# Cooperative Spectrum Prediction in Multi-PU Multi-SU Cognitive Radio Networks

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***Abstract*—Spectrum sensing is considered as the cornerstone of cognitive radio networks (CRNs). Sensing the wide band spectrum, however, may result in delays and reduce the efficiency of resource utilization. Spectrum prediction, therefore, has been proposed as a promising approach to overcome these shortcomings. Prediction of the channel occupancy, when feasible, provides adequate means for an SU to determine, with a high probability, when to evacuate a channel it currently occupies in anticipation of the PU's return. Spectrum prediction has great potential to reduce interference with PU activities and significantly enhance spectral efficiency. In this paper, we propose a novel, coalitional game theory based approach to investigate cooperative spectrum prediction in multi-PU multi-SU CRNs. In this approach, cooperative groups, also referred to as coalitions, are formed through a proposed coalition formation algorithm. A through simulation study is performed to assess the effectiveness of the proposed approach. The simulation results indicate that cooperative spectrum prediction leads to more accurate prediction decisions, in comparison with local spectrum prediction individually performed by SUs. To the best of our knowledge, this work is the first to use coalitional game theory to study cooperative spectrum prediction in CRNs, involving multiple PUs.**

## I. Introduction

With the proliferation of various forms of mobile devices, the radio spectrum has fast become a scarce and expensive resource. Various spectrum utilization studies, however, have shown large portions of the overall spectrum remain severely under-utilized, while the demand for bandwidth continues to increase. To achieve better management of spectral resources, cognitive radio [1]–[6] has emerged as a promising technology to harness the potential of unused spectrum in an opportunistic manner. Cognitive radio networks (CRNs) typically involve two classes of users: primary users (PUs), who are incumbent licensees of the spectrum, and secondary users (SUs), who are allowed to opportunistically operate on licensed spectrum bands, as long as their transmissions do not cause harmful interference with the activities of the PUs.

In order to enhance spectrum sharing, while keeping the impact of interference on PUs at a minimal level, a number of spectrum sensing methods have been proposed to allow SUs to locate spatially and/or temporally available spectrum holes. A major challenge in spectrum sensing is the ability of the underlying sensing technique to detect weak PU signals with minimal delay. Measurement studies, however, have shown that the non-negligible delay, introduced by the underlying hardware platform, can negatively impact the accuracy of spectrum sensing. Moreover, sensing the wide-band spectrum results in a waste of resources. To tackle these shortcomings, spectrum prediction, also known as channel status prediction, has been proposed as an alternative approach to manage spectrum holes.

There are two types of spectrum prediction techniques. *Local spectrum prediction*, in which each SU senses the current channel state and uses a hidden Markov model (HMM) to predict the future channel states, has been investigated in [7], [8] for real-time spectrum sensing to avoid interference caused by the response delay, and in [9] to enable an SU to leave its currently occupied channel before a PU starts transmission. Recent work [10]–[12] show that when the performance of an individual is worse than that within a group, individuals are motivated to form cooperative groups to maximize the benefit of the system and/or themselves, resulting in *cooperative spectrum prediction*. Designing efficient cooperation algorithms with high prediction accuracy and low false alarm rate, however, entail numerous challenges, including the ability of the algorithm to overcome the natural selfish behavior of wireless users and to minimize cooperation overhead. [13] studies the cooperative spectrum sensing problem for a cognitive radio network with one primary user. A cooperative spectrum sensing approach, where the SUs form cooperative groups to improve their sensing accuracy, is proposed. In this approach, the cooperative group formation process is constructed as a coalitional game and each cooperative group, referred to as a coalition, is formed by balancing the tradeoff between the gain in terms of detection probability and the cost in terms of false alarm rate.

In this paper, we use a coalition-based approach for spectrum prediction, but, more general than previous work [13], the focus is on the challenging problem of improving the spectrum prediction accuracy in cognitive radio networks with multiple primary users. Within this framework, three unique and significant contributions are achieved: first, the focus of this work goes beyond a single PU CRN and addresses the more practical and challenging multi-PU scenario [5], [6]; second, we define a preference order for the SUs and propose a novel coalition formation algorithm; last, we conduct simulation with different number of PUs and SUs to validate the effectiveness of the proposed cooperative prediction algorithm in a multi-PU, multi-SU CRN environment. To the best of our knowledge, this work is the first to use a coalitional game theory based framework for accurate cooperative spectrum prediction in CRNs, with multiple PUs.

The rest of the paper is organized as follows. The system model and some preliminary knowledge are briefly described in Section II. We design the coalitional game based cooperative spectrum prediction scheme in Section III. Simulation results are presented and analyzed in Section IV. We conclude the paper in Section V.

## II. Network Model and Preliminaries

### A. System Model and Problem Description

In this paper, we consider a database-assisted CRN, which consists of $M$ PUs and $N$ SUs. The set of PUs and SUs are denoted by $\mathcal{M} = \{1, 2, \cdots, M\}$ and $\mathcal{N} = \{1, 2, \cdots, N\}$, respectively. $M$ orthogonal channels are allocated to $M$ primary users, with $c_i, i \in \{1, 2, \cdots, M\}$, representing the channel owned by PU $i$. In this CRN, a database consisting of the locations and licensed channels associated to all PUs is available to the SUs. It is worth noting that this architecture is similar to the one suggested in the second memorandum opinion and order (FCC 10-174) [14]. Based on the IEEE 802.22 standard specifications, which require that a cognitive radio device vacate its spectrum band within 2 seconds after the appearance of a PU [15], we assume that the CRN system is time-slotted and the length of a slot is expressed in seconds.

| Time slots | 1 | 2 | …… | $\tau$ | …… |
|---|---|---|---|---|---|
| True states | $q_i^1$ | $q_i^2$ | …… | $q_i^\tau$ | …… |
| Observations | $o_{ji}^1$ | $o_{ji}^2$ | …… | $o_{ji}^\tau$ | …… |

Fig. 1. An illustration of the spectrum sensing process in time-slotted system.

At the beginning of each time slot, the busy/idle status of a channel is detected by the SUs via energy detection based spectrum sensing techniques [16], [17]. The spectrum sensing process of SU $j \in \mathcal{N}$ on channel $c_i$, is illustrated in Fig. 1. Based on this process, SU $j$ obtains an observation $o_{ji}^t$ on the true state $q_i^t$ of channel $c_i$ at each time slot $t$. The observation $o_{ji}^t$ is the local decision of SU $j$ regarding the primary channel status $q_i^t$. SU $j$'s decision on $c_i$ is a *detection*, if $o_{ji}^t = busy$ and $q_i^t = busy$, and a *false alarm*, if $o_{ji}^t = busy$ and $q_i^t = idle$. Based on the analytical model presented in [17], the closed-form expression of the detection probability, $P_{dji}$, and the false alarm probability, $P_{fji}$, are represented in (1) and (2), respectively.

$$\begin{aligned} P_{dji} =& e^{-\frac{\delta}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\delta}{2}\right)^n + \left(\frac{1+\overline{\gamma}_{ji}}{\overline{\gamma}_{ji}}\right)^{m-1} \\ & \times \left[ e^{-\frac{\delta}{2(1+\overline{\gamma}_{ji})}} - e^{-\frac{\delta}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\delta \overline{\gamma}_{ji}}{2(1+\overline{\gamma}_{ji})}\right)^n \right] \end{aligned} \tag{1}$$

$$P_{fji} = \frac{\Gamma(m, \frac{\delta}{2})}{\Gamma(\mu)} \tag{2}$$

In the above expressions, $\delta$ is the energy threshold of the energy detector, $m$ is the time bandwidth product, $\overline{\gamma}_{ji}$ is the average SNR of SU $j$ on channel $c_i$, and $\Gamma(.,.)$ represents the incomplete gamma function, while $\Gamma(.)$ represents the gamma function. Furthermore, $\overline{\gamma}_{ji}$ is defined as $\overline{\gamma}_{ji} = \frac{P_i h_{ij}}{\sigma^2}$, where $P_i$ represents the transmit power of PU $i$, $\sigma^2$ represents the Gaussian noise variance and $h_{ij}$ represents the path loss between PU $i$ and SU $j$; $h_{ij}$ is defined as $h_{ij} = \frac{\kappa}{d_{ij}^{\mu}}$, where $\kappa$ is the path loss constant, $\mu$ is the path loss exponent, and $d_{ij}$ is the distance between PU $i$ and SU $j$.

Let $P_{mji}$ be the miss detection ($o_{ji}^t = idle$ and $q_i^t = busy$) probability of SU $j$ on channel $c_i$, then:

$$P_{mji} = 1 - P_{dji} \tag{3}$$

In the spectrum sensing process illustrated by Fig. 1, the channel occupancy states (busy or idle), determined by the PU activities (on or off), form a Markov process [18]. These states are *hidden* since they are not directly observable. On the other hand, each SU $j$ generates its observation sequence based on its spectrum sensing results, which forms the set of *observation states*. This process is a normal random process that depends on both the PU activities and the spectrum sensing accuracy of SU $j$ (i.e., $P_{dji}$ and $P_{fji}$). Therefore, the spectrum sensing process can be modeled as a HMM. Define the hidden state space as $X$=$\{x_0, x_1\}$, with $x_0$=0 and $x_1$=1 indicating that the primary channel is idle and busy, respectively. Similarly, the observation state space is defined as $Y$=$\{y_0, y_1\}$, with $y_0$=0 and $y_1$=1 indicating that the spectrum sensing result is idle and busy, respectively. Then the HMM can be described by its parameters $\lambda$=$(\pi, A, B)$, where $\pi$ is the initial state distribution: $\pi$=$[\pi_i]_{1\times 2}$, with $\pi_i$=Pr$(q^0 = x_i), i = 0, 1$; $A$ is the state transition probability matrix: $A$=$[a_{ij}]_{2\times 2}$, with $a_{ij}$=Pr$(q^{t+1} = x_j | q^t = x_i), i, j = 0, 1$; and $B$ is the emission probability matrix: $B$=$[b_{jk}]_{2\times 2}$, with $b_{jk}$=Pr$(o^t = y_k | q^t = x_j), j, k = 0, 1$. It is clear that in a perfect case it holds that $b_{11}$=$P_{dji}$ and $b_{01}$=$P_{fji}$.

After sensing channel $c_i$ for $T$ slots, SU $j$ forms an observation sequence $O_{ji} = \{o_{ji}^1, \cdots, o_{ji}^T\}$ and trains a specific HMM. As discussed in [19], HMM based local spectrum prediction can be performed by each SU to make a local prediction decision of the future channel status of $c_i$. In order to improve the prediction accuracy, we propose a coalitional game theory based cooperative prediction scheme. Prior to describing the scheme, we briefly introduce in the following two subsections preliminary issues and definitions related to

HMM based local spectrum prediction and coalitional game theory, respectively.

### B. HMM Based Local Spectrum Prediction

There are two stages in the HMM based local spectrum prediction algorithm [19], with the first one being the HMM training process and the second one being the prediction decision making process.

In the HMM training process, each SU estimates the parameters of the HMM. For SU $j \in \mathcal{N}$, it forms an observation sequence $O_{ji} = \{o_{ji}^1, \cdots, o_{ji}^T\}$ through $T$-slot spectrum sensing on channel $c_i$. Then, the training process can be considered as an optimization problem which aims to find the optimal parameters that can maximize the probability of obtaining the observation sequence $O_{ji}$:

$$\lambda_{ji}^* = \arg\max \Pr(O_{ji}|\lambda_{ji}) \tag{4}$$

Performing the Baum-Welch algorithm [20] leads to the solution of the optimization problem described in (4). We use $\lambda_{ji}^* = (\pi_{ji}^*, A_{ji}^*, B_{ji}^*)$ to denote the optimal solution.

With the estimated parameters $\lambda_{ji}^* = (\pi_{ji}^*, A_{ji}^*, B_{ji}^*)$, SU $j$ makes a local prediction about the future state of channel $c_i$ in the prediction decision making process. The prediction decision is made according to the following rule:

$$\widehat{o}_{ji}^{T+1} = \begin{cases} 1, \\ \text{if } \Pr(o_{ji}^{T+1} = 1|O_{ji}, \lambda_{ji}^*) \geq \Pr(o_{ji}^{T+1} = 0|O_{ji}, \lambda_{ji}^*) \\ 0, \\ \text{if } \Pr(o_{ji}^{T+1} = 1|O_{ji}, \lambda_{ji}^*) < \Pr(o_{ji}^{T+1} = 0|O_{ji}, \lambda_{ji}^*) \end{cases} \tag{5}$$

### C. Preliminaries of Coalitional Game Theory

According to [21], a coalitional game can be defined as follows:

**Definition 1** (**Coalitional Game**). *A coalitional game $G$ is a pair $(\mathcal{N}, (\succeq_j)_{j\in\mathcal{N}})$, where $\mathcal{N}$ is a finite player set with $j$ being an individual player. Each player attempts to form a coalition (cooperative group) with others and cooperatively work on certain tasks in order to gain benefits for itself and/or for the whole system. $\succeq_j$ is the preference order of player $j$ on $D_j(\mathcal{N})$ with $D_j(\mathcal{N})$ being the set of coalitions that $j$ belongs to. For any two coalitions $R \in D_j(\mathcal{N})$ and $S \in D_j(\mathcal{N})$, $R \succeq_j S$ indicates that player $j$ prefers to join coalition $R$ than coalition $S$.*

Each player $j \in \mathcal{N}$ tries to form a coalition according to the preference order $\succeq_j$, and different coalition structures can be constructed during the coalition formation process.

**Definition 2** (**Coalition Structure**). *A coalition structure $\omega = \{S_1, S_2, \cdots, S_K\}$, with $K \leq |\mathcal{N}|$ being a positive integer, and $S_k \neq \varnothing$, $k \in \{1, 2, \cdots, K\}$, being a certain coalition, is a partition of the player set $\mathcal{N}$ that satisfies:* 1) $\cup_{k=1}^K S_k = \mathcal{N}$ *and* 2) $S_k \cap S_l = \varnothing$ *for any $k, l \in \{1, 2, \cdots, K\}$ with $k \neq l$.*

Different coalition formation process may lead to different coalition structures and cooperation performances. Therefore, we will design an effective coalition formation algorithm for the cooperative spectrum prediction scheme in the next section.

## III. Coalitional Game Based Cooperative Spectrum Prediction

In this section, we study the cooperative spectrum prediction via a coalitional game based approach, where the secondary users are considered as the players who attempt to form coalitions and cooperatively predict the future channel status. Coalition formation is an important process in our coalitional game based cooperative spectrum prediction; through this process, a coalition structure consisting of several coalitions can be constructed. Within each coalition, an SU is selected to perform as the coalition leader, whose responsibility includes collecting the local prediction results from other members of the coalition and making a final cooperative prediction decision based on the OR rule data fusion.

However, the considered multi-PU multi-SU scenario brings a specific challenge to the design of the cooperative spectrum prediction scheme. Due to the hardware limitations, each SU can only sense one channel and form one observation sequence at a time [22]. According to (4) and (5), however, the observation sequence is necessary in order to predict future states of a channel. Since it is impossible for an SU to make prediction for more than one channel at the same time, each SU should choose only one channel to sense and predict with the assistance of the database. Consequently, the SUs should be first classified into $M$ categories, with each category $C_i, i = \{1, 2, \cdots, M\}$, being the set of SUs choosing channel $c_i$ for sensing and predicting. Based on this classification, a coalition structure $\omega_i = \{S_1^i, S_2^i, \cdots, S_K^i\}$ is formed for each category $C_i$, where $S_k^i$ is the $k$th coalition for category $i$, and $K$ is the total number of coalitions in category $i$. Note that different categories may have different number of coalitions. In the following subsections, we describe the proposed category classification method, define the preference order of the secondary users, and design the coalition formation algorithm.

### A. Category Classification: Channel Selection for Spectrum Sensing and Prediction

In this subsection, we derive a category classification scheme, according to which, each SU chooses a channel for spectrum sensing and prediction.

It can be seen from equations (4) and (5) that both the estimation process and the prediction process are dependent on the observation sequence. Consequently, SU $j$ can more precisely estimate the parameters of the HMM if it can be provided with a more accurate observation sequence $O_{ji}$. Furthermore, using more precise estimation of $\lambda_{ji}^*$ and $O_{ji}$, SU $j$ can make more accurate prediction of future states of channel $c_i$. Thus, if SU $j$ is capable of performing the highest sensing accuracy on channel $c_i$, SU $j$ chooses $c_i$ for spectrum sensing and prediction to improve its sensing and prediction accuracy.

The sensing accuracy of SU $j$ on channel $c_i$ can be defined as $P_{aji} = P_{dji} + (1 - P_{fji})$. According to equation (2), $P_{fji}$

is only dependent on the time bandwidth product $m$ and the energy threshold $\delta$ of the energy detector. Consequently, SU $j$ has the same false alarm probability on all primary channels. That is, for any $i_1 \neq i_2 \in \mathcal{M}$, it holds $P_{fji_1} = P_{fji_2}$. Therefore, $P_{dji}$ has the decisive influence on the sensing accuracy. Substitute $\overline{\gamma}_{ji} = \frac{P_i h_{ij}}{\sigma^2}$ into equation (1), we have:

$$\begin{aligned} P_{dji} =& e^{-\frac{\delta}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\delta}{2}\right)^n + \left(\frac{P_i\kappa + \sigma^2 d_{ij}^{\mu}}{P_i\kappa}\right)^{m-1} \cdot \\ & \left[ e^{\frac{\sigma^2 d_{ij}^{\mu}\delta}{2(\sigma^2 d_{ij}^{\mu} + P_i\kappa)}} - e^{-\frac{\delta}{2}} \sum_{n=0}^{m-1} \frac{1}{n!} \left(\frac{\delta P_i \kappa}{2(\sigma^2 d_{ij}^{\mu} + P_i\kappa)}\right)^n \right] \end{aligned} \tag{6}$$

In (6), $\delta, P_i, \kappa, \mu, \sigma^2$, and $m$ are all constants. $P_{dji}$ is, therefore, a decreasing function of $d_{ij}$, the distance between SU $j$ and PU $i$. Thus SU $j$ has the highest sensing accuracy on channel $c_i$ when PU $i$ is the nearest one from SU $j$, and it will choose $c_i$ for spectrum sensing and prediction to improve its sensing and prediction accuracy.

Therefore, we show that SU $j$ is always classified into category $i$ ($C_i$), when PU $i$ is the nearest primary user from SU $j$.

### B. Preference Order of Secondary Users

After the category classification process, the SUs are classified into $M$ categories. Based on this classification, coalitions are formed within each category. As described in Section II-C, the SUs of a category $C_i, i = 1, 2, \cdots, M$, seek to form coalitions in order to improve the network performance (unselfish players) or their own performance (selfish players). In this paper, we consider the case where SUs are selfish players, whose intention is to improve their own prediction accuracy through forming coalitions. Based on this assumption, we derive the preference order of the secondary users. Since coalitions are formed within each category, we study the coalition formation problem within a specific category $C_i$.

According to [13], the cooperative miss prediction (i.e., the predicted state is idle while the true channel state is busy) probability $\Psi_m$ and cooperative prediction false alarm (i.e., the predicted state is busy while the true channel state is idle) probability $\Psi_f$ of coalition $S_k^i$, with coalition leader $\hat{a}$ (SU $\hat{a}$), are, respectively, defined by:

$$\Psi_m(S_k^i) = \Pi_{j \in S_k^i}[\psi_{mji}(1 - P_{ej\hat{a}}) + (1 - \psi_{mji})P_{ej\hat{a}}] \tag{7}$$

$$\Psi_f(S_k^i) = 1 - \Pi_{j \in S_k^i}[(1 - \psi_{fji})(1 - P_{ej\hat{a}}) + \psi_{fji}P_{ej\hat{a}}] \tag{8}$$

In the above expressions, $\psi_{mji}$ and $\psi_{fji}$ represent the local miss prediction probability and local prediction false alarm probability of SU $j \in S_k^i$, respectively; and $P_{ej\hat{a}}$ represents the probability that an error occurs during the transmission from SU $j$ to the coalition leader $\hat{a}$. In a Rahleigh fading environment, $P_{ej\hat{a}}$ is given by:

$$P_{ej\hat{a}} = \frac{1}{2}\left(1 - \sqrt{\frac{\overline{\gamma}_{j\hat{a}}}{1 + \overline{\gamma}_{j\hat{a}}}}\right) \tag{9}$$

where $\overline{\gamma}_{j\hat{a}}$ is the average SNR from SU $j$ to the coalition leader $\hat{a}$ given by $\overline{\gamma}_{j\hat{a}} = \frac{P_j h_{j\hat{a}}}{\sigma^2}$, with $P_j$ being the transmit power of SU $j$, $h_{j\hat{a}}$ being the path loss between SU $j$ and its coalition leader $\hat{a}$, and $\sigma^2$ being the Gaussian noise variance. In order to minimize the reporting error, coalition leader should be appropriately selected so that the following holds:

$$\hat{a} = \arg\max \frac{\sum_{j \in \{S_k^i \setminus \hat{a}\}} \overline{\gamma}_{j\hat{a}}}{|\{S_k^i \setminus \hat{a}\}|} \tag{10}$$

where $\{S_k^i \setminus \hat{a}\}$ represents the set of SUs in coalition $S_k^i$ except SU $\hat{a}$ and $|\{S_k^i \setminus \hat{a}\}|$ represents the coalition size.

It is clear from (7) and (8) that SU $j$ can decrease its miss prediction probability at the cost of increasing its prediction false alarm probability by joining coalition $S_k^i$. Thus, the improved prediction accuracy for SU $j$ is $(\Psi_d(S_k^i) - \psi_{dji}) - (\Psi_f(S_k^i) - \psi_{fji})$, where $\Psi_d(S_k^i) = 1 - \Psi_m(S_k^i)$ and $\psi_{dji} = 1 - \psi_{mji}$ represent the cooperative prediction (i.e., the predict result is busy while the true channel state is busy) probability and the local prediction probability, respectively. Therefore, a utility function $\phi_j(S_k^i)$ can be associated with each SU $j \in \mathcal{N}$ to evaluate its performance improvement by joining coalition $S_k^i$.

$$\begin{aligned} \phi_j(S_k^i) &= (\Psi_d(S_k^i) - \psi_{dji}) - (\Psi_f(S_k^i) - \psi_{fji}) \\ &= (\Psi_d(S_k^i) - \Psi_f(S_k^i)) - (\psi_{dji} - \psi_{fji}) \end{aligned}$$

Let $V(S_k^i) = \Psi_d(S_k^i) - \Psi_f(S_k^i)$ denote the value of coalition $S_k^i$, we have:

$$\phi_j(S_k^i) = V(S_k^i) - (\psi_{dji} - \psi_{fji}) \tag{11}$$

Based on the above analysis, we define the preference order for SUs in the coalitional game $(\mathcal{N}, (\succeq_j)_{j \in \mathcal{N}})$ as:

$$S_k^i \succeq_j S_l^i := \phi_j(S_k^i) \geq \phi_j(S_l^i) \tag{12}$$

In the above expression, $S_k^i$ and $S_l^i$ are two different potential coalitions within Category $i$ ($C_i$), and $j \in S_k^i \cap S_l^i$. The preference order between two coalitions shows that SU $j$ prefers to joint the coalition which results in the greater improvement of the prediction accuracy.

For a specific SU $j$, the value of $\psi_{dji}$ and $\psi_{fji}$ are both fixed; consequently, $\phi_j(S_k^i) \geq \phi_j(S_l^i) \Leftrightarrow V(S_k^i) \geqslant V(S_l^i)$. In other words,, $V(S_k^i) \geqslant V(S_l^i)$ means coalition $S_k^i$ is more valuable than $S_l^i$ because any SU $j \in S_k^i \cap S_l^i$ prefers coalition $S_k^i$ than $S_l^i$. Similarly, we can define an ordering $\succeq$ among coalitions. More specifically, for any two coalitions $R$ and $S$, we have:

$$R \succeq S := V(R) \geq V(S) \tag{13}$$

### C. Coalition Formation Algorithm

According to the analysis in Section III-B, the coalition value $V(\cdot)$ is an important factor to be considered when forming coalitions. In this subsection, we propose a coalition formation algorithm whose pseudocode is presented in Algorithm 1.

**Algorithm 1** Coalition Formation Algorithm

**for** $i = 1 : M$ **do**
  $C_i \leftarrow \emptyset$
  **for** $j = 1 : N$ **do**
    **if** $d_{ij} = \min d_{i'j}, i' \in \{1, 2, \cdots, M\}$ **then**
      $C_i \leftarrow \{C_i, j\}$
    **end if**
  **end for**
  $k \leftarrow 1$
  $\omega_i \leftarrow \emptyset$
  **while** $C_i \neq \emptyset$ **do**
    Calculate the set of all possible coalitions and their coalition values
    Denote the coalition with highest value among all possible coalitions by $S_k^i$
    $\omega_i \leftarrow \{\omega_i, S_k^i\}$
    $C_i \leftarrow C_i \setminus S_k^i$
    $k \leftarrow k + 1.$
  **end while**
**end for**

## IV. SIMULATION

A simulation study is performed to assess the effectiveness of the proposed coalition formation algorithm. In this simulation study, the parameters are set according to the values listed in Table I [13].

TABLE I
SYSTEM PARAMETERS

| parameter | meaning | value |
|---|---|---|
| $m$ | time bandwidth product | 5 |
| $\kappa$ | path loss constant | 1 |
| $\mu$ | path loss exponent | 3 |
| $\sigma^2$ | Gaussian noise variance | $-90dBm$ |
| $P_{PU}$ | transmission power of PU | $100mW$ |
| $P_{SU}$ | transmission power of SU | $10mW$ |

First, we form a cognitive radio network with 3 PUs (denoted by black squares) and 21 SUs (denoted by blue circles). The PUs and SUs are all randomly deployed in a $3km \times 3km$ square area as shown Fig. 2.

Performing our proposed coalition formation algorithm for the CRN shown in Fig 2, the formed coalition structure is $\omega_1 = \{\{8, 14\}, \{3, 19\}, \{6\}, \{9, 20\}\}$, $\omega_2 = \{\{1\}, \{2, 10, 11, 15\}, \{7, 16, 18, 21\}\}$, $\omega_3 = \{\{4, 12\}, \{5\}, \{13, 17\}\}$. We can see that the coalition sizes of $\omega_2$ are relatively bigger than those of $\omega_1$ and $\omega_3$. As shown in Fig 2, SUs of category 2 are relatively farther from PU 2 so that the local spectrum sensing/prediction gains relatively lower detection/prediction probability, therefore coalitions with larger sizes can provide the SUs more benefits.

Next, we conduct simulations for different number of PUs when the number of SUs is always set to be seven times that of the PUs. We change the number of PUs from 1 to 10 and randomly construct three different networks for each case. We investigate the performance from the perspective of average prediction accuracy, and the simulation results are presented in Fig. 3.

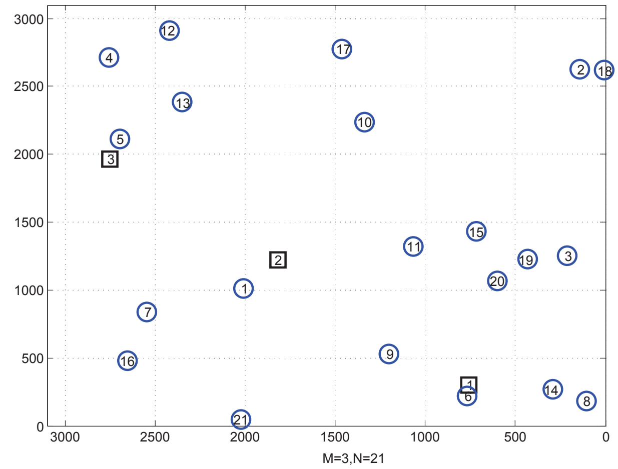


Fig. 2. The Simulated Network.

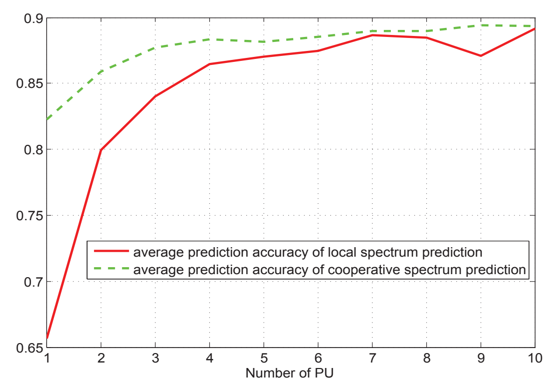


Fig. 3. Prediction accuracy *vs.* the number of PUs.

We can see from Fig. 3 that the average prediction accuracy of both local and cooperative spectrum prediction increases with the number of PUs in the simulated scenarios. The rationalities behind this observation are that the CRN becomes a dense network and the average distance between an SU and a PU decreases as the number of SUs is also increasing (7 times of the number of the PUs). Consequently, the average detection probability of spectrum sensing is increased, and the SU forms a more accurate HMM with more precise model parameters. This in turn increases the average prediction accuracy of spectrum prediction. It is also obvious that the average prediction accuracy of our cooperative spectrum prediction scheme is always higher than the one of a local prediction scheme. Furthermore, the proposed scheme achieves significant performance improvement when the number of PUs is small and the network is sparse. Moreover, it should be noticed that there is a sharp decrease in the prediction accuracy of local spectrum prediction when there exist 9 PUs in the system. This is due to the fact that in the three randomly constructed networks many SUs are located far away from the PUs, thereby resulting in poor local prediction accuracy. However, the prediction accuracy of cooperative spectrum prediction is not affected since the cooperative scheme exploit the benefits of those SUs that near to PUs. This implies that our cooperative spectrum prediction scheme has the potential of achieving steady performance improvement.

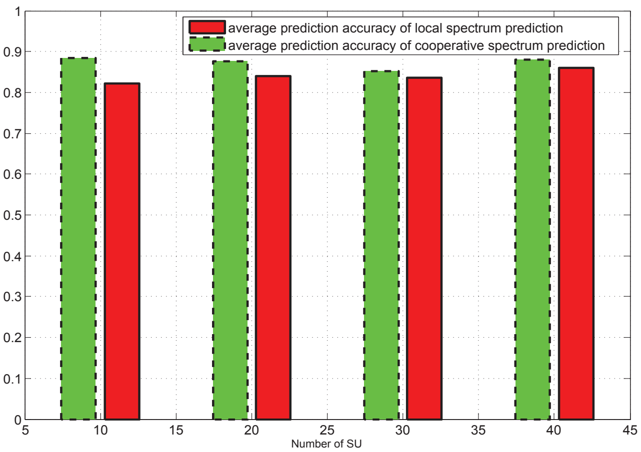


Fig. 4. Prediction accuracy *vs.* the number of SUs.

Then, we investigate the influence of the number of SUs on our cooperative spectrum prediction scheme. We fix the number of PUs to 3 and change the number of SUs from 10 to 40. In Fig. 4, the performance of local and cooperative spectrum prediction are denoted by solid red bar and dashed green bar, respectively. We observe that the proposed cooperative spectrum prediction scheme always improves the spectrum prediction accuracy. It can also be seen that the performance improvement becomes less significant as the number of SUs increases. The reason is similar to the one discussed before.

## V. Conclusions and Future Work

In this paper, we propose a novel cooperative spectrum prediction scheme for multi-PU multi-SU CRNs. We model the cooperative group formation process as a coalitional game and propose a coalition formation algorithm. A series of simulation study is conducted to verify the effectiveness of our design. Our results indicate that the prediction accuracy can be improved as SUs can make better prediction decisions through cooperation. To the best of our knowledge, this work is the first to use coalitional game theory to study cooperative spectrum prediction in CRNs with multiple PUs. We will try to find effective mechanisms that can expand channel status prediction to a larger number of future time slots.

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