Superior Selective Reporting-based Spectrum Sensing in Energy Harvesting-Aided HCRNs

(Invited Paper)

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***Abstract*—In the present contribution we investigate the performance of superior selective reporting (SSR) for cooperative spectrum sensing in an energy harvesting-enabled multi-channel heterogeneous cognitive radio network (HCRN). To this end, we first analyze the throughput of the SSR and the optimal conventional cooperative sensing (CCS). Then, we formulate a nonlinear integer programming problem to find a throughput-optimal set of spectrum sensors scheduled to sense a particular channel, under primary user (PU) interference and energy harvesting constraints. In this context, we derive a solution based on the cross entropy (CE) method, and compare its performance with the exhaustive-search method counterpart. Furthermore, we study the tradeoff between the channel available time and detection accuracy of the SSR and CCS schemes. It is shown that this inherent tradeoff is between the channel available time and the detection accuracy. Furthermore, it is shown that as the number of spectrum sensors increases, the channel available time turns out to be the system's limiting factor in HCRNs.**

I. Introduction

Heterogeneous wireless sensor networks (HWSN) are envisioned to facilitate the recent growth of wireless data services [1]. With the ever-increasing demand for high data rate services, the realization of HWSNs suffers from several pitfalls, including severe interference [2], which limits its spectral efficiency. A promising solution to mitigate this problem is to integrate cognitive radio (CR) technology [3] with HWSN – collectively coined as *heterogeneous cognitive radio networks* (HCRN) [4]. In an HCRN, the deployed sensors periodically scan a primary user (PU) spectrum to detect the availability of unocuppied channels which are, subsequently, used for data transmssion [5]. However, periodic sensing typically results in a higher energy consumption, which is a critical issue in battery operated sensor networks. In this respect, HCRNs with energy harvesting (EH)-based spectrum sensors are envisioned to enhance spectrum and energy efficiencies ([6]-[7]).

A. Related Work

Liang et al. [8] investigated the sensing-throughput tradeoff – the tradeoff between the sensing accuracy and data transmission duration – in CR networks (CRN). Sensing accuracy, in terms of probability of detection is essential to improve the average throughput, which can be achieved by using the optimal L-out-of-M rule at the fusion center (FC) [9]. However, it is noted that although the sensing accuracy increases with the number of sensors, the average throughput decreases due to the increase in reporting overhead. To this effect, in order to improve the secondary network throughput we consider the superior selective reporting (SSR) scheme in [10], which has been shown to achieve a higher probability of detection compared to CCS with the OR fusion rule [10]. The decision reporting overhead in the SSR scheme is significantly reduced, since only one selected node reports its decision to the FC. Accordingly, the SSR scheme yields a better data transmission time which enhances the achievable throughput [11]. In brief, a CRN with the SSR scheme achieves both detection accuracy and higher throughput, for a given primary interference constraint. In addition, the use of EH nodes [12] in CRNs have been proposed to realize a green and a sustainable network.

B. Contributions

We present a thorough analysis of the throughput performance of SSR-based multi-channel HCRNs. In this context, we formulate an optimization problem that maximizes the average achievable throughput to find the optimal sensor-to-channel assignment vector, subject to EH and PU interference constraints. To the best of our knowledge, a throughput analysis of multi-channel HCRNs with EH nodes, and SSR has not been reported in the literature. The main contributions of this paper are summarized as follows:

- We analyze the average achievable throughput of the SSR-based multi-channel HCRN.
- We formulate the problem of finding the optimal set of sensors scheduled for spectrum sensing for each channel such that the average network throughput is maximized, by employing the cross entropy (CE) algorithm, and establish its advantages.
- Through numerical results, we show that as the number of sensors increases, the SSR-based scheme outperforms the optimal CCS scheme.
- Finally, a tradeoff between the average achievable throughput of SSR and CCS schemes is studied, which is the inherent tradeoff between the channel available time and detection accuracy.

The remainder of this paper is organized as follows: The system model for multi-channel HCRNs with EH sensors, employing the SSR scheme is presented in Sec. II. The spectrum sensor scheduling problem that maximizes the average achievable throughput for the SSR scheme is formulated and studied in Sec. III. The numerical results and discussions are presented in Sec. IV, and conclusions are provided in Sec. V.

II. System Model

A. Network Architecture

We consider a HCRN with the following three types of nodes [4]: M EH-enabled spectrum sensors, N battery powered data sensors and a sink (or a fusion center, FC) as shown in Fig. 1 (a). It is assumed that the PUs are uniformly distributed within the coverage area of the HCRN. The licensed spectrum is divided into K non-overlapping channels of equal bandwidth. The data sensors utilize the vacant channels declared by the spectrum sensors, on a priority basis. Each data sensor collects information from an area of interest, and transmits it to the sink over an assigned licensed channel. It is assumed that there are K transceivers mounted on the sink, such that it can support K concurrent data transmissions over K different non-overlapping channels in each time slot [13], as shown in the frame structure of HCRN in Fig. 1 (b). Although the FC controls the scheduling of both types of sensors, in this work, we consider only the scheduling of spectrum sensors. The set of spectrum sensors for each channel is assigned based on the cross entropy (CE) algorithm, as discussed in [4]. We assume that each spectrum sensor can sense multiple orthogonal channels simultaneously [14], [15], and adopt the SSR scheme [10], which is explained in Sec. II-B. Additionally, we assume that every spectrum sensor lies within the coverage of the PU transmitter. Finally, the sink assigns the available channels to the data sensors for data transmission.

Minimizing the energy consumption of power-limited data sensors is of paramount importance. This can be carried out by optimizing the transmission time and power allocation, following the setup described in [4]. However, as mentioned before, the optimal scheduling of data sensors, and analysis of the energy consumption is not considered in this work.

In our setup, periodic sensing is carried out over a frame period of T_{Total} seconds. Each frame duration is divided into two phases, namely, a *sensing phase* and a *data transmission phase*, given by τ_s and $T_{\text{Total}} - \tau_s$ seconds, respectively. In the sensing duration

$$\tau_s \triangleq t_s + t_r \tag{1}$$

a preassigned optimal subset of the M spectrum sensors, denoted by $M^{(k)}$, $k = 1, 2, \ldots, K$, simultaneously sense the presence of the PU for a time t_s, and one among these $M^{(k)}$ sensors is selected based on their SNR (of the link from the node to the FC) to report its decision to the FC during reporting time slot t_r, corresponding to each channel. The advantage of the adopted SSR scheme is that it increases the throughput and reduces the sensing overhead, when compared to the conventional cooperative sensing (CCS) scheme [11]. Subsequently, the data sensors transmit the collected data over all the available channels in the data transmission phase for a duration $T_{\text{Total}} - \tau_s$.

B. Superior Selective Reporting-based Spectrum Sensing

The SSR scheme, proposed in [10], has several advantages over the OR-rule based CCS scheme, as the FC receives the decision only from the *superior sensor*, denoted by

$$M_{sup}^{(k)} = \underset{M_m \in \Phi_k}{\arg\max} \left(\gamma_{M_m} |h_{M_m,FC}|^2 \right), \tag{2}$$

$m = 1, \ldots, M$, which is selected based on the received SNR between the FC and sensors across all sensors. The set of spectrum sensors $M^{(k)}$ that detect the presence of PU constitute a *detection set* Φ_k, $k = 1, \ldots, K$. Each sensor $\{M_m \in \Phi_k, m = 1, \ldots, M\}$ sets off a timer at the end of the sensing phase, with each initial value $\{\mathtt{T}_m, M_m \in \Phi_k\}$ set inversely proportional to its received SNR $\gamma_{M_m}|h_{M_m,FC}|^2$ [10], where γ_{M_m} and $h_{M_m,FC}$ denote the SNR and the fading coefficient of the channel from the FC to M_m, $m = 1, \ldots, M$, respectively, i.e.,

$$\mathtt{T}_m = \frac{\mu}{\gamma_{M_m} |h_{M_m,FC}|^2} \tag{3}$$

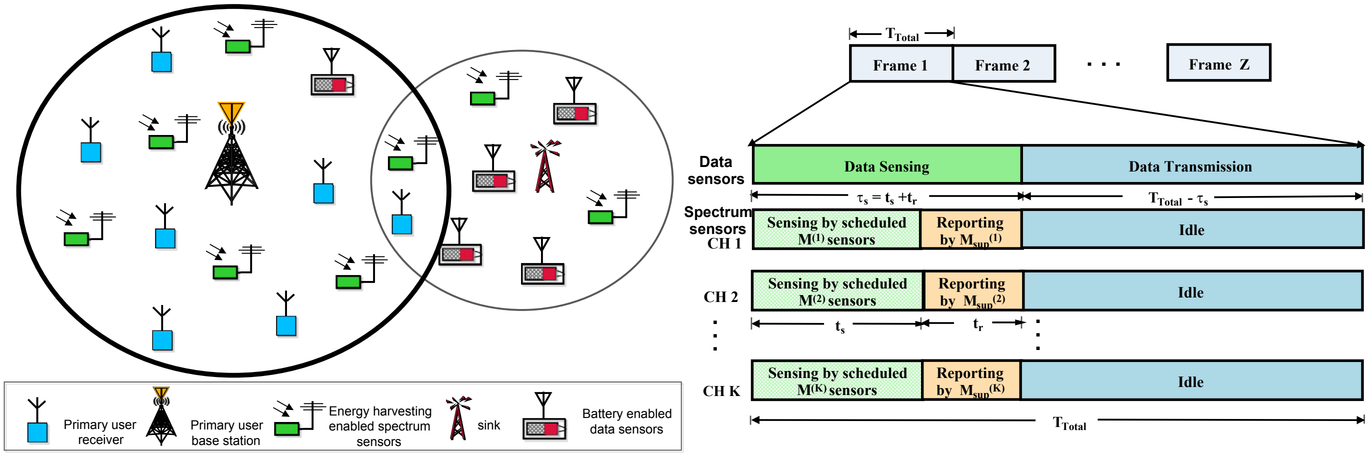
for some $\mu \in \mathbb{R}^+$. The sensor with the highest SNR, termed as the superior sensor, exhausts its timers first and reports to the FC. Hence, only the superior sensor sends its local decision to the sink in time slot t_r by transmitting a short duration flag packet, signaling its presence. All other sensors, waiting for their timers to expire, back off immediately as soon as they receive this flag [16]. Based on this, the corresponding probabilities of false-alarm and signal detection are respectively given by [4]

$$P_f(m,k) = Q\Bigg(\left(\frac{\varepsilon}{\sigma^2} - 1\right) \sqrt{U} \Bigg) \triangleq \overline{P_f}, \tag{4}$$

and

$$P_d(m,k) = Q\left(\frac{Q^{-1}(\overline{P_f}) - \sqrt{U}\gamma_{mk}}{\sqrt{2\gamma_{mk} + 1}} \right), \tag{5}$$

where $Q(\cdot)$ is the complementary CDF of the standard Gaussian distribution, γ_{mk} denotes the received SNR from the PU



(a) (b)

Figure 1: (a) System model of the considered HCRN; (b) Frame structure of the SSR-based HCRN.

to the m^{th} sensor at the k^{th} channel, and U denotes the number of samples of the received signal. Without loss of generality, we set the detection threshold ε to be the same for all the sensors. Hence, the probability of false-alarm is fixed for all SUs and is denoted by $\overline{P_f} \in [0,1]$. Thus, the probabilities of false-alarm, $G_f(k)$, and signal detection, $G_d(k)$, at the FC can be written as [10]

$$G_f(k) = \sum_{j=1}^{2^{M^{(k)}}-1} \left[\prod_{m\in\Phi_{j,k}} P_f(m,k) \prod_{m\in\overline{\Phi}_{j,k}} (1-P_f(m,k)) \right] \quad (6)$$

$$= 1-(1-\overline{P_f})^{M^{(k)}}, \quad (7)$$

and

$$G_d(k) = 1 - \prod_{m=1}^{M^{(k)}} (1-P_d(m,k))^{M^{(k)}}. \quad (8)$$

Here $\Phi_{j,k}$ is the j^{th} nonempty sub collection of detection set Φ_k, and $\overline{\Phi}_{j,k}$ is the complement of $\Phi_{j,k}$. In contrast to the optimal CCS scheme with the L-out-of-M fusion rule, the advantage of the SSR scheme is in saving the reporting time t_r, which increases the channel available time for data transmission as shown in Fig. 1(b), and thereby improving the average achievable throughput for secondary transmission over the k^{th} channel. Next, we formulate an optimization problem for finding the best subset of spectrum sensors per channel, $M^{(k)}$, to maximize the network throughput for a given PU interference constraint.

III. Problem Formulation: Optimal Scheduling

The average number of bits transmitted by the data sensors across all K channels in one time duration is defined as the average achievable throughput of a HCRN [4]. Consider a sensor-to-channel assignment matrix $\mathbf{J} \in \{0,1\}^{M\times K}$. Let the $(m,k)^{\text{th}}$ element $[\mathbf{J}]_{m,k}$, $m=1,\ldots,M$, $k=1,\ldots,K$ of 1 indicate that the sensor m is scheduled for spectrum sensing for channel k, and 0 otherwise. Our aim is to find the optimal $\mathbf{J}$ that maximizes the average throughput in the considered HCRN. The average achievable throughput depends on the available time for data transmission, the probability that favors the inactive state of PU, $P(\mathcal{H}_0)^{(k)}$, of the k^{th} channel, $P_f(m,k)$, $P_d(m,k)$, and the channel capacity, $\mathtt{C}$. Hence, we model the PU dynamics over each channel as a stationary exponential ON-OFF random process [4], with the average available time of the k^{th} channel being the product of stay-over time and the stationary probability. To this end, we let

$$T_{\text{ON}}^{(k)} = \frac{1}{\lambda_0^{(k)}} \quad (9)$$

and

$$T_{\text{OFF}}^{(k)} = \frac{1}{\lambda_1^{(k)}} \quad (10)$$

account for the average values of the stay-over time of the ON state and OFF state of k^{th} channel respectively, where $\lambda_0^{(k)}$ denotes the transition rate from the ON state to OFF state on the k^{th} channel and $\lambda_1^{(k)}$ denotes the transition rate in the opposite direction. Therefore, it follows that the stationary probabilities of the ON and OFF states of PU on each channel are given by [4]

$$P(\mathcal{H}_1)^{(k)} = \frac{\lambda_1^{(k)}}{\lambda_1^{(k)}+\lambda_0^{(k)}} \quad (11)$$

and

$$P(\mathcal{H}_0)^{(k)} = \frac{\lambda_0^{(k)}}{\lambda_1^{(k)}+\lambda_0^{(k)}} \quad (12)$$

respectively.

In what follows, we analyze the the average achievable network throughput under four possible scenarios.

S1: In this scenario, the spectrum sensors successfully detect the absence of PUs with probability $P(\mathcal{H}_0)^{(k)}$ $(1 - G_f(k))$. The throughput for this scenario is expressed as

$$P(\mathcal{H}_0)^{(k)} \left[1-\bar{P}_f\right]^{\sum_{m=1}^{M}[J]_{m,k}} \; I_d^{(k)} \; \mathtt{C}^{(k)}(T_{\text{Total}}-\tau_s)$$

, where $I_d^{(k)}$ is a binary variable introduced as a constraint to satisfy the PU protection requirement, defined as

$$I_d^{(k)} = \begin{cases} 1 & \text{if } 1 - G_d(k) < \overline{PM}_{thr}, \\ 0 & \text{otherwise.} \end{cases} \tag{13}$$

That is, if the miss probability of the k^{th} channel exceeds a predefined $\overline{PM}_{thr} \in [0,1]$, the decision is considered unreliable for communication over the k^{th} channel.

S2: Here, the sensors correctly detect the PU as active, with probability $P(\mathcal{H}_1)^{(k)} G_d(k)$, which results in no throughput.

S3: In this scenario, the sensors falsely detect the PU to be present, with probability $P(\mathcal{H}_0)^{(k)} G_f(k)$. Here, since the CR network misses a transmission opportunity, the throughput achieved is given by

$$P(\mathcal{H}_0)^{(k)} \left[1 - (1 - \overline{P}_f)^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}}\right] \\ \times I_d^{(k)} \; \mathtt{C}^{(k)} \; (T_{\text{Total}} - \tau_s)(-\phi)$$

where $\phi \in [0,1]$ is a suitably chosen penalty factor [17]. Note that a penalty term is introduced in this case to take into account that the CR network missed a transmission opportunity. For simplicity, ϕ can be assumed to be zero.

S4: In this scenario, the sensors make an incorrect decision that the PU is absent, with probability

$$P(\mathcal{H}_1)^{(k)} (1 - G_d(k)).$$

The network causes interference to the PU, with a partial throughput of κ

$$P(\mathcal{H}_1)^{(k)} \left[1 - P_d(m,k)\right]^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}} \; I_d^{(k)} \; \mathtt{C}^{(k)}$$

$(T_{\text{Total}} - \tau_s)$, with some $\kappa \in (0,1)$. Note that a value of any $\kappa \neq 0$ indicates that even though the CR network causes interference to the PU network, it still communicates with a non-trivial data rate. For simplicity, κ can be chosen as zero.

Considering the above four scenarios, the average throughput of the SSR scheme is given by (14), and can be simplified as in (15). For the spectrum sensor scheduling problem, we set constraints related to the EH dynamics to facilitate the sustainability of the sensors. In a given frame T_{Total}, the energy consumption of each sensor should not exceed the EH rate, i.e.,

$$\Big(\sum_{k=1}^{K} [\mathbf{J}]_{m,k}\Big) e_s \leq \delta_m \; T_{\text{Total}} \; \forall m,$$

where e_s is the sensing energy required by each sensor to sense a single channel, and δ_m is the EH rate. Now, the problem to find the optimum $\mathbf{J}$ that maximizes R_{SSR} can be formulated as

$$\mathcal{OP}_{SSR} : \max_{\mathbf{J}} \quad R_{SSR} \tag{16}$$

$$\text{s.t.} \begin{cases} \big(\sum_{k=1}^{K} [\mathbf{J}]_{m,k}\big) e_s \leq \delta_m \; T_{\text{Total}}, & \forall m \\ [\mathbf{J}]_{m,k} = \{0,1\}, & \forall m,k \end{cases} \tag{17}$$

From (14), it is clear that as more channels are assigned to a given set of sensors, i.e., as $\sum_{k=1}^{K} [\mathbf{J}]_{m,k}$ increases, the value of $(1 - \overline{P}_f)^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}}$ decreases, and $I_d^{(k)}$ tends to unity. Therefore, there is a tradeoff between the values of $(1 - \bar{P}_f)^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}}$ and $I_d^{(k)}$. As a consequence, as M increases, there exist a tradeoff between the detection accuracy and the channel available time, which affects the average achievable throughput of the network. The $\mathcal{OP}_{SSS}$, is an integer programming problem, that can be solved by using an exhaustive search method. However, this leads to a search space of 2^{MK} elements which is computationally expensive. Hence, we apply the cross entropy (CE) algorithm, as discussed in [4]. The CE algorithm, although does not guarantee an optimal solution, yields a near-optimal solution at a significantly lesser running time than the exhaustive search [4] – which will be elaborated later in Sec. IV. Towards this end, the problem $\mathcal{OP}_{SSS}$ is transformed into the following unconstrained optimization problem, by applying a penalty of $\omega \in \mathbb{R}^+$ for violating any of the constraints [4]:

$$\max_{\mathbf{J}} \quad R_{SSR} - \omega I_{\left(\sum\limits_{k=1}^{K} [\mathbf{J}]_{m,k} e_s > \delta_m T_{\text{Total}}\right)}, \tag{18}$$

where $I(\cdot)$ is the indicator function. When the solution violates the constraints, the objective function evaluates to a negative value, which is discarded.

The CE algorithm is implemented as discussed below [4]. Initially, the iteration counter is set as $i = 1$ to $i_{\max} \in \mathbb{N}$. Let $\mathbf{C}$ be the set of all possible K-dimensional binary vectors, with $|\mathbf{C}| = 2^K$. To begin with, the row vectors of $\mathbf{J}$ are drawn from the matrix $\mathbf{C}$. Now, Z samples of channel matrix, defined as $\mathbf{V}^{(z)} = \mathbf{v}_{m,\mathbf{c}}^{(z)}, 1 \leq m \leq M, \mathbf{c} \in \mathbf{C}$, $z = 1, \ldots, Z$ of size $M \times 2^K$. Here, $\mathbf{v}_{m,\mathbf{c}}^{(z)}$ denotes the $\mathbf{c}^{\text{th}}$ column vector or $\mathbf{V}^{(z)}$. These column vectors are generated based on a probability mass function (PMF) matrix

$$\mathbf{Q}^{(i)} = \mathbf{q}_{m,\mathbf{c}}^{(i)}, 1 \leq m \leq M, \mathbf{c} \in \mathbf{C},$$

where $q_{m,\mathbf{c}}^{(i)}$ denotes the probability vector that the sensor m is scheduled to sense the channel k in vector $\mathbf{C}$. Now, we calculate the cost function in (18) for each sample z, and arrange them in descending order. We retain $0 \leq \rho \leq 1$ fraction of sorted objective function value $O^{(z)}$ and discard all other values. Let the smallest chosen value of the objective function be η, corresponding to the index $\lceil \rho Z \rceil$. In each step, the PMF matrix is updated as

$$\mathbf{q}_{m,\mathbf{c}}^{(i+1)} = \frac{\sum_{z=1}^{Z} \mathbf{v}_{m,\mathbf{c}}^{(z)} I_{(O^z \geq \eta)}}{\lceil \rho Z \rceil}. \tag{19}$$

The algorithm is stopped after $i_{\max}$ iterations, and the resultant $\mathbf{V}^{(z)}$ is selected to map the solution, i.e., the optimal $\mathbf{J}$. The FC schedules spectrum sensors to detect the licensed channels according to the solution obtained in CE algorithm. After the spectrum-sensing phase, the selected superior spectrum sensors report their decisions on the channel availability to the FC. The FC decides on the availability of each channel based on the sensing decision of superior SUs selected for each channel $(M_{sup}^{(1)}, M_{sup}^{(2)}, \ldots M_{sup}^{(K)})$, and utilizes the available channels to collect data from the data sensors.

IV. Results and Discussion

In this section, we discuss the performance of SSR-based sensing scheme in HCRN in terms of average achievable

$$
\begin{aligned}
R_{SSR} = \sum_{k=1}^{K}\Bigg\{ & P(\mathcal{H}_0)^{(k)}\big[1-\overline{P}_f\big]^{\sum\limits_{m=1}^{M}[\mathbf{J}]_{m,k}} - \phi P(\mathcal{H}_0)^{(k)} \left[1-(1-\overline{P}_f)^{\sum\limits_{m=1}^{M}[\mathbf{J}]_{m,k}}\right] \\
& + P(\mathcal{H}_1)^{(k)} \left[1-P_d(m,k)\right]^{\sum\limits_{m=1}^{M}[\mathbf{J}]_{m,k}} \kappa \Bigg\} I_d^{(k)} \ \mathtt{C}^{(k)}(T_{\text{Total}}-\tau_s), \qquad (14) \\
= \sum_{k=1}^{K}\Big\{ & P(\mathcal{H}_0)^{(k)}(1-G_f(k)) - \phi P(\mathcal{H}_0)^{(k)} G_f(k) + \kappa \ P(\mathcal{H}_1)^{(k)}(1-G_d(k))\Big\} I_d^{(k)} \ \mathtt{C}^{(k)}(T_{\text{Total}}-\tau_s). \qquad (15)
\end{aligned}
$$

Algorithm 1 Cross Entropy (CE) algorithm

procedure INITIALIZATION (i_{max}, z, $\mathbf{Q}^{(i)}$, $\mathbf{V}^1, \ldots, \mathbf{V}^z$)
Step 1:
  for i $\leftarrow$ 1 to $i_{\max}$ **do**
    Set $\mathbf{q}^1_{m,\mathbf{c}} = 1/|\mathbf{C}| = 1/2^K \ \forall m, c$
    for z $\leftarrow$ 1 to z **do**
      Generate $\mathbf{V}^1, \ldots, \mathbf{V}^z$ based on $\mathbf{Q}^i = q^i_{m,c}$ for each spectrum sensor.
Step 2:
  for z' $\leftarrow$ 1 to z **do**
    Calculate the objective function in (18) and sort them as $\mathcal{OP}_{SSR}(\mathbf{V}^1) < \mathcal{OP}_{SSR}(\mathbf{V}^2) < \ldots < \mathcal{OP}_{SSR}(\mathbf{V}^{z'})$.
Step 3:
  Retain $\rho \in (0,1)$ fraction of $\{\mathcal{OP}_{SSR}(\mathbf{V}^z)\}$.
  Let the smallest chosen value of $\mathcal{OP}_{SSR}$ in the retained set be η, corresponding to the index $\lceil \rho Z \rceil$.
Step 4:
  for j $\leftarrow$ 1 to M **do**
    for c = 1 : C **do**
      $\mathbf{q}^{(i+1)}_{m,\mathbf{c}} = \frac{\sum_{z=1}^{Z} \mathbf{v}^{(z)}_{m,\mathbf{c}} I_{(O^z \geq \eta)}}{\lceil \rho Z \rceil}$.
Step 5:
      If $i = i_{max}$ or $||\mathbf{Q}^{i+1} - \mathbf{Q}^i||_{Fr} \leq \epsilon$, stop. Proceed to Step 6. Else, set $i = i+1$ and go to Step 2.
Step 6:
  Return $\mathbf{V}^z$ that corresponds to the largest value of the cost function in $\mathcal{OP}_{SSR}$.
Step 7:
  The channels-to-sensor pattern in $\mathbf{V}^z$ is mapped to the channel-to-sensor assignment in $\mathbf{J}$, which is a solution to the original optimization problem $\mathcal{OP}_{SSR}$.

throughput, and compare it with the CCS scheme following the L-out-of-M rule, with an optimum L chosen as in [9]. Unless otherwise stated, the values of the parameters used are listed in Table I ([18], [4]). The sensors are randomly placed in a circular area where the PU coexists. The channel gain from PU transmitter to the sensor is assumed to be proportional to $1/D_m^{\alpha}$, where D_m is the distance between PU transmitter and the m^{th} spectrum sensor, and α is the path loss exponent. The achievable rates by data sensors are chosen to be $\mathtt{C} = \log_2(1 + SNR) = 6.658$ bits/sec/Hz [4].

The variation of the throughput with different number of licensed channels, K, is shown in Fig. 2. For illustration purposes, we choose $M = 3$, so that a solution using the exhaustive search can be quickly evaluated. The average achievable throughput of SSR-based approach using the CE algorithm is compared with the random assignment and exhaustive search. The exhaustive search finds the optimal assignment vector in the set of all possible assignment vectors, whereas a licensed channel is randomly assigned to spectrum sensors in random assignment. As shown in Fig. 2, the average achievable throughput obtained by the SSR-based CE algorithm is about 75%–90% of that obtained by the exhaustive search. In contrast, the total elapsed time for the evaluation using the exhaustive search method is about 14 times larger than that using the CE algorithm, when K is increased to 4. As K further increases, the elapsed time increases exponentially for the exhaustive search. Thus, the SSR-based CE algorithm attains the maximum throughput with much less computation time when compared to exhaustive search. Note that we have shown the results for a smaller number of channels and spectrum sensors, keeping the effectiveness of the exhaustive search in mind. Increasing the number of channels (or spectrum sensors) will result in a large computation time, and hence those scenarios are not considered. The stability of CE algorithm with respect to the average throughput is shown in Fig. 3, which illustrates the

Table I: Parameter Settings

Parameters	Values
Number of spectrum sensors M	10
Number of data sensors N	30
Target false alarm probability $\bar{P_f}$	0.1
Target miss- detection probability $\bar{P_m}$	0.1
Number of Licensed channel	7
Bandwidth of the licensed channel W	6 MHz
Path-loss exponent α	3.5
Transition rate of PU from ON state to OFF state λ_0^k	0.6 : 0.2 : 1.8
Transition rate of PU from OFF state to ON state,λ_1^k	0.4 : 0.2 : 1.8
Total frame length T_{Total}	100 ms
Sampling rates of spectrum sensors U	6000
Duration of spectrum sensing phase τ_s	7 ms
Duration of spectrum sensing phase t_s	6 ms
Duration of reporting sensing results to sink t_r	1 ms
Sensing power of spectrum sensors P_s	0.1 W
Transmission power of data sensors P_t	0.22 W
Energy consumption per spectrum sensing	0.11 mJ
Fraction of samples retained in CE algorithm ρ	0.6
Stopping threshold ϵ	10^{-3}
partial throughput factor κ	0.5
Penalty factor for miss detection ϕ	0.5
SNR of secondary transmission	20 dB

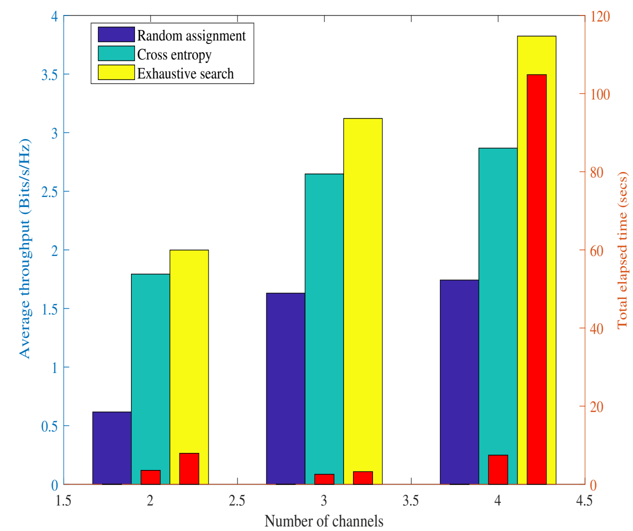


Figure 2: Comparison of throughput for SSR scheme with CE algorithm, random assignment and exhaustive search methods.

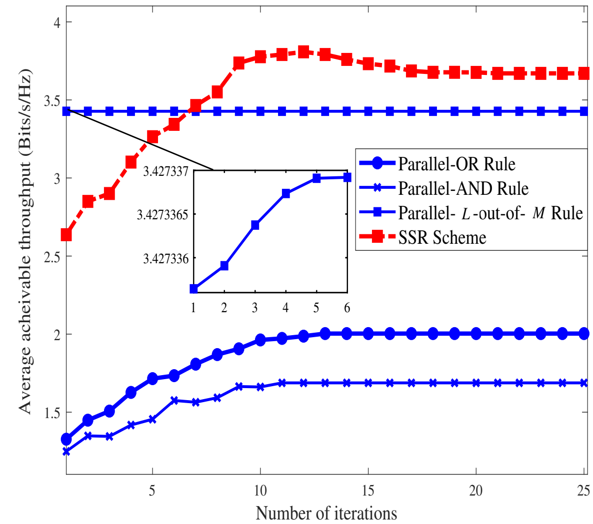


Figure 4: Performance comparison of CE algorithm-based SSR and CCS schemes with various fusion rules and $M = 15$.

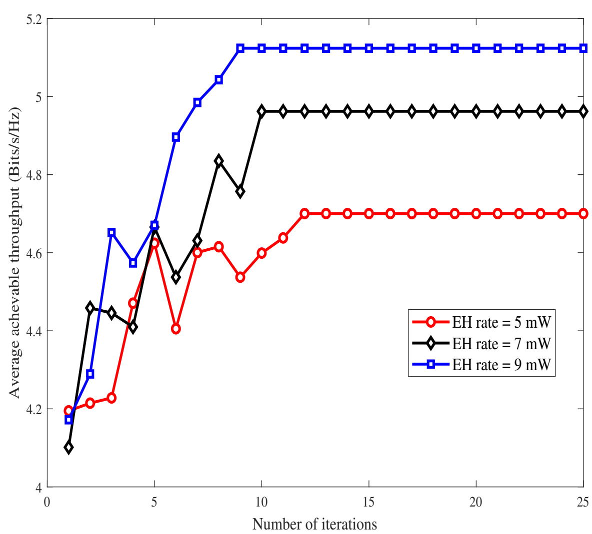


Figure 3: Average achievable throughput vs. number of iterations for different EH rates.

convergence of CE algorithm with the number of iterations for different EH rate values. As expected, the average throughput increases with EH rate.

Next, for a network with $M = 15$ and $K = 7$, the average achievable throughput of SSR-based CE algorithm is compared with conventional fusion rules such as OR, AND, and L-out-of-M rule, as shown in Fig. 4. In the SSR scheme, since only one sensor reports its decision to the sink, it performs better than the optimal CCS scheme employing L-out-of-M, and naturally as compared to the suboptimal OR and AND rules. In other words, the L-out-of-M rule performs the best among the CCS schemes, when optimum value of L is chosen [9]. Finally, we discuss the tradeoff between the optimal performances of SSR scheme with that of the optimal L-out-of-M rule based CCS scheme. The variation of average achievable throughput with M, for different sensing times τ_s is shown in Fig. 5. When M is reduced, the CCS scheme yields a larger throughput due to the better detection accuracy at the expense of relatively smaller channel available time, as opposed to the SSR scheme which saves the channel available time, but loses out on detection accuracy. Interestingly, as M increases, the SSR scheme outperforms the CCS scheme, since even though the detection accuracy of the CCS scheme increases, it loses out on the channel available time. Hence, this tradeoff yields a regime where SSR is preferred over CCS. Inherently, this tradeoff is between the detection accuracy and channel available time for secondary data transmission. Therefore, as M increases, the channel available time is of greater priority as opposed to the detection accuracy in the HCRN, resulting in the SSR scheme being a better choice. However, in the scenario where the detection accuracy is a main concern, the CCS scheme can still be employed.

V. Conclusion

We considered the maximum achievable throughput of SSR-based spectrum sensing in a multichannel HCRN. We have investigated the impact of the EH rate on the maximum achievable throughput of the SSR scheme. We have shown that the achievable throughput increases with the EH rate by optimally scheduling the spectrum sensors to sense a particular channel. Through numerical results, we showed that SSR-based multichannel scheduled sensing scheme outperforms the CCS scheme employing the optimal L-out-of-M rule, and discussed the tradeoff between the average achievable throughput of both schemes. We showed that this tradeoff is the inherent tradeoff between the channel available time and the detection accuracy, and discussed the regime where SSR is preferred over CCS scheme. The results show that the SSR scheme outperforms the CCS scheme when the number of spectrum sensors is large, and therefore, the channel available time is of greater priority in a HCRN than the detection accuracy. Hence, in a scenario where spectral efficiency needs

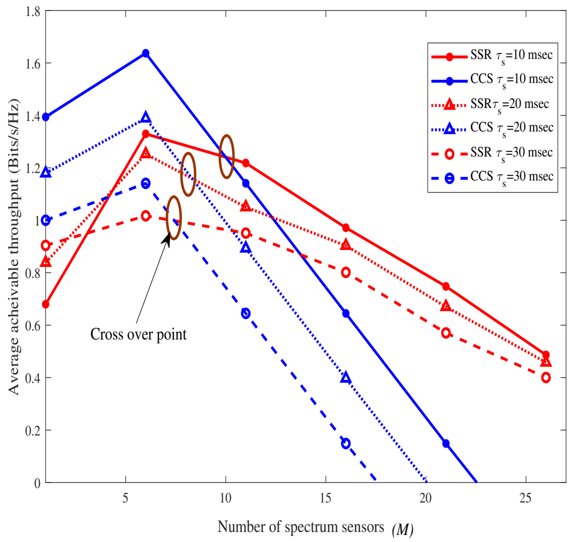


Figure 5: Average achievable throughput vs. number of spectrum sensors, M.

to be improved, SSR is a better choice. Conversely, the CCS should be employed in the scenario where the PU protection and detection accuracy are important.

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References

[1] R. Xie, F. R. Yu, H. Ji, and Y. Li, “Energy-efficient resource allocation for heterogeneous cognitive radio networks with femtocells,” *IEEE Trans. Wireless Commun.*, vol. 11, no. 11, pp. 3910–3920, Nov. 2012.

[2] J. B. Rao and A. O. Fapojuwo, “An analytical framework for evaluating spectrum/energy efficiency of heterogeneous cellular networks,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3568–3584, May 2016.

[3] J. Mitola and G. Q. Maguire, “Cognitive radio: making software radios more personal,” *IEEE Personal Commun. Mag.*, vol. 6, no. 4, pp. 13–18, Aug 1999.

[4] D. Zhang, Z. Chen, J. Ren, N. Zhang, M. K. Awad, H. Zhou, and X. S. Shen, “Energy-harvesting-aided spectrum sensing and data transmission in heterogeneous cognitive radio sensor network,” *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 831–843, Jan. 2017.

[5] M. I. B. Shahid and J. Kamruzzaman, “Interference protection in cognitive radio networks,” in *Proc. VTC*, May 2010, pp. 1–5.

[6] Y. H. Bae and J. W. Baek, “Achievable throughput analysis of opportunistic spectrum access in cognitive radio networks with energy harvesting,” *IEEE Trans. Commun.*, vol. 64, no. 4, pp. 1399–1410, Apr. 2016.

[7] S. Park, H. Kim, and D. Hong, “Cognitive radio networks with energy harvesting,” *IEEE Trans. Wireless Commun.*, vol. 12, no. 3, pp. 1386–1397, Mar. 2013.

[8] Y. C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, “Sensing-throughput tradeoff for cognitive radio networks,” *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008.

[9] I. Y. Hoballah and P. K. Varshney, “Distributed Bayesian signal detection,” *IEEE Trans. Inf. Theory*, vol. 35, no. 5, pp. 995–1000, Sep. 1989.

[10] Z. Dai, J. Liu, and K. Long, “Selective-reporting-based cooperative spectrum sensing strategies for cognitive radio networks,” *IEEE Trans. Veh. Technol.*, vol. 64, no. 7, pp. 3043–3055, Jul. 2015.

[11] R. Kishore, Ramesha C. K., S. Gurugopinath and Anupama K. R., “Performance analysis of superior selective reporting-based energy efficient cooperative spectrum sensing in cognitive radio networks,” *Ad Hoc Networks*, vol. 65, pp. 99–116, Jul. 2017.

[12] Q. Wu, G. Y. Li, W. Chen, D. W. K. Ng, and R. Schober, “An overview of sustainable green 5G networks,” *IEEE Trans. Wireless Commun.*, vol. 24, no. 4, pp. 72–80, Aug. 2017.

[13] D. Zhang, Z. Chen, M. K. Awad, N. Zhang, H. Zhou, and X. S. Shen, “Utility-optimal resource management and allocation algorithm for energy harvesting cognitive radio sensor networks,” *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3552–3565, Dec. 2016.

[14] X. Liu, F. Li, and Z. Na, “Optimal resource allocation in simultaneous cooperative spectrum sensing and energy harvesting for multichannel cognitive radio,” *IEEE Access*, vol. 5, pp. 3801–3812, Mar. 2017.

[15] A. Gokceoglu, S. Dikmese, M. Valkama, and M. Renfors, “Enhanced energy detection for multi-band spectrum sensing under RF imperfections,” in *Proc. CROWNCOM*, Jul. 2013, pp. 55–60.

[16] A. Bletsas, A. Khisti, D. P. Reed, and A. Lippman, “A simple cooperative diversity method based on network path selection,” *IEEE J. Sel. Areas Commun.*, vol. 24, no. 3, pp. 659–672, Mar. 2006.

[17] Y. Zheng and L. Zheng, “Sensing transmission tradeoff over penalty for miss detection in cognitive radio network,” *Wireless Personal Communications*, vol. 92, no. 3, pp. 1089–1105, Feb. 2017.

[18] Y. Pei, Y. C. Liang, K. C. Teh, and K. H. Li, “Energy-efficient design of sequential channel sensing in cognitive radio networks: Optimal sensing strategy, power allocation, and sensing order,” *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1648–1659, Sep. 2011.