Joint Cooperative Spectrum Sensing and Resource Allocation in Dynamic Wireless Energy Harvesting Enabled Cognitive Sensor Networks

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Received: 03 Feb 2022/ Revised: 04 Jan 2023/ Accepted: 26 Feb 2023

Abstract

Due to the limitations of the natural frequency spectrum, dynamic frequency allocation is required for wireless networks. Spectrum sensing of a radio channel is a technique to identify the spectrum holes. In this paper, we investigate a dynamic cognitive sensor network, in which the cognitive sensor transmitter has the capability of the energy harvesting. In the first slot, the cognitive sensor transmitter participates in spectrum sensing and in the existence of the primary user, it harvests the energy from the primary signal, otherwise the sensor transmitter sends its signal to the corresponding receiver while in the second slot, using the decode-and-forward (DF) protocol, a part of the bandwidth is used to forward the signal of the primary user and the remained bandwidth is used for transmission of the cognitive sensor. Therefore, our purposed algorithm is to maximize the cognitive network transmission rate by selection of the suitable cognitive sensor transmitters subject to the rate of the primary transmission and energy consumption of the cognitive sensors according to the mobility model of the cognitive sensors in the dynamic network. Simulation results illustrate the effectiveness of the proposed algorithm in performance improvement of the network as well as reducing the energy consumption.

Keywords: Cognitive Sensor Network; Transmission Rate; Mobility Model; Decode-and-Forward (DF) Protocol; Energy Consumption.

1- Introduction

Cognitive radio is a growing technology to overcome the spectrum scarcity in wireless communications. In fact, spectrum sensing is done in cognitive radio networks to determine the spectrum holes for data transmission. In fact, secondary users (SUs) sense the frequency channel to detect the primary user (PU) activity which has the legacy right for the frequency band usage [1]. A new network is the cognitive radio sensor network (CRSN), which has a lot of applications and can manage the spectrum resources. On the other hand, the sensor nodes sense the frequency band and a fusion center (FC) makes a final decision about the status of the frequency band according to the sensors’ information. However, sensors are powered with batteries which should be recharged or replaced. This problem leads to decrease the network lifetime. Therefore, improving the network lifetime is very important in cognitive radio sensor networks. In this case, reducing the energy consumption leads to reserve the battery power of the sensors. For this purpose, in [2] and [3], the proper sensor nodes are participated in spectrum sensing to minimize the energy consumption while satisfy the detection performance constraints. In [4], in addition to the energy consumption, the remaining energy of each sensor is an important parameter for selection of the sensors for spectrum sensing. Therefore, extending the network lifetime is the main issue in this paper.

Energy harvesting is another issue to improve the network lifetime. On the other words, cognitive sensors can harvest energy from the environment to charge their batteries. In fact, wireless information and power transfer (SWIPT) is a technology to transfer the energy and information simultaneously as the RF signals to the sensor nodes [5], [6]. In [7], SWIPT protocol is used such that the secondary users harvest their energies from the primary signals to send the primary users’ signal and also their signals. In [8], for increasing the energy efficiency, a secondary transmitter is considered as a relay to transmit the signal of the primary user while the secondary receiver does energy...
harvesting. However, in these papers, the same bandwidth is applied for transmission of the primary and sensor signals. It leads to have the interference in the network. However, another issue is the mobility of the sensor nodes. In this case, the dynamic topology of the network cannot be applied for static networks. By mobility of the sensor nodes, the distance between each sensor and primary user and also between each sensor and FC is not fixed while it is a random variable. In this case, two approaches including: “wait-and-see” [9] and “here-and-know” [10] are considered for the optimization problem with the random variable. In this paper, we use “here-and-know” method in which Chebyshev’s inequality is applied for energy consumption value estimation in a cognitive sensor network. On the other words, the suitable sensor nodes are participated in cooperative spectrum sensing to save more energy. We also use a spectrum sharing protocol in which a cognitive sensor transmitter acts as a relay to transmit the primary signal and harvest energy in the determined accessed bandwidth while in the remaining bandwidth, its signal is transmitted to the corresponding cognitive sensor receiver. In [11], an efficient cooperative spectrum sensing based on Kataoka criterion is stated by node mobility patterns consideration in a dynamic cognitive radio sensor network. In [12], two time slots are considered for spectrum sharing: the first slot is considered for energy harvesting of the cognitive sensor transmitter while in the second slot, amplify-and-forward (AF) or decode-and-forward (DF) relaying protocols are used by the cognitive sensor transmitter to send the signals of the primary transmitter to its primary receiver while in the remaining bandwidth, the signal of the cognitive sensor transmitter is sent. However, the sensor node is located in a fixed position. In [13], optimal disjoint and joint spectrum sensing and power allocation method is considered in a cognitive radio (CR) network with two aims: minimizing the false alarm probability while probability of detection is constant and maximizing the average opportunistic CR data rate under detection probability and CR power budget limitations. In [14], an approach is proposed for cluster head selection and cluster forming such that the coverage and lifetime of the network are improved. In [15], three phases are considered in wireless sensor networks. In the first phase, the position of the sensors are determined. In the second phase, the optimal location of the base station is obtained and in the third phase, the cluster head is selected based on the energy remaining, distance and the number of neighbors. In [16], an energy efficient clustering algorithm is proposed for clustering method and improving the coverage of the network. In [17], a cognitive sensor network is considered in which secondary users relay the information of primary user while primary user leases partial spectrum usage time to secondary users. In this paper, a joint sub channel, power and leasing time allocation algorithm is proposed to maximize the network throughput with constraints on the energy harvesting and transmission outage probability. In [18], the optimization problem of power allocation and spectrum access for maximizing the achievable data rate and minimizing the energy consumption at the secondary network, is formulated and solved using Dinkelbach algorithm. In [19], an energy efficient algorithm applies the gravitational search method to determine the optimal number of clusters and cluster heads. In [20], the problem of the network lifetime is proposed to schedule the network coverage using sleep-awake method for sensors. In [21], a resource allocation scheme is proposed based on the Lyapunov optimization theory while the constraints on the network quality of service (QoS) are satisfied. In [22], a game theory approach is applied in energy efficient wireless sensor networks such that the sensor nodes act as players and decide to sleep or not according to the idle listening time.

Therefore, the main contributions of our work are stated as follows

- A dynamic and energy harvesting cognitive sensor network is considered with the random waypoint model. On the other hand, the cognitive sensor node has the capability of the spectrum sensing and energy harvesting form the primary signal while it transmits the primary signal with a determined accessed bandwidth. In the remaining bandwidth, the cognitive sensor node transmits its signal to the corresponding receiver.
- We propose the problem of maximizing the cognitive system transmission rate by selection of the proper sensors for frequency band sensing and sharing such that the total energy consumption and the primary transmission rate constraints are satisfied.
- We formulate the problem and solve it by applying the convex optimization method and Karush–Kuhn–Tucker (KKT) conditions.
- Simulation results validate the effectiveness of our proposed method for improving the transmission rate of the network and decreasing the energy consumption over the benchmark algorithm.

The rest of the paper is organized as follows. The system model of a cognitive sensor network is stated in section 2 while the formulation of the problem and the problem solution is stated in Section 3. In Section 4, an iterative algorithm is proposed based on the bisection method to solve the problem. Simulation results and conclusions are shown in Section 5 and 6, respectively.
2- System Model

We assume a wireless dynamic cognitive sensor network which consists of a primary system and a cognitive sensor system with the energy harvesting capability. In the primary system, one primary transmitter (PT) and one primary receiver (PR) exist in the network while the cognitive sensor system has \( N \) transmitter (ST) and \( N \) receiver (SR). The network also has a fusion center (FC) such that the cognitive sensors send their spectrum sensing results to it. It should be noted that each cognitive sensor transmitter has the capability of the energy harvesting in the licensed spectrum of the primary user while it relays the signal of the primary transmitter to the primary receiver. It also transmits its own signal to its corresponding receiver in the determined bandwidth of the channel. We also note that the sensor nodes are moving randomly in the square field of the environment. In fact, we consider two transmission slots. In the first slot, the selected cognitive sensors sense the frequency band to detect the primary user activity, if the primary user is absent, sensors transmit their signal to their receivers while in the presence of the primary signal, the cognitive sensors receive the primary user signal, harvest their energy from it and decode the information from the remaining signal power. In this case, in the second transmission slot, the best selected cognitive sensor acts as a relay and considers a part of bandwidth to forward the primary transmitter signal to the primary receiver while the cognitive sensor uses from the remaining bandwidth for transmission of its signal to the corresponding receiver. For cooperative spectrum sensing, the sensing sensors send their results about the activity of the primary user to the fusion center (FC) to consider a decision about the availability of the spectrum. In this case, two hypothesis are considered. In the first case, \( H_1: y_t[n] = h_t[n]x_t[n] + n_t[n] \) shows the presence of the primary user. In the second case, \( H_0: y_t[n] = n_t[n] \) states the absence of the primary user. \( n_t[n] \) is the channel gain between the \( i \)th sensor transmitter and the primary user, \( x_t[n] \) is the transmitted signal of the primary user while \( n_t[n] \) is an i.i.d. Gaussian noise with zero mean and variance \( \sigma_{u}^2 \). The main notations used in this work is also presented in Table 1.

![Fig.1 System structure](image)

Table.1. Notations

<table>
<thead>
<tr>
<th>Notations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>Number of cognitive sensor transmitter and receiver</td>
</tr>
<tr>
<td>( \delta )</td>
<td>Duration of spectrum sensing</td>
</tr>
<tr>
<td>( f_s )</td>
<td>Sampling frequency</td>
</tr>
<tr>
<td>( \sigma_u^2 )</td>
<td>Variance of the Gaussian Noise</td>
</tr>
<tr>
<td>( P_{d_i} )</td>
<td>Probability of detection of the ( i )th sensor</td>
</tr>
<tr>
<td>( P_{f_i} )</td>
<td>Probability of false alarm of the ( i )th sensor</td>
</tr>
<tr>
<td>( P_D )</td>
<td>Total Probability of detection</td>
</tr>
<tr>
<td>( P_F )</td>
<td>Total Probability of false alarm</td>
</tr>
<tr>
<td>( \rho_i )</td>
<td>Assignment index of for sensing</td>
</tr>
<tr>
<td>( E_s )</td>
<td>Energy consumed of the sensor transmitter</td>
</tr>
<tr>
<td>( E_{t-etc} )</td>
<td>Energy consumption for the radio electronics</td>
</tr>
<tr>
<td>( e_{amp} )</td>
<td>Power Amplification</td>
</tr>
<tr>
<td>( d_i )</td>
<td>Distance between the ( i )th sensor transmitter and FC</td>
</tr>
<tr>
<td>( \theta )</td>
<td>Probability of energy consumption of each sensor</td>
</tr>
<tr>
<td>( W )</td>
<td>Bandwidth of the licensed spectrum</td>
</tr>
<tr>
<td>( bW )</td>
<td>Part of bandwidth for transmission of the primary signal</td>
</tr>
<tr>
<td>( p )</td>
<td>Transmission power of the primary transmitter</td>
</tr>
<tr>
<td>( P_C )</td>
<td>Transmission power of the sensor transmitter</td>
</tr>
<tr>
<td>( \pi_i )</td>
<td>Assignment index for data transmission</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>Fraction of the received power for harvesting</td>
</tr>
<tr>
<td>( h_{pt,pr} )</td>
<td>Channel gain between the primary transmitter and receiver</td>
</tr>
<tr>
<td>( h_{pt,sr} )</td>
<td>Channel gain between Primary transmitter and sensor</td>
</tr>
<tr>
<td>( h_{st,dr} )</td>
<td>Channel gain between sensor transmitter and sensor</td>
</tr>
<tr>
<td>( R_p )</td>
<td>Data rate of the primary transmitter to its receiver</td>
</tr>
<tr>
<td>( R_s^{11} )</td>
<td>Data rate of the primary user and sensor transmitter</td>
</tr>
<tr>
<td>( R_s^{12} )</td>
<td>Data rate of the sensor transmitter and sensor receiver</td>
</tr>
</tbody>
</table>
Achievable rate of the primary user
Achievable rate of the \(i\)th cognitive sensor node
Distance between the primary user and FC
Cluster radius
Exponent of the path loss in Hata model

For simple implementation of the energy detection method and using the received signal energy, the probabilities of the detection and false alarm of the \(i\)th sensor are obtained as

\[
P_{d_i} = P(E_i > \epsilon | H_i) = Q_T(\sqrt{2}Y_i, \sqrt{\epsilon}) \tag{1}
\]

And

\[
P_{f_i} = P(E_i > \epsilon | H_0) = \frac{\gamma r_{\epsilon}^2}{r(\gamma)} \tag{2}
\]

Where \(E_i\) is the energy obtained from the primary signal to the \(i\)th sensor transmitter while \(\epsilon\) represents the detection threshold. \(\Gamma(a, x)\) and \(Q_m(a, b)\) denote the incomplete gamma function and the generalized Marcum Q-function, respectively. In fact, higher value of \(P_{d_i}\) decreases the probability of interference with the primary signal while lower value of \(P_{f_i}\) increases the opportunity of the spectrum usage. In cooperative spectrum sensing, FC can use OR rule as the combination rule to consider a decision about the spectrum status. According to this rule, the channel is considered busy if at least one sensor transmitter detects the existence of the primary signal. Hence, the global probabilities of detection and false alarm are defined as [2]

\[
P_D = 1 - \prod_{i=1}^{N}(1 - \rho_i P_{d_i}) \tag{3}
\]

And

\[
P_F = 1 - \prod_{i=1}^{N}(1 - \rho_i P_{f_i}) \tag{4}
\]

Where \(\rho_i \in [0, 1]\), \(\rho_i = 0\) denotes that the sensor transmitter is not participated in sensing the frequency channel, otherwise \(\rho_i = 1\). However, one of the important issues in cognitive sensors nodes is the constraints of the energy consumption. For cooperative spectrum sensing in static position of the sensors, the energy consumed of the sensor nodes is denoted by [23], [24]

\[
E_T = \sum_{i=1}^{N} \rho_i (E_s + E_{t-\text{e-ecc}} + e_{\text{amp}}d_i^2) \tag{5}
\]

Where \(E_s\) is the energy consumed of the sensor transmitter for spectrum sensing while \(E_{t-\text{e-ecc}}\) indicates the energy consumption for the radio electronics. \(e_{\text{amp}}\) is considered for power amplification. \(d_i\) indicates the distance between the \(i\)th sensor transmitter and FC. By considering the dynamic position of the sensor nodes according to the random waypoint model, \(d_i^2\) and \(E_T\) will be the random values. In this model, the sensor nodes (transmitters and receivers) move from one location to another position. In random waypoint model, the sensors stay in their positions in a duration time and after the time expiration, they can move to their new locations. By definition of \(E_\varphi\) as the upper bound of the energy consumption, we have [11]

\[
E_\varphi = \rho_1(E_s + E_{t-\text{e-ecc}} + e_{\text{amp}} F_{a^{-2}}(\theta)) \tag{6}
\]

Where \(F_{a^{-2}}(\cdot)\) states the inverse of the cumulative distribution function (CDF) of the squared distance between the sensors and FC. This function depends on the mobility pattern of the sensors nodes, \(\theta \in [0, 1]\) represents the probability that the energy consumption of each sensor transmitter less than or equal to \(E_\varphi\).

For calculation of \(F_{a^{-2}}(\cdot)\), we consider the probability density function(PDF) of \(x = \frac{1}{a^2}\) as the random variable in Fig.2. Then, using the probability density function (PDF) of the random variable of \(y = d^2\), it is possible to obtain

\[
F_{a^{-2}}(\cdot) \tag{7}
\]

Where \(f_y(x)\) and \(f_y(y)\) are the probability density function of \(x\) and \(y\), respectively. For the ease of mathematical solution, it is considered the other parameters except the energy consumption are independent from the differences in nodes’ locations.

In this paper, we use decode- and- forward strategy in which at the first slot, the selected sensing sensors sense the spectrum to detect the activity of the primary user. When the primary user does not exist, the sensors can forward their signal while in the presence of the primary user, the sensors have the energy harvesting capability and also information decoding. Therefore, the data rates of the primary transmitter to its receiver, primary user and sensor transmitter and also the sensor transmitter and sensor receiver can be stated as follows [12]

\[
R_p = \frac{1}{2} W \log_2\left(1 + \frac{P_r|h_{p_t,p_r}|^2}{\sigma_a^2}\right) \tag{8}
\]

And

\[
R_{s_{11}} = \frac{1}{2} W \log_2\left(1 + \frac{P_r|h_{p_t,p_r}|^2}{\sigma_a^2}\right) \tag{9}
\]

And

\[
R_{s_{12}} = \frac{1}{2} W \log_2\left(1 + \frac{P_r|h_{s_t,s_r}|^2}{\sigma_a^2}\right) \tag{10}
\]
where $\pi_i \in \{0,1\}$ is similar to $\rho_i$. It indicates that whether the sensor transmitter is participated in data transmission or not. $P_c$ is the transmission power of the sensor transmitter. $h_{pt,pr}, h_{pt,st}$ and $h_{st,sr}$ are the channel gain between the primary transmitter and the primary receiver, the primary transmitter and the sensor transmitter and also between sensor transmitter and the sensor receiver, respectively. $\alpha$ is the fraction of the received power for harvesting energy. $W$ is the bandwidth of the licensed spectrum while $bW$ is the part of bandwidth for transmission of the primary signal. In the second time slot, the selected sensor transmitter acts as a relay to forward the primary transmitter’s signal while in the remaining bandwidth, it transmits its own signal to the corresponding sensor receiver. Therefore, by applying maximal ratio combination (MRC) through two slots, we have [12]

$$R_p^2 = \frac{1}{2} bW \log_2 \left( 1 + \frac{\epsilon (1-\alpha) P_c [h_{pt,st}]^2}{\sigma^2_t} \right) + \frac{1}{2} (1-b) W \log_2 \left( 1 + \frac{P_p [h_{pt,pr}]^2}{\sigma^2_d} \right) \tag{11}$$

Where the term $\epsilon (1-\alpha) P_c [h_{pt,st}]^2$ is the harvested energy at the cognitive sensor transmitter while $\epsilon$ is the efficiency of the harvested energy at the cognitive sensor transmitter. $P_p$ is the transmission power of the primary transmitter. Hence, the achievable rate of the primary user is obtained as

$$R_p = \min(R_p^1, R_p^2) \tag{12}$$

We also note the achievable rate of the $i$th cognitive sensor node is stated as follows

$$R_s^2 = \frac{1}{2} (1-b) W \log_2 \left( 1 + \frac{P_{c,\pi_i} [h_{st,sr}]^2}{\sigma^2_u} \right) \tag{13}$$

### 3- Problem Formulation

The optimization problem is formulated to maximize achievable rate of the cognitive network with constraints on the achievable rate of the primary transmitter, random energy consumption of the sensor nodes and detection performance by selection of the proper sensing nodes and data transmission sensor. Hence, the problem is formulated as follows

$$\max_{\pi_i, \rho_i} R_s = (R_s^1 + R_s^2 + R_s^2) \tag{14}$$

s.t. $E_{\varphi} \leq \alpha_1$, $R_p \geq \alpha_2$, $P_{c,\pi_i} \leq \alpha_3$, $P_D \geq \alpha_4$, $\rho_i \in [0,1]$, $\pi_i \in [0,1] \tag{14-1} \tag{14-2} \tag{14-3} \tag{14-4} \tag{14-5} \tag{14-6}$

Where $\alpha_1, \alpha_2, \alpha_3$ and $\alpha_4$ are the thresholds for the constraints of the problem. We consider $\rho_i \in [0,1]$ and $\pi_i \in [0,1]$ as continuous parameters to reduce the problem complexity in contrast to the NP-complete [2]. We also note that due to the independence of $P_{f,\pi_i}$ from $y_i$, this metric is the same for all sensor nodes. Although, the problem is not convex; we can use the convex optimization method to solve the problem and obtain the suboptimal solution. In this method, we use the Lagrangian function to express the problem as an unconstrained problem [2]. Therefore, we have

$$L(\pi_i, \rho_i, \lambda_1, \lambda_2, \lambda_3, \lambda_4) = R_s + \lambda_1 (E_{\varphi} - \alpha_1) - \lambda_2 (R_p - \alpha_2) + \lambda_3 (P_{c,\pi_i} - \alpha_3) - \lambda_4 (P_D - \alpha_4) \tag{15}$$

Where $\lambda_1, \lambda_2, \lambda_3$ and $\lambda_4$ are the Lagrangian multipliers which have the nonnegative values. Note that the optimal solution for the problem is the exhaustive search method with high complexity. However, we search a sub optimal method with low complexity by calculation of the cost function for each sensor node and consider the suitable sensors for spectrum sensing and data transmission. Therefore, the cost function of the $i$th sensor for spectrum sensing is evaluated as follows

$$costf(i) = \lambda_1 E_{\varphi} + \lambda_2 P_{f,\pi_i} - \lambda_3 P_{d,\pi_i}$$
As we know, $P_{fa}$ is the same for all sensors. However, this metric determines the maximum number of the sensors for spectrum sensors. Hence, we obtain

$$cost_f(i) = \lambda_1 E_p - \lambda_4 P_d_i$$

(17)

On the other hand, the sensors which consume the lowest energy and have the higher value of probability of detection, can be considered as the candidates for spectrum sensing. For selection of the sensor node for data transmission, the sensor transmitter with higher $R_s$ and $R_p$ can forward data to its corresponding sensor receiver as the following cost function

$$cost_{DT}(i) = -R_s - \lambda_2 R_p$$

(18)

Using Karush Kuhn Tucker conditions (KKT) and the complementary slackness conditions, the optimal conditions for the proposed approach is investigated such that the problem constraints are maintained. It should be noted that sometimes by selection of all sensors for the frequency channel sensing, the detection performance constraints are not satisfied. In this case, the problem has no answer.

We also consider that the cost function should be calculated according to (16) for each sensor transmitter to evaluate the priority of the sensors for sensing. However, (16) is dependent on the inverse probability density function $F_{a^{-1}}(\theta)$ which is related to the mobility model. It should be noted that finding a mathematical function for this metric is difficult; Hence, we should consider the numerical methods to find the best function to this metric.

On the other hand, the simulations should be run to compute the distance between each sensor and FC. By this method, the probability density function $F_{a^{-1}}(\theta)$ is approximated by a polynomial using numerical methods. (using Fig.2). In the next section, we propose an iterative algorithm to find the best sensing sensors and data transmission node as a relay for data transmission of the primary user and itself to the corresponding receiver.

4- Proposed Algorithm

For solving the problem, we propose an iterative algorithm. In the first step, in each iteration, the detection probability is computed for all sensors. By fitting the cumulative density function $F_{a^{-1}}(\theta)$, the cost function in (16) is computed for all sensor nodes. Then, this metric is sorted in ascending order and sensors which have the lowest cost function values, are candidates for spectrum sensing. In this algorithm, the suitable sensors are selected one by one for spectrum sensing. If the detection performance constraints are maintained, the selection is stopped otherwise, another candidate sensor with the higher priority is selected. In the second step, the cost function of sensors are calculated according to (18). On the other hand, the node with the highest priority is selected for data transmission. Then, the Lagrangian multipliers are updated using iterative bisection algorithm such that according to their corresponding constraints, the searching space is halved and algorithm is repeated again. The algorithm ends when the desired accuracy of the Lagrangian multipliers is met or the number of iterations reaches a specified number.

We note that sometimes there is not any feasible solutions for the problem. It means that by selection of all sensors, the detection performance constraints are not met. The implementation of the proposed algorithm is presented in Fig.3. The flowchart for the proposed algorithm is shown in Fig.4.

Note that the complexity of our proposed algorithm with the order of $O(N^2)$ while in exhaustive search method, the order of the complexity is $O(N!)$.
5- Simulation Results

In this section, the performance of our proposed algorithm is evaluated. For this purpose, sensors are distributed randomly over the square field with the length of 100m. The sensors are also moving randomly according to the random waypoint model. FC is located at the center of the square field while the primary user is located outside the cluster which satisfying the following inequality [25]

\[ R_{pu} \geq \frac{0.1}{10^{\theta 1 + 1}} R_c \]

Where \( R_{pu} \) is the distance between the primary user and FC while \( R_c \) is the cluster radius. \( \theta 1 \) is the exponent of the path loss in Hata model. \( \delta = 5 \mu s \) is considered as the duration of the sensing time. The inverse cumulative density function \( F_d^{-1}(\theta) \) is calculated in \( \theta = 0.9 \). The detection performance thresholds are \( \alpha_3 = 0.1 \) and \( \alpha_4 = 0.9 \) while \( f_c = 2.4 \) GHz. The channel gain is modelled according to a free-space path loss model, Raleigh fast fading and large scale log-normal shadowing [26], [27]. According to [28] and [29], the sensing energy \( (E_s) \) has two parts: the listening energy which has the value 40 nJ and the signal processing energy. For a data rate of 250kb/s, the signal processing energy is calculated 150 nJ/bit. The remaining energies are defined as \( E_{elec} = 80nJ \) and \( E_{amp} = 40.4 \text{pJ/m}^2 \). Decision threshold (\( \epsilon \)) is also selected as a multiple of the noise power [2]. \( P_f = 20\text{mW}, \) \( P_c = 60\text{mW} \) and \( \epsilon = 1 \) are considered as the parameters for user’s data rates.

The achievable rate of the cognitive network versus different dimensions of the environment is shown in Fig.5. According to the results, our proposed algorithm has the maximum achievable rate due to the proper selection of the sensor node for transmission of its signal and also the primary user signal. It should be noted that increasing the dimension of the environment, decreases the achievable data rate of the cognitive network. Fig.6 illustrates the consumed energy for spectrum sensing versus different dimensions of the environment. The proposed algorithm has the minimum energy consumption in comparison with the random algorithm. In fact, proper selection of the sensing nodes for sensing the frequency channel and transmission of their results to FC has an important role in saving energy.

Fig.7 presents the achievable rate of the primary network versus different dimensions of the environment. According to the results, it is obvious that the proposed algorithm has a better value while by increasing the dimensions of the environment, the value of this metric is decreased due to the decreasing of the receiving power of the receiver.

Fig.8 shows probability of detection for different dimensions of the environment. In fact, this metric states the opportunity of the sensor nodes for spectrum sensing. In fact, the proposed algorithm has the maximum detection probability due to the proper selection of the sensing sensors. We note that by increasing the dimension of the environment, the distances between sensors also increases, therefore, probability of detection of each sensor decreases.

Fig.9 presents the achievable rate of the cognitive network for different values of \( \alpha \). Note that increasing the value of \( P_c \) leads to increasing the data rate of the cognitive network. However, by increasing \( \alpha \), this metric also increases.

Fig.10 presents the achievable rate of the cognitive network versus different values of \( b \). As we know, by increasing the value of \( b \), the higher value of the bandwidth is associated to transmit the primary user’s signal. Therefore, the achievable rate of the cognitive network is decreased. It is obvious that increasing the value of \( P_c \) leads to increasing the data rate of the cognitive network. According to Fig.11, we also note that when the value of \( b \) increases, the achievable rate of the primary user is increased due to the increasing value of the associated bandwidth for data transmission of the primary user.

Fig.12 illustrates the convergence analysis for the proposed algorithm in computing the optimal value of \( \lambda_4 \) as the Lagrangian parameter for different iterations. It
should be noted that the convergence is obtained according to the probability of detection for the iterations that reach the optimal value of the Lagrangian parameter. In the 12th iteration, the optimal value of the Lagrangian parameter is obtained. In this experiment, the number of sensor nodes and dimension of environment are set to 20 and 100m, respectively.

Fig. 5. Available rate of the cognitive network versus different dimensions of the environment

Fig. 6. Energy consumption of the cognitive network versus different dimensions of the environment

Fig. 7. Available rate of the primary network versus different dimensions of the environment

Fig. 8. Probability of detection versus different dimensions of the environment

Fig. 9. Available rate of the cognitive network versus different values of $\alpha$
6- Analysis on Results

We present an iterative algorithm such that the cognitive system transmission rate is maximized by selection of the proper sensors for frequency band sensing and sharing while the total energy consumption and the primary transmission rate constraints are satisfied. We compare our proposed algorithm with the random algorithm in which the sensors are selected randomly for spectrum sensing and data transmission. This algorithm is selected due to its low complexity. In some figures, we compare our proposed algorithm with different transmission power of the sensors ($P_e$). Fig.5, Fig.9 and Fig.10 show the available rate of the cognitive network in different dimensions of the environment, values of $\alpha$ and b. According to figures, our proposed algorithm has the maximum value due to the proper selection of the sensor node for transmission of its signal and also the primary user signal. On the other hand, by increasing the dimension of the environment, the energy consumption of the network is increased (Fig.6) while the available data rate of the network is decreased (Fig.5 and Fig.7). In fact, by increasing $\alpha$, the fraction of the received power for harvesting energy is increased, therefore, the available rate of the cognitive network is increased while by increasing b, more bandwidth is associated to transmit the primary user’s signal (Fig.11). Therefore, the achievable rate of the cognitive network is decreased. It should be noted that all algorithms are compared when the constraints of the problem are satisfied.
7- Conclusions

In this paper, a dynamic cognitive sensor network is considered in which mobile sensor nodes have the capability of energy harvesting for spectrum sensing and data transmission. For this purpose, two time slots are considered. In the first slot, the cognitive sensor transmitter participates in spectrum sensing and in the existence of the primary user, it harvests the energy; otherwise the sensor transmitter sends its signal to the corresponding receiver while in the second slot, using the decode-and-forward (DF) protocol, a part of the bandwidth is used to transmit the primary signal and the remained bandwidth is used for transmission of the cognitive sensor. To this end, our optimization problem is proposed to maximize the cognitive network rate subject to the rate of the primary transmission, energy consumption of the cooperative spectrum sensing and the detection performance constraints by proper selection of the cognitive sensor transmitters for spectrum sensing and data transmission. Simulation results show the performance of proposed solution while satisfying the constraints of the problem in comparison with the benchmark algorithms.

References

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