Multi-Objective Clustering Optimization for Multi-Channel Cooperative Sensing in CRNs

Abdulkadir Celik, Ahmed E. Kamal
Dept. of Electrical and Computer Eng.
Iowa State University, Ames, IA 50011
{akcelik, kamal}@iastate.edu

***Abstract*—Cooperative spectrum sensing (CSS) has been extensively studied in the literature to mitigate the weakness of spectrum sensing against hostile propagation phenomenon. Especially for large networks, clustered CSS is preferred to alleviate the energy efficiency, delay and overhead problems. In this study, reporting and sensing channels are first modeled with the consideration of path loss and fading. Then, CSS is divided into three phases: 1) In *sensing phase*, optimal sensing time is obtained for each local user subject to local detection and false alarm probability thresholds, 2) In *reporting phase*, adopting *Dijkstra's algorithm*, multi-hop paths with the maximum success rate and cluster head (CH) selection which gives the mimimum total error rate within each cluster is computed, and 3) In *decision phase*, collecting independent but unidentically distributed (i.u.d.) member decisions, the CH decides on channel occupancy based on an optimal voting rule for i.u.d. reports. Next, following the phases above, a multi-objective clustering optimization (MOCO) is formulated to select SUs into cluster seeking energy and throughput efficiency goals subject to global detection and false alarm probability constraints. Finally, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is employed to solve MOCO. Results based on our approach are presented and the merits of this approach are demonstrated.**

I. Introduction

The rapid growth of wireless communications and the demand for high quality of service (QoS) has strained the current fixed spectrum regulation policies. Recent studies by the Federal Communications Commission (FCC) show that temporal and geographical spectrum utilization range from $\%15$ to $\%85$ [1]. The limited availability and under-utilization of the radio spectrum has therefore led FCC to propose the opening of licensed bands to the public. These necessitate a *Dynamic Spectrum Access* strategy in which unlicensed/secondary users (SUs) opportunistically utilize the licensed/primary user's (PUs) spectrum insomuch that it does not cause performance degradation to PUs. As a key technology to realize opportunistic spectrum access techniques, *Cognitive Radios* (CRs) were developed with the ability of periodically sense the licensed spectra for PU's occupancy, and utilize unused spectrum by adjusting their radio parameters to accommodate surrounding environmental variations [2].

For spectrum sensing, signal processing community has proposed a variety of methods, many of which either require *a priori* knowledge of PU signals or an infeasible computational power. *Energy detection* (ED) is considered to be the simplest and most common technique which works well for any kind of signal shape and does not require any prior knowledge about PUs [3]. Denoting the absence and the presence of a PU by the binary hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively, detection performance is subject to two types of error probabilities: false alarm ($P_f = \mathcal{P}[\mathcal{H}_1|\mathcal{H}_0]$) and misdetection ($P_m = \mathcal{P}[\mathcal{H}_0|\mathcal{H}_1]$). While higher P_f results in reduced spectrum utilization, higher P_m causes more collision between PUs and SUs.

However, in practical scenarios, many channel impairments such as path loss, shadowing, multipath fading, and the receiver uncertainty may severely affect the ED performance. Under fading and shadowing, a low signal-to-noise ratio (SNR) signal reception does not necessarily imply PU absence, since SUs may be receiving multiple copies of attenuated PU signal or may be blocked by obstacles. An SU may also experience receiver uncertainty problems due to unawareness of PU transceivers, if it resides outside of the PU network transmission range [4]. Furthermore, ED performance is susceptible to noise power estimation errors, hence, SNR must be above a certain threshold to deal with the noise uncertainty, especially in heavily noisy environments [5]. Even though employing highly sensitive and expensive receivers with the capability of sensing weak signals may temper the performance degradation, this relief is limited by hardware limitations. Particularly, if SNR is under a certain threshold, neither enhancing sensitivity nor prolonging the sensing time can improve ED performance at all [6].

Fortunately, *cooperative spectrum sensing* (CSS) can mitigate the deficiency of local SUs by taking advantage of spatial diversity of SUs because it is highly unlikely that the spatially distributed SUs simultaneously suffer from the same channel impairments. CSS can be divided into two categories based on data sharing method (*centralized* and *distributed*) and data type (*soft data fusion* and *hard decision fusion*). Although employing soft data fusion yields a superior performance, sharing that massive amount of observation data results in communication overhead which cannot be sustained by a bandwidth limited CC. Thus, hard decision fusion stays a step ahead with its low reporting overhead. Nevertheless, as the number of wide-area distributed cooperating SUs increases, CC still experiences bandwidth insufficiency along with reporting unreliability and delay due to long distances. To overcome these issues, dividing SUs into clusters is an attractive and efficient method to reduce cooperation range and overhead [7], [8], [9], [10]. Considering certain objectives and constraints, planning SU selection is a nontrivial task, especially when geoposition information is unavailable. If there exists multiple channels, assignment of SUs into clusters is a more challenging problem which has not been fully investigated in the literature yet.

The objective of the CR technology is to achieve the highest spectrum utilization while protecting PUs from SU interference. Besides, when the mobility and the limited power resource of SUs are taken into account, an energy efficient clustering method plays a vital role for extending the battery life of SUs. If the spectrum utilization and energy consumption are defined as currency and commodity, respectively, ultimate design goal would be clustering SUs within the network in such a way that commodity per currency is maximized subject to a PU protection threshold. Additionally, fairness is another design metric to be considered since an SU would naturally like to get a fair benefit while spending energy for others. An energy efficient clustering may be fulfilled by minimizing the intra-cluster energy consumption and balancing the inter-cluster total sensing times because energy consumption is proportional to sensing duration. Since a *cluster head* (CH), which plays the FC's role in the cluster, would not diffuse back the final decision until it collects all the local decisions from cluster members, minimizing the intra-cluster and balancing the inter-cluster maximum sensing times is equivalent to maximizing and balancing the remaining intra-cluster and inter-cluster achievable throughput, respectively.

Similar to sensing channels, CC is also subject to channel impairments which may result in an imperfect reporting environment. In such a case, instead of using a single-hop reporting technique in which cluster members directly reports to CHs, employing a multi-hop path with the minimum error rate among all other paths results in a better reporting performance in terms of robustness, delay and communication range. Moreover, selecting the CH which yields the maximum multi-hop success rate among all cluster members is another necessity for a reliable reporting among SUs. In contrast with existing works dealing with the independent and identically distributed (i.i.d.) SUs, a decision fusion rule with the ability of handling i.u.d. SU reports is required for i.u.d. path errors.

In this paper, considering the realistic and practical issues pointed out above, we proposed CSS process that consists of three phases: 1) *Sensing phase*, in which optimal sensing time is obtained for local users subject to local detection and false alarm probability thresholds; 2) *Reporting phase*, in which employing *Dijkstra's algorithm*, multi-hop paths with the minimum error rate and CH which gives the maximum success rate within each cluster is calculated; and 3) *Decision phase*, in which reported i.u.d. decisions are gathered, and CH decides on channel occupancy based on an optimal voting rule for i.u.d. reports. For selecting SUs into clusters, Multi-Objective Clustering Optimization (MOCO) is formulated to: 1) minimize and balance intra-cluster and inter-cluster total sensing energy, respectively; and 2) to maximize and balance intra-cluster and inter-cluster achievable throughput, respectively. MOCO is also subject to constraints which guarantee protection of PUs from spectrum collisions with SUs.

The rest of this paper is organized as follows: Section II introduces the system model. Section III gives the details of CSS phases. Then, Section IV develops MOCO and explains its solution with NSGA-II. Next, simulation results and analysis are presented in Section V. Finally, Section VI concludes the paper with a few remarks.

II. System Model

In this section, the details of sensing and control channel propagation environment, as well as ED performance metrics will be provided.

Table of Notations	
Notation	**Description**
$\mathcal{M}$	Number of SUs with indexing $1 \leq m \leq \mathcal{M}$
$\mathcal{N}$	Number of clusters/PU channels with indexing $1 \leq n \leq \mathcal{N}$
$\mathcal{C}_n$	Set of SUs within cluster n with cardinality $\mathbb{C}_n$
$T_{m,n}$	Sensing time of SU m at channel n
$\varepsilon_{m,n}$	Sensing energy of SU m at channel n
$N_{m,n}$	Time-bandwidth product of SU m at channel n
$\lambda_{m,n}$	Detection threshold of SU m at channel n
$\bar{k}_n$	Voting rule for cluster n with optimal value k_n^*
$P_{m,n}^d/P_{m,n}^f$	Local detection/f. alarm prob. of SU m at channel n
$Q_n^d\left(\bar{k}_n\right)$	Global detection prob. of cluster n with voting rule $\bar{k}_n$
$Q_n^f\left(\bar{k}_n\right)$	Global f. alarm prob. of cluster n with voting rule $\bar{k}_n$
$\bar{P}_d$ / $\bar{P}_f$	Local detection / f. alarm prob. constraints
$\bar{Q}_d$ / $\bar{Q}_f$	Global detection / f. alarm prob. constraints
$p_{i,j}$ /$q_{i,j}$	BER/BSR of the single hop between SUs i and j
$q_{i\rightsquigarrow j}$	BSR of the path $i \rightsquigarrow j$ between SUs i and j
$q_{i\rightarrow j}$	BSR of the Dijkstra path between SUs i and j
Γ_n^i	Set of SUs can reach SU i within cluster n
$\mathcal{I}_n\left(m\right)$	Indicator function for membership to cluster n
F, G, H	Objective vectors for inter-cluster energy minimization, throughput maximization, and intra-cluster balance, respectively.

TABLE I: Table of Notations

A. Channel Propagation Model

The wireless propagation channel is a challenging medium for an SU energy detector since it is not only vulnerable to noise and interference from other communicating radios but also sensitive to other channel impairments such as path-loss and multipath fading. Therefore, wherever the energy detector is employed for sensing PU signal existence, channel characteristics of the surrounding environment of SUs must be considered. Based on the model in [11], received signal power by SU m on PU channel n is given by

$$\frac{P_{m,n}^r}{P_n^t} = k_n \left[\frac{d_0}{d_{m,n}}\right]^{\theta_n} \tag{1}$$

where P_n^t and $P_{m,n}^r$ represent the transmitted signal power by PU n and received signal power by SU m on PU channel n, respectively; k_n is a unitless constant that depends on signal wavelength, antenna parameters, and other factors of PU channel n; d_0 is a reference distance; θ_n is the path-loss exponent that represents the rate of PU channel n at which the path loss increases with the distance between SU m and PU n, $d_{m,n}$. With slight index changes, the same argument follows for received signal power at CC for reporting SUs.

B. Energy Detector

For sensing the activities of PUs, we will employ energy detection due to its low computational complexity and applicability to any signal shape without requiring a priori knowledge. Let us consider a frequency band with carrier frequency f_n^0, and bandwidth W_n for PU channel n. The k^{th} sample of the received primary signal taken by SU m during the sensing period $T_{m,n}$ on channel n is given as

$$y_{m,n}(k) \sim \begin{cases} v_n(k) & ,\mathcal{H}_0 \\ h_{m,n}(k)\, s_n(k) + v_n(k) & ,\mathcal{H}_1 \end{cases} \quad (2)$$

where the time-bandwidth product is denoted by $N_{m,n} = T_{m,n}W_n$ which is the number of samples taken during the sensing duration, $v_n(k)$ 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. Assuming the sensing time is smaller than the channel coherence time, $h_{m,n}(k)$ can be viewed as time-invariant during the sensing interval i.e. $h_{m,n}(k) = h_{m,n},$. Then, ED measures energy of received signal and compares it with a threshold to decide on PU presence/absence as follows

$$\mathcal{T}_{m,n}(y) = \sum_{k=1}^{N_{m,n}} |y_{m,n}(k)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda_{m,n} \quad (3)$$

where $\mathcal{T}_{m,n}(y)$ is the test statistics, $|y_{m,n}(k)|^2$ is the energy measured on sample k, and $\lambda_{m,n}$ is the detection threshold. In [12], $\mathcal{T}_{m,n}(y)$ has been shown to have central and non-central chi-square distribution under $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. Both distributions have $2N_{m,n}$ degrees of freedom and the latter has non-centrality parameter $\frac{P^r m,n T_{m,n}}{N_0/2}$ where N_0 is the noise power spectral density. Defining the instantaneous SNR of SU m at channel n as $\gamma_{m,n} = \frac{P^r_{m,n}}{N_0 W_p}$, non-centrality parameter can be shown in terms of SNR as $\frac{P^r m,n T_{m,n}}{N_0/2} = \frac{2P^r m,n T_{m,n} W_n}{N_0 Wn} = 2N_{m,n}\gamma_{m,n}$. In the case of deterministic $h_{m,n}$, using the cumulative distribution functions of the aforestated distributions, probabilities of false alarm, and detection are given as [13]

$$P^f_{m,n} = \mathcal{P}\left(\mathcal{T}_{m,n} > \lambda_{m,n}|\mathcal{H}_0\right) = \frac{\Gamma\left(N_{m,n}, \lambda_{m,n}/2\right)}{\Gamma\left(N_{m,n}\right)} \quad (4)$$

$$\begin{aligned} P^d_{m,n} &= \mathcal{P}\left(\mathcal{T}_{m,n} > \lambda_{m,n}|\mathcal{H}_1\right) \\ &= \mathcal{Q}_{N_{m,n}}\left(\sqrt{2N_{m,n}\gamma_{m,n}}, \sqrt{\lambda_{m,n}}\right) \end{aligned} \quad (5)$$

where $\Gamma(\cdot)$ 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. On the contrary of deterministic channel gain assumption, if $h_{m,n}$ follows a certain distribution, $P^d_{m,n}$ given in Eq. (4) is the conditional probability detection for a given instantaneous SNR, $\gamma_{m,n}$. Therefore, one needs to average this conditional probability over all possible instants as follows

$$P^d_{m,n} = \int_\gamma \mathcal{Q}_{N_{m,n}}\left(\sqrt{2N_{m,n}x}, \sqrt{\lambda_{m,n}}\right) f_\gamma(x)\,dx \quad (6)$$

where $f_\gamma(x)\,dx$ is the fading distribution. In the case of *Rayleigh* fading, $\gamma_{m,n}$ is exponentially distributed and the closed form expression for Eq. (6) is derived as [14]

$$\begin{aligned} P^d_{m,n} = {} & \frac{\Gamma\left(N_{m,n}-1, \lambda_{m,n}/2\right)}{\Gamma\left(N_{m,n}-1\right)} + e^{\frac{\lambda_{m,n}}{2(1+N_{m,n}\bar{\gamma}_{m,n})}} \left(\frac{N_{m,n}\bar{\gamma}_{m,n}+1}{N_{m,n}\bar{\gamma}_{m,n}}\right)^{N_{m,n}-1} \\ & \times \left[1 - \frac{\Gamma\left(N_{m,n}-1, \frac{\lambda_{m,n}N_{m,n}\bar{\gamma}_{m,n}}{2(1+N_{m,n}\bar{\gamma}_{m,n})}\right)}{\Gamma\left(N_{m,n}-1\right)}\right] \end{aligned} \quad (7)$$

where $\bar{\gamma}_{m,n}$ is the average SNR.

III. Cooperative Spectrum Sensing

We consider a cluster based centralized CSS with $\mathcal{M}$ time synchronous SUs and $\mathcal{N}$ PUs. Each cluster is responsible for sensing and utilizing only one channel. Time is divided into fixed-length slots, τ_s, in each of which PU channel is at either busy or idle state for the whole slot. SUs can join at most one cluster during a time slot. In the following subsections, CSS phases will be explained in detail.

A. Sensing Phase

During the sensing phase, 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., $P^s_{m,n} = P^s$, $\forall m,n$, then the optimal energy consumed by SU m for sensing channel n is given by $\varepsilon_{m,n} = P^s T_{m,n}$. 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. If the expression in Eq. (4) is defined as $\mathcal{F}(\lambda_{m,n}|N_{m,n})$, for a given time-bandwidth product $N_{m,n}$ and false alarm constraint, the required threshold $\lambda_{m,n}$ can be derived as $\lambda_{m,n} = \mathcal{F}^{-1}\left(\bar{P}^f|N_{m,n}\right)$. Substituting $\lambda_{m,n}$ and $N_{m,n}$ into Eq. (5), the corresponding $P^d_{m,n}$ can be computed.

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: $\quad P^f_{m,n} \leq \bar{P}_f$

B. Reporting Phase

In the reporting phase, SUs report their local decisions over a noisy CC to CH and receive decision and control feedback from CHs. Even though many studies in the literature have only focused on a direct single-hop reporting link between SUs and CHs, this may not always result in a reliable and energy efficient cooperation between SUs and CHs, especially when SUs with limited maximum transmission power in a cluster are spread over a wide area. In this case, the limited communication range of CHs/SUs may cause some SUs/CHs to lie outside the communication range of each other, and SUs/CHs will not be able to reliably get information from CHs/SUs due to the channel impairments over relatively large distances. Alternatively, exploiting a multi-hop method for the reporting phase does not only alleviate the communication range limitation but also gives a chance to employing an algorithm which finds the multi-hop path with maximum success probability from cluster member to a specific CH. Based on this idea, we can decide on the SU to act as an CH such that the total minimum error rate among other members is achieved. Taking all of these into consideration results in a better reporting performance in terms of robustness, reporting delay and communication range.

Initially, SUs transmit pilot signals to recognize which SUs are in their communication range by identifying the channel quality metrics among themselves. Consider a cluster for PU channel n as a set of SUs denoted by $\mathcal{C}_n$ with cardinality, $|\mathcal{C}_n| = \mathbb{C}_n$. We denote the set of SUs which reside in the transmission range of SU i in cluster n as $\Gamma_n^i = \{j|\, \gamma_{j,i} \geq \bar{\gamma},\, \forall j \in \mathcal{C}_n\}$ where $\gamma_{i,j}$ and $\bar{\gamma}$ are the received pilot signal SNR by SU j from SU i and the SNR threshold for communication range, respectively. Following the pilot tone, SUs arbitrarily and temporarily select an SU among them to be CH and share the channel metrics measured during the pilot tone. Then, the temporary CH run an algorithm which yields the best CH with maximum success rate multi-hop routes. Based on the result of this algorithm, temporary CH announce the new CH to SUs and devolve its responsibilities. Next, we explain the algorithm which will be exploited by CHs.

The cluster graph $\mathcal{G}_n(\mathcal{C}_n, \mathcal{L}_n)$ is defined with the set of vertices $\mathcal{C}_n$ representing SU nodes and the set of links $\mathcal{L}_c = \left\{ l_{i,j}^n \,|\, i,j \in \mathcal{C}_n,\, i \neq j,\, i \in \Gamma_n^j,\, j \in \Gamma_n^i \right\}$ representing the direct hop between SU nodes i and j. Even if the path loss for the links $l_{i,j}^n$ and $l_{j,i}^n$ may be the same, it is highly probable to experience a different fading effect due to channel randomness. Therefore, we do not assume link symmetry between SU pairs within the clusters. We further assume that CC is subject to *Rayleigh Fading* and employs binary phase shift keying (BPSK) modulation in order to facilitate a fair comparison to existing reporting methods. Thus, bit error probability from SU i to SU j under Rayleigh fading is denoted by p_{i_j}. Then, the bit success probability (BSP) from SU i to SU j is $q_{i,j} = 1 - p_{i,j}$. Denoting any multi-hop path from SU i to SU j as $i \rightsquigarrow j$, BSP of the path $i \rightsquigarrow j$ is given by $q_{i \rightsquigarrow j} = \prod_{k,l \in i \rightsquigarrow j} q_{k,l}$. Indeed, maximizing $q_{i \rightsquigarrow j}$ is equivalent to minimizing the negative sum of logarithm of $q_{i \rightsquigarrow j}$ as follows

$$\max\left(q_{i \rightsquigarrow j}\right) = \max\left(\log\left(q_{i \rightsquigarrow j}\right)\right) = \min\left(-\sum_{k,l \in i \rightsquigarrow j} \log\left(q_{k,l}\right)\right)$$

where terms $\log\left(q_{i,j}\right) \leq 0$ since $0 < q_{i,j} \leq 1$, by transforming the computation of $q_{i \rightsquigarrow j}$ from a multiplication operation into a summation operation, Dijkstra's algorithm can be employed to calculate the route with minimum path cost from SU i to SU j. Denoting the route from SU i to SU j with minimum error and its cost calculated by Dijkstra's algorithm as $i \rightarrow j$ and $D_{i \rightarrow j}$, respectively, the SU which yields the minimum total cost, i.e. the maximum total success rate, is selected to be the CH as follows

$$CH^n = \underset{j \in \mathcal{C}_n}{argmin} \sum_{\substack{i \in \mathcal{C}_n \\ i \neq j}} D_{i \rightarrow j} \tag{8}$$

C. 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 $i \rightarrow j$. Defining the random variable $k_n \triangleq \sum_{i \in \mathcal{C}_n} u_i^n$, under perfect reporting channel and i.i.d. SUs ($P_{i,n}^d = \bar{P}_d$ and $P_{i,n}^f = \bar{P}_f$, $\forall i \in \mathcal{C}_n$), k_n is binomially distributed, 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 reports 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 observations as follows

$$\tilde{P}_{i,n}^d = q_{i \rightarrow j} \bar{P}^d + \left(1 - q_{i \rightarrow j}\right)\left(1 - \bar{P}^d\right) \tag{9}$$

$$\tilde{P}_{i,n}^f = q_{i \rightarrow j} \bar{P}^f + \left(1 - q_{i \rightarrow j}\right)\left(1 - \bar{P}^f\right) \tag{10}$$

where SU j is selected to be CH. For i.u.d. SUs, k_n has *Poisson-Binomial* distribution which is given by [15]

$$Q_n^d\left(\bar{k}_n\right) = \sum_{A \in F_{\bar{k}_n}} \prod_{i \in A} \tilde{P}_{i,n}^d \prod_{i \in A^c} \left(1 - \tilde{P}_{i,n}^d\right) \tag{11}$$

$$Q_n^f\left(\bar{k}_n\right) = \sum_{A \in F_{\bar{k}_n}} \prod_{i \in A} \tilde{P}_{i,n}^f \prod_{i \in A^c} \left(1 - \tilde{P}_{i,n}^f\right) \tag{12}$$

where $F_{\bar{k}_n}$ is the set of all subsets of $\bar{k}_n$ integers that can be selected from $\{1, 2, 3, \ldots, \mathbb{C}_n\}$. Since $F_{\bar{k}_n}$ has $\binom{\mathbb{C}_n}{\bar{k}_n}$ elements, using an efficient method to calculate Eq. (11-12) is very important, especially when $\mathbb{C}_n$ is very large. For this purpose, discrete Fourier Transform (DFT) method in [16] will be used in simulations.

Another important decision phase design parameter is the optimal voting rule selection for clusters. The *OR* rule ($\bar{k}_n = 1$) works best if $\mathbb{C}_n$ is large. Likewise, The *AND* rule ($\bar{k}_n = \mathbb{C}_n$) works best if $\mathbb{C}_n$ is small. For intermediate size clusters, *Majority* rule ($\bar{k}_n \geq \mathbb{C}_n/2$) can provide better results. Since there is no single value which minimizes the detection errors for all cases, deciding on a proper $\bar{k}_n$ value for cluster n is important. In [17], an optimum voting rule which minimizes the total error rate, $Q_n^T\left(\bar{k}_n\right) = Q_n^f\left(\bar{k}_n\right) + \left(1 - Q_n^d\left(\bar{k}_n\right)\right)$, is given for i.i.d. SUs under perfect reporting channels, i.e $q_{i \rightarrow j} = 1$. Using the average multi-hop success rate within a cluster, we modify the optimal voting rule provided by [17] for CSS with identical SUs under imperfect reporting channel conditions. Let us denote the average success rate within cluster n as q_n, identical probability of detection and false alarm are given by

$$\hat{P}_n^d = q_n \bar{P}^d + \left(1 - q_n\right)\left(1 - \bar{P}^d\right) \tag{13}$$

$$\tilde{P}_n^f = q_n \bar{P}^f + \left(1 - q_n\right)\left(1 - \bar{P}^f\right) \tag{14}$$

Then, the optimal voting rule for imperfect channel will be

$$k_n^* = min\left(\mathbb{C}_n, \left\lceil \frac{\mathbb{C}_n}{1 + \alpha} \right\rceil\right) \tag{15}$$

where $\alpha = \ln \frac{\hat{P}^f_n}{\hat{P}^d_n} / \ln \frac{1-\hat{P}^d_n}{1-\hat{P}^f_n}$. In the results section, we show that although Q^{T}_n changes for different route success rates, the optimal voting k^*_n does not change for a given cluster size.

IV. Multi-Objective Clustering Optimization

Even though the clustered cooperative spectrum sensing paradigm is highly exploited in the literature for sensing a single channel, the multi-channel case, which requires clustering potential SUs to sense multiple PU channels with the consideration of energy-throughput efficiency objectives along with sensing reliability constraints, has not been studied in depth yet. For a given sensing period, if there exists $\mathcal{M}$ SUs available to help with sensing and there exists $\mathcal{N}$ potential PU channels to sense, a clustering of the SUs is required such that minimizing/maximizing the intra-cluster and balancing the inter-cluster energy expenditure/throughput is optimized subject to cooperation reliability constraints. We define the indicator function $\mathcal{I}_n(m)$ which indicates the membership of SU m in cluster 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 2 which clusters the network as follows:

Algorithm 2 : MOCO

1: Min $\;\mathbf{F}, \mathbf{G}, \mathbf{H}$
2: s.t. $\;\sum_{n=1}^{N} \mathcal{I}_n(m) \le 1, \forall m$
3: $\;\sum_{m=1}^{M} \mathcal{I}_n(m) \ge 1, \forall n$
4: $\;Q^d_n\left(k^*_n\right) \ge \bar{Q}_d, \forall n$
5: $\;Q^f_n\left(k^*_n\right) \le \bar{Q}_f, \forall n$
6: $\;T_{m,n} \le \tau, \forall m, n$

Since, an SU can sense at most one channel during a sensing period, $\sum_{n=1}^{N} \mathcal{I}_n(m) \le 1$ in Line 2. Moreover, Line 3 makes sure that each PU channel is sensed by at least one SU. Line 4-5 are global decision probability constraints need 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.

Algorithm 2 is a multi-objective mixed-integer combinatorial optimization problem which is NP-hard. Since it has conflicting objectives, there may exists a set of *nondominated solutions* by which none of the objective functions can be improved without degrading some of the other objective values. Finding nondominated solutions of such a combinatorial problem requires infeasible computation time, especially for large numbers of SUs and PU channels. Therefore, employing meta-heuristic methods to obtain a sufficient solution within a reasonable time frame is preferable in practice. Multi-objective evolutionary algorithms (MOEA), which are generic population based meta-heuristic approaches inspired by biological evolution, were shown to be performing well for many problems if it is adapted and applied carefully. Hereupon, we will use the Nondominated Sorting Genetic Algorithm-II (NSGA-II) which is a fast and elitist multi-objective genetic algorithm (MOGA) [18]. Due to space limitations, we skip the details of GAs and NSGA-II and refer interested readers to references [19] and [18]. The problem specific adaptation of NSGA-II is explained below.

Initially, a random parent population $\mathcal{P}_0$ with size $\mathbb{P}$ is generated, in which each solution is coded into a chromosome vector $\mathbf{s} \in \mathbb{Z}^{+M}$ whose indices (genes) represent SUs and corresponding values of the vector represent the cluster to which SUs are assigned. Using the coding scheme given in Table II, the constraint in Line 2 which requires an SU can be assigned at most one PU is already satisfied. For the constraint in Line 3, chromosomes are checked at the end of every genetic operation and genes violating these constraints are replaced with a proper value randomly. Constraints in Line 4 and 5 are handled directly by the method proposed in NSGA-II. At each generation, we group the indices of solution $\mathbf{s}$ which have common values into the same cluster, and evaluate fitness functions and constraint values following the steps detailed in Section III-B and Section III-C. Finally, solutions are ranked and sorted based on their fitness value to create the next generation. This iterative procedure is repeated until a target generation size, $\mathbb{G}$, is satisfied.

PUs	$\mathcal{N}-5$	$\mathcal{N}$	2	$\cdots$	n	$\cdots$	2	$\mathcal{N}-1$
SUs	1	2	3	$\cdots$	m	$\cdots$	$\mathcal{M}-1$	$\mathcal{M}$

TABLE II: A random chromosome representation for solution **s**

Par.	Value	Par.	Value	Par.	Value
f^s_n	$\sim 0.9MHz$	f^r_n	$2.1MHz$	W_n	$1MHz$
d_0	$100m$	θ_n	$3-6$	N_0	$-174dBm$
$\mathcal{N}$	9	$\mathcal{M}$	90	τ	$0.15s$
$\bar{P}_d$	0.9	$\bar{P}_f$	0.1	$\mathbb{P}$	50
$\bar{Q}_d$	0.9	$\bar{Q}_f$	0.1	$\mathbb{G}$	20

TABLE III: Default parameter values used for obtaining results

V. Results and Analysis

All simulation results were obtained and plotted using Matlab. SUs in the network were randomly distributed over an area of 2 $km \times 2$ km. Without loss of generality, PUs are located in certain positions for simulation and demonstration easiness as in Fig. 3. Throughout the simulation, the values in Table III are employed, unless it is explicitly stated otherwise.

For Algorithm 1 in the *sensing phase*, we have employed the non-linear optimization toolbox of Matlab which achieves the optimal solution in an iterative manner. During simulation, optimal $\varepsilon_{m,n}$ values are obtained using at most 20 iterations.

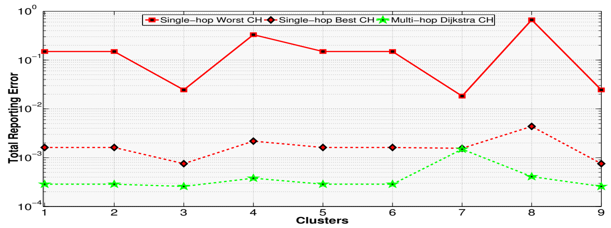

Fig. 1: Comparison between single-hop and multi-hop approach

Fig. 1 shows the error performance enhancement comes with the method proposed in the *reporting phase*. In Fig. 1, the green dashed line with star markers shows the total reporting error caused by multi-hop technique for each cluster based on the clustering topology in Fig. 3. On the other hand, the solid red line with square markers and the dashed red lines with diamond markers show the worst and the best case of single-hop technique, respectively. As it is expected, with comparison to the best case single-hop reporting, a superior performance is obtained through the proposed method.

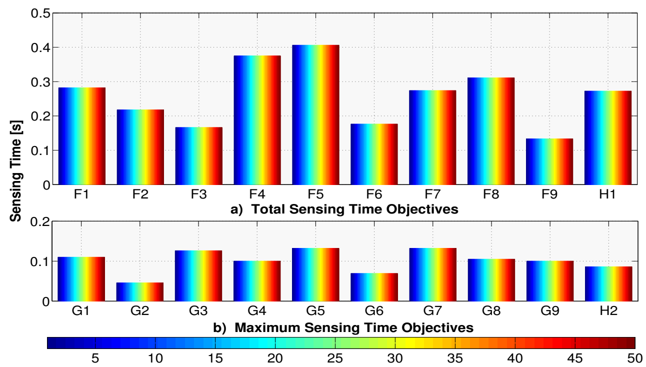

Fig. 2: MOCO Results for different objectives

For the population and generation sizes given in Table III, the results for MOCO objective values and clustering topology of the network using NSGA-II are shown in Fig. 2 and Fig. 3, respectively. At the bottom of the Fig. 2, colorbar ranges from 1 to 50 represents the populations of the final generation. In Fig. 3, the amoeba-like shapes with opaque colors represent the clusters in each of which square shape represents the PU with the number inside, diamond shapes represent cluster members along with SNR values in dB units, and hexagon shapes represents CH which is selected by the technique proposed in this paper.

VI. Conclusions

In this study, an energy and throughput efficient multi-objective clustering algorithm is developed subject to PU protection and spectrum utilization constraints in the existence of multiple PU channels. The CH of each cluster along with the maximum success rate multi-hop reporting route jointly evaluated during the optimization process. Moreover, an optimal voting rule is analyzed in the case of i.u.d. SU reports.

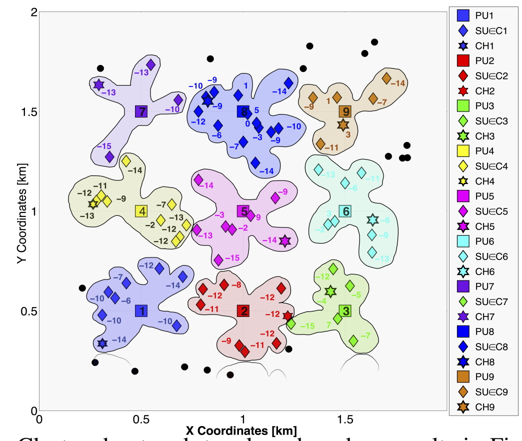

Fig. 3: Clustered network topology based on results in Fig. 2

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