

More Spectrum for Less Energy: Green Cooperative Sensing Scheduling in CRNs

Abdulkadir Celik, Ahmed E. Kamal
Dept. of Electrical and Computer Eng.,
Iowa State University, Ames, IA 50011

Abstract—Due to the increasing bandwidth demand of mobile users and their devices with energy hungry wireless networking modules, attention of research efforts has been recently shifting to find answers to the paradox of achieving more spectrum for less energy consumption. In this paper, cognitive radios have been employed to obtain more spectrum by utilizing unused licensed spectrum in an opportunistic manner. Defining the *opportunity cost* as the consumed energy per achieved unit of free spectrum, we propose a cooperative sensing scheduling framework to optimize the cost with the consideration of the sensing, reporting and channel switching costs in terms of energy expenditure subject to a licensed user protection threshold. In the proposed scheme, all primary channels are scheduled to be cooperatively sensed within a cycle which consists of rounds. In every round, secondary/unlicensed users (SUs) are first assigned to cooperatively sense the scheduled primary/licensed user (PU) channels. Consequently, SUs report their local sensing results to a fusion center for a global decision. Finally, SUs assigned to sense other PU channels perform channel switching for the next round. This scheme not only provides a feasible network set up in case there does not exist a sufficient number of SUs to satisfy the PU protection in a single round, but also offers an apparent reduction in the opportunity cost.

Index Terms—Green Cooperative Sensing, Rounds, Cycles, Green Scheduling, Energy Efficient Cognitive Radio Networks, Green Communications.

I. INTRODUCTION

The motivation behind the cognitive radio technology is rooted in the insufficiency of the current inflexible spectrum allocation policy to meet the ever-increasing quality of service (QoS) demands of today's wireless communication networks. Conventionally, radio spectrum resource is allocated for long-running time periods and exploited merely by licensees. Recent studies by Federal Communications Commission (FCC), however, have revealed that this limited resource is considerably underutilized in the spectral, spatial and temporal dimensions [1]. Therefore, cognitive radios (CRs) are introduced to detect and utilize unused spectrum bands in an opportunistic manner such that primary users (PUs), who are incumbent licensees, are protected against performance degradation caused by CRs which are also referred as secondary users (SUs).

To fulfill the appeal of new emerging technologies for more bandwidth, early studies within the literature has mainly focused on maximizing the discovered unused spectrum without considering the energy restrictions. However, a substantial part of this demand has been recently emigrated to mobile wireless networks and devices with limited energy resources. Considering the fact that 30% of the energy expenditure

of mobile devices is caused by wireless networking and computing [2], energy efficient CRNs play a vital role to provide portable devices with more spectrum for less energy consumption. Optimizing energy utilization not only leads to a more affordable network with reduced cost, but also an environmentally friendly network [3]. Because approximately 2% of the worldwide CO_2 emissions is caused by the communications and information technologies [4], energy efficient policies are becoming more important to achieve green communication standards. If we define the discovered available spectrum in cognitive radio networks (CRNs) and the energy consumption as commodity and currency, respectively, an energy efficient CRN should maximize the earned commodity per spent currency.

Nonetheless, modeling such an optimal system is not trivial since it involves designers in many tradeoffs to be balanced and many real life challenges to be taken care of. First of all, the wireless propagation medium is a challenging environment due to channel impairments such as path loss, multipath fading and shadowing etc. Hence, spectrum sensing techniques are subject to two detection errors: probabilities of misdetection ($P_m = \mathcal{P}[\mathcal{H}_0|\mathcal{H}_1]$) and false alarm ($P_f = \mathcal{P}[\mathcal{H}_1|\mathcal{H}_0]$) where \mathcal{H}_0 and \mathcal{H}_1 denote hypotheses for channel vacancy and occupancy, respectively. 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. Therefore, unlicensed users are obligated to satisfy PU protection thresholds determined by regulatory bodies. A decision taken with the consideration of these constraints does not necessarily imply the absence of the PU since the SU may be positioned in a place which is blocked from receiving existing PU signals. This phenomenon is also known as the *hidden terminal problem*. To surmount this issue, cooperation among SUs is proposed to get benefit from geographical diversity of individual SUs. In *cooperative spectrum sensing* (CSS), individual SUs report their local results to a decision maker which collects all sensing information and feed the global conclusion back to SUs. In practice, local result reports are subject to channel errors which are needed to be taken into account to assure whether the global detection error probabilities are met.

Although SUs obtain more reliable sensing decisions against channel uncertainties, cooperative gain is not free of cooperation overhead and costs. In reality, there exists multiple PU channels within a network at the same time. Thus, the selection

of SUs to sense PU channels lead to a combinatorial problem. Furthermore, to enforce global detection probabilities to follow predetermined thresholds, there is usually need for more than one SU in cooperation. This is also an inherent requirement of cooperation that we seek for spatial diversity of SUs. Accordingly, denoting the number of PUs, SUs and minimum number of SUs per PU channel by \mathcal{M} , \mathcal{N} and ρ , respectively, a feasible network setting would require $\mathcal{N} \geq \rho\mathcal{M}$ SUs to sense all PU channels subject to the reliability constraints. In the case of $\mathcal{N} < \rho\mathcal{M}$, sensing \mathcal{M} PU channels may be divided into $\mathcal{R} \geq \lceil \rho \frac{\mathcal{M}}{\mathcal{N}} \rceil$ rounds, so that we can not only attain a feasible network setup but also more selection variety for SU \leftrightarrow PU assignment. For instance, if an SU is in a good choice for multiple PUs due to its good channel quality, and hence its less sensing duration, it could be assigned to these PUs in different rounds with the additional cost of channel switching. The proposed scheme in this study, however, still offers an apparent reduction in opportunity cost in case of $\mathcal{N} \geq \rho\mathcal{M}$ due to the SU selection diversity attained by rounds. Assuming we have statistical information about *a priori* probabilities of being idle through long term observations, such kind of behavior model could be represented by radio environment maps (REM) [5], we can schedule the sensing order of PU channels such that the probability of finding idle PU channels are maximized throughout the rounds.

In [6], Sun et. al. develop a three step approach to the non-linear binary programming nature of the multi-band cooperative sensing scheduling problem. In [7], an energy efficient cooperative sensing with an optimal scheduling method is considered for sensor aided CRNs which suffers from battery limitation of sensors. Another energy efficient spectrum sensing is studied based on an optimal periodic scheduling framework in [8]. In [9], authors propose a scheduling method which minimizes the energy cost caused by sensing, reporting and channel switching actions under the assumption that $\mathcal{N} \gg \mathcal{M}$ employing the OR fusion rule under perfect reporting channel.

In multi channel cooperative sensing scheduling methods, there are three leading energy consumptive factors to be dealt with : *sensing energy*, *reporting energy* and *channel switching energy*. In a similar manner to economics jargon, we define the *opportunity cost* as the total *energy consumption* triggered from sensing, reporting and switching throughout a scheduling scheme among other alternatives in return for achieved *free spectrum*. In this paper, deriving the benefit of rounds, we contribute to the literature by modeling an optimal cooperative sensing scheduling framework with minimum opportunity cost for sensing multiple primary channels given a limited number of SUs, which gives favorable results for both cases, $\mathcal{N} \gg \mathcal{M}$ and $\mathcal{N} < \mathcal{M}$.

The rest of the paper is organized as follows: Section II introduces local and cooperative sensing procedures. In Section III, opportunity cost is formulated in terms of sensing, reporting and channel switching factors. Then, Section IV explains optimal optimization algorithm details. Simulation results and analyses are presented in Section V. Finally,

Section VI concludes the paper with a few remarks.

Table of Notations	
Notation	Description
\mathcal{M}	Number of PU channels with indexing $1 \leq m \leq \mathcal{M}$
\mathcal{N}	Number of SUs with indexing $1 \leq n \leq \mathcal{N}$
\mathcal{R}	Number of Rounds with indexing $1 \leq r \leq \mathcal{R}$
$\mathcal{H}_{m,r}^0$	Hypothesis for being idle on channel m at round r
$\mathcal{H}_{m,r}^1$	Hypothesis for being busy on channel m at round r
$\pi_{m,r}^0$	Probability of channel m being idle at round r
$\pi_{m,r}^1$	Probability of channel m being busy at round r
$\tau_{m,n}^r$	Sensing time of SU n on channel m at round r
f_m^0	Carrier frequency of PU channel m
$B_{m,n}^r$	Time-bandwidth product of SU n on channel m at round r
$\lambda_{m,n}^r$	Detection threshold of SU n on channel m at round r
$\gamma_{m,n}^r$	Received SNR at SU n on channel m at round r
\mathbb{K}_m^r	Voting rule for channel m in round r
P_b	Reporting error rate of the common control channel
$P_{d,n}^{d,r}$	Local detection probability of SU n on channel m at round r
$P_{f,n}^{f,r}$	Local false alarm probability of SU n on channel m at round r
$\bar{P}_{d,n}^{d,r}$	Reported detection probability of SU n on channel m at round r
$\bar{P}_{f,n}^{f,r}$	Reported false alarm probability of SU n on channel m at round r
Q_m^d	Global detection prob. of channel m with voting rule \bar{k}_m
Q_m^f	Global f. alarm prob. of channel m with voting rule \bar{k}_m
\bar{P}_d	Local detection probability constraint
\bar{P}_f	Local false alarm probability constraint
\bar{Q}_d	Global detection probability constraint
\bar{Q}_f	Global false alarm probability constraint
$u_{m,n}^r$	Local hard decision of SU n on PU channel m in round r
$\bar{u}_{m,n}^r$	Reported local hard decision of SU n on PU channel m in round r
\mathbb{P}^s	Sensing Power
$T_{m,r}^s$	Total sensing time of SUs on channel m at round r
$E_{m,r}^s$	Total sensing energy of SUs on channel m at round r
\mathbb{P}^x	Reporting Power
$T_{m,r}^x$	Total reporting time of SUs on channel m at round r
$E_{m,r}^x$	Total reporting energy of SUs on channel m at round r
\mathbb{P}^{sw}	Switching Power
$T_{m,r}^{sw}$	Total switching time of SUs on channel m at round r
$E_{m,r}^{sw}$	Total switching energy of SUs on channel m at round r
$x_{m,n}^r$	Binary variable for assigning SU n for sensing channel m at round r
y_m^r	Binary variable for assigning channel m to be sensed at round r

TABLE I: Table of Notations

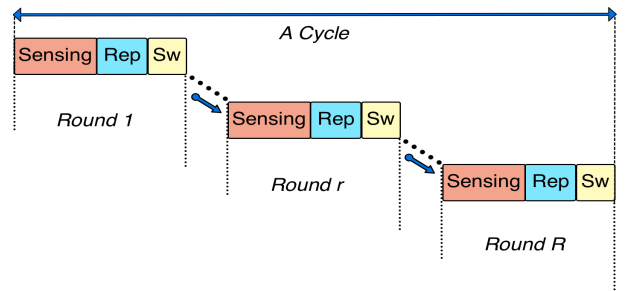


Fig. 1: Illustration of rounds and a cycle.

II. SYSTEM MODEL

We consider a CRN scenario in which the assignment of SUs to sense PU channels is determined by a central cognitive base station (CBS). The numbers of time synchronous SUs and PUs are denoted by \mathcal{N} and \mathcal{M} , respectively. Time is divided into *cycles* in each of which all available PU channels are scheduled to be sensed by centrally committed SUs at most once. As depicted in Fig. 1, every cycle is further split into

\mathcal{R} rounds in each of which an SU is assigned to at most one PU channel. A PU channel is sensed in exactly one round during the cycle, and by at least one SU. Multiple SUs may cooperatively sense a PU channel, and then report their hard decision of the sensing operation to a fusion center (FC) which implements a \mathbb{K} -out-of- \mathbb{N} voting rule to decide on the status of the channel. For their convenience, we refer readers to notation list given in Table I where energy, time and frequency parameters are in units of joule, second and Hz, respectively.

A. Local Spectrum Sensing

Since we concern ourselves more about scheduling aspects of CRNs, a generic sensing method like *energy detection* is adequate. Energy detectors (EDs) have been extensively exploited as the ubiquitous sensing technique in the literature due to its simplicity, compatibility with any signal type, and low computational and implementation complexity [10], [11]. To detect primary signals, EDs measure the received signal energy for a time interval and compares it with a predetermined threshold to decide on the PU activity status.

Let us consider PU channel m with carrier frequency f_m^0 , and bandwidth W_m . The i^{th} sample of the received primary signal taken by SU n during the sensing period $\tau_{m,n}^r$ on channel m at round r is given as

$$y_{m,n}^r(i) \sim \begin{cases} v_m(i) & , \mathcal{H}_{m,r}^0 \\ \alpha_{m,n}^r s_m^r(i) + v_m(i) & , \mathcal{H}_{m,r}^1 \end{cases} \quad (1)$$

where $v_m(i)$ is additive white Gaussian noise (AWGN), $s_m^r(i)$ is the primary signal, and $\alpha_{m,n}^r$ is a deterministic constant due to path loss effect. Using samples defined in Eq. (1), ED calculates the test statistics and compares it with a threshold to decide on PU presence/absence as follows

$$\mathcal{T}_{m,n}^r(y) = \sum_{i=1}^{N_{m,n}^r} |y_{m,n}^r(i)|^2 \underset{\mathcal{H}_{m,r}^0}{\overset{\mathcal{H}_{m,r}^1}{\geq}} \lambda_{m,n}^r \quad (2)$$

where $\mathcal{T}_{m,n}^r(y)$ is the test statistic, the time-bandwidth product is denoted by $N_{m,n}^r = \tau_{m,n}^r W_m$ which is the number of samples taken during the sensing duration, $|y_{m,n}^r(i)|^2$ is the energy measured on sample i , and $\lambda_{m,n}^r$ is the detection threshold.

In his early work, Urkowitz has shown that $\mathcal{T}_{m,n}^r(y)$ have central and non-central chi-square distribution under $\mathcal{H}_{m,r}^0$ and $\mathcal{H}_{m,r}^1$, respectively [12]. Both distributions have $2N_{m,n}^r$ degrees of freedom. If $\gamma_{m,n}^r = \frac{P_{m,n}^r}{N_0 W_n}$ is defined as the instantaneous signal to noise ratio (SNR) of SU n on channel m , one can express the non-centrality parameter of the latter distribution in terms of SNR as $2N_{m,n}^r \gamma_{m,n}^r$ where $P_{m,n}^r$ is the received signal power at SU n on channel m and N_0 is the noise power spectral density. Exploiting the aforesaid distributions' cumulative distribution functions, local false

alarm and detection probabilities are given by [13]

$$P_{m,n}^{f,r} = \mathcal{P}(\mathcal{T}_{m,n}^r > \lambda_{m,n}^r | \mathcal{H}_{m,n}^0) = \frac{\Gamma(N_{m,n}^r, \lambda_{m,n}^r/2)}{\Gamma(N_{m,n}^r)} \quad (3)$$

$$P_{m,n}^{d,r} = \mathcal{P}(\mathcal{T}_{m,n}^r > \lambda_{m,n}^r | \mathcal{H}_{m,n}^1) \\ = \mathcal{Q}_{N_{m,n}^r} \left(\sqrt{2N_{m,n}^r \gamma_{m,n}^r}, \sqrt{\lambda_{m,n}^r} \right) \quad (4)$$

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 $(m-1)^{\text{th}}$ order modified Bessel function of the first kind.

B. Cooperative Spectrum Sensing (CSS)

EDs rely upon the underlying assumption of perfect noise power estimation. As a consequence, the uncertainty in noise power evokes *SNR wall* and high false alarm probability. Moreover, implications because of radio propagation characteristics such as *receiver uncertainty* and *hidden terminal problem* are other challenging issues which arise from using EDs [14]. Since it is highly unlikely that the spatially distributed SUs concurrently experience similar channel impacts, CSS exploits the spatiotemporal diversity of SUs to alleviate the aforementioned problems.

In this paper, we consider a *centralized* CSS in which SUs report binary local decisions over a dedicated common control channel (CC) to the fusion center which combines and diffuses the final decision back to SUs. Sensing proceeds in rounds, such that in each round a subset of PU channels are sensed, and all SUs are involved in a sensing round. All rounds constitute a cycle in which all PU channels are sensed. At the end of each round, discovered available channels are used by SUs according to a certain resource sharing strategy, which is beyond the scope of this paper.

In the case that SU n is assigned to sense PU channel m in round r , SU n runs a local optimization which is given in Algorithm 1 to find the minimum sensing duration $\tau_{m,n}^r$ such that local detection and false alarm probabilities, $P_{m,n}^{d,r}$ and $P_{m,n}^{f,r}$, satisfy the local thresholds \bar{P}_d and \bar{P}_f , respectively.

Algorithm 1 : Optimal local sensing time of the SU n

- 1: Min $\tau_{m,n}^r$
 - 2: s.t. $P_{m,n}^{d,r} \geq \bar{P}_d$
 - 3: $P_{m,n}^{f,r} \leq \bar{P}_f$
-

Following the local sensing process, assigned SUs send their hard results $u_{m,n}^r$ to the FC over an binary symmetric CC. Denoting the reporting error probability as $P_b = \mathcal{P}[\tilde{u}_{m,n}^r = 1 | u_{m,n}^r = 0] = \mathcal{P}[\tilde{u}_{m,n}^r = 0 | u_{m,n}^r = 1]$ where $\tilde{u}_{m,n}^r$ is the hard decision received by the FC, local false alarm

and detection probabilities at the FC side are given by

$$\begin{aligned}\tilde{P}_{m,n}^{f,r} &= \mathcal{P} [\tilde{u}_{m,n}^r = 1 | u_{m,n}^r = 0] \mathcal{P} [u_{m,n}^r = 0 | \mathcal{H}_{m,r}^0] \\ &+ \mathcal{P} [\tilde{u}_{m,n}^r = 1 | u_{m,n}^r = 1] \mathcal{P} [u_{m,n}^r = 1 | \mathcal{H}_{m,r}^0] \\ &= P_b (1 - P_{m,n}^{f,r}) + (1 - P_b) P_{m,n}^{f,r}\end{aligned}\quad (5)$$

$$\begin{aligned}\tilde{P}_{m,n}^{d,r} &= \mathcal{P} [\tilde{u}_{m,n}^r = 1 | u_{m,n}^r = 0] \mathcal{P} [u_{m,n}^r = 0 | \mathcal{H}_{m,r}^1] \\ &+ \mathcal{P} [\tilde{u}_{m,n}^r = 1 | u_{m,n}^r = 1] \mathcal{P} [u_{m,n}^r = 1 | \mathcal{H}_{m,r}^1] \\ &= P_b (1 - P_{m,n}^{d,r}) + (1 - P_b) P_{m,n}^{d,r}\end{aligned}\quad (6)$$

It is noteworthy that local decisions are not equal for all PUs, SUs and round pairs, that is, decision maker receives independent but unidentically distributed (i.u.d) probabilities. Thus, this prevents the use of binomial distribution which requires independent and identically distributed (i.i.d) reports. Consequently, the random variable $K_m^r \triangleq \sum_n \tilde{u}_{m,n}^r x_{m,n}^r$ follows the *Poisson-binomial* distribution. Using equations (5-6) in Poisson-binomial distribution, the FC obtains the global false alarm and detection probabilities by fusing the local reports as follows

$$\begin{aligned}Q_{m,r}^f &= \mathcal{P} [K_m^r \geq \bar{K}_m^r | \mathcal{H}_{m,r}^0] \\ &= \sum_{A \in F_{\bar{K}_m^r}} x_{m,n}^r \prod_{n \in A} \tilde{P}_{m,n}^{f,r} \prod_{n \in A^c} (1 - \tilde{P}_{m,n}^{f,r})\end{aligned}\quad (7)$$

$$\begin{aligned}Q_{m,r}^d &= \mathcal{P} [K_m^r \geq \bar{K}_m^r | \mathcal{H}_{m,r}^1] \\ &= \sum_{A \in F_{\bar{K}_m^r}} x_{m,n}^r \prod_{n \in A} \tilde{P}_{m,n}^{d,r} \prod_{n \in A^c} (1 - \tilde{P}_{m,n}^{d,r})\end{aligned}\quad (8)$$

where $F_{\bar{K}_m^r}$ is the set of all subsets of \bar{K}_m^r integers that can be selected from $\{1, 2, 3, \dots, N_m^r\}$ and $N_m^r = \sum_n x_{m,n}^r$ is the total number of SUs assigned to sense PU channel m in round r . Since $F_{\bar{K}_m^r}$ has $\binom{N_m^r}{\bar{K}_m^r}$ elements, using an efficient method to calculate Eq. (7-8) is very important, especially when N_m^r is very large. For this purpose, the discrete Fourier Transform (DFT) method in [15] will be used in simulations. Deciding on an optimal voting rule is still a design issue since a fixed \bar{K}_m^r does not result in an optimal value in all cases. Hence, we will employ the optimal voting rule which minimizes the total error rate of the global decisions, $Q_{m,r}^T = Q_{m,r}^f + (1 - Q_{m,r}^d)$, with imperfect reporting channel [16].

III. OPPORTUNITY COST

There are three main sources of energy consumption which contribute to the spectrum opportunity cost: *sensing cost*, *reporting cost* and *channel switching cost*. For the problem formulation, we define the following optimization variables:

- $x_{m,n}^r \in \{0, 1\}$ is a binary variable which indicates that SU n is committed to sense PU channel m in round r .
- $y_m^r \in \{0, 1\}$ is a binary variable which indicates that PU channel m is scheduled to be sensed at round r .

In the following subsections, spectrum opportunity cost will be expressed in terms of optimization variables.

A. Sensing Energy

Total sensing duration spent by SUs which sense scheduled PU channels within round r is given by

$$\mathbb{T}_s^r = \sum_{m=1}^{\mathcal{M}} \sum_{n=1}^{\mathcal{N}} \tau_{m,n}^r x_{m,n}^r \quad (9)$$

Then, denoting the sensing power as \mathbb{P}_s , the total energy spent for sensing is given by

$$\mathbb{E}_S = \sum_{r=1}^{\mathcal{R}} \mathbb{E}_s^r = \sum_{r=1}^{\mathcal{R}} \mathbb{P}_s \mathbb{T}_s^r \quad (10)$$

B. Transmission Energy

Total reporting duration spent by SUs which report local results for scheduled PU channels within round r is given by

$$\mathbb{T}_x^r = \sum_{m=1}^{\mathcal{M}} \sum_{n=1}^{\mathcal{N}} t_x x_{m,n}^r \quad (11)$$

where t_x is the reporting duration. Then, denoting the sensing power as \mathbb{P}_s , the total energy spent for reporting is given by

$$\mathbb{E}_X = \sum_{r=1}^{\mathcal{R}} \mathbb{E}_x^r = \sum_{r=1}^{\mathcal{R}} \mathbb{P}_x \mathbb{T}_x^r \quad (12)$$

C. Switching Energy

Suppose that SU n is assigned to sense PU channels $m - 1$ and m in rounds $r - 1$, and r , respectively. To implement these sensing assignments, the SU has to switch its operating frequency to desired channel's parameters in corresponding rounds, which can be done by adjusting the voltage level of the voltage controlled oscillator (VCO) of the phase locked loop (PLL) circuit. We assume that the switching time satisfies the triangularity and linearity properties, $t_{sw} = \beta \times |f_{m-1}^0 - f_m^0|$, where β [s/Hz] is a switching factor that depends on parameters such as power consumption, error rate, and used technology. Accordingly, the total switching time of SUs switching their frequencies at the beginning of the round r is given by

$$\mathbb{T}_{sw}^r = t_{sw} \sum_{n=1}^{\mathcal{N}} \left| \sum_{m=1}^{\mathcal{M}} f_m x_{m,n}^r - \sum_{m=1}^{\mathcal{M}} f_m x_{m,n}^{r-1} \right| \quad (13)$$

Thus, denoting the sensing power as \mathbb{P}_s , the total energy spent within a cycle for switching is given by

$$\mathbb{E}_{SW} = \sum_{r=0}^{\mathcal{R}} \mathbb{E}_{sw}^r = \sum_{r=0}^{\mathcal{R}} \mathbb{P}_{sw} \mathbb{T}_{sw}^r \quad (14)$$

where $r = 0$ represents the initial frequency adjustments of SUs. Therefore, the accumulated energy consumption within a cycle due to these three factors is given by

$$\mathbb{E}_T = \mathbb{E}_S + \mathbb{E}_X + \mathbb{E}_{SW} \quad (15)$$

IV. SCHEDULING OPTIMIZATION

In this section, we will formulate our optimization problem which minimizes the opportunity cost overall possible channel sensing order permutations such that PU protection and spectrum utilization thresholds are satisfied along with other defined system constraints explained at the beginning of Section II. Until now, we have not considered the achieved spectrum opportunity in return for the total energy spent throughout the rounds, \mathbb{E}_T . For this purpose, we can use the probability that the FC decides that PU channel is idle while it is indeed idle. That is,

$$\begin{aligned} \pi_{m,r}^0 &= \mathcal{P}[\mathcal{H}_{m,r}^0] \mathcal{P}[\mathcal{H}_{m,r}^0 | \mathcal{H}_{m,r}^0] \\ &= \mathcal{P}[\mathcal{H}_{m,r}^0] [1 - Q_{m,r}^f] \end{aligned} \quad (16)$$

where $\mathcal{P}[\mathcal{H}_{m,r}^0]$ is the *a priori* probability that channel m is idle at round r . Thus, the overall opportunity cost for the entire scheduling frame work is given by

$$\eta = \frac{\mathbb{E}_T}{\pi_0} = \frac{\mathbb{E}_T}{\sum_{m,r} \pi_{m,r}^0 y_m^r W_m} \quad (17)$$

which is nothing but the inverse of the *energy efficiency* in metrics [*Joule/Hz*]. Based on the discussion above, we formulate the optimization problem which minimizes the opportunity cost (or equivalently maximizes the energy efficiency) in Algorithm 2

Algorithm 2 : Sensing Scheduling Optimization

- 1: Min η
 - 2: s.t. $\bar{Q}_d \leq Q_{m,r}^d \quad \forall r; \forall m$
 - 3: $Q_{m,r}^f \leq \bar{Q}_f \quad \forall r; \forall m$
 - 4: $\sum_{m=1}^{\mathcal{M}} x_{m,n}^r \leq 1 \quad \forall r; \forall n$
 - 5: $\sum_{r=1}^{\mathcal{R}} y_m^r = 1 \quad \forall m$
 - 6: $x_{m,n}^r \leq y_m^r \quad \forall r; \forall n$
 - 7: $y_m^r \leq \sum_{n=1}^{\mathcal{N}} x_{m,n}^r \quad \forall r; \forall m$
 - 8: $0 \leq \mathbb{T}_s^r, \mathbb{T}_x^r, \mathbb{T}_{sw}^r, \tau_{m,n}^r \quad \forall r; \forall m; \forall n$
 - 9: $x_{m,n}^r, y_m^r \in \{0, 1\} \quad \forall r; \forall m; \forall n$
-

In Algorithm 2, Line 2 and Line 3 enforce global detection and false alarm probabilities to satisfy the requirements of regulatory bodies. Line 4 ensures that an SU is assigned to at most one PU channel in every round. Line 5 meets the requirement that a PU channel is sensed once throughout the cycle. Line 6 and Line 7 are for defining variable y_m^r in terms of $x_{m,r}^r$ by implementing logic OR function such that $y_m^r = \bigvee (x_{m,n}^r)$. Line 8 requires the time related variables to be non-negative. Finally, Line 9 defines the variable types.

V. RESULTS AND ANALYSIS

All simulation results were obtained and plotted using Matlab. SUs in the network were randomly distributed over an

area of $800 m \times 800 m$. Without loss of generality, PUs are located in certain positions for simulation and demonstration easiness. Unless it is explicitly stated otherwise, we employ the parameters given in Table II where \mathbb{P}_s and \mathbb{P}_x are taken from [18] and \mathbb{P}_{sw} and t_{sw}

Par.	Value	Par.	Value	Par.	Value
\mathbb{P}_s [18]	0.25W	\mathbb{P}_x [18]	0.11W	\mathbb{P}_{sw} [19]	4.2mW
t_x	100 μ s	t_{sw} [19]	120 μ s	W_m	1MHz
d_0	20m	θ_m	3 – 6	N_0	-174 dBm
\bar{P}_d, \bar{Q}_d	0.9	\bar{P}_f, \bar{Q}_f	0.1	P_b	10^{-3}

TABLE II: Default parameter values used for obtaining results

Path loss constant between PU m and SU n , $\alpha_{m,n}^T$, in Eq.(1) has been calculated based on the simplified path loss model in [17]. Lifetimes for busy and idle period of PU channels are sampled using gamma distribution which is highly preferred to model many lifetime related random variables. After generating gamma random variables for each PU channel, the corresponding shape and scale parameters of the corresponding probability density function is estimated using maximum likelihood estimation.

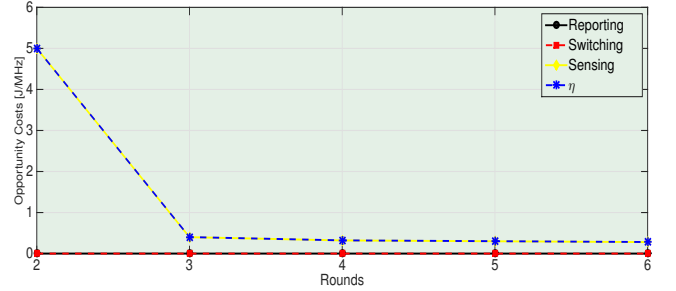


Fig. 2: Opportunity costs vs. rounds for 4 PUs and 8 SUs

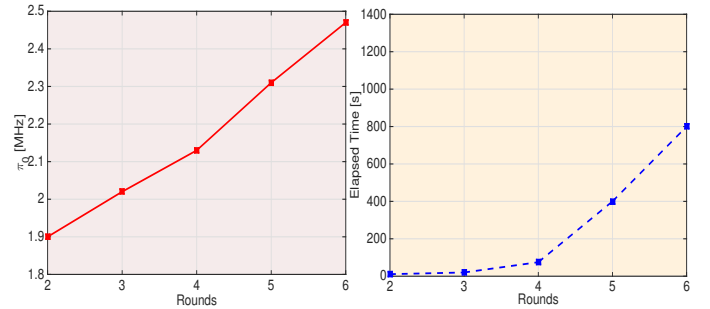


Fig. 3: π_0 and optimization time vs. rounds for 4 PUs and 8 SUs

For Algorithm 1 in the Section II-A, we have employed the non-linear optimization toolbox of Matlab which achieves the optimal solution in an fast and iterative manner. For solving Algorithm 2, we use the Solving Constraint Integer Programs (SCIP) which is currently one of the fastest non-commercial solvers for MINLP [20]. Proposed algorithms are successively divided into smaller subproblems (branching) and solved recursively, in a similar technique used for solving both Integer Programs (IP) and Constraint Programs (CP). SCIP is also accessible to be used in Matlab via the optimization

interface (OPTI) platform which interfaces many high-quality optimization tools within the rapid development environment of Matlab [21].

In Fig.2, opportunity cost, η , in units [*Joule/MHz*] is plotted versus the number of rounds for optimal and suboptimal algorithms for $\mathcal{M} = 4$ and $\mathcal{N} = 8$. A feasible solution is found for a cycle consisting of 2 rounds and the energy cost is dramatically reduced with 3 rounds. This dramatic change is mostly because SUs with favorable sensing times for more than one PU channel are assigned to the different PU channels in different rounds. For the remaining rounds, η keeps decreasing due to the increase in the π_0 as shown in the Fig.3 where the discovered spectrum gain attained by proposed scheduling method is apparent.

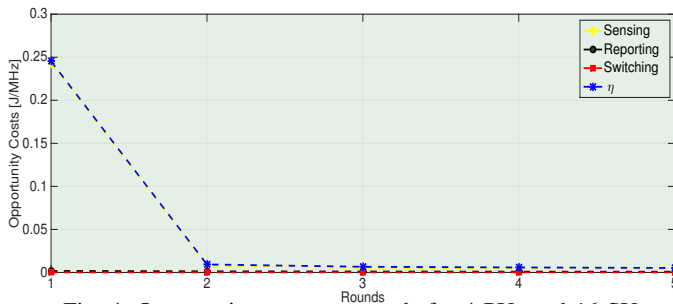


Fig. 4: Opportunity costs vs. rounds for 4 PUs and 16 SUs

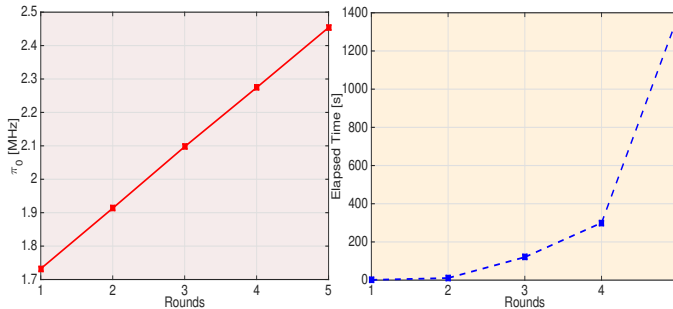


Fig. 5: π_0 and optimization time vs. rounds for 4 PUs and 16 SUs

In Fig 4, where $\mathcal{M} = 4$ and $\mathcal{N} = 16$, the feasibility of the solution is satisfied at the very beginning, that is, $1 \geq \lceil \rho \frac{\mathcal{M}}{\mathcal{N}} \rceil$. The advantage of using multiple rounds per cycle is still evident, which can be seen from the reduction in η at round 2. The explanation of this enhancement follows the same reasoning above. The achieved free spectrum attained via proposed scheduling method and the time complexity are also shown in Fig.5.

VI. CONCLUSIONS

In this study, an energy efficient multi-channel cooperative spectrum sensing scheduling framework has been proposed with the consideration of energy spent on sensing, reporting and channel switching. Total energy expenditure over all the scheduling scheme is optimized to obtain maximum free spectrum gain subject to global false alarm and detection probabilities which are obtained over an imperfect control

channel. The idea of sensing in rounds has been shown to be beneficial to obtain a feasible network setup in case the number of SUs is insufficient to meet the PU protection thresholds. In particular, this idea provides us with SU selection diversity for SU \leftrightarrow PU assignments, so that, we can assign favorable SUs with their lower sensing times to multiple PUs through rounds.

REFERENCES

- [1] F. C. Commission *et al.*, "Spectrum policy task force report, fcc 02-155," 2002.
- [2] S. Pollin, R. Mangharam, B. Bougard, L. Van der Perre, I. Moerman, R. Rajkumar, and F. Cathoor, "Meera: Cross-layer methodology for energy efficient resource allocation in wireless networks," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 1, pp. 98–109, 2008.
- [3] G. Gur and F. Alagoz, "Green wireless communications via cognitive dimension: an overview," *Network, IEEE*, vol. 25, no. 2, pp. 50–56, 2011.
- [4] M. Webb *et al.*, "Smart 2020: Enabling the low carbon economy in the information age," *The Climate Group. London*, vol. 1, no. 1, pp. 1–1, 2008.
- [5] Y. Zhao, J. Gaeddert, K. K. Bae, and J. H. Reed, "Radio environment map enabled situation-aware cognitive radio learning algorithms," in *Software Defined Radio Forum (SDRF) technical conference*, 2006.
- [6] X. Sun and D. Tsang, "Energy-efficient cooperative sensing scheduling for multi-band cognitive radio networks," 2013.
- [7] R. Deng, J. Chen, C. Yuen, P. Cheng, and Y. Sun, "Energy-efficient cooperative spectrum sensing by optimal scheduling in sensor-aided cognitive radio networks," *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 2, pp. 716–725, 2012.
- [8] R. Deng, S. He, J. Chen, J. Jia, W. Zhuang, and Y. Sun, "Energy-efficient spectrum sensing by optimal periodic scheduling in cognitive radio networks," *IET communications*, vol. 6, no. 6, pp. 676–684, 2012.
- [9] S. Eryigit, S. Bayhan, and T. Tugcu, "Channel switching cost aware and energy-efficient cooperative sensing scheduling for cognitive radio networks," in *Communications (ICC), 2013 IEEE International Conference on*. IEEE, 2013, pp. 2633–2638.
- [10] B. Wang and K. R. Liu, "Advances in cognitive radio networks: A survey," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 5, no. 1, pp. 5–23, 2011.
- [11] E. Axell, G. Leus, E. G. Larsson, and H. V. Poor, "Spectrum sensing for cognitive radio: State-of-the-art and recent advances," *Signal Processing Magazine, IEEE*, vol. 29, no. 3, pp. 101–116, 2012.
- [12] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523–531, 1967.
- [13] A. Ghasemi and E. S. Sousa, "Opportunistic spectrum access in fading channels through collaborative sensing," *Journal of communications*, vol. 2, no. 2, pp. 71–82, 2007.
- [14] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *Communications Surveys & Tutorials, IEEE*, vol. 11, no. 1, pp. 116–130, 2009.
- [15] M. Fernandez and S. Williams, "Closed-form expression for the poisson-binomial probability density function," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 46, no. 2, pp. 803–817, 2010.
- [16] A. Celik and A. E. Kamal, "Multi-objective clustering optimization for multi-channel cooperative sensing in crns," in *GLOBECOM Wireless Communications Symposium*. IEEE, 2014.
- [17] A. Goldsmith, *Wireless communications*. Cambridge university press, 2005.
- [18] C. Jiang, H. Zhang, Y. Ren, and H.-H. Chen, "Energy-efficient non-cooperative cognitive radio networks: micro, meso, and macro views," *Communications Magazine, IEEE*, vol. 52, no. 7, pp. 14–20, 2014.
- [19] S. Shin, K. Lee, and S.-M. Kang, "4.2 w cmos frequency synthesizer for 2.4 ghz zigbee application with fast settling time performance," in *Microwave Symposium Digest, 2006. IEEE MTT-S International*. IEEE, 2006, pp. 411–414.
- [20] T. Achterberg, "Scip: solving constraint integer programs," *Mathematical Programming Computation*, vol. 1, no. 1, pp. 1–41, 2009.
- [21] J. Currie and D. I. Wilson, "OPTI: Lowering the Barrier Between Open Source Optimizers and the Industrial MATLAB User," in *Foundations of Computer-Aided Process Operations*, N. Sahinidis and J. Pinto, Eds., Savannah, Georgia, USA, 8–11 January 2012.