

A Comprehensive Sensor Selection Method based on Energy Constraints for Cooperative Spectrum Sensing

Maryam Monemian*, Mehdi Mahdavi*, and Mohammad Javad Omidi*

*Electrical and Computer Engineering Department

Isfahan University of Technology, Isfahan, Iran

m.monemian@ec.iut.ac.ir, m_mahdavi@cc.iut.ac.ir, omidi@cc.iut.ac.ir

Abstract—In order to improve the accuracy of the identification of Primary Users (PU) in Cognitive Radio Networks (CRNs), Cooperative Spectrum Sensing (CSS) has been introduced. However, there are various challenges in the implementation of CSS which should be properly addressed. One of the most challenging issues which should be considered is the energy consumption for CSS. In this paper, the purpose is to solve such an issue through the effective management of sensors for CSS. In order to do so, a sensor selection algorithm for CSS is proposed for a CRSN including sensors with various detection capabilities. The proposed algorithm selects the appropriate sensors satisfying the desired exactitude of CSS while their energy constraints are carefully considered. The simulation results confirm the benefits of the proposed algorithm in term of energy efficiency compared to other state-of-the-art methods.

Index Terms—Energy consumption; Sensing accuracy; Sensor selection; Network lifetime.

I. INTRODUCTION

To solve the problems of scarcity of the spectrum resources and the increased number of requests for wireless services, Cognitive Radio Networks (CRNs) have been proposed. In such networks, unlicensed Secondary Users (SUs) opportunistically transmit data on the bandwidth dedicated to some licensed Primary Users (PUs) [1]. SUs should not cause harmful interference with PU's transmissions [1,2]. Cognitive Radio Sensor Networks (CRSNs), as an important subset of CRNs, are wireless sensor networks in which the cognitive radio capability is added to sensors. The problem of resource scarcity in CRSNs is solved by opportunistic access to the available spectrum resources [3].

In order to improve the reliability of spectrum sensing, Cooperative Spectrum Sensing (CSS) has been extensively used in the literature [2,4-9]. In CSS, several SUs cooperatively sense the spectrum and jointly decide about the presence of PU on the frequency spectrum. False alarm and detection probabilities are two parameters which determine the exactitude of CSS. The former is the probability of false identification of PU when it is actually not present. The latter represents the probability of correct detection of PU on the frequency spectrum when it is actually present.

The significant benefits of CSS appear in terms of improved reliability. However, there are important problems in its implementation. Each SU that participates in CSS

should listen to the frequency spectrum and reports its sensing result to a Fusion Center (FC). Then, FC makes the final decision about the presence of PU on the spectrum based on a special rule. Significant energy consumption for performing CSS by power-limited sensors is an important problem of CSS that should be properly managed. Several research works have been proposed in [4-9] to reduce energy consumption for CSS. An energy saving method is proposed in [4] in which some sensors sleep during the sensing phase of CSS and a subset of sensors sensing the spectrum censor their results and do not transmit them to FC. However, one of the main assumptions of such a study is to consider all sensors with the same values of received SNR from PU. Such an assumption is not practical. Two energy efficient methods for CSS have been proposed in [5-6]. The main idea of such methods is to dynamically choose proper sensors for CSS with respect to their energy constraints. Such methods help to increase the average number of live sensors. However, the sensors of CRSN receive approximately same SNRs from PU.

In [7] a sensor selection method for CSS is proposed to minimize the energy consumption for CSS per frame. The proposed method gives priorities to sensors based on their detection probabilities and the energy amounts they consume for CSS. However, such a selection method leads to the unfair rapid battery drain of the sensors with higher priorities and imperfect coverage of the network. Another sensor selection method has been proposed in [8] which periodically calculates a function for all sensors to dynamically determine their priorities for participation in CSS. The function considers the remaining energy of sensors and their detection probabilities. However, the implementation of such a method requires a considerable volume of computations which should be periodically performed.

In this paper, a CRSN is considered which includes sensors with different values of received SNR from PU. First, all the subsets of sensors that can satisfy the desired accuracy of CSS are formed. Then, the average energy consumption for CSS is computed. It is shown that the average energy consumption for CSS increases when more sensors are engaged in CSS. Thus, a CSS framework is designed for such a network in which a minimum number of sensors are engaged in CSS in each time frame while their

remaining energy values are carefully considered. Then, a heuristic algorithm is proposed to solve such an optimization problem.

The structure of this paper is as follows. System model and main assumptions are described in section II. The problem formulation has been described in section III. The novel heuristic algorithm for solving the optimization problems is presented in section IV. Numerical results and comparisons are explained in section V. Finally, Section VI consists of the concluding remarks.

II. SYSTEM MODEL

A CRSN with interweave structure consisting of N sensors is considered. The j^{th} sensor is denoted by s_j . The sensors have the duty of sensing some environmental parameters and transmitting the obtained information to FC. Frequency spectrum belongs to one Primary Base Station. The sensors can opportunistically use the bandwidth, if the presence of PU is not detected on the frequency spectrum. The sensors use energy detection method for spectrum sensing. The network model is presented in Fig. 1.

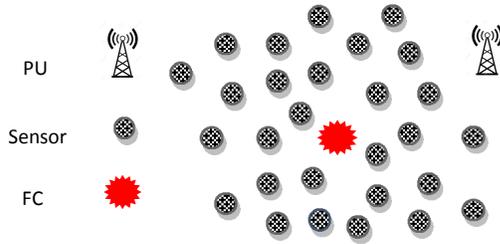


Fig. 1. The structure of system model.

To make reliable decisions about the presence of PU, CSS is used. The chosen sensors for CSS should satisfy the desired sensing accuracy. A time slotted channel is considered where time is divided in equal frames. Duration of each frame is equal to T second. The structure of frame is shown in Fig. 2. There are three phases in each frame called sensing, reporting and data transmission. The maximum number of sensors that participate in CSS per frame and can satisfy the desired sensing accuracy is denoted by M .

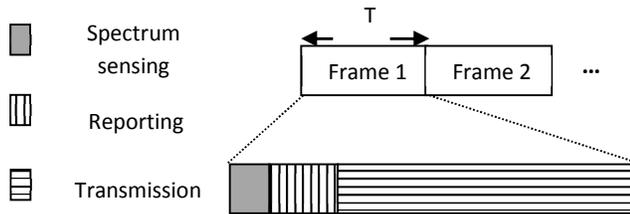


Fig. 2. The structure of frame.

At the beginning of each frame, the sensors engaged in CSS collect sufficient samples during the sensing phase. In the reporting phase, each sensor that is engaged in CSS has the right of transmitting its result about the presence of PU by one bit. The value of such a bit is “1” for the presence of PU and “0” for the absence of PU. In the following, pd_j ($j =$

$1, \dots, N$) and pf denote the detection probability of s_j and the false alarm probability of each sensor, respectively. The rule used in FC to combine the sensors’ sensing results is OR like most previous studies [4,7,8]. Let us denote the detection and false alarm probabilities obtained through cooperation between sensors in the n^{th} frame by P_d^n and P_f^n , respectively. P_d^n and P_f^n are computed for OR rule as follows.

$$P_d^n = 1 - \prod_{s_j \in P(n)} (1 - pd_j) \quad (1)$$

$$P_f^n = 1 - (1 - pf)^M \quad (2)$$

Where in (1-2) $P(n)$ denotes the set of sensors engaged in CSS at the beginning of n^{th} frame. To continue, Δ_{sf} , Δ_{se} , Δ_{rj} , Δ_{tj} and E_n^j are introduced. Δ_{sf} represents the energy amount consumed for collecting sufficient samples in the sensing phase by each sensor that participates in CSS. Δ_{se} indicates the energy amount consumed by each sensor for sensing the environmental parameter. Δ_{rj} indicates the amount of energy consumption to report one bit result by s_j . When a sensor’s decision is “absence of PU” or “0”, its one bit report has no effect on the result of an OR operation. Thus, because of OR rule in FC, only those sensors whose decisions are “1” send their decisions to FC and the rest of sensors engaged in CSS, avoid transmission of their results. The amount of energy consumption of s_j for data transmission in the transmission phase is indicated by Δ_{tj} . Let E denote the initial energy level of all sensors. The remaining energy level of s_j at the beginning of n^{th} frame is denoted by E_n^j , $n \geq 1, 1 \leq j \leq N$. Based on the above explanations, we can write,

$$E_n^j = E_{n-1}^j - \mathbf{1}(\Delta_{se}) - \mathbf{1}(\Delta_{tj}) - \mathbf{1}(\Delta_{sf}) - \mathbf{1}(\Delta_{rj}) \quad (3)$$

Where $\mathbf{1}(\Delta_{se}) = \Delta_{se}$ if s_j participates in sensing environment. Otherwise, $\mathbf{1}(\Delta_{se}) = 0$. Description of $\mathbf{1}(\Delta_{sf})$, $\mathbf{1}(\Delta_{rj})$ and $\mathbf{1}(\Delta_{tj})$ are same as $\mathbf{1}(\Delta_{se})$ and is not repeated. To follow this section, we introduce $p_{n,j}^{(se)}$, $p_n^{(pu)}$, $p_{1,j}$ and $p_{n,j}^{(sf)}$. In this paper, we consider the time-driven applications where sensors sense the environment with a certain period denoted by r frames [10-11]. The probability of sensing the environment by s_j at the beginning of n^{th} frame is denoted by $p_{n,j}^{(se)}$. Note that s_j starts to sense environment from the frame the number of which is equal to the remnant of dividing j by r . Thus,

$$p_{n,j}^{(se)} = \begin{cases} 1, & \text{if } n = kr + j \text{ mode } r, k = 0, 1, \dots, j = 1, \dots, N \\ 0, & \text{Otherwise} \end{cases} \quad (4)$$

In the following, $p_n^{(pu)}$ denotes the probability of identification of PU on the frequency spectrum at the beginning of n^{th} frame. We can write,

$$p_n^{(pu)} = P(H_0)P_f^n + P(H_1)P_d^n \quad (5)$$

Where in (5) $P(H_0)$ and $P(H_1)$ denote the probabilities of absence and presence of PU on the spectrum, respectively.

Let $p_{1,j}$ indicate the probability of producing the result of "1" by s_j in the sensing phase. In fact, we have,

$$p_{1,j} = P(H_0)pf + P(H_1)pd_j \quad (6)$$

Finally, we can easily find $P(E_n^j|E_{n-1}^j), n \geq 1$ using equations (3)-(6) as follows.

$$\begin{aligned} P(E_n^j = E_{n-1}^j - a\Delta_{se} - b\Delta_{tj} - c\Delta_{sf} - d\Delta_{rj}|E_{n-1}^j) \\ = (p_{n-1,j}^{(se)})^a (1 - p_{n-1,j}^{(se)})^{(1-a)} (p_{n-1,j}^{(sf)})^c \times \\ (1 - p_{n-1,j}^{(sf)})^{(1-c)} p_{1,j}^d (1 - p_{1,j})^{(c-d)} \times \\ (1 - p_{n-1}^{(pu)})^b (p_{n-1}^{(pu)})^{(a-b)}, a, b, c, d = 0, 1 \end{aligned} \quad (7)$$

Where in (7) $p_{n,j}^{(sf)}$ denotes the probability of the engagement of s_j in CSS at the beginning of n^{th} frame and is computed in section IV. With respect to this point that $P(E_0^j = E) = 1$ for all $s_j (j=1, \dots, N)$, we can find $P(E_n^j)$ in a recursive approach using $P(E_n^j|E_{n-1}^j)$ as follows.

$$P(E_n^j) = \sum_{All E_{n-1}^j} P(E_n^j|E_{n-1}^j)P(E_{n-1}^j) \quad (8)$$

III. PROBLEM FORMULATION

The problem of choosing possible proper sensors for CSS, is formulated in this section.

A. Clustering of Sensors

In this section, the purpose is to find different sets of sensors satisfying the desired sensing accuracy. Let S_N denote the set of all sensors. Also, $f_k \subseteq S_N$ denotes a possible set of k sensors which can satisfy the desired detection and false alarm probabilities that is

$$f_k = \left\{ s_j \left| \begin{array}{l} 1 - \prod_{j=i_1}^{i_k} (1 - pd_j) \geq \delta_1, \\ 1 - (1 - pf)^M \leq \delta_2 \\ 1 \leq l \leq k, s_{i_l} \in S_N \end{array} \right. \right\} \quad (9)$$

Where in (9) δ_1 and δ_2 denote the minimum acceptable detection and maximum acceptable false alarm probabilities, respectively. In the following, f_k is called k -set for simplicity. Regarding the definition of M in section II, the range of k in k -sets is $1 \leq k \leq M$. Given k , we define C^k as the set of all possible k -sets. We can write

$$C^k = \{f_k, 1 \leq k \leq M\} \quad (10)$$

Each set which belongs to C^k can be considered as a candidate group for CSS. Without loss of the generality the members of C^k (i.e. the k -sets for CSS) are numbered from 1 to $|C^k|$ where $|C^k|$ is the number of k -sets in C^k . Let us denote the i^{th} ($i = 1, \dots, |C^k|$) member of C^k ($k = 1, \dots, M$) by g_i^k that is $g_i^k = \{s_{i_1}, \dots, s_{i_k}\} \in C^k, s_{i_l} \in S_N, l = 1, \dots, k$. In the

following, $\overline{P_i^k}$ denotes the average detection probabilities of the sensors that belong to g_i^k .

$$\overline{P_i^k} = \frac{\sum_{s_j \in g_i^k} pd_j}{k} \quad (11)$$

The average energy consumption for CSS when the members of g_i^k are chosen for CSS is denoted by e_i^k . We can write,

$$e_i^k = k\Delta_{sf} + \sum_{s_j \in g_i^k} p_{1,j} \mathbf{1}(\Delta_{rj}) \quad (12)$$

Where $k\Delta_{sf}$ indicates the total energy amount consumed for sensing by of all the members of g_i^k . Also, the second term in (12) indicates the average reporting energy consumption for the members of g_i^k .

In most practical cases, the more number of sensors participate in CSS, the more average energy amount is consumed for CSS. In fact, the following condition is true.

$$\forall C^j, C^k, j < k \text{ and } \forall g_i^j \in C^j, g_i^k \in C^k: e_i^k > e_i^j \quad (13)$$

The reason is that the following condition is usually true in most practical cases in CRSNs.

$$\forall i, l, 1 \leq i \leq |C^k|, 1 \leq l \leq |C^{k+1}|:$$

$$\Delta_{sf} + \sum_{s_j \in g_i^{k+1}} p_{1,j} \mathbf{1}(\Delta_{rj}) \geq \sum_{s_j \in g_i^k} p_{1,j} \mathbf{1}(\Delta_{rj}) \quad (14)$$

Note that Δ_{sf} is usually is greater than $p_{1,j} \mathbf{1}(\Delta_{rj})$. In this paper, we consider the cases where the above condition is true for. Verification of the other cases is the subject of future studies.

B. Problem Definition

In this section, our aim is to minimize the number of sensors engaged in CSS (i.e. $|P(n)|$) during each frame. Therefore, the optimization problem is as follows.

$$\mathbf{P1}: \min_{g_i^k} |P(n)| \quad (15)$$

$$\mathbf{s. t.} E_n^j \geq \lambda_{th}, \forall s_j \in g_i^k \quad (15-1)$$

Where in (15-1) λ_{th} is an energy threshold value by which it is possible to categorize the k -sets formed by (9-10) based on the remaining energy levels of sensors. Using such an energy threshold, the energy constraints of sensors can be considered in the sensor selection for CSS. Based on the optimization problem defined in (15), our goal is to find the minimum number of sensors (i.e. an appropriate candidate k -set, g_i^k) for CSS in each frame.

After some frames, it may be possible that the constraint (15-1) is not valid for any k -set, $k = 1, \dots, M$, that is **P1** cannot be solved. In such a case it is reasonable to change the constraint of (15-1) to the constraint of $E_n^j \geq E_{min}^j, \forall s_j \in g_i^k$. Thus, the optimization problem **P1** is changed to the optimization problem of **P2** as follows.

$$\mathbf{P2}: \min_{g_i^k} |P(n)| \quad (16)$$

$$\mathbf{s. t.} E_n^j \geq E_{min}^j, \forall s_j \in g_i^k \quad (16-1)$$

Where in (16-1) E_{min}^j denotes the minimum energy value of s_j such that the sensor can be considered alive at the beginning of n^{th} frame, if $E_n^j \geq E_{min}^j$.

IV. HEURISTIC ALGORITHM

In this section, a heuristic algorithm is proposed to solve the optimization problems defined in the previous section.

Before describing the proposed heuristic algorithm, it is necessary to introduce two subsets $S^k(n)$ and $T^k(n)$ of C^k . Let $S^k(n)$ denote a subset of k -sets where the energy levels of the members of such k -sets are more than λ_{th} at the beginning of n^{th} frame. In other words,

$$S^k(n) = \{g_i^k | \forall s_j \in g_i^k, E_n^j \geq \lambda_{th}, 1 \leq i \leq |C^k|\} \quad (17)$$

Let $T^k(n)$ denote a subset of k -sets where the members of such k -sets are alive at the beginning of n^{th} frame. In fact, we have,

$$T^k(n) = \{g_i^k | \forall s_j \in g_i^k, E_n^j \geq E_{min}^j, 1 \leq i \leq |C^k|\} \quad (18)$$

A. OSSEC Algorithm

In this section, a heuristic algorithm called Optimum Sensor Selection with Energy Constraints (OSSEC) is proposed to solve the optimization problems. The pseudo-code for OSSEC algorithm is presented in Fig. 3.

In line 2 the average detection probabilities of all candidate groups are calculated. In line 3, all the candidate groups that belong to C^k , $k = 1, \dots, M$ are sorted based on the values of average detection probabilities in an ascending order. Then, a loop is executed to periodically choose proper sensors for CSS at the beginning of each frame (lines 4 to 28). The loop is repeated until it is not possible to form a suitable group for CSS due to the battery drain of sensors (lines 20 to 22). To satisfy constraint (15-1), the algorithm searches the candidate sets that the energy levels of their members are more than the pre-defined threshold, λ_{th} . Thus, we search all $S^k(n)$ s ($k = 1, \dots, M$) to find the first one that includes at least one candidate set (lines 7 to 12). After choosing the proper $S^k(n)$, one of its candidate sets having the least average detection probability is chosen for CSS (line 9). If it is impossible to find a $S^k(n)$ that includes at least one candidate set, it means that no candidate set can satisfy constraint (15-1). In such a situation, we begin to solve the optimization problem **P2**. As can be observed in lines 14 to 19 of Fig. 3, to solve **P2**, we search all $T^k(n)$ s ($k = 1, \dots, M$) to find the first one which consists of at least one candidate set. If it is not possible to find a $T^k(n)$ with such a condition, the algorithm stops due to the battery drain of sensors. If the proper candidate set is chosen for CSS, the energy levels of its sensors are updated according to their energy consumptions (lines 24 to 26).

Algorithm OSSEC

```

1:  $n = 0$ ;
2: Calculate  $\overline{P}_i^k$  for all  $g_i^k, i=1, \dots, |C^k|, k=1, \dots, M$ 
3: Sort  $g_i^k \in C^k$  ( $k = 1, \dots, M$ ) based on  $\overline{P}_i^k$  in an ascending order
4: WHILE(TRUE)
5: Let  $P(n) = \emptyset$ .
6: Form  $S^k(n)$  and  $T^k(n)$  based on comparisons between
 $E_n^j$  ( $j = 1, \dots, N$ ) and  $\lambda_{th}$ .
7: FOR  $k = 1$  to  $M$ 
8:   IF ( $|S^k(n)| \geq 1$ )
9:     Choose  $g_i^k \in S^k(n)$  with the least  $\overline{P}_i^k$  from  $S^k(n)$  as  $P(n)$ ;
10:    BREAK;
11:   END IF
12: END FOR
13: IF ( $P(n) = \emptyset$ )
14:   FOR  $k = 1$  to  $M$ 
15:     IF ( $|T^k(n)| \geq 1$ )
16:       Choose  $g_i^k \in T^k(n)$  with the least  $\overline{P}_i^k$  from  $T^k(n)$  as  $P(n)$ ;
17:      BREAK;
18:     END IF
19:   END FOR
20:   IF ( $P(n) = \emptyset$ )
      It is not possible to perform CSS.
21:   BREAK;
22: END IF
23: END IF
24: IF ( $P(n) \neq \emptyset$ )
25:   Update the energy levels of the members of  $P(n)$ ;
26: END IF
27:  $n = n + 1$ ;
28: END WHILE

```

Fig. 3. The pseudo code for OSSEC algorithm.

B. Determination of $p_{n,j}^{(sf)}$

Herein, the probability of the engagement of s_j in CSS at the start of n^{th} frame is computed. Using such a probability, it is possible to compute $P(E_n^j | E_{n-1}^j)$ (See section II).

In the following, X^j denotes the set of all formed subsets such that s_j belongs to them. In other words,

$$X^j = \{g_i^k \in C^k | s_j \in g_i^k, 1 \leq j \leq N\} \quad (19)$$

If $p_n(g_i^k)$ denotes the probability of performing CSS by g_i^k at the beginning of the n^{th} frame, we can write,

$$p_{n,j}^{(sf)} = \sum_{g_i^k \in X^j} p_n(g_i^k) \quad (20)$$

Where in (20) the value of $p_n(g_i^k)$ for OSSEC algorithm, can be obtained as follows.

$$p_n(g_i^k) = \begin{cases} \forall g_i^k \in S^k(n) & \\ \left\{ \begin{array}{l} 0, \text{ if } |S^{k-1}(n)| \geq 1 \\ 0, \text{ if } |S^{k-1}(n)| = 0, \overline{P}_i^k \neq \min_{g_l^k \in S^k(n)} \overline{P}_l^k \\ 1, \text{ if } |S^{k-1}(n)| = 0, \overline{P}_i^k = \min_{g_l^k \in S^k(n)} \overline{P}_l^k \end{array} \right. & (21) \end{cases}$$

$$\begin{cases} \forall g_i^k \notin S^k(n), g_i^k \in T^k(n) \\ p_n(g_i^k) = \begin{cases} 0, \text{if } |T^{k-1}(n)| \geq 1 \\ 0, \text{if } |T^{k-1}(n)| = 0, \overline{P}_i^k \neq \min_{g_i^k \in S^k(n)} \overline{P}_i^k \\ 1, \text{if } |T^{k-1}(n)| = 0, \overline{P}_i^k = \min_{g_i^k \in T^k(n)} \overline{P}_i^k \end{cases} \end{cases} \quad (22)$$

V. NUMERICAL RESULTS

A. Performance Metrics

In this section, the necessary performance metrics are introduced. Then, the performance of OSSEC algorithm is evaluated using the introduced metrics.

Let $F(\alpha)$ denote the maximum lifetime of network at the beginning of which αN sensors are still live. As mentioned in previous literature [12-13], various definitions can be presented for lifetime which are addressed as in the following equation.

$$F(\alpha) = \arg \max_n \{|N(n)| \geq \alpha N\} \quad (23)$$

Where in (23) α is a multiplier between 0 and 1. Also, $N(n) = \{s_j | E_n^j \geq E_{min}^j\}, j = 1, \dots, N$ denotes the set of live sensors at the beginning of n^{th} frame. Furthermore, $|N(n)|$ denotes the number of members of $N(n)$. Using equation (8) we can find $N(n)$. Let us denote the total energy consumption for reporting the sensing results to FC by E_{rep} . If $R(n)$ ($R(n) \subseteq P(n)$) denote a subset of cooperating sensors which report their results to FC at the beginning of n^{th} frame, we have,

$$E_{rep} = \sum_{n=0}^F \sum_{s_j \in R(n)} \Delta_{rj} \quad (24)$$

Where in (24) F is the maximum frame number at the beginning of which there are sufficient live sensors to perform CSS.

Let E_c denote the total energy consumption for CSS during the network lifetime. In other words, we have,

$$E_c = \sum_{n=0}^F |P(n)| \Delta_{sf} + E_{rep} \quad (25)$$

B. Simulation Results and Comparisons

In this section, we compare the performance of OSSEC algorithm with several important research works. The type of sensors is Chipcon CC2420 transceiver which works based on IEEE 802.15.4/Zigbee [14]. The sensors are uniformly placed in a circular field with a radius of 100 m. The location of FC is at the center of the field. Table. 1 presents the values of parameters used in the simulations. The research works selected to be compared with the proposed algorithms are introduced in the following.

1-Modified Energy Efficient Sensor Selection (MEESS) [7],

In MEESS, the sensors receive priorities for CSS based on a function. The priority function for s_j , $cost(j)$, is presented as follows [7].

$$cost(j) = \Delta_{sf} + \Delta_{rj} - \lambda pd_j \quad (26)$$

Where in (26) λ is a multiplier weighting the effect of pd_j . 2-Network Lifetime Improvement Sensor Selection (NLISS) [8],

In NLISS, FC should periodically compute a function to prioritize sensors for CSS. Let us denote the priority function for s_j by $pri - func(j)$. $pri - func(j)$ is presented as follows [8].

$$pri - func(j) = 0.5 \left(E_{rj} - (\Delta_{sf} + e_{amp} d_j^2) \right) + \frac{\lambda}{2\varepsilon_j} pd_j^{FC} - \frac{\eta}{2\varepsilon_j} \quad (27)$$

Where in (27) E_{rj} and d_j denote the remaining energy value and the distance of s_j from FC, respectively. Also, e_{amp} is the required amplification to satisfy receiver sensitivity at FC. λ , η , and ε_j are the multipliers that should also be updated during each frame.

Table. 1. The values of parameters used in simulations.

Parameter	Value
Δ_{ti}	$\in (0.07, 0.48) \mu\text{j}$
Δ_{se}	0.1 μj
Δ_{sf}	0.2 μj
Δ_{ri}	$\in (0.07, 0.48) \mu\text{j}$
δ_1	0.9
δ_2	0.1
E	250 μj
λ_{th}	100 μj
N	10-40
r	5
pd_j	$\in (0.42, 0.82)$
p_f	0.02

Fig. 4 presents the maximum lifetime of network, $F(\alpha)$, versus different values of α . As can be seen in Fig. 4 for different values of α between 0.2 and 0.8, the maximum lifetime of network in OSSEC is considerably more than those of MEESS and NLISS. However, for the values of α between 0.9 and 1, the maximum network lifetime in NLISS is more than OSSEC. The reason is that it periodically calculates a priority function to assign priorities to sensors for CSS. It should be noted that a significant volume of computations should be performed to periodically calculate such a priority function (see Equation. (27)). Thus, the better performance of NLISS in terms of network lifetime for the values of α between 0.9 and 1 is obtained at the price of such periodic computations.

Table. 2 presents the percentage of frames during which $|P(n)| = 2, 3, 4$ for OSSEC, MEESS and NLISS algorithms. As can be observed in the table, more than 90 percent of frames in OSSEC are the frames in which only two sensors take part in CSS. Such a percent is significantly more than those of MEESS and NLISS. On the other hand, the percentage of frames during which three or more sensors participate in CSS in OSSEC is considerably lower than that of other algorithms. This implies that in the majority of frames in OSSEC, CSS is performed by the minimum number of sensors satisfying the desired detection and false alarm probabilities. Such a characteristic for OSSEC leads to network lifetime improvement, because the candidate groups

with less number of sensors consume less average energy amount for CSS.

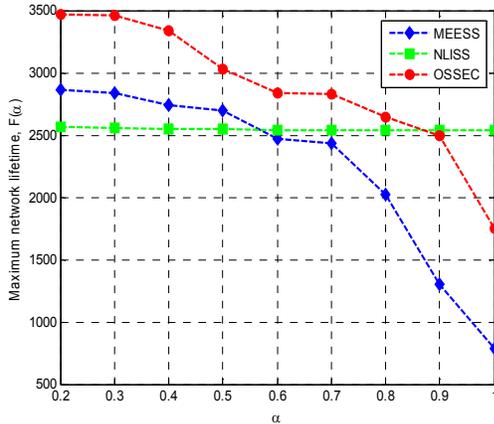


Fig. 4. Maximum network lifetime, $F(\alpha)$, vs. different values of α in MEESS, NLISS and OSSEC.

Table 2. The percentage of frames during which $|P(n)|$ has a special value in OSSEC, MEESS and NLISS.

Percentage of frames during which $ P(n) $ has a special value			Algorithm
$ P(n) =2$	$ P(n) =3$	$ P(n) =4$	
0.935	0.065	0	OSSEC
0.715	0.24	0.045	MEESS
0.535	0.458	0.007	NLISS

Fig. 5 presents the total energy amount consumed for CSS during the network lifetime, E_c and total energy consumption for reporting the sensing results to FC, E_{rep} , versus different number of sensors. As can be observed, the values of E_c and E_{rep} in OSSEC algorithm are considerably lower than those in MEESS and NLISS algorithms.

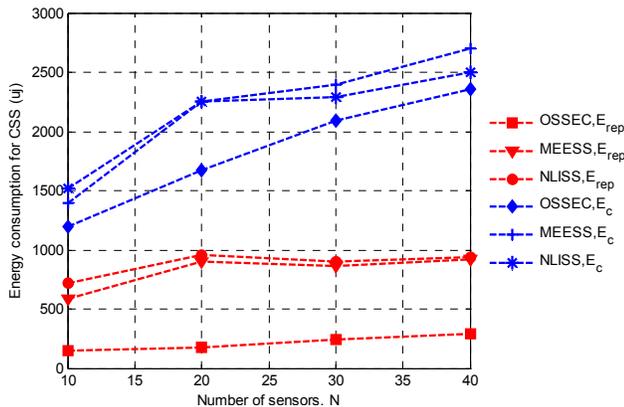


Fig. 5. Energy consumption for CSS vs. the number of sensors in MEESS, NLISS and OSSEC algorithms.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper a novel idea was proposed to make all the categories of sensors that can satisfy the desired sensing accuracy. Also, a new parameter was introduced to measure

the average energy consumption for CSS for each formed category. It was mentioned that in most practical cases the subsets of sensors which include less number of sensors, consume the less average energy amount for CSS. Thus, it is reasonable to minimize the number of sensors participating in CSS in each frame. Then, an algorithm was proposed to do so. The simulation results show that the proposed algorithm has better performance in term of energy efficiency compared to other existing methods. To investigate the cases where it is possible to find the subsets with more sensors which consume less average energy amount for CSS is the subject of future studies.

REFERENCES

- [1] J. Mitola and G. Q. Maguire. (1999. Aug.). Cognitive radio: Making software radios more personal. *IEEE Pers. Commun. Mag.* 6(4), pp. 13–18.
- [2] A. Ghasemi and E. S. Sousa. “Collaborative spectrum sensing for opportunistic access in fading environments”. in *Proc. 1st IEEE Int. Symp. New Frontiers Dyn. Spectr. Access Netw.*, 2005, pp. 131–136.
- [3] O. B. Akan, O. Karli, and O. Ergul (2009. Aug.). Cognitive radio sensor networks. *IEEE Net. J.* 23(4), pp. 34–40.
- [4] S. Maleki, A. Pandharipande, and G. Leus. (2011. June.). Energy-efficient distributed spectrum sensing for cognitive sensor networks. *IEEE Sensors. J.* 11(3), pp. 565–573.
- [5] M. Monemian, M. Mahdavi. (2014. May.). Analysis of a new energy-based sensor selection method for cooperative spectrum sensing in cognitive radio networks. *IEEE Sensors. J.* 14(9), pp. 3021–3032.
- [6] M. Monemian, M. Mahdavi, “Sensing user selection based on energy constraints in cognitive radio networks”, In *Proc. IEEE WCNC*, Istanbul, Turkey, 2014, pp. 3379–3384.
- [7] M. Najimi, A. Ebrahimzadeh, S. M. H. Andargoli, and A. Fallahi. (2013. Jan.). A novel sensing nodes and decision node selection method for energy efficiency of cooperative spectrum sensing in cognitive sensor networks. *IEEE Sensors. J.* 13(5), pp. 1610–1621.
- [8] M. Najimi, A. Ebrahimzadeh, S.M.H. Andargoli, A. Fallahi. (2014. Mar.). Lifetime maximization in cognitive sensor networks based on the node selection. *IEEE Sensors. J.*, 14(7), pp. 2376–2383.
- [9] N. N. Thanh, and I. Koo. (2013. June.). A cluster-based selective cooperative spectrum sensing scheme in cognitive radio. *Eurasip J. Wireless. Commun. and Netw.* pp. 1–9.
- [10] A. Abuarqoub, M. Hammoudeh and T. Alsboui “An overview of information extraction from mobile wireless sensor networks”, *Springer Internet.Of.Things.Smart Spaces and Next. Gen. Net.* 7469, 2012, pp. 95–106.
- [11] Y. Zhang, N. Meratnia, P. Havinga, (2010. Apr.). Outlier detection techniques for wireless sensor networks: a survey. *IEEE Commun. Surveys Tuts.* 12(2), pp. 159–170.
- [12] E. Duarte-Melo and M. Liu, “Analysis of energy consumption and lifetime of heterogeneous wireless sensor networks”, in *IEEE GLOBECOM’02*, 2002, pp. 17–21.
- [13] D. Tian and N. D Georganas. “A coverage-preserving node scheduling scheme for large wireless sensor networks”, In *Proc. WSNA’02*, 2002, pp. 32–41.
- [14] Part 15.4:Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs), *IEEE 802.15.4 Standard*, 2006.