathcal{S}_{\alpha_j}^{(r)}$ from $DN_{\alpha_j}^{(r)}$
13: $\mathcal{S}_{\alpha_j}^{(r)} := \mathcal{S}_{\alpha_j}^{(r)} \bigcup \{j\}$
14: **if** $\mathcal{S}_{\alpha_j}^{(r)} \in h(j)$ **then**
15: $\mathcal{S}_{\alpha_j}^{(r)} := \mathcal{S}_{\alpha_j}^{(r)} \backslash \{j\}$
16: $\mathcal{S}_i^{(r)} := \mathcal{S}_i^{(r)} \bigcup \{j\}$
17: **else**
18: ST_j computes $x_j^{\mathcal{S}_{\alpha_j}^{(r)}} := v(\mathcal{S}_{\alpha_j}^{(r)})/|\mathcal{S}_{\alpha_j}^{(r)}|$
19: **if** $x_j^{\mathcal{S}_{\alpha_j}^{(r)}} \leq x_j^{\mathcal{S}_i^{(r)}}$ **then**
20: $\mathcal{S}_{\alpha_j}^{(r)} := \mathcal{S}_{\alpha_j}^{(r)} \backslash \{j\}$
21: $\mathcal{S}_i^{(r)} := \mathcal{S}_i^{(r)} \bigcup \{j\}$
22: **end if**
23: **end if**
24: **end if**
25: ST_j updates $h(j)$ by adding its current coalition at the end of $h(j)$
26: **end for**

IV. Algorithms for Coalition Formation

In this section, we describe how to implement the CSSA scheme and the hedonic coalition formation game. We propose a DN selection algorithm, and a coalition formation algorithm based on the switch rule.

In order for the N SUs to play the hedonic coalition formation game, two stages are involved. In *stage one*, the AP gathers information about the number of PUs in the CRN, the operating frequency, bandwidth B_i of PU_i, $\forall\, i \in \mathcal{M}$, the locations of the PUs, the transmit power of the PUs $\sigma_{s,i}^2$, $\forall\, i \in \mathcal{M}$, and channel models. Although the AP has some information about the PUs, we assume that it does not know exactly when the PUs will be active. Then, all the SUs will communicate with the AP in order to obtain the information of the PUs. The AP will set the initial partition $\mathcal{S}^{(0)}$ and convey this initial partition to all the SUs. The initial partition is set as $\mathcal{S}_1^{(0)} = \mathcal{N}$ and $\mathcal{S}_l^{(0)} = \emptyset$, $\forall\, l \in \mathcal{M}\backslash\{1\}$. In *stage two*, all the SUs will perform the switch operations until the CRN converges to a final Nash-stable partition $\mathcal{S}^*$, which requires a total number of MAX iterations. Since the number of channels M and the number of SUs N are both finite, if the number of iterations MAX is large enough, the CRN can always converge to a final Nash-stable partition $\mathcal{S}^*$ according to Theorem 1. At each time frame, only one SU can leave its current coalition and move to another coalition in order to obtain a higher utility. In this stage, Algorithm 1 is used for the selection of DN_i, $\forall\, i \in \mathcal{M}$, and Algorithm 2 is used for the switch operations in coalition formation. After the coalition structure converges to the final Nash-stable partition $\mathcal{S}^*$, the SUs will stay in their current coalitions in $\mathcal{S}^*$ to sense and access the channels according to our proposed CSSA scheme.

We first present an algorithm for the DN selection in each coalition in Algorithm 1. We propose to choose the SU with the highest detection probability, which is defined in (2), in coalition $\mathcal{S}_i$ as DN_i. The reason is that the sensing results can be corrupted due to transmission error when they are sent by ST_j, $j \in \mathcal{S}_i$ to DN_i. If the SU with the highest detection probability is chosen as the DN, the most reliable sensing result from that SU is not required to be sent for reporting, and it can thus be used in the decision fusion without experiencing any corruption. Since DN_i decides the status of channel i, if PU_i is active, the primary data transmission can be protected by guaranteeing the most reliable sensing result is not corrupted, especially if the OR rule is used.

In the r-th iteration, Algorithm 1 is executed by ST_j, $\forall\, j \in \mathcal{S}_i$ in order to select $DN_i^{(r)}$ for channel $i \in \mathcal{M}$. Since ST_j determines which channel it should sense and access in each frame, ST_j knows the value of $i \in \mathcal{M}$. In the r-th iteration, all the SUs in coalition $\mathcal{S}_i^{(r)}$ have to exchange their measured SNR information in a dedicated error-free control channel [28] (lines 2-3). Besides, the information of transmission rate $R_{j,i}$ is also exchanged in order to compute the utilities in Algorithm 2. The SU with the highest measured SNR is chosen as $DN_i^{(r)}$ (lines 4-5). Since $P_{d,i,j}(\varepsilon,\, \delta,\, \sigma_{n,i}^2,\, \gamma_{i,j})$ is an increasing function of $\gamma_{i,j}$, we have the following proposition.

Proposition 2: The DN_i selected by Algorithm 1 has the highest detection probability in $\mathcal{S}_i$.

Next, we discuss the coalition formation based on the switch rule in Algorithm 2, which is executed by ST_j, $\forall\, j \in \mathcal{N}$ in the r-th iteration. In each iteration, Algorithm 2 consists of two phases: phase one (lines 3-8) and phase two (lines 9-25).

In phase one, one SU has to be selected, which is carried out as follows. A random number is first generated by each SU (line 4) and is broadcast in the dedicated control channel [28] (lines 6-7). The SU with the largest random number is selected (line 8) to perform the switch operation in phase two. At the beginning of phase two, we assume that user $ST_j \in \mathcal{S}_i^{(r)}$ and channel $\alpha_j \in \mathcal{M}$, where $\alpha_j \neq i$ (line 5), are selected. ST_j will be temporarily switched from its current coalition $\mathcal{S}_i^{(r)}$ to another coalition $\mathcal{S}_{\alpha_j}^{(r)}$ (lines 11-13). In line 12, ST_j obtains information of $\mathcal{S}_{\alpha_j}^{(r)}$ from $DN_{\alpha_j}^{(r)}$, which include data rates R_{k,α_j} ($\forall\, k \in \mathcal{S}_{\alpha_j}^{(r)}$), coalition size $|\mathcal{S}_{\alpha_j}^{(r)}|$, and statistics P_{d,α_j}, P_{f,α_j}, and $P_{\mathcal{H}_{0,\alpha_j}}$. If ST_j has already been to $\mathcal{S}_{\alpha_j}^{(r)}$ before (lines 14-17) or its achieved utility is reduced that $x_j^{\mathcal{S}_{\alpha_j}^{(r)}} \leq x_j^{\mathcal{S}_i^{(r)}}$ (lines 19-22), then ST_j will be switched back to its original coalition $\mathcal{S}_i^{(r)}$ (i.e., there is no net effect in the partition in the r-th iteration). Otherwise, ST_j will remain in coalition $\mathcal{S}_{\alpha_j}^{(r)}$. After that, ST_j will update its history set $h(j)$ (line 25).

Our proposed algorithms are *adaptive* to changes in network settings. When new PUs and SUs are deployed, existing PUs and SUs are removed, or the wireless channel conditions are changed, both stages one and two will be performed again in order to find the new Nash-stable partition. In practice, these two stages will be performed periodically for the CRN, where changes in network settings may occur occasionally.

V. Model Extension: Hedonic Coalition Formation Game with Nontransferable Utility

In this section, we extend the model considered in the previous sections and consider the coalition formation game under the *nontransferable utility* (NTU) framework. In Section III, we present the *cooperative* setting, where a SU considers the *average* data rate, penalty, and energy consumption of the *whole coalition* in its utility function in (9). Thus, all the users belonging to the same coalition receive the same utility, and we can apply the coalition formation algorithm for TU games. Alternatively, we consider the *non-cooperative* setting [20] in this section, where a SU considers its *individual* data rate, penalty, and energy consumption in its utility function. The coalition formation problem is formulated under the NTU framework. Specifically, in a NTU game, the value $v(\mathcal{S}_i)$ of coalition $\mathcal{S}_i$ is a $|\mathcal{S}_i|$-dimensional real vector that contains the utilities of all the players in the coalition. That is, $v(\mathcal{S}_i) = (x_j^{\mathcal{S}_i}, \forall\, j \in \mathcal{S}_i)$.

A. Utility Function

The *payoff* of player ST_j in $\mathcal{S}_i$ is defined as the *reward* (i.e., the amount of data transmitted by ST_j in $\mathcal{S}_i$) minus the *penalty* (i.e., the payment required by ST_j in $\mathcal{S}_i$ for interfering with PU_i's transmission) in the data transmission subframe. Similar to the analysis in Section III-A, we have four different scenarios related to the activity of the PU_i and the decision of DN_i in channel $i \in \mathcal{M}$.

Scenario 1: PU_i is silent and the decision made by DN_i is not a false alarm. In this scenario, $ST_j, \forall\, j \in \mathcal{S}_i$ transmits data during the data transmission subframe successfully. The payoff of ST_j is given by $x_{0|0,D,j}^{\mathcal{S}_i} = R_{j,i}(T-\delta)/|\mathcal{S}_i|$. The energy consumption of ST_j is given by $x_{0|0,E,j}^{\mathcal{S}_i} = P_s\delta + P_t(T-\delta)/|\mathcal{S}_i|$.

Scenario 2: PU_i is silent and the decision made by DN_i is a false alarm. In this scenario, since $ST_j, \forall\, j \in \mathcal{S}_i$ does not transmit during the idle data transmission subframe, and there is no interference with the PU. The payoff of ST_j is $x_{1|0,D,j}^{\mathcal{S}_i} = 0$, and the energy consumption of ST_j is $x_{1|0,E,j}^{\mathcal{S}_i} = P_s\delta$.

Scenario 3: PU_i is active and DN_i fails to detect the presence of the primary signal. In this scenario, ST_j interferes with PU_i's transmission. The payoff of ST_j is $x_{0|1,D,j}^{\mathcal{S}_i} = -D_0(T-\delta)/|\mathcal{S}_i|$, and the energy consumption of ST_j is $x_{0|1,E,j}^{\mathcal{S}_i} = P_s\delta + P_t(T-\delta)/|\mathcal{S}_i|$.

Scenario 4: PU_i is active and DN_i detects the presence of the primary signal. In this scenario, ST_j does not transmit during the data transmission subframe. The payoff of ST_j is $x_{0|1,D,j}^{\mathcal{S}_i} = 0$, and the energy consumption of ST_j is $x_{0|1,E,j}^{\mathcal{S}_i} = P_s\delta$.

Combining the analysis of the above four scenarios, the expected payoff of ST_j is given by

$$x_{D,j}^{\mathcal{S}_i} = \sum_{a=0}^{1}\sum_{b=0}^{1} P_{a|b,i}\, x_{a|b,D,j}^{\mathcal{S}_i}. \tag{12}$$

The expected energy consumption of ST_j is given by

$$x_{E,j}^{\mathcal{S}_i} = \sum_{a=0}^{1}\sum_{b=0}^{1} P_{a|b,i}\, x_{a|b,E,j}^{\mathcal{S}_i}. \tag{13}$$

The utility function of $ST_j, \forall\, j \in \mathcal{S}_i$ is thus given by

$$x_j^{\mathcal{S}_i} = \frac{x_{D,j}^{\mathcal{S}_i}}{x_{E,j}^{\mathcal{S}_i}} = \frac{P_{0|0,i}R_{j,i}(T-\delta) - P_{0|1,i}D_0(T-\delta)}{P_s|\mathcal{S}_i|\delta + (P_{0|0,i}+P_{0|1,i})P_t(T-\delta)}. \tag{14}$$

From (14), the utility function of $ST_j, \forall\, j \in \mathcal{S}_i$ depends only on the SUs in coalition $\mathcal{S}_i$, $i \in \mathcal{M}$. By applying the same preference function in (11), the NTU game described in this section is still a hedonic coalition formation game from Definition 3.

B. Coalition Formation Algorithm

Our proposed algorithms can be applied to the NTU setting with minor modifications. Notice that the main difference between the TU and NTU approaches is the definitions of the utility functions for each SU as given by (9) and (14), respectively. Therefore, we can still apply the switch rule to update the network partition, and all the SUs will still converge to the final partition $\mathcal{S}^* = \{\mathcal{S}_1^*, \ldots, \mathcal{S}_M^*\}$, which is both Nash-stable and individually stable [29]. Furthermore, we only need to make minor changes to the proposed Algorithms 1 and 2 for decision node selection and coalition formation in the NTU setting. Specifically, since we define the utility function of each SU in a different way in our NTU approach, the information of the transmission rate do not need to be exchanged in lines 2 and 3 of Algorithm 1. Also, in lines 10 and 18 of Algorithm 2, the utility $x_j^{\mathcal{S}_i}$ should be computed as in (14). With these modifications, our proposed hedonic coalition formation game framework is applicable in the NTU setting.

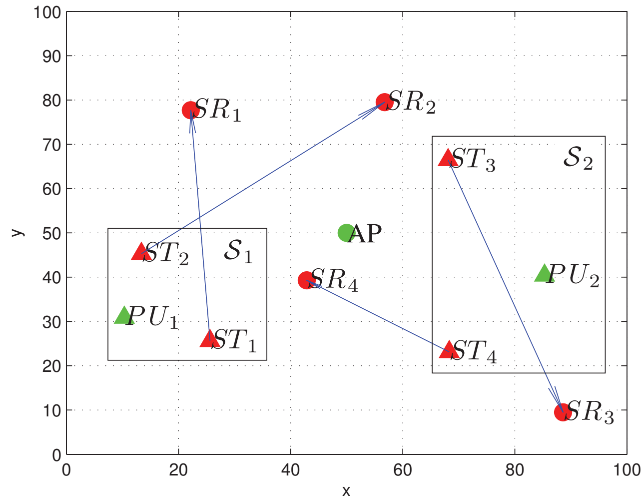


Fig. 2. An example of the Nash-stable partition ($M = 2$, $N = 4$). In this example, ST_1 and ST_2 belong to coalition $\mathcal{S}_1$, while ST_3 and ST_4 belong to coalition $\mathcal{S}_2$.

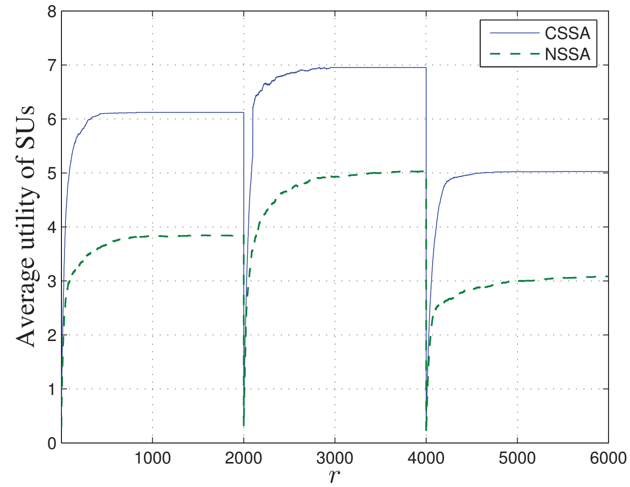


Fig. 3. The average utility of the SUs versus iteration index r ($M = 5$, $N = 10$). We can see that Algorithm 2 converges quickly to a stable partition again for both the CSSA and the NSSA schemes after the change in network topology. The change in network topology at $r = 2000$ and $r = 4000$ are due to the deployment of new PU and SUs, respectively.

VI. Performance Evaluation

In this section, we first present the results for the convergence of our algorithms. We then evaluate the performance gain of our CSSA scheme over the closest PU (CPU) scheme, where each SU chooses to sense the closest PU and joins that coalition to perform cooperative sensing. We also compare the CSSA scheme with the noncooperative spectrum sensing and access (NSSA) scheme, where the SUs perform local spectrum sensing only and do not combine their sensing results. Unless specified otherwise, we consider that there are one AP, five PUs (i.e., $M = 5$) and ten ST-SR pairs (i.e, $N = 10$). The positions of each node are randomly placed in a 100 m $\times$ 100 m square region. Notice that when M (or N) increases, the computational complexity of our algorithms is increased. However, a promising feature of our algorithms is that the average utility of the SUs improves in every iteration if the network condition is fixed. The bandwidth of the primary channel B_i is 10 MHz, $\forall\, i \in \mathcal{M}$. For all $i \in \mathcal{M}$ and $j \in \mathcal{N}$, we model the average channel gain of the link between PU_i and ST_j as $|g_{i,j}|^2 = 1/d_{i,j}^{\gamma}$, where $d_{i,j}$ is the distance between PU_i and ST_j, and γ is the path loss exponent. Also, we model the average channel gain of the link between ST_j and SR_j as $|h_{j,i}|^2 = 1/d_{j,i}^{\gamma}$, where $d_{j,i}$ is the distance between ST_j and SR_j. We choose γ to be equal to 2. Other parameters used in our simulations are as follows: the length of each time frame T is 100 ms; the sampling frequency f_s is 1 kHz; the transmit power of each ST P_t is 10 mW; the sensing power of each ST P_s is 10 mW; the detection threshold ε is 0.2 mW; the noise power $\sigma_{n,i}^2$ is 0.1 mW for all $i \in \mathcal{M}$. The probability that $PU_i, i \in \mathcal{M}$ is active is $P_{\mathcal{H}_{1,i}} = P_{\mathcal{H}_1} = 0.8, \forall\, i \in \mathcal{M}$. We choose the sensing duration δ to be 5 ms and the unit penalty per second D_0 to be 100. We assume that the OR rule is used for the data fusion. Each point is averaged over 100 independent simulation runs.

Fig. 2 shows an example of the Nash-stable partition. The AP is deployed at the centre of the square region with two PUs and four ST-SR pairs randomly placed. The nodes in the same rectangle represent the SUs belonging to the same coalition. From Fig. 2, we can see that ST_1 and ST_2 form a coalition in the channel of PU_1, while ST_3 and ST_4 form another coalition in the channel of PU_2. Therefore, the Nash-stable partition is $\{\{1, 2\}, \{3, 4\}\}$. In this Nash-stable partition, since ST_1 and ST_2 is closer to PU_1 than to PU_2, their probabilities of detecting the activity of PU_1 is higher than that of PU_2. Thus, they choose to sense and access the channel of PU_1 in the Nash-stable partition.

Fig. 3 shows the average utility of the SUs in each iteration using our proposed algorithms for the CRN. We assume that there is a new PU deployed in the CRN at $r = 2000$, and there are four SUs deployed at $r = 4000$. After each of these changes in the network topology, Algorithm 2 results in the organization of the SUs that eventually converges to a new Nash-stable partition. We can see that the average utility of the SUs at the Nash-stable partition is increased when a new PU joins the CRN, and decreased when four SUs join the CRN. Moreover, we can see that the average utility of the SUs achieved under the CSSA scheme is higher than that under the NSSA scheme.

In Fig. 4, we show the average utility of the SUs obtained by our algorithms versus the number of PUs M in the CRN when N is equal to 10. Our results show that the performance of CSSA is better than those of CPU and NSSA. For all schemes, the average utility of the SUs first increases with M, because the SUs can achieve higher utilities by utilizing the spectrum when the spectrum resources are increased. As for the CPU scheme, the SUs choose to sense the closest PU and that corresponding coalition can be too crowded. Thus, the performance of CPU is worse than CSSA. When $M < 10$ and $N > M$, the performance of CSSA is better than that of NSSA due to the *cooperative gain* [6] of cooperative spectrum sensing. When $M \geq 10$, each SU will choose to sense and access a different channel under CSSA and NSSA. Since there is only one SU in one channel, the average utilities of the SUs for both the CSSA scheme and the NSSA scheme are the same. Beside, when $M \geq 10$, the average utility of the SUs still

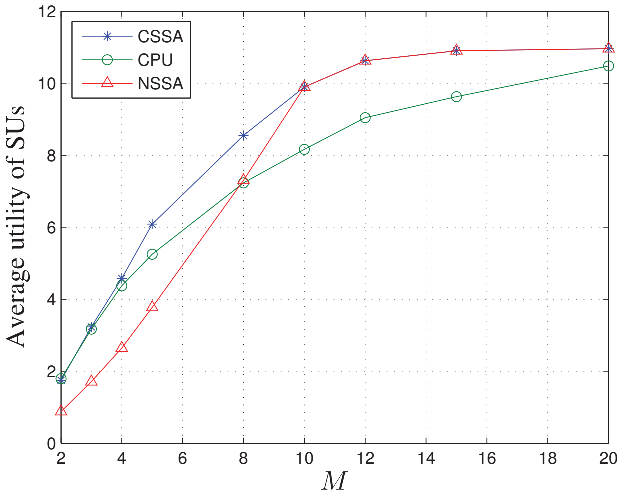


Fig. 4. The average utility of the SUs versus the number of PUs M ($N = 10$).

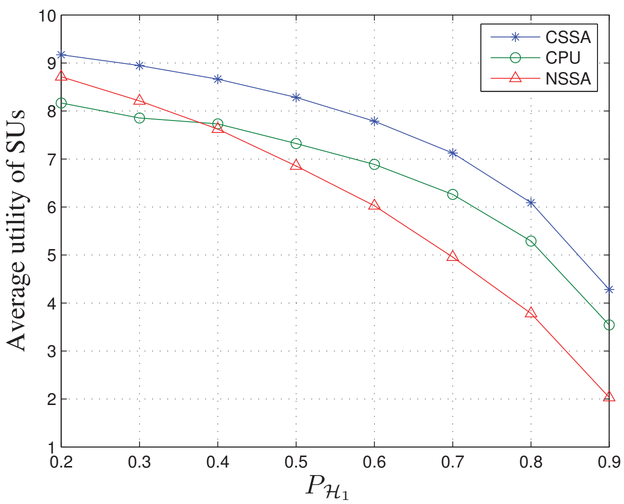


Fig. 5. The average utility of the SUs versus the probability for PUs being active $P_{\mathcal{H}_1}$ ($M = 5$, $N = 10$).

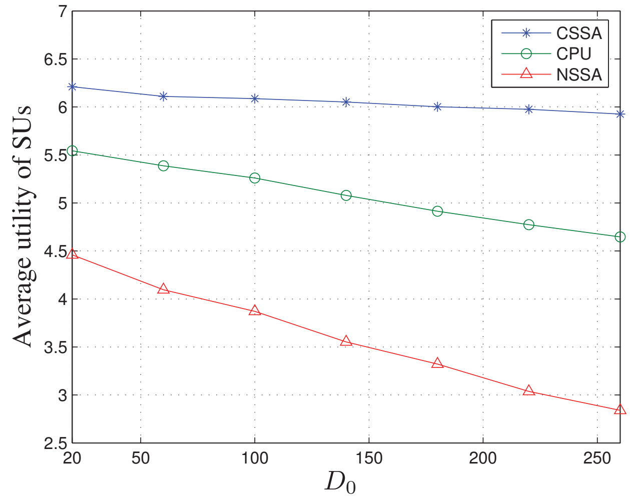


Fig. 6. The average utility of the SUs versus the unit penalty per second D_0 ($M = 5$, $N = 10$).

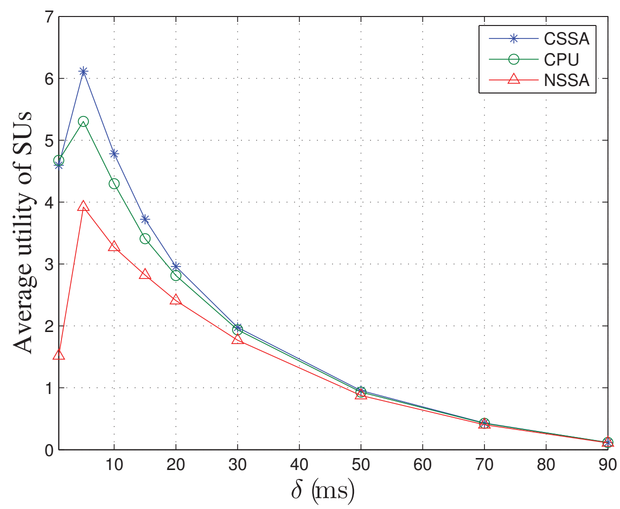


Fig. 7. The average utility of the SUs versus the sensing duration δ ($M = 5$, $N = 10$, $T = 100$ ms).

increases with M. It is because each SU may have a better choice of channels when there are more available channels in the CRN. When M is large, increasing M further will not improve the spectrum utilization too much, because the number of SUs is limited and the additional spectrum cannot be utilized by the SUs.

In Fig. 5, we show the average utility of the SUs versus the probability that PUs being active $P_{\mathcal{H}_1}$. Our results show that the performance of CSSA is better than CPU and NSSA. We can see the performance gap between CSSA and CPU does not change too much with $P_{\mathcal{H}_1}$, but the performance gap between CSSA and NSSA increases with $P_{\mathcal{H}_1}$. When $P_{\mathcal{H}_1}$ is small such that the channels are not often occupied by the PUs, the improved sensing accuracy due to cooperative spectrum sensing is not significant as the channels are vacant for most of the time. When $P_{\mathcal{H}_1}$ increases so that the PUs occupy the channels more frequently, the improved sensing accuracy by applying cooperative spectrum sensing helps the SUs detect the activities of the PUs correctly. Thus, the SUs pay less penalty for interfering the PUs' transmission and makes an effective use of the energy that has been consumed for sensing.

In Fig. 6, we show the average utility of the SUs obtained by the proposed algorithms versus the unit penalty D_0. Our results show that the performance of CSSA is better than CPU and NSSA. When D_0 is increased, the average utility of the SUs is decreased under all schemes. However, the rate of reduction of the average utility with D_0 for CSSA is much smaller so the performance gap between CSSA and the other two schemes increases with D_0. The reason is that when D_0 is large, each SU is incurred with a larger penalty if there is a missed detection. Since the probability of detection of the CSSA is higher than those of CPU and NSSA, therefore, the average utility of the SUs for CSSA will not decrease as significantly as CPU and NSSA when D_0 is increased.

In Fig. 7, we show the average utility of the SUs versus the sensing duration δ. Our results show that the CSSA scheme performs better than the CPU and NSSA schemes. Besides, for all three schemes, the average utility of the SUs first increases with δ, and then decreases with δ after reaching the optimum point. Therefore, there exists an optimal sensing duration for our proposed CSSA scheme, which is similar to the result in [9].

VII. Conclusions

In this paper, we studied cooperative spectrum sensing and channel access in a CRN with multiple licensed channels. We proposed a CSSA scheme and formulated the multi-channel spectrum sensing and channel access problem as a hedonic coalition formation game. The value function of each coalition and the utility function of each SU consider both the sensing accuracy and energy consumption. We proposed algorithms to find a Nash-stable partition, where no SU has the incentive to perform the switch operation in order to achieve a higher utility. Simulation results showed that the performance of our CSSA scheme is better than that of the CPU and NSSA schemes. Besides, the results showed that our algorithms result in the organization of the SUs that achieves a higher average utility of the SUs after each iteration, and that there is a Nash-stable partition for our formulated hedonic coalition formation game. Furthermore, the algorithms enable the SUs to adapt to changes in network conditions. For future work, we will extend our hedonic coalition formation game to a more general setting, where each SU can choose its sensing duration as part of its strategy.

References

[1] X. Hao, M. H. Cheung, V. W. S. Wong, and V. C. M. Leung, "A coalition formation game for energy-efficient cooperative spectrum sensing in cognitive radio networks with multiple channels," in *Proc. of IEEE Globecom*, Houston, TX, Dec. 2011.

[2] "Spectrum policy task force," Federal Communications Commission, Tech. Rep., 2002.

[3] J. Mitola III and G. Q. Maguire Jr., "Cognitive radio: Making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[4] X. Hao, M. H. Cheung, V. W. S. Wong, and V. C. M. Leung, "A Stackelberg game for cooperative transmission and random access in cognitive radio networks," in *Proc. of IEEE PIMRC*, Toronto, Canada, Sept. 2011.

[5] Y. Yi, J. Zhang, Q. Zhang, T. Jiang, and J. Zhang, "Cooperative communication-aware spectrum leasing in cognitive radio networks," in *Proc. of IEEE Symposium on New Frontiers in Dynamic Spectrum (DySPAN)*, Singapore, April 2010.

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

[7] M. Gandetto and C. Regazzoni, "Spectrum sensing: A distributed approach for cognitive terminals," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 3, pp. 546–557, April 2007.

[8] T. C. Aysal, S. Kandeepan, and R. Piesiewicz, "Cooperative spectrum sensing with noisy hard decision transmissions," in *Proc. of IEEE ICC*, Dresden, Germany, June 2009.

[9] Y.-C. Liang, Y. Zeng, E. C. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, April 2008.

[10] W. Saad, Z. Han, T. Basar, M. Debbah, and A. Hjorungnes, "Coalition formation games for collaborative spectrum sensing," *IEEE Trans. on Vehicular Technology*, vol. 60, no. 1, pp. 276–297, Jan. 2011.

[11] W.-Y. Lee and I. F. Akyildiz, "Optimal spectrum sensing framework for cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 7, no. 10, pp. 3845–3857, Oct. 2008.

[12] W. Wang, B. Kasiri, J. Cai, and A. S. Alfa, "Distributed cooperative multi-channel spectrum sensing based on dynamic coalitional game," in *Proc. of IEEE Globecom*, Miami, FL, Dec. 2010.

[13] C. Song and Q. Zhang, "Cooperative spectrum sensing with multi-channel coordination in cognitive radio networks," in *Proc. of IEEE ICC*, Cape Town, South Africa, May 2010.

[14] Q. Zhao, S. Geirhofer, L. Tong, and B. M. Sadler, "Opportunistic spectrum access via periodic channel sensing," *IEEE Trans. on Signal Processing*, vol. 56, no. 2, pp. 785–796, Feb. 2008.

[15] H. Su and X. Zhang, "Energy-efficient spectrum sensing for cognitive radio networks," in *Proc. of IEEE ICC*, Cape Town, South Africa, May 2010.

[16] L. Lu, H.-C. Wu, and S. Iyengar, "A novel robust detection algorithm for spectrum sensing," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 2, pp. 305–315, Feb. 2011.

[17] J. Meng, W. Yin, H. Li, E. Hossain, and Z. Han, "Collaborative spectrum sensing from sparse observations in cognitive radio networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 2, pp. 327–337, Feb. 2011.

[18] K. Koufos, K. Ruttik, and R. Jantti, "Distributed sensing in multiband cognitive networks," *IEEE Trans. on Wireless Communications*, vol. 10, no. 5, pp. 1667–1677, May 2011.

[19] A. Bogomolnaia and M. O. Jackson, "The stability of hedonic coalition structures," *Games and Economic Behavior*, vol. 38, pp. 201–230, Feb. 2002.

[20] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar, "Coalitional game theory for communication networks," *IEEE Signal Processing Magazine*, vol. 26, no. 5, pp. 77–97, Sept. 2009.

[21] W. Saad, Z. Han, T. Basar, M. Debbah, and A. Hjorungnes, "Hedonic coalition formation for distributed task allocation among wireless agents," *IEEE Trans. on Mobile Computing*, vol. 10, no. 9, pp. 1327–1344, Sept. 2011.

[22] IEEE 802.22 working group on wireless regional area networks. [Online]. Available: http://www.ieee802.org/22/

[23] W. Zhang and K. B. Letaief, "Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 7, no. 12, pp. 4761–4766, Dec. 2008.

[24] G. Ganesan and Y. Li, "Agility improvement through cooperative diversity in cognitive radio," in *Proc. of IEEE Globecom*, St. Louis, MO, Dec. 2005.

[25] S. Atapattu, C. Tellambura, and H. Jiang, "Energy detection based cooperative spectrum sensing in cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 10, no. 4, pp. 1232–1241, April 2011.

[26] O. Simeone, I. Stanojev, S. Savazzi, Y. Bar-Ness, U. Spagnolini, and R. Pickholtz, "Spectrum leasing to cooperating secondary ad hoc networks," *IEEE Journal on Selected Areas in Communications*, vol. 26, no. 1, pp. 203–213, Jan. 2008.

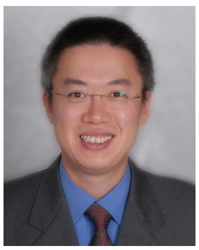
[27] D. Ray, *A Game-Theoretic Perspective on Coalition Formation*. Oxford University Press, 2007.

[28] B. F. Lo, I. F. Akyildiz, and A. M. Al-Dhelaan, "Efficient recovery control channel design in cognitive radio ad hoc networks," *IEEE Trans. on Vehicular Technology*, vol. 59, no. 9, pp. 4513–4526, Nov. 2010.

[29] W. Saad, Z. Han, T. Basar, A. Hjorungnes, and J. B. Song, "Hedonic coalition formation games for secondary base station cooperation in cognitive radio networks," in *Proc. of IEEE WCNC*, Sydney, Australia, Apr. 2010.

Xiaolei Hao (S'11) was born in Lanzhou, Gansu, China, in 1987. He received the B.Eng. degree in Communication Engineering from the Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2009, and the M.A.Sc. degree in Electrical and Computer Engineering from the University of British Columbia (UBC), Vancouver, BC, Canada, in 2011. He worked as a Software Engineer at Microsoft, Beijing, China, in 2008, and at Key Laboratory of Optical Communications in BUPT, Beijing, China, in 2009. Since October 2011, he has been with the TELUS Mobility, Vancouver, Canada, where he is now working as a Radio Frequency (RF) Engineer. His research interests include wireless communication, optical communication, game theory, and protocol design.

Man Hon Cheung (S'06) received the B.Eng. and M.Phil. degrees in Information Engineering from the Chinese University of Hong Kong (CUHK) in 2005 and 2007, respectively, and the Ph.D. degree in Electrical and Computer Engineering from the University of British Columbia (UBC) in 2012. Currently, he is a postdoctoral fellow in the Department of Information Engineering in CUHK. He received the IEEE Student Travel Grant for attending *IEEE ICC 2009*. He was awarded the Graduate Student International Research Mobility Award by UBC, and the Global Scholarship Programme for Research Excellence by CUHK. He serves as a Technical Program Committee member in *IEEE ICC* and *WCNC*. His research interests include the design and analysis of medium access control protocols in wireless networks using optimization theory, game theory, and dynamic programming.



Vincent W.S. Wong (SM'07) received the B.Sc. degree from the University of Manitoba, Winnipeg, MB, Canada, in 1994, the M.A.Sc. degree from the University of Waterloo, Waterloo, ON, Canada, in 1996, and the Ph.D. degree from the University of British Columbia (UBC), Vancouver, BC, Canada, in 2000. From 2000 to 2001, he worked as a systems engineer at PMC-Sierra Inc. He joined the Department of Electrical and Computer Engineering at UBC in 2002 and is currently a Professor. His research areas include protocol design, optimization, and resource management of communication networks, with applications to the Internet, wireless networks, smart grid, RFID systems, and intelligent transportation systems. Dr. Wong is an Associate Editor of the *IEEE Transactions on Communications* and *IEEE Transactions on Vehicular Technology*, and an Editor of *KICS/IEEE Journal of Communications and Networks*. He is the Symposium Co-chair of *IEEE Globecom'13 − Communication Software, Services, and Multimedia Application Symposium*. Dr. Wong has also served as the Symposium Co-chair of *IEEE Globecom'11 − Wireless Communications Symposium*.

Victor C. M. Leung (S'75, M'89, SM'97, F'03) received the B.A.Sc. (Hons.) degree in electrical engineering from the University of British Columbia (U.B.C.) in 1977, and was awarded the APEBC Gold Medal as the head of the graduating class in the Faculty of Applied Science. He attended graduate school at U.B.C. on a Natural Sciences and Engineering Research Council Postgraduate Scholarship and completed the Ph.D. degree in electrical engineering in 1981.

From 1981 to 1987, Dr. Leung was a Senior Member of Technical Staff at MPR Teltech Ltd., specializing in the planning, design and analysis of satellite communication systems. In 1988, he was a Lecturer in the Department of Electronics at the Chinese University of Hong Kong. He returned to U.B.C. as a faculty member in 1989, where he is currently a Professor and the inaugural holder of the TELUS Mobility Research Chair in Advanced Telecommunications Engineering in the Department of Electrical and Computer Engineering. Dr. Leung has co-authored more than 600 technical papers in international journals and conference proceedings, several of which had been selected for best paper awards. His research interests are in the broad areas of wireless networks and mobile systems.

Dr. Leung is a registered professional engineer in the Province of British Columbia, Canada. He is a Fellow of IEEE, the Engineering Institute of Canada, and the Canadian Academy of Engineering. He has served on the editorial boards of the *IEEE Journal on Selected Areas in Communications - Wireless Communications Series*, the *IEEE Transactions on Wireless Communications* and the *IEEE Transactions on Vehicular Technology*, and is serving on the editorial boards of the *IEEE Transactions on Computers*, *IEEE Wireless Communications Letters*, the *Journal of Communications and Networks*, *Computer Communications*, as well as several other journals. He has guest-edited many journal special issues, and served on the technical program committee of numerous international conferences. He has chaired or co-chaired many conferences and workshops. Dr. Leung was the recipient of the IEEE Vancouver Section Centennial Award and the 2011 U.B.C. Killam Research Prize.