# Cluster-Based Cooperative Spectrum Sensing Assignment Strategy in Cognitive Radio Networks

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***Abstract*—Cognitive radio is proposed as an efficient way to address the issue of spectrum shortage and under-utilization, in which cooperative spectrum sensing (CSS) is used to enhance the sensing performance. One of the most fundamental problems of CSS is: how to appropriately assign the secondary users (SUs) to sense the primary user (PU) channels? In this paper, We study the CSS problem under a more practical scenario where taking the heterogeneous characteristics of both SUs and PU channels into consideration. With the objective to maximize the achievable throughput for SUs, we propose a cluster-based CSS to obtain a proper assignment policy, in which all the cluster members cooperative in sensing the same channels, moreover, the CSS problem is formulated as a Maximum Weight One-Sided Biclique Problem, and a greedy heuristic algorithm is proposed to find the suboptimal assignment policy. To evaluate the tradeoff between sensing accuracy and spectrum opportunity, the simulation is conducted between the number of sensed channels and the achievable throughput.**

## I. Introduction

As the rapid development of wireless technologies, more and more spectrum resources are expected to support the requirement of wireless applications. However, due to the fixed spectrum allocation policy, most of the radio frequency spectrum bands are exclusively allocated to specific licensed users. In fact, according to the report in [1], most allocated spectrum experiences a low utilization. This motivates to consider a new technology called cognitive radio, which requires the secondary users (SUs) to identify the spectrum white hole by means of spectrum sensing [2]. If the primary users (PUs) are not using the authorized frequency bands, the SUs can utilize these vacant spectrum for data transmission. However, the sensing accuracy easily suffers from the fading and shadowing environment, which can cause the hidden terminal problem. Cooperative spectrum sensing (CSS) is therefore proposed to address this performance degradation. Multiple SUs sense the spectrum independently, and send the binary decision results to the common receiver where the final decision is made to infer if the spectrum is occupied by the PU [3].

How to appropriately assign a set of SUs cooperatively in sensing a set of PU channels in order to enhance the performance of CSS while keeping the interference to the PUs at an acceptable lever? This is the so called CSS problem. Thus to study CSS we have to address the following problems: 1) How many SUs should cooperative in spectrum sensing? 2) How many PU channels should be sensed by a set of SUs? 3) How to model the heterogeneities of both SUs and PU channels? These fundamental problems have been investigated in [4]-[7]. In [4], the CSS problem is formulated as an NP-Hard integer programming problem. However, the discussion on how to assign SUs to sense multiple channels is missing. In [5], the CSS problem is modeled as a combinatorial optimization problem with the objective of improving energy efficiency in cognitive radio networks (CRNs). In [6], the authors formulate the CSS problem into a nonlinear integer programming problem with the objective to find an optimal and efficient SUs assignment scheme under a scenario where the PU channels are heterogeneous. However, the consideration of heterogeneous characteristics of SUs is left in future work. In [7], by jointly taking the heterogeneities of the PU channels and that of SUs into account, the authors formulate the spectrum assignment into a Maximum Weight Matching problem. However, in [7], the authors focus on assigning the PU channel to the most suitable SU for sensing and transmission, it is one-by-one case. Thus cooperation is not considered.

In our paper, we exploit this CSS problem with the objective to maximize the achievable throughput for SUs while providing sufficient protection to PUs. Our work is different with the previous in the following:

1) The CSS problem considered in our paper is more practical, which investigates the heterogeneous characteristics in both SUs and PU channels.

2) In [4]-[6], the target of the CSS is to find a set $\{n_1, n_2, ..., n_K\}$ to achieve a good sensing performance, where $n_i$ denotes the number of SUs cooperatively in sensing channel $i$. However, to tackle the tradeoff between sensing accuracy and the transmission opportunity, we propose a cluster-based CSS to obtain a proper assignment policy $A = [A_{ijk}]$ that accurately indicates which SU should sense which channel due to the consideration of heterogeneities of PU channels and SUs. Moreover, we can achieve $a = \{a_1, a_2, ..., a_K\}$ and $b = \{b_1, b_2, ..., b_K\}$, where $a_k$ is the number of members in cluster $k$, who cooperative in sensing $b_k$ PU channels.

3) With the objective to maximize the throughput for SUs subject to protect the PUs, we formulate this CSS into maximum weight one-sided biclique problem, and a greedy heuristic algorithm is proposed to find the suboptimal assignment policy.

The rest of this paper is organized as follows. The overview of system model is introduced in Section II. The key part: the

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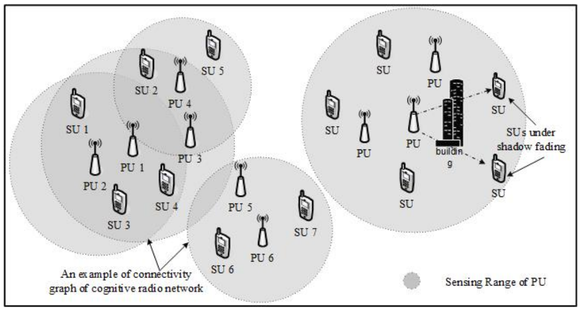



Fig. 1. The cognitive radio network architecture.

problem statement which formulates the CSS problem into maximum weight one-sided biclique problem is described in Section III. Simulation results and evaluations are given in Section V. Finally, Section VI concludes the paper.

## II. System Model

In this paper, we attempt to consider the CSS problem under a more practical scenario where the heterogenous characteristics in both PU channels and SUs are investigated. The PU channel is characterized by channel idle probability and channel capacity, while the SU is depicted by the energy detection threshold, received SNR and geographical location.

We consider a CRN with $N$ SUs and $M$ PU channels. Each channel is exclusively used by the PU. However the PU may not be active all the time and the SU can opportunistically utilize the channel when it is available. Most of research on spectrum sensing has focused on detecting large-scale PU signals, e.g., TV signals which have a high transmission power (e.g., 100kW) [8] and a large transmission range (up to 150km). The detection range of this kind of signal is relatively large. On the other hand, for small-scale signal, e.g., wireless microphone uses a weak transmit power around 10-50mW, and its transmission range is limited to only 150-200m [9]. In this case, the PU signal may not cover the whole network but only a part of the system. Some SUs located far from the PU will report only the noise power. If we employ cooperative spectrum sensing including all of those SUs, a large number of noise reports may adversely affect the detection performance. We use "detection range" to represent the PU signal cover range. A channel $j$ is said to be opportunistically accessible by SU $i$ only if the SU is within the detection range of channel $j$, thus it can detect the PU activity. Otherwise, if the SU is outside the detection range of the PU channel, the detection probability is zero [10]. The CRN model is shown in Fig.1. It demonstrates that the channel heterogeneity-spectrum availability varies across the SUs. For simplicity, there are many PUs and SUs not marked in Fig.1. Moreover, we may note that even when the SUs are within the detection range of PU channel, it may not detect the channel status correctly due to fading and shadowing as shown in Fig.1.

Spectrum sensing is a fundamental functionality in cognitive radio communications, it is required to be performed firstly before data transmission. For each channel $j$, the detection is basically a binary hypothesis between $H_j^1$ and $H_j^0$, which denote the presence and absence of PU respectively. The sensing performance can be measured by two parameters: detection probability (i.e., the probability that the SUs correctly identify the presence of the PU) and false alarm probability (i.e., the probability that the SUs falsely declare the idle channel as busy). We assume that the received primary signal is complex PSK with zero mean and variance $\sigma_{s_{i,j}}^2$, and the noise is the independent circular symmetric complex Gaussian (CSCG) with zero mean and variance $\sigma_{u_{i,j}}^2$. Using energy detection, the the false alarm probability $P_{f,(i,j)}$ and the detection probability $P_{d,(i,j)}$ for channel $j$ at SU $i$ are given by

$$P_{f,(i,j)} = Q((\frac{\varepsilon_i}{\sigma_{u_{i,j}}^2} - 1)\sqrt{f_s \tau}) \tag{1}$$

$$P_{d,(i,j)} = Q((\frac{\varepsilon_i}{\sigma_{u_{i,j}}^2} - 1 - \gamma_{i,j})\sqrt{\frac{f_s \tau}{2\gamma_{i,j} + 1}}) \tag{2}$$

where the energy detection threshold at SU $i$ is $\varepsilon_i$, $\gamma_{i,j} = \frac{\sigma_{s_{i,j}}^2}{\sigma_{u_{i,j}}^2}$ is the average SNR of the PU in channel $j$ received by SU $i$, and $Q(x)$ is the tail probability of the standard normal distribution.

One of the most important challenges for implementing spectrum sensing is the hidden terminal problem, which happens when the SUs suffer from fading and shadowing environment. Cooperative spectrum sensing is therefore adopted to address this issue. To protect the PU, $OR$ decision fusion rule is considered in this paper. We assume that each SU can perform spectrum sensing independently, if $m$ out of $N$ SUs participate in coordinate sensing channel $j$, the cooperative detection probability and false alarm probability for channel $j$ are formulated as

$$Q_{d,j} = 1 - \prod_{i=1}^{m}(1 - P_{d,(i,j)}) \tag{3}$$

$$Q_{f,j} = 1 - \prod_{i=1}^{m}(1 - P_{f,(i,j)}) \tag{4}$$

It can be observed from (3) that as the number of cooperative SUs increases, the detection probability increases, which results in more accurately in detecting the PUs.

## III. Problem Statement for Cluster-Based CSS Assignment Policy

Under some environment, the detection range of the PUs may not cover the whole CRN, thus some SUs cannot detect the activity of the PU. In this case, it may generate negative effect on the sensing outcome if all the SUs cooperative in spectrum sensing. This motivates to partition the CRN into clusters, SUs in each cluster can cooperative in sensing the same set of PU channels. The basic tradeoff of the cluster-based CSS assignment problem lies in: including more PU channels in the cluster can achieve higher throughput, since more transmission opportunities can be discovered; However, this may result in the cluster of small size, thus the benefit comes from the cooperation among SUs due to spatial diversity will not be well exploited. Moreover, the more the PU channels are included in the cluster, the less the sensing time can be allocated to sense each channel, which results in a lower detection accuracy. We study this cluster-based CSS assignment problem with the objective of maximizing the achievable throughput for SUs subject to protect the PU.

### A. Mapping to Biclique Graph

A bipartite graph $G(X \cup Y, \varepsilon)$ is a graph whose vertices can be divided into two disjoint sets, such that every edge in $\varepsilon$ connects a vertex in $X$ to one in $Y$; that is, $X$ and $Y$ are each independent sets [11] [12]. In CRN, the topology of SUs and PU channels can be represented as a bipartite graph $G(X \cup Y, \varepsilon)$. Vertex set $X$ corresponds to the SUs in the network, and set $Y$ contains the sensed PU channels. An edge exits between $(x, y)$, $x \in X$ and $y \in Y$, if and only if the SU $x$ is within the detection range of the PU channel $y$, thus SU $x$ can detect the PU channel $y$ status.

Take the example of the connectivity graph in Fig.1 as an instance, which can be represented as a bipartile graph $G(X \cup Y, \varepsilon)$, with $X = \{SU_1, SU_2, SU_3, SU_4, SU_5, SU_6, SU_7\}$ and $Y = \{PU_1, PU_2, PU_3, PU_4, PU_5, PU_6\}$ as illustrated in Fig.2(a). Throughout this paper, $X_k$ and $S_k$ are the sets that contain SUs, $Y_k$ and $B_k$ are the PU channel sets, without confusion, the symbols 'SU' and 'PU' are omitted. A complete bipartite graph (biclique graph) $Q(S, B)$ is a bipartite graph such that for any two vertices $x \in S$ and $y \in B$, there has one edge in $Q$. The biclique graph is totally dominated by $S$ and $B$, thus it can be represented by $Q(S, B)$. For CRN, a biclique graph $Q(S, B)$ can be extracted from its bipartite graph $G(X \cup Y, \varepsilon)$. This biclique graph represents a cluster of nodes $S$ that cooperative in sensing all the channels in $B$. In Fig.2(b), Fig.2(c) and Fig.2(d), we show three possible biclique graphs extracted from Fig.2(a). The biclique graph Fig.2(b) represents the cluster 1 with cluster members $S_1 = \{1, 3, 4\}$ and the set of sensed channels is $B_1 = \{1, 2, 3\}$, all the SUs in $S_1$ coordinate in sensing and transmission on all the PU channels in $B_1$. The biclique graph Fig.2(c) represents the cluster 2 with cluster members $S_2 = \{6, 7\}$ and the set of sensed PU channels is $B_2 = \{5, 6\}$. And the biclique graph Fig.2(d) represents the cluster with cluster members $S_3 = \{2, 5\}$ and the set of sensed channel is $B_3 = \{4\}$. The algorithm for how to obtain the biclique graphs from its bipartite graph will be given later.

### B. Lower Bound of the Cooperative SUs [13]

In order to provide sufficient protection to the PUs, it is required to keep the detection probability above a given threshold $Q_{th}$, that is $Q_{d,j} \geq Q_{th}$. Hence we have

$$1 - \prod_{i=1}^{m}(1 - P_{d,(i,j)}) \geq Q_{th} \Longleftrightarrow m \geq \lceil \frac{\log(1 - Q_{th})}{\log(1 - P_{d,j}^{min})} \rceil = \bar{m}$$

where $\lceil z \rceil$ is the ceiling function which returns the smallest integer not less than $z$. $P_{d,j}^{min}$ is the minimum detection probability among all the cooperative SUs. Observe that the

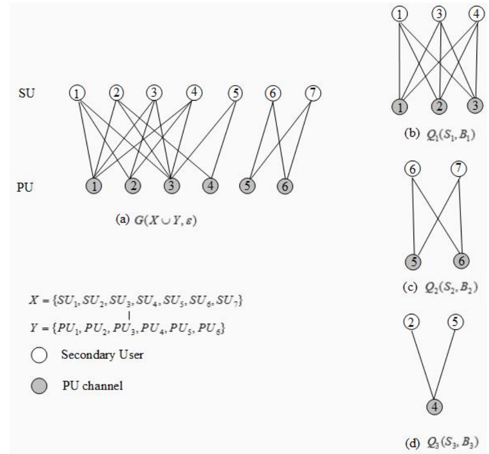



Fig. 2. The connectivity graph represented by bipartile graph in (a), and (b)-(d) are the biclique graphs extracted from the bipartite graph in (a).

detection probability is monotonically increasing with regard to the SNR $\gamma_{i,j}$ for a fixed sensing time, thus

$$P_{d,j}^{min} = \min\{P_{d,(i,j)} | \gamma_j^{min} = \min_{1 \leq i \leq m}\{\gamma_{i,j}\}\} \tag{5}$$

$\bar{m}$ is the desired least number of cooperative SUs in order to provide sufficient protection to the PUs.

### C. Weight Definition for the Maximum Weight One-Sided Biclique Problem

One one hand, the SUs are heterogeneous, they may have significant different sensing outcomes for the same channel due to their different detection threshold, received SNR and the geographical location. One the other hand, the PU channels are generally heterogeneous in terms of channel capacity and channel idle probability. One of our main contributions is to incorporate all these heterogeneous characteristics in both PU channels and SUs into the weight definition of the Maximum Weight One-Sided Biclique Problem.

Let $K$ denote the number of clusters in the system and $T$ denote the length of a time slot, $\tau$ is the total sensing time allocated to sense the PU channels. Then the average throughput of channel $j$ can be expressed

$$R_j^k(S_k, B_k) = \frac{T - \tau}{T} P(\mathcal{H}_j) C_j (1 - Q_{f,j}^k(S_k, B_k)) \tag{6}$$

where $P(\mathcal{H}_j)$ denotes the idle probability for channel $j$, and $C_j$ is the transmission capacity for channel $j$. Furthermore, we use $S_k$ to represent the set of SUs in cluster $k$, $|S_k| = a_k$, and use $B_k$ to denote the set of channels that are sensed and utilized by SUs in cluster $k$ $|B_k| = b_k$. Where $Q_{f,j}^k$ is given by

$$Q_{f,j}^k(S_k, B_k) = 1 - \prod_{i \in S_k}(1 - P_{f,(i,j)}(\tau / b_k)) \tag{7}$$

Thus the total throughput for cluster $k$ is

$$R_k(S_k, B_k) = \sum_{j \in B_k} \frac{T - \tau}{T} P(\mathcal{H}_j) C_j (1 - Q_{f,j}^k(S_k, B_k)) \tag{8}$$

### D. Maximum Weight One-Sided Biclique Problem

Based on above definition, to evaluate our cluster-based CSS assignment problem is equal to extract some biclique graphs $Q(S_k, B_k)$ from the bipartite graph $G(X \cup Y, \varepsilon)$, while satisfying a lower bound on the number of cooperative SUs. Such a formulation is related to Maximum Weight One-Side Biclique Problem. In our problem, this corresponds to imposing a lower bound on each $|S_k|$ and maximizing the total throughput for all the clusters. To represent the assignment policy, we define a matrix $A_{N\times M\times K}$ as follows:

$$A_{ijk} = \begin{cases} 1 & \text{if} \quad i \in S_k \ \ and \ \ j \in B_k \\ 0 & \text{Otherwise} \end{cases} \tag{9}$$

The meaning of $A_{ijk}$ is three fold: First, SU $i$ is within the detection range of PU channel $j$. Second, SU $i$ is grouped into cluster $k$; Third, channel $j$ is sensed and utilized by the SUs in cluster $k$. Given the CRN, we aim at finding the assignment policy $A$ such that the achievable throughput for SUs is maximized subject to provide sufficient protection to PUs. Moreover, we can determine the set of $a = \{a_1, a_2, ..., a_K\}$ and $b = \{b_1, b_2, ..., b_K\}$, where $a_k = |S_k| = \sum_{i\in S_k} A_{ijk}$, and $b_k = |B_k| = \sum_{j\in B_k} A_{ijk}$. All the $a_k$ SUs cooperate in sensing and utilizing all the $b_k$ channels. The problem can be formulated as

$$\begin{aligned} \max_{A} \quad & \sum_k R_k(S_k, B_k) I_k & (10) \\ s.t. \quad & I_k = \prod_{i\in S_k} \prod_{j\in B_k} A_{ijk}, \forall\, k \\ & \sum_k A_{ijk} \le 1, \forall\, i, j \\ & |S_k| \ge \bar{m}, \forall\, k \\ & A_{i,j,k} \in \{0,1\}, \forall\, i, j, k \end{aligned}$$

Solving the Maximum Weight One-Side Biclique Problem is NP-hard, when the number of SUs and PU channels increases, the complexity to find the optimal solution will grow exponentially. Thus we develop a greedy heuristic algorithm that can effectively extract the biclique graphs from its bipartite graph such that the performance is optimized and the constraints are satisfied. Initially, we have $X_1 = X$ and $Y_1 = Y$. For $k$ cluster, $X_k = X_{k-1}/S_{k-1}$ and $Y_k = Y_{k-1}/B_{k-1}$. The algorithm to yield the maximum weight biclique graph $Q_k(S_k, B_k)$ from the bipartite graph $G(X_k \cup Y_k, \varepsilon_k)$ is demonstrated as follows: Initially $B_k$ is empty, and $S_k$ is set to contain all the SUs, that is $S_k = X_k$. In $l$ iteration, we will find the channel $y_l$, $y_l \in Y_k/B_k$, that is able to be detected by the largest number SUs in $S_k$, i.e., the channel with the highest connectivity degree $deg(y_l)$ in $S_k$, we then add $y_l$ to $B_k$ and remove the SUs who cannot detect the channel $y_l$ from $S_k$. If more than one channel have the same highest degree, the one that can bring more throughput increase will be chosen. Then calculate the update achievable throughput and record in vector $\Gamma_k$ according to the following rules:

$$B_k \leftarrow B_k \cup y_l \qquad\qquad S_k \leftarrow S_k \cap \psi_{y_l}$$

$$R_k(S_k, B_k) = \sum_{j\in B_k} \frac{T-\tau}{T} P(\mathcal{H}_j) C_j (1 - Q^k_{f,j}(S_k, B_k))$$

and update $A_{ijk}$ according to (9). Here $\psi_{y_l}$ denotes the set of SUs that can detect PU channel $y_l$. Then repeat this process, until either one of the following conditions is satisfied 1) $|S_k| \le m_k$, where $m_k$ is the desired least number of cooperative SUs for cluster $k$; 2) the remaining channel in $Y_k$ is empty. The algorithm is described in detailed as follows.

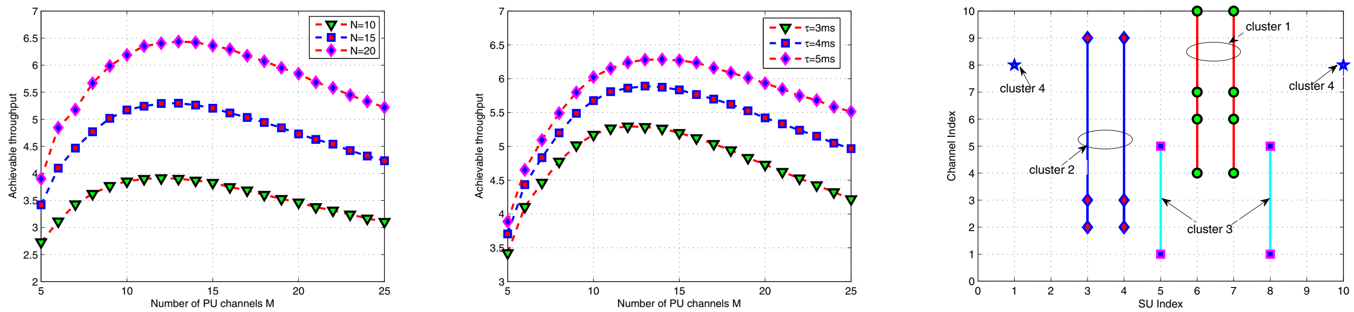
**Algorithm 1** Greedy heuristic algorithm for computing the maximum weight one-side edge biclique problem.

```
Input: G_k(X_k ∪ Y_k, ε_k), m_k.
Initialization: S_k = X_k, B_k = ∅, A^(k−1), l ← 1,
y_1 = arg max_{y∈Y_k} deg(y)
while |S_k| ≥ m_k and |Y_k| > 0 do
    y_l = arg max_{y∈Y_k/B_k} deg(y)
    if deg(y) < m_k then
        break;
    else
        P_k[l] = l; Y_k ← Y_k − y_l; S_k ← S_k ∩ ψ_{y_l};
        ψ_{y_l} = {SU ∈ S_k | SUs can detect channel y_l};
        B_k ← B_k ∪ y_l; Γ_k[l] = R_k(S_k, B_k); update A_ijk;
    end if
    l = l + 1;
end while
Find l* = arg max_l Γ_k[l];
S_k = ∩_{l=1}^{l*} ψ_{y_l}; B_k = {CH_{P_k[1]}, CH_{P_k[2]}, ..., CH_{P_k[l*]}}.
Output: Q*_k(S_k, B_k), A^(k), a_k = |S_k| and b_k = |B_k|.
return rules
```

We illustrate the algorithm to the connectivity graph of CRN in Fig.2(a). For simplicity here, we associate each edge with weight 1 (different weight will be evaluated in simulation). Let $m = 2$ for all the clusters. Initially, we have $S_1 = X_1 = \{1, 2, 3, 4, 5, 6, 7\}$, $Y_1 = \{1, 2, 3, 4, 5, 6\}$ and $B_1 = \emptyset$. In the first iteration, $CH_3$ has the highest degree, $CH_3$ is included in $B_1$, and $S_1 = S_1 \cap \psi_{CH_3} = \{1, 2, 3, 4, 5\}$, $\Gamma_k[1] = 5$; In the second iteration, $CH_1$ has the highest degree with the SUs in $S_1$, $CH_1$ is selected, $B_1 = B_1 \cup CH_1 = \{1, 3\}$, $S_1 = S_1 \cap \psi_{CH_1} = \{1, 2, 3, 4\}$, $\Gamma_k[2] = 8$; Next, $CH_2$ has highest degree, thus it is included in $B_1 = \{1, 2, 3\}$, $S_1 = S_1 \cap \psi_{CH_2} = \{1, 3, 4\}$, $\Gamma_k[3] = 9$. In the subsequent iteration, since $deg(y) < 2$, $\forall y \in Y_1/B_1$, the algorithm terminates. Thus the biclique graph for cluster 1 $Q_1(S_1, B_1)$ is obtained as shown in Fig.2(b). For cluster 2, we have $X_2 = X_1/S_1 = \{2, 5, 6, 7\}$ and $Y_2 = Y_1/B_1 = \{4, 5, 6\}$, according to the algorithm, biclique graphs $Q_2(S_2, B_2)$ and $Q_3(S_3, B_3)$ can be obtained in Fig.2(c) and Fig.2(d), respectively. Thus the optimal assignment policy is $a = \{3, 2, 2\}$ and $b = \{3, 2, 1\}$.

## IV. Simulation Results

In all the following simulations, we set $f_s$ = 6MHz and T = 100ms. To model the heterogeneous characteristics of PU channels, the channel idle probability and channel capacity are randomly generated with mean 0.7 and 0.9, respectively. The energy detection threshold and noise power are generated randomly with means 1.03 and 1 respectively, which are the parameters chosen in [14].




(a) Throughput for different number of SUs.

(b) Throughput for different sensing time

(c) Cluster-based spectrum allocation results.

Fig. 3. Simulation results.

Fig.3(a) depicts the achievable throughput for the SUs as a function of the number of sensed PU channels. It can be observed that there exists an optimal number of sensed PU channels such that the achievable throughput for SUs can be maximized. On one hand, increasing the number of sensed PU channels will improve the spectrum utilization but will incur a lower detection accuracy, since less SUs will participate in cooperative sensing and less time can be allocated to sense each channel. On the other hand, the smaller the number of sensed PU channels, the less the channels that can be utilized by SUs, the lower the achievable throughput. Hence, we observe the tradeoff phenomenon. Moreover, it is easy to note that the achievable throughput increases with an increase in the number of SUs. This is reasonable due to the fact that a larger number of SUs $N$ in the network indicates a higher probability that partitioning clusters with larger size, which leads to a high detection quality. Furthermore, we plot the achievable throughput vs. the number sensed PU channels for different total sensing time in Fig.3(b). As illustrated in Fig.3(b), there also exists an optimal value of the number of sensed PU channels.

The cluster-based spectrum allocation results are shown in Fig.3(c). As discussed before, we take the heterogeneous characteristics of both PU channels and SUs into consideration so that a more detailed result that accurately indicates which SU should sense which channel can be achieved. As shown in Fig. 3(c), SUs $\{6,7\}$ constitute cluster 1 and they cooperate to sense channels {4,6,7,10}; SUs $\{3,4\}$ in cluster 2 cooperate to sense channels {2,3,9}, so are the results for clusters 3 and 4. Thus the CRN is partitioned into 4 clusters, and the allocation policy $A$ as well as $\{a_1, a_2, a_3, a_4\} = \{2, 2, 2, 2\}$ and $\{b_1, b_2, b_3, b_4\} = \{4, 3, 2, 1\}$ can be obtained.

## V. Conclusions

In this paper, we focus on the cooperative spectrum sensing problem: How to appropriately assign the most suitable SUs to sense the PU channels? We take the heterogeneities of both the PU channels (channel idle probability and channel capacity) and SUs (energy detection threshold, received noise power, SNR and the geographical location) into consideration, which has not been fully studied in most of the literatures. With the objective to maximize the achievable throughput for SUs, we propose a cluster-based CSS to obtain a proper assignment policy. Moreover, the CSS problem is formulated as a Maximum Weight One-Sided Biclique Problem, and a greedy heuristic algorithm is proposed to find the assignment policy. Due to page limited, comparison between the simulation and theoretical results will be done in future work.

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