Sensing Strategies for Channel Discovery in Cognitive Radio Networks

(Invited Position Paper)

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***Abstract*—We consider spectrum sensing strategies used to discover available spectrum in Cognitive Radio Networks (CRNs), using both non-cooperative sensing and cooperative sensing approaches. After introducing the background to sensing techniques, this position paper focuses on strategies and algorithms for conducting sensing such that the sensing time and energy are minimized, and the likelihood of finding available spectrum is maximized. The paper mainly focuses on two approaches. The first is the ordering of channels to be sensed, and the second is cooperative spectrum sensing. After discussing the available strategies under each of these two approaches, we introduce our own proposed approaches. We first introduce a method for sorting the channels to be sensed in order to optimize the sensing time, while satisfying PUs' protection and false alarm constraints. Then, we introduce a framework for cooperative sensing of multiple PUs' channels by a group of SUs. The framework includes strategies for assigning different SUs to sense different PUs' channels, selection of the fusion center for each of the SUs clusters, and routing sensing data within the cluster from the SUs to the fusion center. We show how this framework is capable of optimizing different objective functions. Several open problems and future research directions are also introduced.**

I. Introduction

Cognitive Radio Networks (CRNs) were introduced to solve the problem of the under utilization of the wireless spectrum, which has already been exhausted due to allocation to licensees [1]. In CRNs licensed users, called Primary Users (PUs), should be able to use their licensed spectrum bands whenever they want, and in the licensed localities. However, if the PUs are not active, unlicensed users, termed Secondary Users (SUs), may use the PUs' spectrum bands, but they must also monitor these bands for resumed PUs' activities to vacate the spectrum bands in a timely manner, hence avoiding interference with the PUs.

The above requires that the SUs be aware of the PUs' channels status, and this is done by sensing the PUs' channels. There are two modes of sensing: 1) out-of-band sensing, which refers to sensing PUs' channels to determine whether PUs are active or not, and if not active, determine that the channels are usable by the SUs; and 2) in-band sensing, or monitoring, which refers to monitoring the status of the channels used by the SUs to determine if the owner PUs have become active again or not. This paper focuses on out-of-band sensing, which is the discovery of usable channels.

In this position paper, we consider the problem of out-of-band sensing, and discuss the properties that the sensing function must satisfy. We also survey the most prominent channel sensing techniques. However, this paper is more focused on the sensing strategies, which deal with issues such as determining the channels to be sensed, and their order, and also determining the sensing times that will satisfy the required properties and constraints. Therefore, we discuss the state-of-the-art in the development of sensing strategies and algorithms, and discuss the advantages and disadvantages of such techniques. We then introduce two of our group's contributions. The first one is an algorithm to sort PUs' channels for sensing, such that the likelihood of finding an available channel is maximized, while spending the minimum sensing time and energy. The second one is a framework for cooperative spectrum sensing in the presence of multiple PUs, which optimizes the assignment of SUs to PUs' channels. The approach also optimizes the selection of the fusion center within each cluster of SUs sensing a PU channel, and optimizes the routing of sensing information within this cluster. Several open research problems will also be introduced.

II. Spectrum Sensing Techniques

Spectrum sensing is the task of achieving the spectral awareness about the PU occupancy in the *sensing space* with *spectral*, *spatial* and *temporal* dimensions. We define binary hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ which represent idle and busy states of the channel, respectively. Then, the purpose of sensing is to determine which hypothesis is valid. Contingent upon the available information about the primary signal characteristics, a variety of spectrum sensing methods are studied in the literature.

If the receiver has an absolute *a priori* knowledge about primary signal, *matched filters* (MFs) are known to be the optimal method for detection within a short sensing time to achieve a certain processing gain [2]. *Cyclostationary feature detectors* (CFDs) exploit the known statistical properties of primary signals which arise from the spectrum redundancy caused by periodicity of modulated and/or coded signals. CFDs have the ability of recognizing the distinctive features of different primary signals and relatively better performance under low SNR regimes [3]. *Covariance-based sensing* employs the fact that the statistical covariance matrices of primary signal and noise are different from each other. Thus, it is robust against noise estimation uncertainty. In particular, it gives a superior performance for detecting correlated signals [4].

The techniques mentioned above either depend upon the accurate knowledge regarding primary signal characteristics or some other assumptions which are not always readily available in practice. In the absence of *a priori* knowledge of primary signals, however, energy detection has been shown to be robust to the unknown dispersed channels and fading. To detect a primary signal, energy detector (ED) simply measures the received signal energy for a time interval and compares it with a predetermined threshold to decide on the PU activity. Under energy detection, the k^{th} sample of the received primary signal taken by SU m during the sensing period $T_{m,n}$ on channel n with bandwidth W_n is given as

$$y_{m,n}(k) \sim \begin{cases} v_n(k) & ,\mathcal{H}_0 \\ h_{m,n} s_n(k) + v_n(k) & ,\mathcal{H}_1 \end{cases} \quad (1)$$

where $v_n(k)$ is additive white Gaussian noise (AWGN), $s_n(k)$ is the primary signal, and $h_{m,n}$ is the convex envelope of the channel gain under the slow fading assumption. Then, ED measures the test statistic $\mathcal{T}_{m,n}(y)$ which is energy of the received signal and compares it with a threshold $\lambda_{m,n}$to decide on PU presence/absence. In [5], $\mathcal{T}_{m,n}(y)$ has been shown to have central and non-central chi-square distribution under $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. In the case of deterministic $h_{m,n}$, the probabilities of false alarm, and detection are given as [6]

$$P^f_{m,n} = \mathcal{P}\left[\mathcal{H}_1|\mathcal{H}_0\right] = \frac{\Gamma\left(N_{m,n}, \lambda_{m,n}/2\right)}{\Gamma\left(N_{m,n}\right)} \tag{2}$$

$$P^d_{m,n} = \mathcal{P}\left[\mathcal{H}_1|\mathcal{H}_1\right] = \mathcal{Q}_{N_{m,n}}\left(\sqrt{2N_{m,n}\gamma_{m,n}}, \sqrt{\lambda_{m,n}}\right) \tag{3}$$

where $N_{m,n} = T_{m,n}W_n$ is the time-bandwidth product, $\Gamma(\cdot)$ is the gamma function, $\Gamma(x,a) = \int_x^\infty e^{-t}t^{a-1}dt$ is the incomplete gamma function, and $\mathcal{Q}_m(x,a)$ is the generalized Marcum-Q function defined as $\mathcal{Q}_m(x,a) = \frac{1}{a^{m-1}}\int_x^\infty t^m \exp^{-\frac{t^2+a^2}{2}} I_{m-1}(at)\,dt$ where I_{m-1} is the $(m-1)^{th}$ order modified Bessel function of the first kind. In the case of *Rayleigh* fading, the closed form expression for equation (3) is derived in [7].

Out of the above sensing techniques, energy detection is usually the preferred approach and this is due to a number of desirable properties, including: 1) its low computational complexity; 2) applicability to any signal shape; and 3) it does not require any a priori knowledge about the PUs and their transmission characteristics [8]. Therefore, in the rest of this paper, we only consider spectrum sensing using energy detection.

III. Sensing Time and Threshold Optimization

The most significant purpose of cognitive radio technology is to increase the spectral efficiency of wireless networks in an opportunistic manner. Therefore, the first trend in the sensing optimization studies has focused on maximizing the achievable throughput subject to detection errors: probabilities of misdetection $(P_m = \mathcal{P}\left[\mathcal{H}_0|\mathcal{H}_1\right])$ and false alarm $(P_f = \mathcal{P}\left[\mathcal{H}_1|\mathcal{H}_0\right])$. While minimizing the former result in a higher level of PU protection from SU interference, minimizing the latter is the key part to maximize unused spectrum utilization. Furthermore, sensing for longer duration provides more measurements for the decision maker, hence decreasing the error probabilities with increasing the measurements. If a slotted time frame is considered, sensing for a longer duration results in achievable throughput reduction. If the energy detection is chosen for sensing white space, threshold determination impacts P_f. Moreover, P_m decreases as the sensing duration increases for a given P_f and received SNR. Thus, required detection threshold should be jointly optimized along with sensing duration in order to maximize the achievable throughput when the optimization is constrained on PU protection and spectrum utilization.

In this paper, we consider path loss and Rayleigh fading for both control and sensing channels. If we consider SU m sensing channel n, based on received SNR $\gamma_{m,n}$ and corresponding threshold $\lambda_{m,n}$, each SU can locally find its own optimal sensing time subject to a PU protection and spectrum utilization threshold. Assuming sensing power is constant for every PU and SU pair, i.e., $\mathbb{P}^s_{m,n} = \mathbb{P}^s, \forall m, n$, then the optimal energy consumed by SU m for sensing channel n is given by $\varepsilon_{m,n} = \mathbb{P}^s T_{m,n}$. Accordingly, the optimal local sensing energy $\varepsilon_{m,n}$ is calculated using Algorithm 1 where $\bar{P}_d$ and $\bar{P}_f$ are required thresholds for detection and false alarm probability, respectively. The constraints in Lines 2 and 3 protect PUs from SU interference, and ensure adequate spectrum utilization by SUs, respectively.

Algorithm 1 : Optimal sensing energy of the SU m at channel n

1: Min $\quad \varepsilon_{m,n}$
2: s.t. $\quad P^d_{m,n} \geq \bar{P}_d$
3: $\quad P^f_{m,n} \leq \bar{P}_f$

IV. Channel Sorting

Channel sorting is an approach to find the sequential order of the channels to be followed during searching an idle channel. Sorting criteria may differ from application to application. Some sorting techniques may favor sorting the channels based on channel capacity. Channel sorting techniques which reduce search time should ideally take three factors into consideration:

1) The probability of the channel being idle, $\mathcal{P}(\mathcal{H}_0)$, which can also be conditional on the last sensed status and time sensing. This can also be based on modeling the channel activities, using either parametric, or non-parametric statistical models.
2) Channel sensing time, which is influenced by the characteristics of the channels between the PUs and the SUs, as described in Section III. And,
3) Switching times between the channels that are sensed, which is dependent on the difference between the central frequencies of these channels, and is also dependent on the technology of the Phase-Locked Loops (PLL) used. Switching times can be significant, and therefore, they have to be taken into consideration.

The literature includes three basic approaches for channel sorting to minimize search time:

- The first approach is sequential searching, in which the channels are searched sequentially, typically starting from the lowest frequency channel[9]. Although it provides a minimized switching time, this approach suffers from the fact that the channel sorting does not take into consideration the channel availability likelihood, e.g., in terms of $\mathcal{P}(\mathcal{H}_0)$, or the channels characteristics, which impact the sensing time.
- The second approach considers the likelihood that the channels will be idle. Kim and Shin [10] introduced such an approach where sensing-sequence sorts channels in descending order of the probability of being idle. Also, [11] finds a search sequence that helps in finding spectrum opportunities with minimal delay. To achieve their goal, [11] maintains two channel lists: back-up channel list (BCL) and candidate channel list (CCL). Both of these two approaches do not optimize the sensing

time per channel, and they also do not take channel switching times into consideration.
- The third approach sorts channels randomly.

We believe that a sensing strategy that takes all above three factors into consideration will result in better performance, in terms of faster discovery of available channels, and minimum sensing energy consumption. However, this problem is hard, and can only be solved offline. Hence, developing algorithms for sorting channels, while taking into consideration all three factors, is an important problem. Our group has developed a heuristic algorithm for channel sorting that takes all above factors into account, which is shown in Algorithm 2.

Algorithm 2 : Finding the best sequence of channels

1: For $i = 1$ up to M
2: Min=∞ , MinIndex=-1
3: For $s = i$ up to M
4: Min $t(s) = [ts(s) + t_{sw}(f_0, f_s)] * Pr_s(\mathcal{H}1)$
5: s.t. $Pr(\mathcal{H}1|\mathcal{H}1) \geq \bar{P}_d(s)$
6: $Pr(\mathcal{H}1|\mathcal{H}0) \leq 0.1$
7: if ($t(s) \leq$ Min)
8: Min=$t(s)$
9: MinIndex=s
10: End if
11: End For
12: Temp=$f(i)$
13: $f(i)$=f(MinIndex)
14: f(MinIndex)=Temp
15: f_0 = f(MinIndex)
16: End For

The algorithm minimizes the sensing plus switching time among the remaining channels, and it works in iterations. In iteration i of the outer for loop, a channel that minimizes the sensing + switching time will be found. The inner for loop searches the $M - i$ channels to find the channel which minimizes the sensing plus switching time and makes it the i^{th} channel to be sensed. Lines 4-6 find the minimum sensing + switching time for each channel given the current channel. Lines 7-10 keep track of the channel that minimizes the sensing + switching time. Lines 12-15 swap the next channel with the channel that minimizes sensing + switchingtime.

A. Search Sequence Results

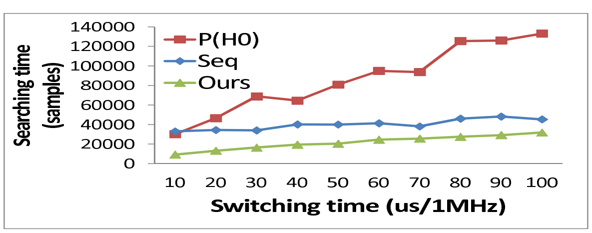

Fig. 1: Comparison of search times for different switching times

We compare our approach of sorting the channels with: 1) searching the channels sequentially which does not consider any other properties of the channels like $\mathcal{P}(\mathcal{H}_0)$, SNR, or required sensing time; 2) the approach that sorts the channels according to the $\mathcal{P}(\mathcal{H}_0)$. We simulate 51 channels in the ranges of 470MHz to 770 MHz. Each channel is 6MHz wide. Each channel has: 1) random SNR between -10 dB and -20 dB, 2) random $\mathcal{P}(\mathcal{H}_0)$ between 0.2 and 0.8, and 3) random required detection probability $\bar{P}_d$ between 0.92 and 0.99. We consider different switching times that can range from $10\mu s/1MHz$ up to $0.1ms/1MHz$. Figure 1 compares our approach to the other two approaches. It is clear that our approach is better than the other approaches because our approach considers both the switching time and the probability of being idle. Sorting according $\mathcal{P}(\mathcal{H}_0)$ takes the longest time. This is because $\mathcal{P}(\mathcal{H}_0)$ does not take into consideration sensing and switching times.

V. Cooperative Spectrum Sensing (CSS)

The use of energy detection for channel sensing is based on an underlying assumption of perfect noise power estimation. Therefore, the uncertainty in noise results in *SNR wall* and high false alarm probability. Furthermore, *receiver uncertainty* and *hidden terminal problem* caused from radio propagation characteristics are other matters of challenge for EDs [3].

CSS can alleviate the shortage of individual SUs by getting benefits of spatial diversity of SUs since it is highly unlikely for spatially distributed SUs to concurrently suffer from similar channel impairments. CSS can be grouped into subcategories based upon the cooperation method within the network (*centralized* and *distributed*) and the shared data type (*soft data fusion* and *hard decision fusion*). Even though exploiting the soft data fusion results in a superior performance, sharing large amount of measurement data ends up with communication overhead which cannot be sustained by a bandwidth limited CC. Hence, hard decision fusion surpass the soft data fusion with its low reporting overhead. Nonetheless, as the number of cooperating SUs and the geographical area of the network increase, CC still experiences bandwidth insufficiency along with reporting unreliability, power consumption and delay due to long distances. To surmount these problems, grouping SUs into clusters is a favorable and effective technique to reduce cooperation range and communication overhead [12], [13]. In particular, an energy efficient clustering method plays a vital role for extending the battery life of SUs if the mobility and power resource limitations of SUs are taken into consideration.

If we define the spectrum utilization and energy consumption as currency and commodity, respectively, an energy and throughput efficient design would be clustering SUs such that commodity per currency is maximized subject to a PU protection level. For energy efficiency, the total energy consumption within each cluster will be minimized i.e. intra-cluster energy minimization. For throughput efficient design, we will minimize the maximum sensing duration within each cluster to maximize remaining time for secondary data transmission. This objective is based on the fact that a cluster head would not diffuse back the final decision until the SU with longest sensing time finish and report its sensing results. Furthermore, fairness is another design factor to be focused on because an SU would like to get a fair benefit in return for spending energy for others. Since sensing energy consumption is proportional to sensing duration, a fair energy efficient clustering may be achieved by minimizing the total energy consumption difference among clusters i.e. inter-cluster energy minimization. Similarly, a fair throughput efficient design may be obtained by minimizing the achievable throughput difference among clusters.

Considering the objectives and constraints above, planning the selection of SUs into clusters is a nontrivial task, especially when geolocation information is not available. Even if the optimal clustering of a CRN is given, picking an optimal *cluster head* (CH) among cluster members is still a design issue. Decision fusion rules employed by each CHs is also required to be designated under imperfect CC conditions. Moreover, if there exists multiple channels, the matters given above become a complicated optimization problem. In the following, we introduce a framework for addressing all the issues above, which is based on our recent work in [14].

A. Phases of Cooperation

Assume that for a given sensing period, there exists $\mathcal{M}$ SUs available to help with sensing and there exists $\mathcal{N}$ potential PU channels to sense, we propose a CSS process that consists of three phases:

1) Sensing Phase: This is done using the procedure and algorithm described in Section III based on received SNR $\gamma_{m,n}$ and corresponding threshold $\lambda_{m,n}$, for SU m and channel n. Each SU can locally find its own optimal sensing time subject to a PU protection and spectrum utilization threshold.

2) Reporting Phase: Under noisy CC and maximum transmission power limitation, single-hop reporting links between SUs and CHs may not always yield a reliable and energy efficient collaboration among SUs. Preferably, employing a multi-hop method for the reporting phase does not only mitigate the communication range limitation but also gives an opportunity for exploiting an algorithm which finds the multi-hop path with minimum error probability from cluster members to a specific CH.

Let us consider an asymmetric directed graph of cluster n, $\mathcal{G}_n(\mathcal{C}_n, \mathcal{L}_n)$, with the set of vertices $\mathcal{C}_n$ representing SU nodes and the set of links representing the direct hop between SU nodes i and j. Denoting the bit error probability (BEP) of the link $l_{i,j}$ as $p_{i,j} = 1 - q_{i,j}$, any multi-hop path from SU i to SU j, $i \rightsquigarrow j$, has the bit success probability (BSP) of $q_{i \rightsquigarrow j} = \prod_{k,l \in i \rightsquigarrow j} q_{k,l}$. Indeed, maximizing $q_{i \rightsquigarrow j}$ is equivalent to minimizing the negative sum of logarithm of $q_{i \rightsquigarrow j}$. By doing so, Dijkstra's algorithm can be employed to calculate the route with minimum path cost from SU i to SU j. Hence, the best CH among members of cluster n with minimum BEP can be determined as follows

$$CH^n = \underset{j \in \mathcal{C}_n}{argmin} \sum_{\substack{i \in \mathcal{C}_n \\ i \neq j}} D_{i \to j} \tag{4}$$

where $i \to j$ and $D_{i \to j}$ are Dijkstra path and its cost, respectively.

3) Decision Phase: After the final CH assignment, each SU within cluster n reports its final binary decision $u_i^n = \{0, 1\}$ to CH over the route $i \to j$. Defining the random variable $k_n \triangleq \sum_{i \in C_n} u_i^n$, k_n is binomially distributed under perfect reporting channel and i.i.d. SU reports, which is a.k.a. *k-out-of-N rule*. Under the k-out-of-N rule, CH decides on $\mathcal{H}_1$ for PU n if at least $\bar{k}_n$ of SUs report 1, i.e. $k_n \geq \bar{k}_n$. Although all local observations are i.i.d. before the reporting phase, since each multi-hop path has a different success rate, CH receives non-identical detection and false alarm probabilities which are denoted by $\tilde{P}^d_{i,n}$ and $\tilde{P}^f_{i,n}$, respectively. For independent and nonidentically distributed (i.n.d.) SUs, k_n has *Poisson-Binomial* distribution [15]. The optimal $\bar{k}_n$ ($\bar{k}_n^*$), however, may not be the same for all scenarios. Therefore, we numerically find $\bar{k}_n^*$ which minimizes the total error rate, $Q_n^T\left(\bar{k}\right) = Q_n^f\left(\bar{k}\right) + \left(1 - Q_n^d\left(\bar{k}\right)\right)$.

B. Multi-objective Clustering Optimization (MOCO)

To fulfill the objectives mentioned earlier, we define the function $\mathcal{I}_n(m)$ which indicates the membership of SU $m \in [1, \mathcal{M}]$ in cluster $n \in [1, \mathcal{N}]$. For each cluster, three types of objective vectors are defined to be minimized: $\mathbf{F} \in \mathbb{R}^{\mathcal{N}}$, $\mathbf{G} \in \mathbb{R}^{\mathcal{N}}$, and $\mathbf{H} \in \mathbb{R}^2$ with elements

$$F_n = \sum_{m \in \mathcal{C}_n} \varepsilon_{m,n} \;\; , \qquad G_n = \max_{m \in \mathcal{C}_n} \left(T_{m,n}\right),$$
$$H_1 = \max_n \left(F_n\right) - \min_n \left(F_n\right), \quad H_2 = \max_n \left(G_n\right) - \min_n \left(G_n\right)$$

where F_n is for intra-cluster total energy consumption minimization within cluster n, G_n is for intra-cluster maximum sensing time minimization within cluster n, such that the time available after sensing phase is maximized for maximizing the achievable throughput. H_1 and H_2 handle the inter-cluster total energy consumption and throughput balance, respectively. Based on these objectives, we formulate Algorithm 3 which clusters the network as follows:

Algorithm 3 : MOCO

1:	Min	$\mathbf{F}, \mathbf{G}, \mathbf{H}$
2:	s.t.	$\sum_{n=1}^{N} \mathcal{I}_n(m) \leq 1, \forall m$
3:		$\sum_{m=1}^{M} \mathcal{I}_n(m) \geq 1, \forall n$
4:		$Q_n^d\left(k_n^*\right) \geq \bar{Q}_d, \forall n$
5:		$Q_n^f\left(k_n^*\right) \leq \bar{Q}_f, \forall n$
6:		$T_{m,n} \leq \tau, \forall m, n$

Since, an SU can sense at most one channel during a sensing period, $\sum_{n=1}^{N} \mathcal{I}_n(m) \leq 1$ in Line 2. Moreover, Line 3 makes sure that each PU channel is sensed by at least one SU. Lines 4-5 are global decision probability constraints which are needed to be satisfied for reporting and decision phase reliability. The constraint in Line 6 on the sensing time is especially beneficial to take SUs with unnecessarily long sensing duration out of consideration.

C. Results and Analysis

Algorithm 3 is a multi-objective mixed-integer combinatorial optimization problem which is NP-hard, therefore, employing meta-heuristic methods to obtain a sufficient solution within a reasonable time frame is preferable in practice. Hereupon, we will use the Nondominated Sorting Genetic Algorithm-II (NSGA-II) [16] for solving MOCO. Fig. 2 shows the error performance enhancement which comes with the method proposed in the *reporting phase*, where the green dashed line, red dashed line and red solid line show the total reporting error of proposed multi-hop technique, the worst and the best case of single-hop technique, respectively. As we expect, a superior performance is obtained through the proposed

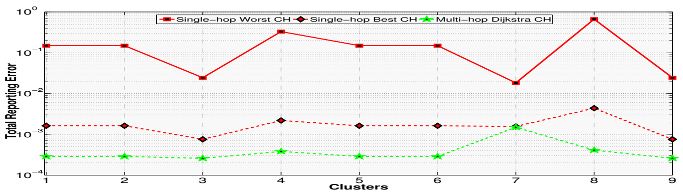

Fig. 2: Comparison between single-hop and multi-hop approach

method. For the population size of 50 and generation size of 20, the results for MOCO objective functions and clustering topology of the network using NSGA-II are shown in Fig. 3(a) and Fig. 3(b), respectively. At the bottom of the Fig. 3(a), colorbar ranges from 1 to 50 represents the populations of generations. In Fig. 3(b), the amoeba-like shapes represent the clusters in each of which square shape represents the PU with the number inside, diamond shapes represent cluster members with SNR values in dB, and hexagon shapes represents CH selected by the proposed technique.

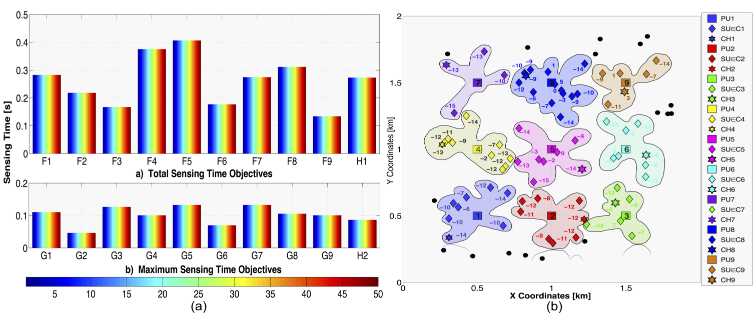

Fig. 3: (a) MOCO Results for different objectives and (b) Final clustered network topology

VI. Open Research Issues

Although the problem of spectrum sensing has been extensively studied in the literature, there are still open issues that need to be dealt with. We outline some of these research issues here:

- Under CSS, SUs are expected to participate in the sensing process, and they find channels which may then be used by other SUs, which requires a motivation or incentive. Game theory has been used in the literature to facilitate participating in cooperative sensing, e.g., [17], and it was shown that this can result in improving SUs' throughput. However, there are still open issues when applying incentives to facilitate CSS. These include the sensing energy consumption, especially when SUs are battery operated, and how this affects their participation in sensing. These also include the level of traffic that each of the SUs generates, and how this will be related to its participation in sensing.
- Another issue is the dynamic channel sensing and scheduling of sensing. In our framework in Section V, we considered the case of the SUs being allocated to sense a group of PUs' channels. In reality, there may be a very large number of channels and the cluster formations may not be able to cover all channels while guaranteeing effective sensing. In particular, under the scarcity of available SUs to cooperate, there may not be sufficient SUs to search PU channels. Hence, assigning SUs with better channel qualities to different clusters in different sensing rounds would result in a feasible and more energy efficient scheduling scheme. Therefore, assignment of SUs to clusters and scheduling the clusters to perform sensing is another hard open problem.
- Related to the above problems is the problem of the trust of sensor nodes. If a sensor node, that is involved in CSS, has been compromised, then this node may send incorrect sensing information which may change the sensing outcome. Therefore, strategies to detect and filter out sensing results from compromised nodes need to be developed.
- Channel sorting discussed above only considered from a single SU's perspective. With cooperative sensing, however, the sorting order may be different for different SUs. Hence, a sorting criterion for cooperative sensing is required to be developed and applied together with the CSS.

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