Channel Switching Cost Aware and Energy-Efficient Cooperative Sensing Scheduling for Cognitive Radio Networks

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***Abstract*—In this paper, we formulate the energy-efficient cooperative sensing scheduling scheme for a cognitive radio network (CRN) with heterogeneous primary signal-to-noise ratio at each secondary user (SU). In the considered CRN, cognitive base station assigns a set of SUs for each frequency with the aim of minimizing the total energy consumption for sensing while meeting the asserted probability of detection and false alarm requirements by employing cooperation. Sensing duration for a target detection performance increases with degrading channel quality. Thus, an SU with better channel conditions consumes lower energy for sensing. Additionally, an SU also spends energy to switch to the next frequency in its sensing sequence. Our scheduling scheme discovers the appropriate set of SUs for each frequency by considering the sensing and channel switching energy as well as the energy consumed for reporting the sensing outcomes. We also present a polynomial time heuristic, Energy Aware Spectrum sEnsing (EASE) that performs close to the optimal solution.**

***Index Terms*—Cognitive radio, cooperative sensing scheduling, energy-efficient sensing, heterogeneous sensing.**

I. INTRODUCTION

Energy efficiency, which used to be considered an issue only for battery powered wireless sensors, has become one of the major design criteria for all types of networks. This can be attributed to three main factors: operators, increasing carbon emissions, and mobile users. Regarding operators, energy costs of running a network is reported to be almost 20-30 percent of the operational expenses [1]. As energy prices increase consistently, such a percentage motivates the operators to take the energy efficiency as a principal performance criterion. Regarding carbon emissions, although currently Information and Communication Technologies emit only 2% of the global carbon emissions [2], it is naive to underestimate this amount considering the exponential increase in data traffic. Apart from using renewable energy sources for electricity [3], increasing energy efficiency of the system is a viable solution for declining carbon emissions. Finally, regarding the mobile society, accessing the Internet from mobile devices is daily practice. Power-hungry mobile video traffic has a significant share in total mobile traffic, which brings energy efficiency as an important measure for mobile users. Unfortunately, achieving high energy efficiency while preserving the user satisfaction is one of the major research questions [4]. Hence, energy efficiency should be considered as a basic design criterion at every scale - from hardware at the small scale and design of the whole Internet in the large scale.

In this work, we approach this problem from the mobile user viewpoint and focus on energy consumption of cooperative sensing scheduling (CSS) in a centralized cognitive radio network (CRN). In a CRN, secondary users (SUs) discover the spectrum opportunities via spectrum sensing. However, as sensing outcomes are prone to errors due to the wireless channel, cooperation among SUs is preferred to enhance reliability. In a multi-channel CRN, a CSS scheme implemented at the cognitive base station (CBS) determines the set of SUs to sense each channel such that spectrum opportunities are discovered with high accuracy (i.e. high detection probability) and high efficiency (i.e. low false alarm probability). We consider the signal-to-noise ratio (SNR) of individual SUs for each channel since sensing performed by SUs with higher SNR results in less sensing energy expenditure and better performance. Most of the prior works take the detection accuracy as the main criterion without articulating their energy performance whereas our goal is energy efficiency with satisfactory PU protection and SU efficiency.

Similar to our work, works in [5], [6] and [7] focus on the energy efficiency of CSS and formulate it as a combinatorial optimization problem. However, as these works do not differentiate SUs, the problem is reduced to deciding on the number of SUs to sense each channel. Sun et al. [5] presume the identical SNR at each SU and identical sensing duration for all SUs. Likewise, Zhang et al. [6] determine the number of SUs to sense a channel and duration of sensing for each frame. Hao et al. devise a sensing scheme in which each SU determines the set of channels to be sensed on its own [7]. Unlike these works, we consider a heterogeneous environment in terms of SNR of the primary signal at each SU. Using the relationship between SNR and sensing duration in [8], we determine the set of SUs for each primary channel together with the sensing duration. In our previous work [9], we provided the energy-optimal CSS scheme in a CRN with heterogeneous primary channels. Different from [9], we incorporate the channel switching cost

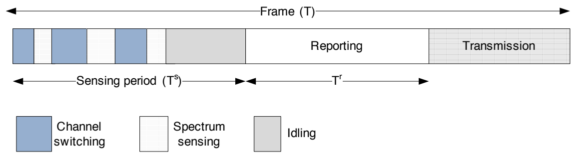


Fig. 1: Frame organization.

into our design, provide the optimal solution, and develop a heuristic algorithm with low complexity.

The remainder of this paper is organized as follows: Section II defines the system under consideration while Section III provides a formal definition of the problem using network flows. Next, Section IV first presents the outer linearization based solution methodology and then introduces Energy Aware Sensing schEduler (EASE), the heuristic solution with lower complexity for the considered problem. Section V evaluates the performance of the presented schemes. Finally, Section VI derives conclusions.

II. SYSTEM MODEL

We assume an infrastructure based CRN where the CBS coordinates the SUs. The system operates in a frame based fashion, and there is a quiet sensing period with length T^s at the beginning of each frame. During this *sensing period*, SUs sense the channels assigned to them. In a sensing period, an SU may sense multiple channels one after another by tuning its antenna to the corresponding channel. However, channel switching is not immediate and comes with a time and an energy overhead so deciding on the order of sensing is of paramount importance. For the sake of energy saving, an SU that completes all its sensing tasks switches to low energy consuming *idling mode* till the end of sensing period. The sensing period is followed by a *reporting period* during which SUs report their local sensing results to CBS for fusion. Fusion operations are performed using OR rule. After the reporting period, *data transmission* begins and continues until the end of the frame. Fig. 1 depicts the organization of a frame.

Let M and N denote the number of primary channels and the number of SUs, respectively. We assume that $M \ll N$, and the SNR value of the received primary user (PU) signal is assumed to differ for each SU over each channel, which is denoted by $\gamma_{m,n}$. We require that each channel is sensed by at least δ^{min} SUs to ensure diversity. Our goal in this paper is to sense all M channels with minimum energy consumption while providing adequate accuracy such that cooperative detection and false alarm probabilities are in accordance with their respective thresholds.

Energy Consumption Model: In a typical cognitive radio, the total energy spent for sensing (E^{total}) has three components:

Sensing Energy (E^s): This energy is consumed while SUs listen to the channel to detect the presence of PUs. Let P^s and $\tau_{m,n}$ denote the sensing power and sensing duration for channel m for SU_n, respectively. Then, E^s is given by $\sum_{m=1}^{M}\sum_{n=1}^{N} P^s \tau_{m,n}$.

Channel Switching Energy (E^{cs}): This is the energy consumed when SUs switch channels during the sensing period. Frequency switching is performed via changing the input voltage of the voltage-controlled oscillator (VCO) operating in a phase locked loop (PLL) to generate the desired output frequency. The power required to complete this operation is referred to as channel switching power (P^{cs}) and the related energy consumption is given as $P^{cs}T^{cs}$ where T^{cs} is the total time required for completing the channel switch. T^{cs} is given by $t^{cs}|f-f'|$ where t^{cs} is the time required to switch to the adjacent channel and $|f-f'|$ is the absolute value of separation between the two frequencies [10]. Let f_n^0 denote the frequency of the channel to which the antenna of the SU_n is tuned at the beginning of the quiet period, and $\mathcal{C}_n$ be the ordered set of frequencies that are going to be sensed by SU_n, i.e., $\mathcal{C}_n = \{f_n^1, f_n^2, \ldots\}$. Then $E^{cs} = P^{cs}t^{cs}\sum_{n=1}^{N}(|f_n^0 - f_n^1| + \sum_{k=1}^{|\mathcal{C}_n|-1}|f_n^k - f_n^{k+1}|)$ where $|\mathcal{C}_n|$ is the cardinality of $\mathcal{C}_n$.

Reporting Energy (E^r): The reporting energy is the energy spent by the SUs for transmitting their local sensing results to CBS through the common control channel. We assume that the reporting period is long enough such that all SUs can transmit their local results and regardless of the number of channels sensed, an SU transmits a single packet if it participates in sensing. Furthermore, we also assume that the channel is error free so all transmitted packets are successfully received. Let E_n^{tx} denote the energy required by SU_n to transmit a single packet, and let $\mathcal{S}$ denote the set of SUs participating in sensing. Then, E^r is given by $\sum_{n\in\mathcal{S}} E_n^{tx}$.

III. PROBLEM FORMULATION

We assume that all SUs have the same false alarm probability for all channels, denoted by P^F. The relationship between probability of detection for SU_n over channel m ($P_{m,n}^D$) is given by

$$P_{m,n}^D = \mathcal{Q}\left(\frac{\mathcal{Q}^{-1}(P^F) - \sqrt{\tau_{m,n}f_s}\gamma_{m,n}}{\sqrt{2\gamma_{m,n}+1}}\right) \tag{1}$$

where f_s is the sampling frequency and $\mathcal{Q}$ is the complementary cumulative distribution of a standard Gaussian [8]. The cooperative probability of detection using OR rule for channel m, Q_m^D, is given as

$$Q_m^D = 1 - \prod_{n\in\mathcal{S}_m}(1 - P_{m,n}^D) \tag{2}$$

where $\mathcal{S}_m$ is the set of SUs sensing channel m. In our previous work [9], we showed that the cooperative detection probability for channel m is a concave function of $\tau_{m,n}$ if all the individual detection probabilities of SUs participating in the sensing of channel m are greater than 0.5. Let $\tau_{m,n}^{min}$

denote the minimum time required to achieve a $P^D_{m,n}$ value of 0.5, that is given by

$$\tau^{min}_{m,n} = \left(\frac{\mathcal{Q}^{-1}(P^F)}{\gamma_{m,n}\sqrt{f_s}} \right)^2 . \tag{3}$$

In addition, to ensure a cooperative false alarm threshold of ${}_{th}Q^F$, a channel should be sensed by at most $\lfloor \frac{\log(1 - {}_{th}Q^F)}{\log(1-P^F)} \rfloor$ number of SUs.

In the following, we present our model which makes use of network flows in order to represent the set of frequencies sensed by an SU and the sensing sequence of these channels. Let ϕ denote a virtual terminal channel that indicates the end of sensing, and f_m be the frequency of channel m. Fig. 2 illustrates the network flow representation for the sensing actions for an SU. At the beginning of a frame, SU_n's antenna is tuned to f^0_n. Likewise, each SU tunes to a virtual channel ϕ after performing all sensing tasks. Since there are M frequencies in the system, an SU may sense all these M channels one after another. However, it can also sense less channels resulting in SU to have an outgoing arrow directly after kth sensing. For instance, in Fig. 2 the arrow from f^0_n to ϕ marked with $k = 0$ shows a case in which SU senses no channels whereas the arrow from f_1 to ϕ marked with $k = 1$ shows a case in which SU senses f_1 and ends sensing. This can be generalized to k step sensing similarly.

We now present the optimization model that minimizes energy consumption related to sensing corresponding to the given system model. Let $\tau_{m,n}$ be a non-negative continuous variable (i.e., $\tau_{m,n} \geq 0$) denoting the time SU_n spends for sensing channel m, $x^k_{m,m',n}$ be a binary variable (i.e., $x^k_{m',m,n} \in (0,1)$) with value 1 if SU_n switches from f_m to f'_m at step k, and y_n be a binary variable (i.e., $y_n \in (0,1)$) with value 1 if SU_n transmits its sensing outcomes to the base station. Our decision variables are $\tau_{m,n}$, $x^k_{m',m,n}$, and y_n. Then the optimization model can be written as:

$$\begin{aligned} \textbf{P1:}\ \min\ w = & \sum_{m=1}^{M}\sum_{n=1}^{N} P^s \tau_{m,n} + \sum_{n=1}^{N} E^{tx}_n y_n \\ & + P^{cs} t^{cs} \sum_{n=1}^{N} (\sum_{m=1}^{M} |f^0_n - f_m| x^0_{f^0_n,m,n} \\ & + \sum_{m=1}^{M} \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} |f_m - f_{m'}| x^k_{m,m',n}) \end{aligned} \tag{4}$$

subject to:

Flow related constraints:

$$x^0_{f^0_n,\phi,n} + \sum_{m=1}^{M}\sum_{k=1}^{M} x^k_{m,\phi,n} = 1,\ \forall n \tag{5}$$

$$x^0_{f^0_n,\phi,n} + \sum_{m=1}^{M} x^0_{f^0_n,m,n} = 1,\ \forall n \tag{6}$$

$$x^0_{f^0_n,m,n} - (x^1_{m,\phi,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} x^1_{m,m',n}) = 0,\ \forall m, \forall n \tag{7}$$

$$\sum_{\substack{m'=1\\m'\neq m}}^{M} x^{M-1}_{m',m,n} - x^M_{m,\phi,n} = 0,\ \forall m, \forall n \tag{8}$$

$$\sum_{\substack{m'=1\\m'\neq m}}^{M} x^k_{m',m,n} - \sum_{\substack{m'=1\\m'\neq m}}^{M} x^{k+1}_{m,m',n} = 0,\ \forall m, \forall n, k = 1, \ldots, M-2 \tag{9}$$

$$x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} x^k_{m',m,n} \leq 1,\ \forall m, \forall n \tag{10}$$

Sensing time related constraints:

$$\tau_{m,n} - \tau^{min}_{m,n}(x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} x^k_{m',m,n}) \geq 0,\ \forall m, \forall n \tag{11}$$

$$\begin{aligned} t^{cs} \sum_{m=1}^{M} (|f^0_n - f_m| x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} |f_m - f_{m'}| x^k_{m,m',n}) + \\ \sum_{m=1}^{M} \tau_{m,n} \leq T^s y_n,\ \forall n \end{aligned} \tag{12}$$

Sensing quality related constraints:

$$\sum_{n=1}^{N} (x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} x^k_{m',m,n}) \geq \delta^{min},\ \forall m \tag{13}$$

$$\sum_{n=1}^{N} (x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} x^k_{m',m,n}) \leq \lfloor \frac{\log(1 - {}_{th}Q^F)}{\log(1-P^F)} \rfloor,\ \forall m \tag{14}$$

$${}_{th}Q^D - Q^D_m \leq 0, \qquad \forall m \tag{15}$$

where Q^D_m is calculated as follows:

$$Q^D_m = 1 - \prod_{n=1}^{N} \left(1 - P^D_{m,n}(x^0_{f^0_n,m,n} + \sum_{\substack{m'=1\\m'\neq m}}^{M} \sum_{k=1}^{M-1} x^k_{m',m,n}) \right). \tag{16}$$

Hence, SUs that switch to channel m contribute to the multiplication with $1 - P^D_{m,n}$ corresponding to their $\tau_{m,n}$, whereas other SUs contribute with 1, not effecting the result of the multiplication. The objective in (4) minimizes the total energy expenditure due to sensing for a frame. The first part of the third term is the energy consumption due to the initial channel switch from f^0_n whereas the second part is for the succeeding channel switches. Constraint (5) indicates that the sensing of all SUs should end at some step k. Constraint (6) ensures

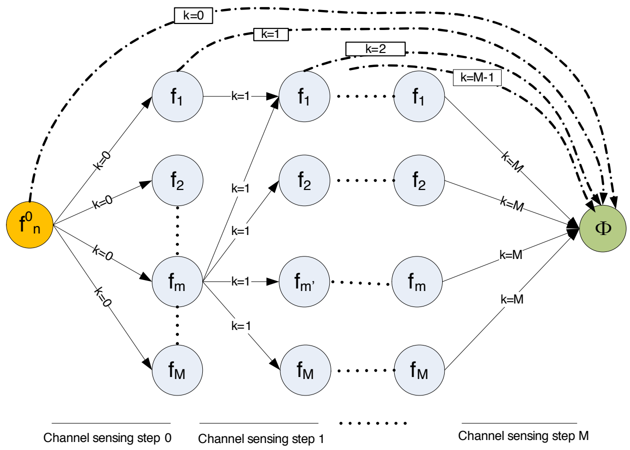


Fig. 2: Channel sensing sequence.

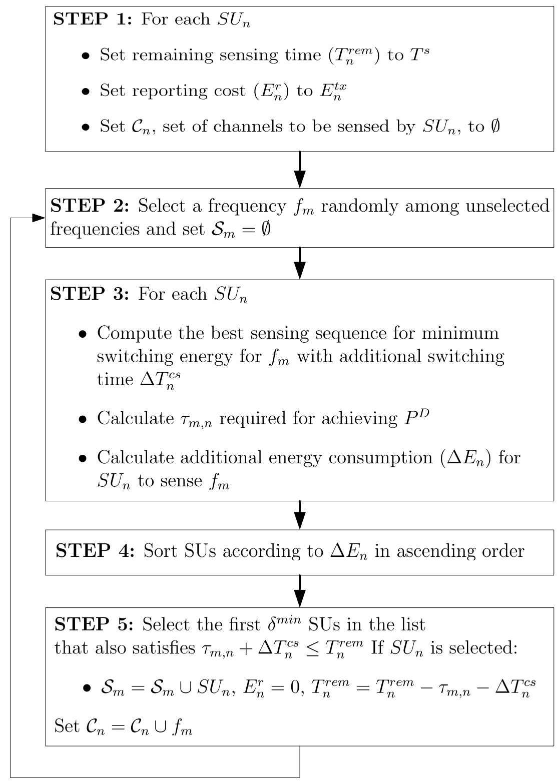


Fig. 3: EASE algorithm flow diagram.

that sensing operation of all SUs should start with step 0. In this equation, having $x_{f_n^0,\phi,n} = 1$ implies that SU_n does not sense a channel. Constraints (7), (8) and (9) are flow conservation equations for step 0, step M, and intermediate steps, respectively. They imply that if SU_n switches from channel m' to channel m, then it should switch from channel m to some other channel where switching to ϕ denotes the end of sensing for SU_n. As switching consumes energy, an SU performs a channel switch to channel m only for sensing channel m. Constraint (10) states that an SU can sense a given channel at most once for a frame. Constraint (11) enforces $\tau_{m,n}$ to be greater than or equal to $\tau_{m,n}^{min}$ if SU_n switches to channel m, which in turn enforces the concavity condition for Q_m^D to hold. The requirement that total time spent on sensing be smaller than quiet sensing period for each SU is expressed in Constraint (12). The first two terms on the left hand side constitute the total time spent for channel switching, and the third term is the total of actual time spent for sensing by SU_n. Constraint (13) forces each channel to be sensed by at least δ^{min} SUs. On the other hand, Constraint (14) forces the cooperative false alarm probability be smaller than the respective threshold for each channel. Constraint (15) is the cooperative detection probability constraint.

IV. Outer Linearization (OL)

The given model is a mixed integer non-linear problem with a linear objective in which the non-linearity comes from Constraint set (15). However, it is convex once $x_{m',m,n}^k$ are fixed since Q_m^D is concave in terms of $\tau_{m,n}$. Thus, we apply the outer linearization algorithm which first ignores all the non-linear constraints, then iteratively linearizes the violated ones by using the gradient until all of them are satisfied [11]. The algorithm works as follows:

Step 1: Let h denote the step number, and set $h = 1$. Ignore the non-linear constraints of the original problem, solve the relaxed problem (**P2**) to obtain a solution $\tau_{m,n}^h, x_{m',m,n}^{k,h}, y_n^h$.

Step 2: Find the most violated constraint among the M previously ignored constraints, say constraint θ with the current solution, $\tau_{m,n}^h, x_{m',m,n}^{k,h}, y_n^h$. Let us call the maximum violation v_θ, and the corresponding constraint g_θ. If $v_\theta < \epsilon$, then the current solution is optimal with ϵ feasibility tolerance. Otherwise, proceed with the next step.

Step 3: Linearize g_θ by adding the following constraint:

$$\nabla g_\theta(\dots x_{m',\theta,n}^{k,h}, \dots \tau_{\theta,n}^h, \dots)^T \begin{pmatrix} \vdots \\ x_{m',\theta,n}^k - x_{m',\theta,n}^{k,h} \\ \vdots \\ \tau_{\theta,n} - \tau_{\theta,n}^h \\ \vdots \end{pmatrix} + v_\theta \leq 0$$

where $\nabla g_\theta(\dots x_{m',\theta,n}^{k,h}, \dots \tau_{\theta,n}^h, \dots)$ is the gradient vector of g_θ evaluated at the current solution.

Step 4: Set h=h+1, solve the modified problem to obtain a new solution, and proceed with Step 2.

A. A Low Complexity Heuristic Algorithm: Energy Aware Sensing schEduling (EASE)

EASE is a fast heuristic that assigns δ^{min} SUs to sense a channel such that all assigned SUs have the same detection probability, P^D, that is calculated as $1 - (1 - {}_{th}Q^D)^{1/\delta^{min}}$ for OR rule. The aim of our heuristic, given in Fig. 3, is to choose the set of SUs that will consume the least energy for sensing each channel. At each iteration (i.e., assignment for f_m), SUs are sorted in increasing order according to their

TABLE I: Model parameters

δ^{min}	3
T^s	20ms
P^F	0.01
f_s	1kHz
P^s	1000mW
P^{cs}	1000mW
E_n^{tx}	1mJ, $\forall n$
μ^{SNR}	Between -5 and 0 dB
t^{cs}	Between 0.5ms and 1.5ms per 100kHz
${}_{th}Q^D$	0.9
${}_{th}Q^F$	0.1
ϵ	10^{-4}

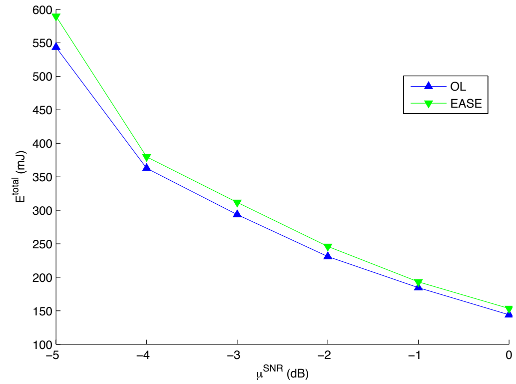


Fig. 4: Energy vs μ^{SNR} with t^{cs}=1ms/100kHz.

additional energy consumption required to sense this channel (ΔE_n) which includes channel switching, spectrum sensing and reporting costs. Our algorithm assigns SUs to channels sequentially and updates the channel sensing sequence to obtain the least channel switching energy. For finding the best sequence, an SU first tunes to the channel with the minimum or maximum frequency depending on which one is the closest to its initial frequency. If the minimum one is visited first, then the other ones are visited in ascending order of their frequencies whereas if the maximum one is the first, then the others are visited in descending order. As an example, suppose an SU is initially tuned to f_{10} and it is assigned to sense f_{11}, f_{13}. Suppose f_9 is added to the sequence. Then the ideal sequence will be f_9, f_{11}, f_{13}. If f_2 is added to the sequence at a subsequent step, then the ideal sequence becomes f_{13}, f_{11}, f_9, f_2.

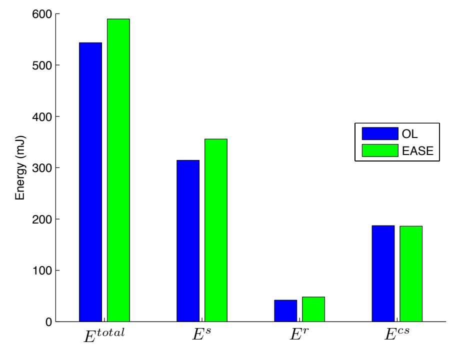
Considering the reporting energy, an SU that is not assigned a channel for sensing incurs a reporting energy cost. On the contrary, an SU that is already assigned a channel has no reporting cost for this channel. Among all sorted SUs, first δ^{min} SUs that have sufficient remaining sensing time are added to $\mathcal{S}_m$, the set of SUs sensing channel m. Remaining sensing time for these selected SUs are reduced accordingly. The complexity of our algorithm is $O(MNlogN)$ due to the sorting of SUs in `Step 4` being in the order of $O(NlogN)$ and repeating this for all M frequencies as in `Step 2`.

V. PERFORMANCE EVALUATION

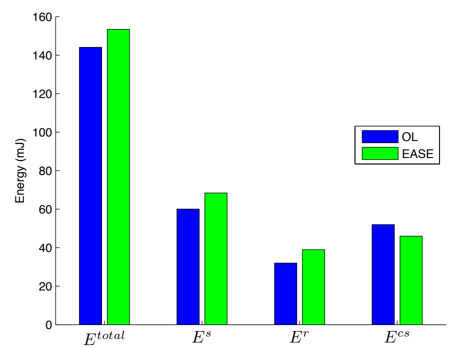
We analyze the performance of both methods in a network with 20 contiguous channels with 100kHz bandwidth each and 100 SUs. We assign f_n^0 randomly. Furthermore, we assume $\gamma_{m,n}$ values are exponentially distributed with mean μ^{SNR}. For both f_n^0 and $\gamma_{m,n}$, we use the same randomly assigned values for fair comparison. The other parameters are given in Table I. The results given below are for a single frame. Hence, cumulative energy savings in the long run will be noticeably higher. As the results of EASE depend on the order of the channels for assignment, we run EASE with 20 random orderings and give the results for the ordering with the minimum total energy consumption.

We first give the impact of μ^{SNR} value on E^{total} in Fig. 4. Increasing μ^{SNR} improves E^{total} as less sensing time is required to achieve a particular detection probability. Moreover, the improvement in E^{total} for 1 dB increase in μ^{SNR} is diminishing. For instance, going from -5 dB to -4 dB provides 181 mJ savings whereas the savings for going from -1 dB to 0 dB is 40 mJ. Another point to note is that EASE performs well, always within 10% of OL.

The breakdown of E^{total} into individual components for high and low values of μ^{SNR} is given in Fig. 5. We observe that E^r is almost the same for both cases. E^s is the most

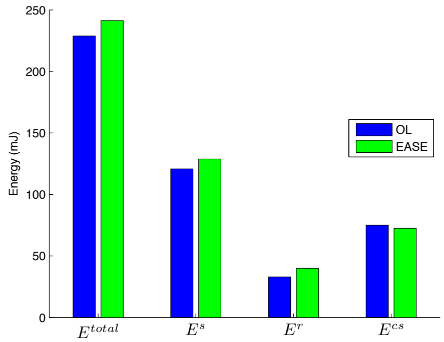


(a) μ^{SNR} = -5 dB.

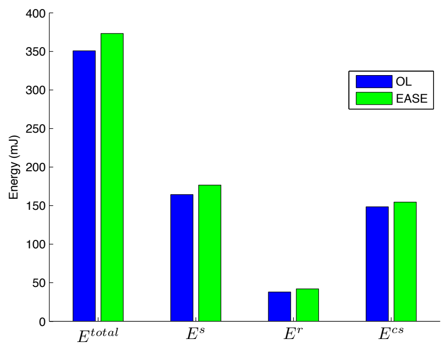


(b) μ^{SNR} = 0 dB.

Fig. 5: Energy consumption profiles with t^{cs} =1ms/100kHz.



(a) t^{cs} = 0.5ms/100kHz.



(b) t^{cs} = 1.5ms/100kHz.

Fig. 6: Energy consumption profiles with μ^{SNR}=-3dB.

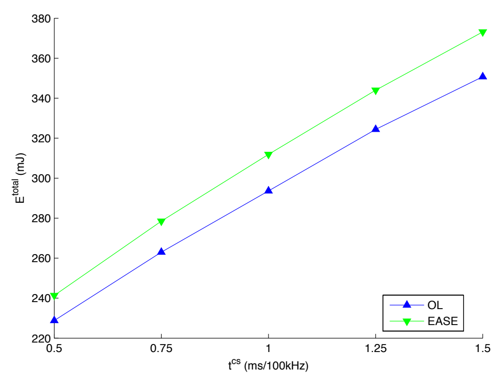


Fig. 7: Energy vs t^{cs}.

dominating factor for low μ^{SNR}, accounting about 60% of E^{total} followed by E^{cs} with 35%. On the other hand, with high μ^{SNR}, the percentage of E^s drops to 40%. The share of E^{cs} remains almost the same whereas the share of E^r increases from 8% to 22%. One last thing to note is that, even though E^{cs} is not directly related to μ^{SNR}, increasing μ^{SNR} also decreases E^{cs}, as more SUs become candidates for sensing a particular channel within sensing period, which in turn helps the algorithms to find better sensing sequences.

The effect of t^{cs} on E^{total} is shown in Fig. 7. For both methods, increasing t^{cs} causes an almost linear increase in E^{total}. Again, EASE performs close to OL (within 7%). As t^{cs} depends on the hardware, we emphasize that fast switching mobile hardware is essential for energy savings.

The individual components of E^{total} for high and low values of t^{cs} are shown in Fig. 6. Increasing t^{cs} increases both E^{cs} and E^s. E^{cs} is directly proportional to t^{cs} so the increase is expected. On the other hand, a high t^{cs} implies less time for sensing, which in turn decreases the number of candidate SUs that can sense a particular channel. Furthermore, an SU with a high SNR for a channel may refrain from sensing that channel as switching cost becomes significant and some other SU with smaller SNR can be assigned to that channel if its switching cost is smaller. Hence, E^s also increases with increasing t^{cs}.

VI. Conclusion

In this paper, a cooperative sensing scheduling scheme that minimizes energy consumption of spectrum sensing while ensuring satisfactory sensing quality for each channel is proposed. SUs with better SNR are favoured to sense a channel due to the inverse relationship between sensing time and channel SNR. Additionally, cost of channel switching between frequencies is taken into account. Optimal solution and a low complexity heuristic that achieves close to the optimum are presented.

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