Lifetime Maximization by Dynamic Threshold and Sensor Selection in Multi-Channel Cognitive Sensor Network

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Abstract

The tiny and low-cost sensors cannot simultaneously sense more than one channel since they do not have high-speed Analog-to-Digital-Convertors (ADCs) and high-power batteries. It is a critical problem when they are used for multi-channel sensing in cognitive sensor networks (CSNs). One solution for this problem is that the sensors sense various channels at different sensing periods. Due to the energy limitation in these scenarios, the lifetime maximization will become an important issue. In this paper, maximizing the lifetime of a CSN is investigated by selecting both the cooperative sensors and their detector threshold, such that the desired detection performance constraints are satisfied. This is a NP-complete problem, and obtaining the optimum solution needs exhaustive search with exponential complexity order. Here we have proposed two convex-based optimization algorithms with low order of complexity. First algorithm applies the known instantaneous Signal-to-Noise-Ratio (SNR) and obtains the proper detector thresholds by solving an equation for every channel. Investigation the effect of detector thresholds on the energy consumption, the false alarm probability and the detection probability shows that we can minimize the detector thresholds such that the detection constraints are met. In the second algorithm in order to reduce the needed time for obtaining answers, the Bisection method is proposed for determining detector thresholds. Because knowing the instantaneous SNR is difficult, we have investigated the performance of the second algorithm by average value of SNR. Simulation results show that the proposed algorithms improve the performance of the network in case of lifetime and energy consumption.

Keywords: Cognitive Sensor Network; Detection Probability; False Alarm Probability; Lifetime; Multi-Channel Cooperative Spectrum Sensing.

1. Introduction

With the increasing use of wireless applications, the lack of spectrum issue has emerged. Cognitive radio networks (CRNs) have been proposed to overcome this issue. In these networks secondary users (SUs) sense the spectrum to find and access free sections of the licensed bands as long as they do not cause harmful interference with the primary users (PUs). Because of fading or shadowing effects, SUs might not be able to reliably monitor all PUs. Therefore, cooperative spectrum sensing (CSS) schemes are proposed in which the detection results from spatially distributed multiple sensors are combined to make a final decision [1].

If an SU performs both sensing the channels and transmission on the detected idle channels, it cannot sense and transmit simultaneously, because of hardware limitations, so it reduces the opportunistic access efficiency. Also, one SU may fail to sense all the channels simultaneously. Therefore, CSN composed of tiny and low-cost frequency sensors is one solution, where sensors are used for spectrum sensing [2] [3], and then the sensing results are sent to the SUs. The CSN provides higher throughput for the SUs, and better protection of PUs against interference.

Multi-channel spectrum sensing is ambitiously proposed to efficiently monitor a wideband spectrum which is used by multiple PUs. This functionality causes to increase the SUs throughput, to improve spectrum's maintenance, and to reduce transmission interruptions, while it increases the complexity and requirements for adequate quality of sensing. The limited sampling rate of ADCs complicates the multi-channel spectrum sensing [4]. A practical method is monitoring the channels separately, which in this method, sensors cooperate with each other to sense all the channels.

Simple implementation, low computational complexity and energy consumption are the reasons that determine energy detector (ED) as a useful detector for multi-channel sensing [4]. The cooperation between cognitive sensors improves the performance of this technique, too. Employing an array of EDs, each of which detects one frequency channel, has been used for multi-channel joint detection.

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This method enables SUs to simultaneously detect PU signals across multiple channels [5], but this scheme is complicated costly and non-applicable for such a CSN.

On the other hand, ED with fixed threshold is sensitive to noise and it cannot perform well in low SNR. So, it leads to interference with PUs, and decreases the throughput of SUs. Dynamic threshold selection for energy detector improves its performance [6], because the threshold is adjusted on demand with regard to the different SNR. Also, dynamic threshold selection is a way to energy conservation of a cognitive network [7].

Because of small size and weight of sensors, there are limitations on their energy and cost. These physical constraints of sensors and the prohibitive costs to replace the depleted sensors in the CSNs make energy an important consideration to design a long lifetime network [3]. Mechanism of energy consumption of a CSN has a great impact on the network lifetime. Lifetime extending techniques can improve the energy utilization and hardware efficiencies. Therefore, reducing the energy consumption and balancing the residual energy of sensors are both critical in CSN design. If all the sensors perform sensing, it leads to high energy consumption and it raises the false alarm probability without increasing significant detection probability [8]. So sensor selection is a way to reduce energy cost while satisfying sensing quality constraints. In this paper, two ways are investigated for reducing the energy consumption and balancing the residual energy of sensors in a CSN. First is sensor selection for CSS, and the second is dynamic threshold selection for ED of the sensors. The two problems are combined and simultaneously solved.

1.1 Prior Works

[7] is a rich survey on the energy efficient schemes for CSS. Optimization of sensing nodes number and sensing settings are two main directions of possible energy conservation methods in CSS [7]. Reducing number of sensing nodes have been investigated with methods such as censoring [9], determining the optimum number of SUs [10]- [11], clustering [12], and node selection [13], in order to reduce energy consumption of CSS. They assumed monitoring of only one channel which is utilized by one PU. Also, methods such as energy harvesting (EH) [14], compressive sensing (CS) [15], and clustering [16], have been proposed for energy conservation of multi-channel CSS in a CRN. The former two methods are complicated and needs particular capabilities, but the third method is applicable in any CSN.

The detector threshold selection is a way of CSS settings optimization for energy conservation which has been proposed in studies such as [17]-[18]. In [17], both the sensor selection and ED threshold optimization for CSS in a CSN was investigated, although for monitoring only a single channel. In [18], assuming multi-channel CSS, schemes for assigning nodes to sense various channels, and then threshold optimization were proposed. They used clustering method for assigning all the nodes to adequate channels, to increase the overall throughput. Although this node assignment scheme improves energy conservation, it uses all the sensors for sensing, which is not optimal, meanwhile it causes to increase the false alarms. Also, the fixed thresholds were determined which is not optimum due to the time-varying nature of the lifetime problem. Jointly determining the optimum threshold of detector of sensors, and selecting sensors for all channels is a challenging problem, because the selected sensors change for different channels, and it is efficient to dynamically select threshold of EDs for selected sensors. The lifetime problem becomes more complicated, because the status of channels and the energy of sensors changes by time (i.e. channels are time varying and some nodes run out of battery). This paper pays attention to all of these challenges in node selection and threshold determining for the multi-channel CSS problem. In this paper, both dynamic thresholds and sensor selections for cooperative multi-channel sensing are assumed, with aim to energy conservation and lifetime maximization. For a CSN, two algorithms are proposed to assign the adequate sensors to various licensed channels, while the optimization of the detector threshold is done for reducing energy consumption and increasing the network lifetime. This paper aims to prolong the CSS lifetime while improving the detection performances, too. In the first algorithm the detector thresholds are optimized for cooperative sensors, but it needs a long time for finding the optimal solution. Second, another algorithm is proposed which finds efficient solution at a shorter time.

The rest of the paper is organized as follows. In section 2, system model is expressed. Section 3 discusses the problem formulation based on the instantaneous SNR of sensors. In section 4 the algorithms are presented. The generalization of the algorithm to the average SNR scenario will be presented in section 5. The simulation results are explained in section 6. Finally, the conclusions are presented in section 7.

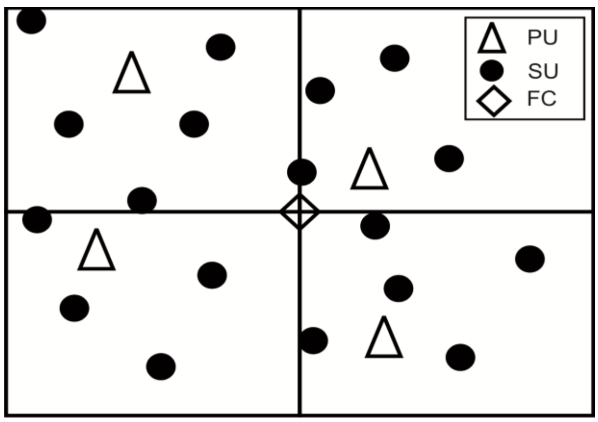

Fig. 1. A sample of system model.

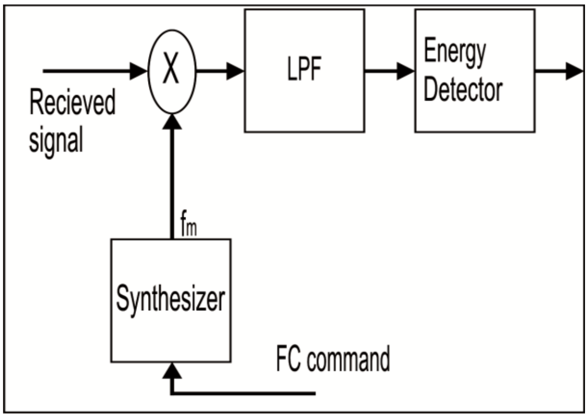

Fig. 2. The receiver circuit of every cognitive sensor.

2. System Model

We consider a CSN with an FC and N sensors which are distributed uniformly. We assume the wideband is divided to M channels with the same bandwidth. M PUs are distributed uniformly and use the channels to transmit their signals with the same modulation, while each PU can use from a single channel. A sample CSN is depicted in Fig.1. Because sensors have limited hardware, so a tiny sensor cannot sense more than one channel, simultaneously. A solution is proposed in which the CSN can simultaneously sense more than one channel by cooperation between sensors. It is assumed that every sensor is equipped with a receiver circuit which composed of a synthesizer, a narrowband filter, and an ED. The simple and low-cost receiver circuit is plotted in Fig. 2. In fact the narrow-band detector can only scan one PU at a time. However, the synthesizer tunes frequency with a command from FC to the center frequency of a channel. Because of low complexity energy detector is proposed for sensing the spectrum. $\gamma_{m,n}$ denotes sensor *n* detector threshold for the channel *m*. Generally, the optimal thresholds are not equal even in case of sensing a single channel with equal channel gains at all sensors, but an equal threshold for sensing a channel is asymptotically optimal when the number of sensors goes to infinity [15]. For reducing the complexity of the algorithms, it is assumed that all the sensors assigned to a single channel use equal energy detector thresholds (i.e., $\gamma_{m,n} = \gamma_m$), but in different durations of sensing this thresholds are determined dynamically. The signal energy at channel *m* is measured by sensor *n* as: $T_{m,n} = \sum_{k=1}^{K} |x_{m,n}(k)|^2$, where $x_{m,n}(k)$ denotes the k-th sample of the discrete received signal of channel *m* that is observed by the n-th node, and K is the number of samples which is calculated as δf_s, where f_s is the Nyquist sampling rate of detector according to the channel bandwidth, and δ is the sensing time. In table 1, the description of each notation used in the paper is shown.

We define two hypotheses for every sensor. The first, i.e. $H_{0,m}$, says that the m-th PU is not transmitting, i.e. channel *m* is idle, and the second, i.e. $H_{1,m}$, says that the m-th PU is transmitting, i.e. channel *m* is busy. So we have:

$$\begin{cases} H_{1,m}; \ x_{n,m}(k) = g_{n,m}.s_m(k) + v_{n,m}(k) \\ H_{0,m}; \ \ x_{n,m}(k) = v_{n,m}(k) \end{cases} \tag{1}$$

$$\begin{cases} H_{1,m}; \ T_{n,m} \geq \gamma_m \ ; \quad T_{n,m} \sim \mathcal{N}(0, {\sigma_{1,n,m}}^2) \\ H_{0,m}; \ T_{n,m} \leq \gamma_m \ ; \quad T_{n,m} \sim \mathcal{N}(0, {\sigma_V}^2) \end{cases} \tag{2}$$

The k-th sample of transmitted primary signal on channel m is denoted by $s_m(k)$, that is assumed to be an i.i.d random process with zero mean and variance σ_S^2. $v_{n,m}$ is the Gaussian i.i.d random noise with zero mean and variance ${\sigma_V}^2$, and it is assumed that s_m and $v_{m,n}$ are independent. $g_{m,n}$ denotes the channel gain between the m-th PU and sensor *n*. The path loss, Rayleigh fading and shadowing effects are considered in order to model the PU-sensor channels. Hence; the channel gains are modeled as [19]:

$$g_{m,n} = 9^{\frac{20\log\left(\frac{\Lambda}{4\pi d_{m,n}}\right)+z_{m,n}}{20}} \widetilde{g_{m,n}} \tag{3}$$

which $\widetilde{g_{m,n}}$ is a standard complex Gaussian random process (Rayleigh fading), $z_{m,n}$ is a Gaussian random variable (in dB) with zero mean and variance σ_z^2 (Lognormal shadowing), and the expression $\left(\frac{\Lambda}{4\pi d_{m,n}}\right)^2$ is free-space path loss component, when Λ is the wavelength and $d_{m,n}$ is the distance between the PU that uses channel *m* and sensor *n*.

Under the hypothesis $H_{1,m}$, the ratio of measured signal of sensor *n* from the m-th PU to the noise power is defined as [13]:

$$SNR_{m,n} = \frac{p_t |g_{m,n}|^2 \sigma_S^2}{\sigma_V^2} \tag{4}$$

We assume the FC knows the instantaneous received SNR of the sensors. Since the goal of this paper is not the SNR estimation, we ignore the estimated SNR error. Although, this assumption seems unrealistic for some scenarios, it does not have effect on the procedures of the proposed algorithms [9]. The sensor selection can be done based on the average SNR or the estimated SNR, similarly, which is discussed in section 5.

There are two important metrics for the spectrum sensing quality which are called as false alarm and detection probabilities. The larger detection probability and the lower false alarm probability of a node provide more reliable spectrum sensing by the node. These metrics for sensor *n* which senses channel *m* are calculated respectively as [13]:

$$P_{f_{m,n}} = P(H_{1,m}|H_{0,m}) = Q\left(\left(\frac{\gamma_m}{\sigma_V^2} - 1\right)\sqrt{\delta f_s}\right) \tag{5}$$

$$P_{d_{m,n}} = P(H_{1,m}|H_{1,m}) = Q\left(\left(\frac{\gamma_m}{\sigma_V^2} - SNR_{m,n} - 1\right) * \sqrt{\frac{\delta f_s}{2SNR_{m,n}+1}}\right) \tag{6}$$

Here $Q(.)$ denotes the complimentary distribution function. It is noted that the false alarm probability does not depends on the received SNR of sensors, but the detection probability depends on the sensors received SNR.

It is assumed that the FC uses the logic OR rule to fuse the decision of sensors [9]. According to the logic OR fusion rule, if at least one sensor detects the primary signal transmitting on channel *m*, the final decision shows that the PU is transmitting. If all sensors participate simultaneously in sensing, it leads to high energy consumption and it raises the false alarm probability without increasing significant detection probability [8]. Therefore, a coefficient $\varphi_{m,n}$ is considered to determine selected sensors, such that: $\varphi_{m,n} = 0$ if sensor *n* does not sense channel *m* and $\varphi_{m,n} = 1$ if sensor *n* senses channel *m*. Also, because every sensor at most can sense a channel for every sensing period, so for every sensor *n* it is assumed that: $\sum_{m=1}^{M} \varphi_{m,n} \leq 1$. We want to select cooperative nodes such that J_m denotes the set of selected sensors which cooperate with each other in sensing channel *m*. Because of limitation of sensors in sensing more than one channel, it is assumed that:

$$\begin{cases} J_m \cap J_{m'} = \emptyset \\ J_m \cup J_{m'} \subset \{1, \dots, N\} \end{cases} \forall m, m' \in \{1, .., M\}, m \neq m' \quad (7)$$

Table 1. The description of parameters

N	Number of sensors	$d_{m,n}$	Distance between m-th PU to sensor n
M	Number of channels/PUs	$d_{0,n}$	Distance between sensor n to FC
δ	the sensing time	Λ	The PU-signal wavelength
f_s	Nyquist sampling	γ_m	Detector threshold for channel m
$g_{m,n}$	PU-sensor channel gains	$H_{0,m}/H_{1,m}$	Assumption of off/on for m-th PU
s_m	PU signal with variance ${\sigma_S}^2$ over channel m	$P_{d_{m,n}}/P_{f_{m,n}}$	Detection/false alarm probability of sensor n about channel m
$v_{m,n}$	Noise of PU-sensor channel$\sim\mathcal{N}(0, {\sigma_v}^2)$	P_{d_m}/P_{f_m}	Global detection/false alarm prob. about channel m
$\widetilde{g_{m,n}}$	Rayleigh fading over PU-sensor channels	J_m	Selected nodes set for sensing channel m
$z_{n,m}$	Lognormal shadowing with variance σ_z^2 of PU-sensor channels	E_{t-elec}	Energy for the electronic circuits of transmitters
E_s / E_{t_n}	Sensing / Transmission energy	e_{amp}	Amplifying coefficient
EC_n	Energy consumption for sensor n	$H_{0,m}/H_{1,m}$	Assumption of off/on for m-th PU
$E_{0,n}$	Initial energy of sensor n	β_m/α_m	The detection/false alarm prob. limits for channel m
E_n	Residual energy of sensor n	$\mathcal{L}$	The ratio of live sensors to all nodes in lifetime moment

where m and m′ denote two different channels. Therefore, the global detection probability (P_{d_m}) and the global false alarm probability (P_{f_m}) for CSS of channel *m* are respectively written as [20]:

$$P_{d_m} = 1 - \prod_{n \in J_m} (1 - \varphi_{m,n} P_{d_{m,n}}) \quad (8)$$

$$P_{f_m} = 1 - \prod_{n \in J_m} (1 - \varphi_{m,n} P_{f_{m,n}}) \quad (9)$$

We want to maximize the lifetime of the multi-channel CSS for a CSN under the global detection and false alarm probabilities constraints. There are different definition for a sensor network lifetime based on the network application [20]. In this paper, the lifetime of a CSN is defined as the time in which a certain percentage of the sensors run out of battery.

Definition 1. The lifetime of a CSN is defined as the moment time that the number of live sensors drops under $\mathcal{L}.N$ where $0 < L \leq 1$, i.e., (1-$\mathcal{L}$).N of sensors have the minimum of energy and cannot sense [20]. ■

As mentioned before, because of battery size and weight limitations of sensors, energy utilization mechanism is an important issue in CSN which imposes a time limit on the network operation life. In order to formulate the lifetime maximization problem, first the needed energy consumption and the residual energy of sensors are calculated. We assume sensing energy of sensor *n*, i.e. $E_s$constant, is the same for all sensors (It is a fair assumption because of equal sensing rate and similar detector of sensors). Also, the energy for transmitting sensor *n* decision to the FC is denoted with E_{t_n}, and it is calculated as [13]:

$$E_{t_n} = E_{t-elec} + e_{amp}.{d_{0,n}}^2 \quad (10)$$

in which E_{t-elec} is the energy used for the electronic circuits of transmitter, e_{amp} is the amplifying coefficient and $d_{0,n}$ is the distance between sensor n and the FC. Therefore, energy consumption of sensor *n* for participating in CSS of every channel is calculated as [13]:

$$EC_n = E_s + E_{t_n} \quad (11)$$

3. The Problem with Instantaneous SNR

Our goal is lifetime maximization of a CSN by jointly selecting the appropriate cooperative nodes for sensing each channel, and determining the optimum detector threshold of selected sensors, so that, the constraints on the global detection probability and the global false alarm probability of multi-channel CSS are satisfied. These constraints are assumed to guarantee acceptable sensing quality for all channels. Max-min method is used to solve the problem [21]. In this method, to maximize lifetime, the minimum of residual energy of sensors is maximized, such that the sensors which have larger residual energy and need lower energy consumption are selected for sensing. Therefore, the sensors residual-energy-levels are kept balanced, which leads to extend the network lifetime significantly. On the other hand, the level of detector threshold affects the energy consumption, the detection probability, and the false alarm probability of sensors. Hence, the optimum threshold for sensing every channel, in every duration of network life is found, such that, the global probability of detection and the global probability of false alarm constraints are satisfied. This multi-channel

CSS lifetime maximization is written in an optimization problem framework as follows:

Problem1: $max_{\varphi_{m,n},\ \gamma_m}\{\min_n\{E_n\}\}$

subject to;

$E_n \geq \varphi_{m,n}.E_{th} \quad \forall m,n$ (12-1)

$P_{f_m} - \alpha_m \leq 0 \quad \forall m$ (12-2)

$\beta_m - P_{d_m} \leq 0 \quad \forall m \in \{1,\ldots,M\}$ (12-3)

$\sum_{m=1}^{M}\varphi_{m,n} - 1 \leq 0 \quad \forall n \in \{1,\ldots,N\}$ (12-4)

$\varphi_{m,n} \in \{0,1\} \quad \forall m,n$ (12-5)

In this problem the minimum of residual energy of sensors is defined as $E_{th} \triangleq \min_n\{E_n\}$. The first constraint shows that the minimum of residual energy of all sensors is E_{th}, and there is at least one sensor with this amount of energy. To guarantee the fair sensing quality, the detection constraints are assumed on every channel. The larger detection probability leads to lower interference with PUs, and the lower false alarm probability means the better usage of free channels. The second constraint states that the global false alarm probability for cooperative sensing of channel *m* should be lower than the desired parameter α_m. The third constraint states that the global detection probability for CSS of channel *m* should be more than the desired parameter β_m. The constraint (12-2) is simplified thanks to the fact that global probability of false alarm is independent of the $SNR_{m,n}$. Therefore, it is concluded from (5), (9), and (12-2) that:

$$|J_m| \leq J_{m\_max} \triangleq \left\lfloor \frac{\ln(1-\alpha_m)}{\ln\left(1-Q\left(\left(\frac{\gamma_m}{\sigma_V^2}-1\right)\sqrt{\delta f_s}\right)\right)} \right\rfloor \quad (13)$$

For a constant γ_m, if more than J_{m_max} sensors are selected for channel *m*, the false alarm probability constraint for the channel is not satisfied, meanwhile the energy consumption increases due to higher number of selected sensors. Thus, for every level of γ_m, the maximum number of selected cooperative nodes for CSS of the channel is J_{m_max}.

However, Problem1 is a NP-complete problem because of the integer nature of $\varphi_{m,n}$. Finding only sensors under fixed threshold needs an exhaustive search algorithm with complexity order of $O(N!)$ [20]. Since the threshold level of detector is a continuous parameter, finding the optimal solution for the threshold and sensor selection is not possible. The aim of this paper is finding an optimum answer with a lower complexity. Hence, it is assumed that $\varphi_{m,n}$ is a non-negative continuous parameter in order to apply a continuous search algorithm. In fact, this continuous parameter represents the priority of sensor *n* for sensing channel *m*. After solving the problem, $\varphi_{m,n}$ is mapped to '0' or '1', in this way that, the $\varphi_{m,n}$ for sensors with the larger priority, which are selected, are denoted by '1', and for the other nodes are denoted by '0'. Therefore, the standard optimization problem is written as:

Problem2: $max_{\varphi_{m,n},\ \gamma_m}\{E_{th}\}$

subject to;

$$\varphi_{m,n}\left(E_{th} - \left(E_{0,n} - \sum_{m=1}^{M}\varphi_{m,n}EC_n\right)\right) \leq 0$$

$\forall m,n$ (14-1)

$$\beta_m - \left(1 - \prod_{n\in J_m}\left(1-\varphi_{m,n}.P_{d_{m,n}}(\gamma_m)\right)\right) \leq 0$$

$\forall m$ (14-2)

$\sum_{m=1}^{M}\varphi_{m,n} - 1 \leq 0 \quad \forall n$ (14-3)

$\sum_{n=1}^{N}\varphi_{m,n} - J_{m\_max} \leq 0 \quad \forall m$ (14-4)

$-\varphi_{m,n} \leq 0 \quad \forall m,n$ (14-5)

The convex optimization method can be used for finding a sub-optimal but efficient solution, although the problem is not convex because of the second constraint. This is a popular method to solve non-convex problems in a simple but efficient way [22]. Because only sensors are selected that their residual energy is larger than E_{th}, the constraint (14-5) is satisfied, and so this constraint is removed. The Lagrange function is formed as follows [22]:

$$L(\varphi_{m,n},\gamma_m,\rho_{m,n},\lambda_m,\eta_n,\xi_m) = E_{th} - \sum_{n,m}\rho_{m,n}\varphi_{m,n}(E_{th} - (E_{0,n} - \sum_{m=1}^{M}\varphi_{m,n}EC_n)) - \sum_m\lambda_m\left(\beta_m - 1 + \prod_{n\in J_m}\left(1-\varphi_{m,n}.P_{d_{m,n}}(\gamma_m)\right)\right) - \sum_n\eta_n\left(\sum_{m=1}^{M}\varphi_{m,n} - 1\right) - \sum_m\xi_m\left(\sum_{n=1}^{N}\varphi_{m,n} - |J_{m\_max}|\right) \quad (15)$$

where the Lagrange multipliers $\rho_n, \lambda_m, \eta_n,$ and ξ_m are considered for the constraints (14-1), (14-2), (14-3), and (14-4), respectively. The efficient value of $\varphi_{m,n}$ are found by differentiating L with respect to $\varphi_{m,n}$ as [22]:

$$\frac{\partial L}{\partial\varphi_{m,n}} = \lambda_m P_{d_{m,n}}\prod_{\substack{\ell\in J_m\\ \ell\neq n}}\left(1-\varphi_{m,\ell}P_{d_{m,\ell}}\right) - \rho_n(E_{th} - E_{0,n}) - 2\rho_n\varphi_{m,n}EC_n - \eta_n - \xi_m = 0 \quad (16)$$

Now, the sensors priority to detect channel *m*, are obtained as:

$$\varphi_{m,n} = \frac{-\xi_m - \eta_n - \rho_n(E_{th}-E_{0,n}) + \lambda_m P_{d_{m,n}}\prod_{\substack{\ell\in J_m\\ \ell\neq n}}(1-\varphi_{m,\ell}P_{d_{m,\ell}})}{2\rho_n EC_n} \quad (17)$$

We calculate the optimum value of detector threshold of selected sensors, by differentiating L with respect to γ_m, as [22]:

$$\frac{\partial L}{\partial\gamma_m} = \lambda_m\sum_{n=1}^{N}\varphi_{m,n}\sqrt{\frac{\delta f_s}{2\pi\sigma_V^2(2SNR_{m,n}+1)}} . \exp\left(-\frac{\delta f_s}{4SNR_{m,n}+2}\left(\frac{\gamma_m}{\sigma_V^2} - SNR_{m,n} - 1\right)^2\right) . \prod_{\substack{\ell\in J_m\\ \ell\neq n}}(1-\varphi_{m,\ell}P_{d_{m,\ell}}) = 0 \quad \forall m \quad (18)$$

Therefore, the optimum value of γ_m is found from solving the following equation:

$$\sum_{n\in J_m} \varphi_{m,n}\sqrt{\frac{\delta f_s}{2\pi\sigma_v^2(2SNR_{m,n}+1)}}\frac{1}{1-\varphi_{m,n}P_{d_{m,n}}} * \exp\left(-\frac{\delta f_s}{4SNR_{m,n}+2}\left(\frac{\gamma_m}{\sigma_v^2} - SNR_{m,n} - 1\right)^2\right) = 0 \quad (19)$$

To obtain the optimum values of Lagrange multipliers in (17), the complimentary slackness conditions are analyzed [13]. Since the selected nodes are removed from the set of remained nodes, a node is not selected for more than one channel, thus the η_n can be removed from (17). Because ξ_m is independent from sensors number and is a fixed value for every m, therefore, the ξ_m is removed from (17), and just the selected nodes number are checked in order to satisfy the (14-4). The Subgradient method is used for finding the optimal answer of the other Lagrange multipliers in (17). The $\rho_{m,n}$ and the λ_m with step sizes $\ell 1(i) = \frac{C1}{i}$ and $\ell 2(i) = \frac{C2}{i}$ are updated as [22]:

$$\rho_{m,n}(i) = \rho_{m,n}(i-1) + \ell 1(i)\left(E_{th} - E_{0,n} + E_{cn}\right) \quad (20)$$

$$\lambda_m(i) = \lambda_m(i-1) + \ell 2(i)\left(\beta_m - P_{d_m}\right) \quad (21)$$

where "i" is Subgradient iteration number, C1 and C2 are constant values. This algorithm is running until maximum size of changes becomes lower than a small value ϵ, i.e. the algorithm is running while:

$$\max\left(|\lambda_m(i) - \lambda_m(i-1)|, |\rho_{m,n}(i) - \rho_{m,n}(i-1)|\right) \geq \epsilon \quad (22)$$

Now, priority function of sensors for sensing channel *m* is calculated as:

$$\varphi_{m,n} \triangleq \frac{E_{0,n} - E_{th}}{2EC_n} + \frac{\lambda_m P_{d_{m,n}} \prod_{\substack{\ell\in J_m \\ \ell\neq n}}\left(1-\varphi_{m,\ell}P_{d_{m,\ell}}\right)}{2\rho_{m,n}E_{cn}} \quad (23)$$

Thus, the sensor with the larger measure of $\varphi_{m,n}$, has the more priority for being selected for cooperative sensing channel *m*. It is noted that the priority function is inversely related to the required energy consumption of sensors for participating in sensing, and is directly related to their residual energy and their detection probability of a channel.

The above solution needs to solve the equation (19) which takes few seconds. Although this time is much shorter than exact search time, it causes a significant delay for sensing in a CSN. On the other hand, the energy consumption of sensors is an increasing function of detector thresholds [17]. Because increasing the threshold level decreases the detection probability of sensors. Therefore, more numbers of sensing nodes is required to satisfy the detection performance which increases the energy consumption. Hence, the minimum threshold is found so that the global probability of detection constraint is satisfied. The threshold optimization problem for every channel is written as:

Problem3: $\quad min\ \{\gamma_m\} \qquad \forall m \in \{1, \dots, M\}$
subject to;

$$\left(1 - \prod_{n\in J_m}\left(1 - \varphi_{m,n}.P_{f_{m,n}}(\gamma_m)\right)\right) - \alpha_m \leq 0 \quad (24\text{-}1)$$

$$\beta_m - \left(1 - \prod_{n\in J_m}\left(1 - \varphi_{m,n}.P_{d_{m,n}}(\gamma_m)\right)\right) \leq 0 \quad (24\text{-}2)$$

, in which (24-1) is replaced with another constraint, the same as (14-4). Direct solving the optimization problem needs to solve (19). However, after sensors were selected, the thresholds minimization can be done by a simple iterative algorithm. The Bisection method is used for finding the optimum thresholds for selected sensors sensing every channel. The threshold levels of different channels are independent; therefore, the detector threshold selection for every channel is a one-dimensional problem which Bisection algorithm is used for determining the dynamic optimum threshold. The details of these algorithms are described in the next section.

4. The Proposed Algorithms

In this section, two algorithms for jointly sensor and detector threshold selection are proposed. Both of them are based on the known instantaneous SNR of sensors. The sensor selection algorithm for extending lifetime of a CSN, with fixed thresholds has been proposed in [20], which we call it as OLBSS (Optimal Lifetime Based Sensor Selection). The pseudo code of this algorithm is plotted in Table 3 of [20]. Here it is extended to the dynamic threshold selection scenario.

In this paper, it is assumed that the PU with more distance from center of the region has more priority for assigning sensors to sense its channel. Our reason for this distance based order is that probably the lower numbers of sensors are located around the PUs which are far from the center. Therefore, there is limited number of sensors with adequate detection probability for being selected for monitoring the PUs. This method is not optimum necessarily, but it provides good solution with low complexity, and it is proper for high number of channels. Also, in all of algorithms, if the problem converged to an acceptable answer that satisfies detection constraints for all channels, the iteration is calculated as successful iteration of lifetime. These algorithms continue until the number of active-sensors is lower than $\mathcal{L}.N$.

4.1 Joint Sensors and Dynamic Thresholds Selection

In every duration of lifetime, at first, with initial thresholds, maximum number of sensing nodes, for every channel is determined. Then, based on the instantaneous SNR of sensors, the detection probability of all sensors for all channels are determined. Now, sensor selection is done the same as OLBSS (save the sensors in S1 matrix). Then, the optimum thresholds are calculated from (19), and with the new measures of thresholds, another sensor selection is done the same as OLBSS (save the new sensors in S2 matrix). If the new selected sensors satisfy the global probability constraint for channel *m*, the loop is repeated. If the global probability constraint is not satisfied for channel *m*, γ_m is increased to the last selection. Finally, the residual energy of selected sensors is updated. The proposed algorithm is called the multi-channel lifetime maximization by jointly sensors and thresholds selection (JLMTSS). The pseudo code of this algorithm is plotted in Table 2.

4.2 The Reduced Time Joint Sensors and Dynamic Thresholds Selection

An initial feasible set with upper and lower bounds for every $\boldsymbol{\gamma_m}$ is determined. $\mathbf{J_{m\_max}}$ for all channels are determined with initial thresholds which are middle of the feasible sets. Then, based on the thresholds and the instantaneous received SNR of nodes the detection probability of sensors for all the channels are determined. Now, sensor selection is done the same as OLBSS. If the selected sensors for channel *m* satisfied the global probability constraint, the $\boldsymbol{\gamma_m}$ decreases, otherwise the $\boldsymbol{\gamma_m}$ increases. This loop is repeated until the terminating criterion of Bisection algorithm is met. Then residual energy of sensors is updated. This algorithm is called the first reduced time multi-channel lifetime maximization by jointly sensors and thresholds selection (RJLMTSS1). The pseudo code of this algorithm is plotted in Table3.

TABLE 2 JLMTSS1 ALGORITHM

Step1 and Step2 are done the same as OLBSS,([20], **Table 2) and save Set1 in S1.**
Step3: **for** n=1:N
  for m=1:M
    if there is node n in m-th row of S1, $\varphi_{m,n}$=1;
    else $\varphi_{m,n}=0$;
      end
    end
  end
Calculate optimum thresholds from Eq.(19).
Step4: Repeat Step1 and Step2 with the new thresholds, and save the new Set1 in S2.
  for m=1:M
  $P_{d_m}=1$
   for j=1: J_{m_max}
    if $(S2(m,j)\neq 0)$
    ns= $S2(m,j)$ & $P_{d_m}=1-(P_{d_m}*(1-\mathrm{P_{d_{m,ns}}}))$
    end
   end
  end
Step5: **if** $(P_{d_m}\geq\beta_m)$ clear S1, save S2 in S1, clear S2 and go to step3
  else S1 are the selected nodes and do step 3 of OLBSS.
  end

TABLE 3 RJLMTSS1 ALGORITHM

Step0 is done the same as OLBSS. The feasible set for every γ_m is determined.
Step2: **for** m=1:M $\boldsymbol{\gamma_m}=\frac{\gamma_{m_{\min}}+\gamma_{m_{\max}}}{2}$ **end**
  Select nodes for every channel the same as step1 and step2 in OLBSS
Step3: **if** $(P_{d_m}\geq\beta_m)$
   $\boldsymbol{\gamma_{m_{\min}}=\gamma_m}$
  else $\boldsymbol{\gamma_{m_{\max}}=\gamma_m}$
  end
Step4: **if max**$(\boldsymbol{\gamma_{m_{\max}}-\gamma_{m_{\min}}})<\varepsilon$
   Do step3 of OLBSS
  else Go to step2**.**
  end

Table 2. The values of simulation parameters

$\mathcal{L}=0.25$	$\mathrm{E_{0,n}}=0.2\ \mathrm{mJ}$	$\mathrm{E_{t-elec}}=80\ \mathrm{nJ}$	σ_Z^2=3db
$\alpha_m=0.1$	$E_s=190\ \mathrm{nJ}$	$\mathrm{e_{amp}}=40.4\ \mathrm{pJ/m^2}$	p_t=20mW
$\beta_m=0.9$	$\sigma_0^2=10^{-11}\mathrm{W}$	$f_c=2.45\ \mathrm{GHZ}$	M=8

5. The problem with average SNR

Since calculating the instantaneous SNR is difficult, in this section the joint sensors and thresholds selection algorithm for multi-channel CSS is extended to the case that the FC knows only the average SNR of sensors. In this case, the false alarm probability of sensors is the same as (5) because it does not depends on the SNR of sensors. Therefore, the average global probability of false alarm for this problem is the same as (9), but the detection probability of sensors depends on their received SNR. For the case that the FC knows only the average SNR information, the average detection probability is used for sensors and thresholds selection. The average detection probability is calculated as [13]:

$$\overline{\mathrm{P_{d_{m,n}}}}=\int_0^\infty \mathrm{P_{d_{m,n}}}.\,\mathrm{f}_{\varpi_{m,n}}(\varpi_{m,n}).\,d\varpi_{m,n} \tag{25}$$

where $\mathrm{f}_{\varpi_{m,n}}(\varpi_{m,n})$ denotes the probability density function (PDF) of the received SNR of sensor *n* from m-th PU ($\mathrm{SNR_{m,n}}\triangleq\varpi_{m,n}$). Under the assumed channel gain in (3), the PDF is an exponential distribution with the average as [17]:

$$\overline{\mathrm{SNR}}_{m,n}\triangleq\overline{\varpi_{m,n}}=\frac{p_t}{\sigma_v^2}\left(\frac{\Lambda}{4\pi d_{m,n}}\right)^2.\exp\left(\frac{(\ln 9)^2\sigma_Z^2}{220}\right) \tag{26}$$

Thus, the average detection probability is calculated as:

$$\overline{\mathrm{P_{d_{m,n}}}}=\int_0^\infty Q\left(\left(\frac{\gamma_m}{\sigma_v^2}-\varpi_{m,n}-1\right)\sqrt{\frac{\delta f_s}{2\varpi_{m,n}+1}}\right)$$

$$.\frac{1}{\overline{\varpi_{m,n}}}\exp\left(\frac{-\varpi_{m,n}}{\overline{\varpi_{m,n}}}\right).\,d\varpi_{m,n} \tag{27}$$

which the closed form of $\overline{\mathrm{P_{d_{m,n}}}}$ is calculated as [25]:

$$\overline{\mathrm{P_{d_{m,n}}}}=\frac{1}{2\overline{\varpi_{m,n}}}\frac{\exp\left(\sqrt{\delta f_s}\left(\frac{\gamma_m}{\sigma_v^2}-1\right)\left(\sqrt{\frac{\delta f_s}{7}+\frac{1}{2\overline{\varpi_{m,n}}}}-\sqrt{\frac{\delta f_s}{7}}\right)\right)}{2\sqrt{\frac{\delta f_s}{7}+\frac{1}{2\overline{\varpi_{m,n}}}}\left(\sqrt{\frac{\delta f_s}{7}+\frac{1}{2\overline{\varpi_{m,n}}}}-\sqrt{\frac{\delta f_s}{7}}\right)} \tag{28}$$

Then, the average global probability of detection is a function of average SNR of sensors as following:

$$\overline{\mathrm{P_{d_m}}}=1-\prod_{n\in J_m}(1-\varphi_{m,n}\overline{\mathrm{P_{d_{m,n}}}}) \tag{29}$$

Similar to the RJLTMSS1 algorithm, the optimization problem is solved with constraints on the average global detection probability. We call the investigation of RJLTMSS1 under the scenario as RJLMTSS2, which is compared to show that the proposed algorithm can be extended to realistic scenarios.

6. Simulation results

In this section, the algorithms are numerically evaluated through computer simulations using MATLAB. The Monte-Carlo method is used with 5000 number of iterations. An square region with $200m$ length is assumed. An FC is located in the center of the region. *N* sensors and *M* PUs are distributed identically in this region. The IEEE *802.15.4/Zigbee* is used for the cognitive sensors [26]. The simulation parameters are presented in Table 2. The performance of the proposed algorithms is compared with the following algorithms:

- *Detection based serially sensor selection and thresholds setting:* First this algorithm selects sensors based on the detection probability of nodes, and then determines optimum detector thresholds for the selected sensors. This scheme is a conclusion from [18] by a different object. In that work, in multi-channel CSS with the aim at throughput maximization, first clustering all the sensors was done, then the optimum thresholds for the sensors was determined such that the detection and false alarm probability constraints are satisfied. The lifetime maximization by serially sensors and thresholds selection algorithm is called as LMSST.
- *Random based serially sensor selection and thresholds setting:* This algorithm is compared because of its lower order of complexity respect with the proposed algorithms. First the sensors are selected randomly. Then, a random detector threshold, from the feasible set of γ_m, is determined for channel *m*. This algorithm is called the random sensor and threshold selection algorithm (RTSS).

One of the metrics for efficiency of algorithms is the rate of satisfying the problem constraints. A success metric is defined as the ratio of the successful-iterations-number to the maximum-iterations-number. A successful iteration is iteration that an algorithm finds answer which satisfies all the constraints. Also, for better scaling, the success percentage is normalized on the basis of the maximum iterations between all the simulated algorithms. In Fig. 3, the success ratio of the both algorithms, that are proposed based on the known instantaneous SNR, i.e. the JLMTSS and RJLMTSS1 are compared at different total number of sensors. The higher number of sensors leads to higher success ratio for both algorithms, because there are more proper sensors for being selected. It is concluded that the success ratio of JLMTSS is higher than RJLMTSS1, because JLMTSS finds the optimum thresholds for selected sensors by solving the equation (19), but the RJLMTSS1 finds a suboptimum threshold for sensing every channel via a reduced complexity algorithm. This superior performance of JLMTSS is obtained in exchange for longer processing time. In Fig.4, the lack of instantaneous SNR effect of sensors is presented by comparing the success ratio of the RJLMTSS1 and RJLMTSS2. This plot shows that knowing the instantaneous SNR leads to better selection of sensors and thresholds, because RJLMTSS2 selects more sensors than RJLMTSS1 to satisfy the detection probability constraint. It is noted that, since the procedures of these algorithms are similar, the changes in the success ratios versus sensors number are almost the same.

Fig. 5 compares the success ratio of the RJLMTSS1 with the benchmark methods. It is obvious that, the higher number of sensors leads to higher success ratio for all the algorithms. The proposed algorithm has the top success ratio, which it leads to successful response in more than 95% of iterations. The LMSST algorithm which serially selects sensors and thresholds leads to the second highest success ratio. Because in LMSST the sensors are selected based on their detection probability, in which the consumption and residual energy of sensors are neglected. Also, non-jointly sensors and thresholds selection is another reason of the lower success rate of LMSST. The OLBSS algorithm which only selects suitable sensors with a predefined-fixed-threshold for sensing the channels has the third highest success ratio. This algorithm does not find efficient thresholds for sensors; therefore more sensors are selected for satisfying the detection constraints. The RTSS algorithm has the lowest success ratio. This algorithm has lower order of complexity but cannot efficiently extend the network lifetime.

In Fig. 6, the average number of selected sensors for sensing the channels is plotted. When the total number of sensors increases, the problem constraints are satisfied with lower number of selected sensors, because number of sensors with higher detection probability increases. This plot shows that the proposed algorithms use the least number of sensors. However, the JLMTSS finds optimal thresholds for the selected sensors which increases the detection probability of sensors, and therefore, it satisfies the detection constraints with lower number of sensors. RJLMTSS1 finds sub-optimal thresholds for the selected sensors, but its performance is more effective than other benchmark methods. LMTSS is the third, which it is concluded from ignoring the energy conservation in sensor selection and non-jointly sensors and thresholds selection. This algorithm selects sensors with higher detection probability that needs the lowest number of selected sensors at first glance. However this metric amount is averaged over the total number of iterations. It is noted that the sensors that has the highest detection probability may require a lot of energy to send their decision bit to the FC. So the selected sensors in the early iterations of network lifetime are selected frequently, and therefore the sensors batteries drain faster. Hence, on average, the number of selected sensors of LMSST is higher than the proposed algorithms. The OLBSS algorithm is the forth because it does not set the efficient threshold levels for sensor`s detector, therefore more sensors will be selected for satisfying the detection constraints. Also, the effect of knowing the instantaneous SNR on the number of selected sensors is shown in this plot by comparing the results of RJLMTSS2 with other algorithms.

Note that all the algorithms use the instantaneous SNR except for RJLMTSS2. Although, estimating the instantaneous SNR is difficult, but using the average SNR necessitate us to select more sensors for satisfying the detection constraints. The RTSS requires the highest number of sensors for the multi-channel CSS because of ignoring the detection probability of selected sensors, and not setting efficient thresholds for detector. In Fig. 7, the average energy consumption for every sensing period of multi-channel CSS is presented. This metric for every algorithm is averaged on the all iterations of the network lifetime. The proposed algorithms provide the least energy consumption, because they jointly select sensors and thresholds. When the total number of sensors increases, the average measure of energy consumption reduces for all algorithms, because number of sensors with higher detection probability increases, and therefore, lower number of sensors are required for satisfying the detection constraints.

In table 3, the average time for finding sensors and detector thresholds for every iteration of multi-channel CSS is shown, meanwhile the successful lifetime of the algorithms is compared. It is noted that the optimal method for finding sensors and determining optimal thresholds is not possible to compare. The JLMTSS needs the longest time and the RTSS needs the shortest time to find answer. But, RTSS consumes more energy and it leads to shorter lifetime for the network. Also, most of the times, solution of this algorithm is not accepted because it does not satisfy the detection quality constraints. The RJLMTSS1 needs lower time to find the efficient solution for the problem than the JLMTSS. The RJLMTSS2 needs processing time the same as RJLMTSS1, because their procedures are similar. The LMTSS and OLBSS need shorter time than the proposed algorithms, but their solutions are not as efficiency as the proposed algorithms.

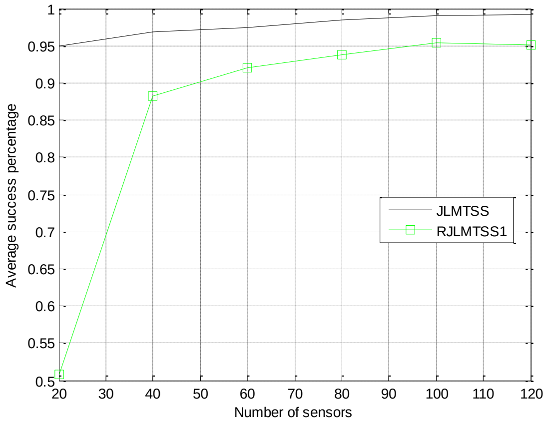

Fig. 3. The success ratio versus the total number of sensors.

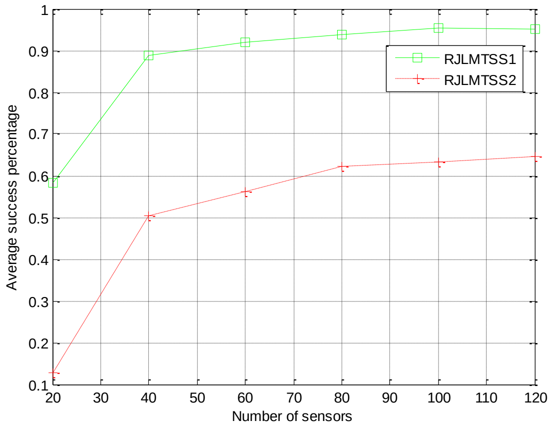

Fig. 4. The success ratio versus the total number of sensors.

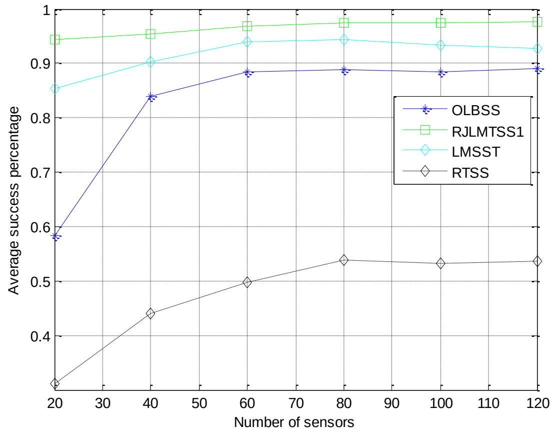

Fig. 5. The success ratio versus the total number of sensors.

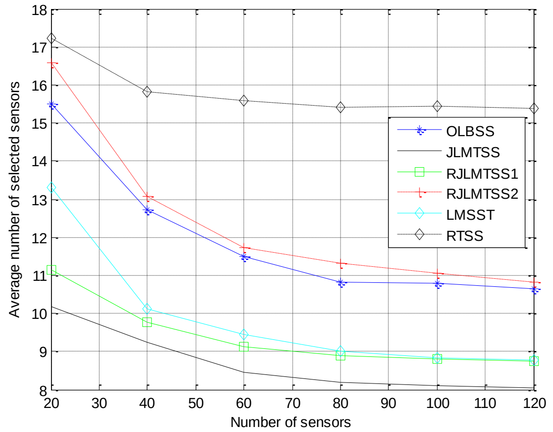

Fig. 6. The number of selected sensors versus the total number of sensors.

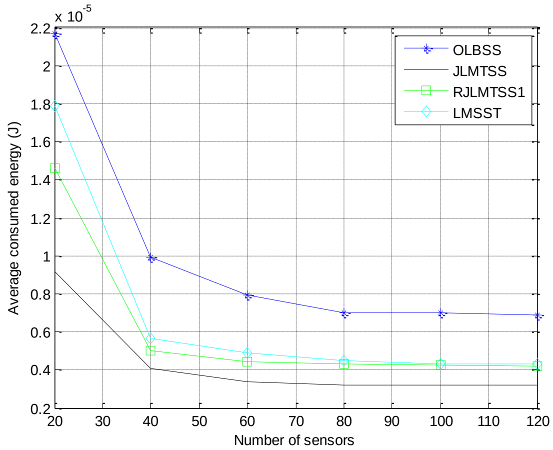

Fig. 7. The average energy consumption for multi-channel CSS versus the total number of sensors.

Table 3. The average time and successful lifetime comparison

The average time to find answer			The average successful lifetime	
Number of sensors	60	120	60	120
JLMTSS	37.722 s	73.174 s	2312	4616
RJLMTSS1	1.0226 s	4.3317 s	2171	4429
LMSST	0.4440 s	1.7484 s	2038	4115
OLBSS	0.1891 s	0.7546 s	1971	4004
RTSS	0.079s	0.841s	1108	2306

7. Conclusion

In CSNs usually apply the tiny and low-cost sensors. These sensors cannot simultaneously sense more than one channel because they do not have high-speed ADCs and high-energy. In order to overcome this problem, in this paper it was proposed two novel algorithms that maximize the network lifetime by selecting both the cooperative sensors and their detector threshold. First algorithm applies the known instantaneous SNR and obtains the proper detector thresholds by solving an equation for every channel. In the second algorithm in order to reduce the complexity of the problem it is proposed the Bisection method for determining detector thresholds. In the first algorithm, i.e. JLMTSS, the detector thresholds are optimized for cooperative sensors, based on the known instantaneous received SNR of sensors. This algorithm provides the longest lifetime for the CSN, but it is complicated and needs longest time to find the optimal solution. Of course this time is very short in compare with the exact search algorithm which finds the optimal sensors and thresholds. The second algorithm, i.e. RJLMTSS1, finds efficient solution at a processing time which is applicable, while its performance is relatively good. From table 2 it is concluded that its performance is *94%* of the JLMTSS algorithm when its processing time is *0.05%* of the JLMTSS processing time (when the total number of sensors is *120*). knowing the instantaneous SNR is difficult so we have investigated the performance of the second algorithm by average value of SNR. It was concluded that knowing the instantaneous SNR leads to better performance. Also, the proposed algorithms were compared with the other benchmark methods that can be performed in similar conditions. The comparisons showed that the proposed algorithms extend lifetime of a CSN with a good rate. The effect of thresholds setting on the energy conservation of a CSN was studied, which concluded that it can improve the network successful lifetime more than *10%* (*N=120*, comparison between OLBSS and RJLMTSS1). Also, jointly sensors and thresholds selection based via max-min method improves the network lifetime more than *7.6%* respect with serially sensors and thresholds selection based on the detection probability of sensors (*N=120*, comparison between LMSST and RJLMTSS1). The comparison between the proposed algorithms with a low-complexity algorithm showed that the proposed algorithms improve the network lifetime more than *90%* respect with the random sensors and thresholds selection algorithm (*N=120*).

References

[1] I. F. Akyildiz, B. F. Lo and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," Physical Communication Elsevier, vol. 4, no. 1, pp. 40-62, 2011.
[2] J. Soa and T. Kwon, "Limited reporting-based cooperative spectrum sensing for multiband cognitive radio networks," International Journal of Electronics and Communications (AEU), vol. 70, no. 4, pp. 386-397, 2016.
[3] G. P. Joshi, S. Y. Nam and S. W. Kim, "Cognitive Radio Wireless Sensor Networks: Applications, Challenges and Research Trends," Sensors , vol. 13, no. 9, pp. 11196-11228, Sep 2013.
[4] H. Sun, A. Nallanathan, C.-X. Wang and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: a survey," IEEE Wireless Communications, vol. 20, no. 2, pp. 74-81, 2013.
[5] Z. Quan, S. Cui, A. H. Sayed and H. V. Poor, "Optimal multiband joint detection for spectrum sensing in cognitive radio network," IEEE Transactions on Signal Processing, vol. 57, no. 3, pp. 1128-1140, 2009.
[6] D. M. M. Plata and Á. G. A. Reátiga, "Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold," Procedia Engineering, vol. 35, no. 1, pp. 135-143, 2012.
[7] K. Cicho´n, A. Kliks and H. Bogucka, "Energy-efficient cooperative spectrum sensing: a survay," IEEE Communications Survay & Tutorials, vol. 18, no. 3, pp. 1861-1886, 2016.
[8] A. Ghasemi and S. Sousa, "Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs," IEEE Communications Magazine, vol. 46, no. 4, pp. 32-39, April 2008.
[9] S. Maleki, G. Leus, S. Chatzinotas and B. Ottersten, "To AND or to OR: on energy-efficient distributed spectrum sensing with combined censoring and sleeping," IEEE Transactions on Wireless Communications, vol. 14, no. 8, pp. 4508-4521, 2015.
[10] S. Maleki, S. P. Chepuri and L. Geert, "Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks," Physical Communication, vol. 9, pp. 193-198, 2013.
[11] M. Najimi, A. Ebrahimzadeh, S. M. Hosseini Andargoli and A. Fallahi, "Energy-efficient sensor selection for cooperative spectrum sensing in the lack or partial information," IEEE Sensor Journal, vol. 15, no. 7, pp. 3807-3818, 2015.
[12] M. Najimi, A. Ebrahimzadeh, S. M. Hosseini Andargoli and A. Fallahi, "A novel sensing node and decision node selection method for energy efficiency of cooperative spectrum sensing in cognitive radio networks," IEEE Sensor Journal, vol. 13, no. 5, pp. 1610-1621, 2013.
[13] M. Najimi, A. Ebrahimzadeh, S. Hosseni Andargoli and A. Fallahi, "Lifetime Maximization in Cognitive Sensor Networks Based on the Node Selection," IEEE Sensors Journal, 2014.
[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, 2017.
[15] Y. Ma, Y. Gao, Y. C. Liang and S. Cui, "Reliable and efficient sub-Nyquist wideband spectrum sensing in cooperative cognitive radio networks," IEEE Journal on

Selected Areas in Communications, vol. 34, no. 10, pp. 2750-2762, 2016.
[16] A. Celik and A. Kamal, "Multi-objective clustering optimization for multi-channel cooperative spectrum sensing in heterogeneous green CRNs," IEEE Transactions on Cognitive Communications and Networking, vol. 2, no. 2, pp. 150-161, 2016.
[17] A. Ebrahimzadeh, M. Najimi, S. M. Hosseini Andargoli and A. Fallahi, "Sensor selection and optimal energy detection threshold for efficient cooperative spectrum sensing," IEEE Transactions on Vehicular Technology, vol. 64, no. 4, pp. 1565 - 1577, 2015.
[18] P. Kaligineedi and V. Bhargava, "Sensor allocation and quantization schemes for multi-band cognitive radio cooperative sensing system," IEEE Transaction on Wireless Communications, vol. 10, no. 1, pp. 284-293, 2011.
[19] B. Sklar, "Rayleigh fading channels in mobile digital communication systems part1:Characterization," IEEE Communication Magzaine, vol. 35, no. 7, pp. 90-100, 1997.
[20] A. Bagheri, A. Ebrahimzadeh and M. Najimi, "Sensor selection for extending lifetime of multi-channel cooperative sensing in cognitive sensor networks," Physical communication, vol. 26, pp. 96-105, 2017.
[21] M. Noori and M. Ardakani, "Lifetime analysis of random event-driven clustered wireless sensor networks," IEEE Transactions on Mobile Computing, vol. 10, no. 10, pp. 1448-1458, 2011.
[22] P. Li, S. Guo and Z. Cheng, "Max-min lifetime optimization for cooperative communications in cognitive radio networks," IEEE Transactions on Parallel and Distributed Systems, vol. 25, no. 6, pp. 1533-1542, 2014.
[23] S. Boyd and L. Vandenberghe, Convex Optimization, Cambridge, U.K.: Cambridge University Press, 2004.
[24] I. Gradshteyn and I. Ryzhik, Table of integrals, series, and products, Elsevier , 2007.
[25] D. Han and J. h. Lim, "Smart home energy management system using IEEE 802.15.4 and zigbee," IEEE Transactions on Consumer Electronics, vol. 56, no. 3, pp. 1403-1410, 2010.

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