Journal of Information Systems and Telecommunication
Vol.11, No.4, October-December 2023, 320-330
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

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

Maryam Najimi[1*]

[1].Faculty of Electrical & Computer Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran

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

✉ **Maryam Najimi**
Email Address: M.najimi@mazust.ac.ir

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, $H_1: y_i[n] = h_i[n]x_i[n] + n_i[n]$ shows the presence of the primary user. In the second case, $H_0: y_i[n] = n_i[n]$ states the absence of the primary user. $n\epsilon\{1,2,\dots,\delta f_s\}$ is the time index while δ is the duration of spectrum sensing, f_s is the sampling frequency and T= δf_s states the total number of samples. $h_i[n]$ is the channel gain between the ith sensor transmitter and the primary user. $x_i[n]$ is the transmitted signal of the primary user while $n_i[n]$ is an $i.i.d.$ Gaussian noise with zero mean and variance σ_u^2. The main notations used in this work is also presented in Table 1.

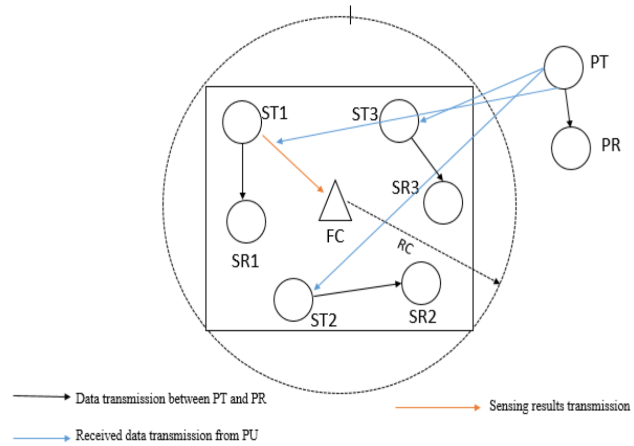

Fig.1 System structure

Table.1. Notations

Notations	Description
N	Number of cognitive sensor transmitter and receiver
δ	Duration of spectrum sensing
f_s	Sampling frequency
σ_u^2	Variance of the Gaussian Noise
P_{d_i}	Probability of detection of the ith sensor
P_{f_i}	Probability of false alarm of the ith sensor
P_D	Total Probability of detection
P_F	Total Probability of false alarm
ρ_i	Assignment index of for sensing
E_s	Energy consumed of the sensor transmitter for spectrum sensing
E_{t-elec}	Energy consumption for the radio electronics
e_{amp}	Power Amplification
d_i	Distance between the ith sensor transmitter and FC
θ	Probability of energy consumption of each sensor transmitter
W	Bandwidth of the licensed spectrum
bW	Part of bandwidth for transmission of the primary signal
P_p	Transmission power of the primary transmitter
P_C	Transmission power of the sensor transmitter
π_i	Assignment index for data transmission
α	Fraction of the received power for harvesting energy
$h_{pt,pr}$	Channel gain between the primary transmitter and primary receiver
$h_{pt,sr}$	Channel gain between Primary transmitter and sensor transmitter
$h_{st,sr}$	Channel gain between sensor transmitter and sensor receiver
${R_p}^1$	Data rate of the primary transmitter to its receiver
${R_s}^{11}$	Data rate of the primary user and sensor transmitter
${R_s}^{12}$	Data rate of the sensor transmitter and sensor receiver

R_p	Achievable rate of the primary user
${R_s}^2$	Achievable rate of the ith cognitive sensor node
R_{pu}	Distance between the primary user and FC
R_c	Cluster radius
$\theta 1$	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 ith sensor are obtained as

$$P_{d_i} = P(E_i > \epsilon|H_1) = Q_T\left(\sqrt{2\gamma_i}, \sqrt{\epsilon}\right) \quad (1)$$

And

$$P_{f_i} = P(E_i > \epsilon|H_0) = \frac{\Gamma(T,\frac{\epsilon}{2})}{\Gamma(T)} \quad (2)$$

Where E_i is the energy obtained from the primary signal to the ith sensor transmitter while ϵ 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]

$$P_D = 1 - \prod_{i=1}^{N}(1 - \rho_i\, P_{d_i}) \quad (3)$$

And

$$P_F = 1 - \prod_{i=1}^{N}(1 - \rho_i\, P_{f_i}) \quad (4)$$

Where $\rho_i \epsilon \{0,1\}$. $\rho_i = 0$ 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]

$$E_T = \sum_{i=1}^{N} \rho_i(E_s + E_{t-elec} + e_{amp}d_i^2) \quad (5)$$

Where E_s is the energy consumed of the sensor transmitter for spectrum sensing while E_{t-elec} indicates the energy consumption for the radio electronics. e_{amp} is considered for power amplification. d_i indicates the distance between the ith 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_φ as the upper bound of the energy consumption, we have [11]

$$E_\varphi = \rho_i(E_s + E_{t-elec} + e_{amp}F_{d^2}^{-1}(\theta)) \quad (6)$$

Where $F_{d^2}^{-1}(.)$ 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_φ.

For calculation of $F_{d^2}^{-1}(.)$, we consider the probability density function(PDF) of $x = \frac{1}{d^2}$ 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

$F_{d^2}^{-1}(.)$. Therefore we have,

$$f_Y(y) = \frac{1}{y^2} f_X(\frac{1}{y}) \quad (7)$$

Where $f_X(x)$ 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]

$${R_p}^1 = \frac{1}{2} W log_2(1 + \frac{P_p|h_{pt,pr}|^2}{\sigma_u^2}) \quad (8)$$

And

$${R_s}^{11} = \frac{1}{2} W log_2(1 + \frac{\alpha P_p \pi_i |h_{pt,st}|^2}{\sigma_u^2}) \quad (9)$$

And

$${R_s}^{12} = \frac{1}{2} W log_2(1 + \frac{P_C \pi_i |h_{st,sr}|^2}{\sigma_u^2}) \quad (10)$$

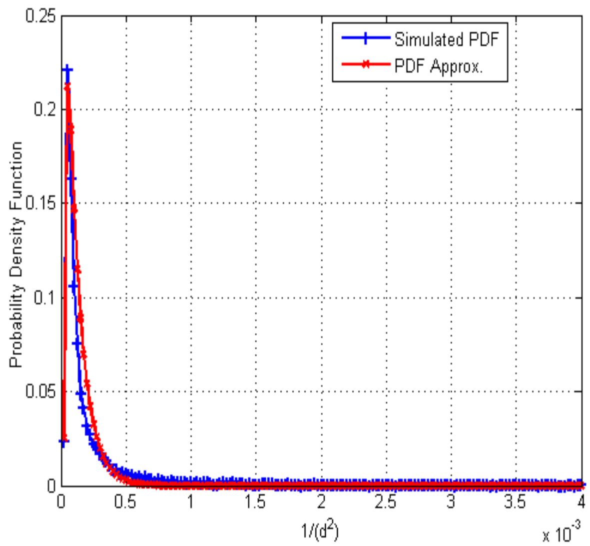

Fig.2. Theoretical and simulated probability density function of $\frac{1}{d^2}$

where $\pi_i \in \{0,1\}$ is similar to ρ_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. α 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]

$$R_p{}^2 = \frac{1}{2} bWlog_2\left(1 + \frac{\varepsilon(1-\alpha)P_p\pi_i|h_{pt,st}|^2|h_{st,Pr}|^2}{\sigma_u^2} + \frac{P_p|h_{pt,pr}|^2}{\sigma_u^2}\right) + \frac{1}{2}(1-b)Wlog_2(1 + \frac{P_p|h_{pt,pr}|^2}{\sigma_u^2}) \quad (11)$$

Where the term $\varepsilon(1-\alpha)P_p|h_{pt,st}|^2$ is the harvested energy at the cognitive sensor transmitter while ε 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

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

We also note the achievable rate of the ith cognitive sensor node is stated as follows

$$R_s{}^2 = \frac{1}{2}(1-b)Wlog_2(1 + \frac{P_C\pi_i|h_{st,sr}|^2}{\sigma_u^2}) \quad (13)$$

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

$$max_{\pi_i,\rho_i} R_s = (R_s{}^{11} + R_s{}^{12} + R_s{}^2) \quad (14)$$

$$S.t.\ \ E_\varphi \le \alpha_1 \quad (14\text{-}1)$$
$$R_p \ge \alpha_2 \quad (14\text{-}2)$$
$$P_F \le \alpha_3 \quad (14\text{-}3)$$
$$P_D \ge \alpha_4 \quad (14\text{-}4)$$
$$\rho_i \in [0,1] \quad (14\text{-}5)$$
$$\pi_i \in [0,1] \quad (14\text{-}6)$$

Where α_1 , α_2 , α_3 and α_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_i} from γ_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

$$L(\pi_i, \rho_i, \lambda_1, \lambda_2, \lambda_3, \lambda_4) = R_s + \lambda_1(E_\varphi - \alpha_1) - \lambda_2(R_p - \alpha_2) + \lambda_3(P_F - \alpha_3) - \lambda_4(P_D - \alpha_4) \quad (15)$$

Where $\lambda_1, \lambda_2, \lambda_3$ and λ_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 ith sensor for spectrum sensing is evaluated as follows

$$costf(i) = \lambda_1 E_\varphi + \lambda_3 P_{f_i} - \lambda_4 P_{d_i}$$

(16)

As we know, P_{f_i} is the same for all sensors. However, this metric determines the maximum number of the sensors for spectrum sensors. Hence, we obtain

$$costf(i) = \lambda_1 E_\varphi - \lambda_4 P_{d_i} \tag{17}$$

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

$$costf_{DT(i)} = -R_s - \lambda_2 R_p \tag{18}$$

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 $F_{d^2}^{-1}(\theta)$ 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 $F_{d^2}^{-1}(\theta)$ 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 $F_{d^2}^{-1}(\theta)$, 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 the 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 $O(N!)$.

Proposed Algorithm

Initial Parameters($\lambda_{1_{min}}, \lambda_{1_{max}}, \dots$)
Fit function $F_{d^2}^{-1}(\theta)$ for the movement model
ε is a small number
N1=maximum number of iterations
$n1$=number of iterations
M= Maximum number of sensing nodes
While ($n1$ <N1)
$\lambda_k = \frac{\lambda_{k_{min}}, \lambda_{k_{max}}}{2}$ $k = 1,2,3,4$
Compute $costf(i) = \lambda_1 E_\varphi - \lambda_4 P_{d_i}$ for each node
While (select n sensor with higher priority< M)
Compute P_d
If $P_d > \alpha_4$, break, end
$n1 = n1 + 1$
end
compute $costf_{DT(i)} = -R_s - \lambda_2 R_p$ for all nodes to obtain the best node for transmitting its data and acts as a relay for primary user's data
Update the Lagrangian multipliers using bisection method
end

Fig.3. Pseudo code for the proposed algorithm

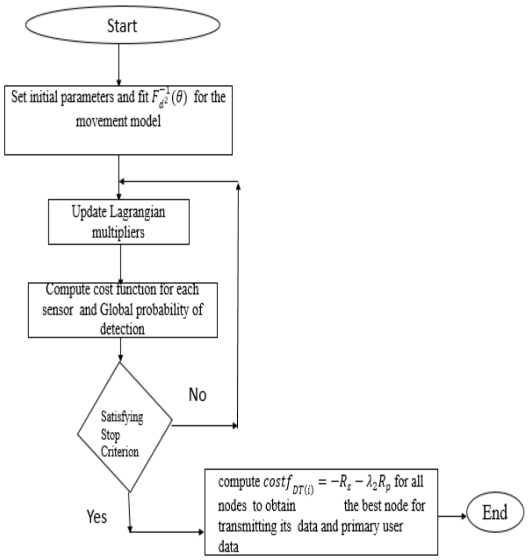

Fig.4. Flowchart for the proposed algorithm

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]

$$R_{pu} \geq \frac{10^{\frac{0.1}{\theta 1}}+1}{10^{\frac{0.1}{\theta 1}}-1} R_c \tag{19}$$

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 $F_{d^2}^{-1}(\theta)$ 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 pars: 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 $\mathrm{E_{t-elec}}$ = 80nJ and $\mathrm{e_{amp}}$=40.4 $\mathrm{pJ/m^2}$. Decision threshold (ϵ) is also selected as a multiple of the noise power [2]. P_p=20mW, P_C= 60mW and ε=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 α. Note that increasing the value of P_C leads to increasing the data rate of the cognitive network. However, by increasing α, 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 λ_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.

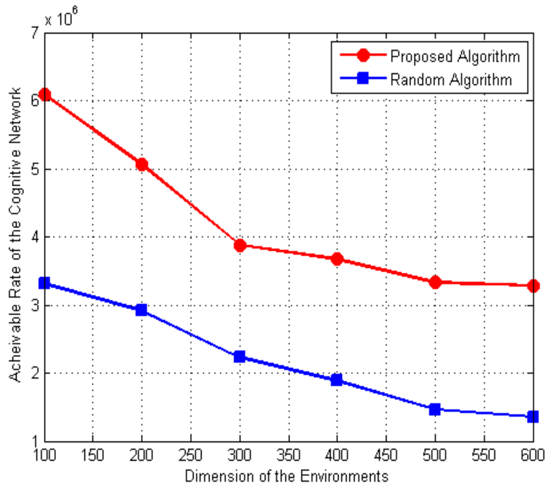

Fig.5. Available rate of the cognitive network versus different dimensions of the environment

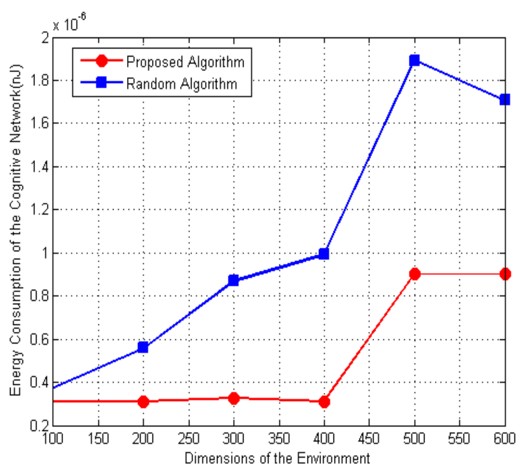

Fig.6. Energy consumption of the cognitive network versus different dimensions of the environment

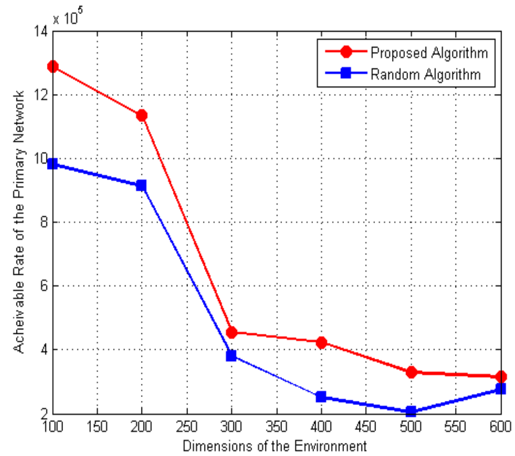

Fig.7. Available rate of the primary network versus different dimensions of the environment

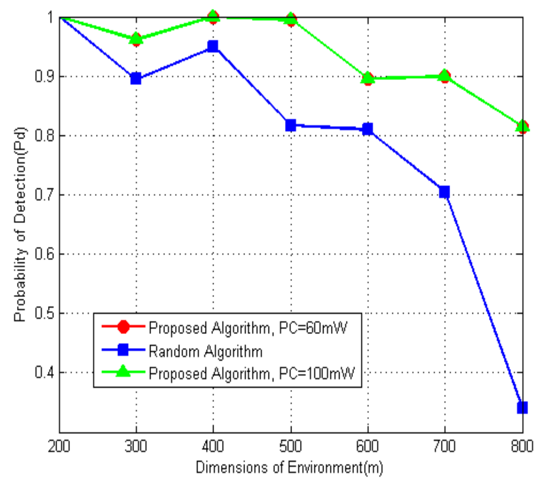

Fig.8. Probability of detection versus different dimensions of the environment

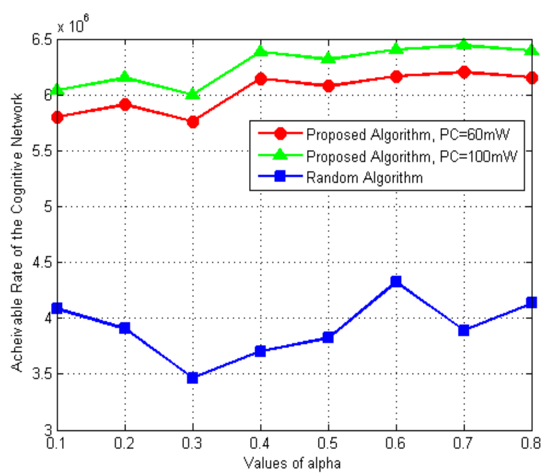

Fig.9. Available rate of the cognitive network versus different values of α

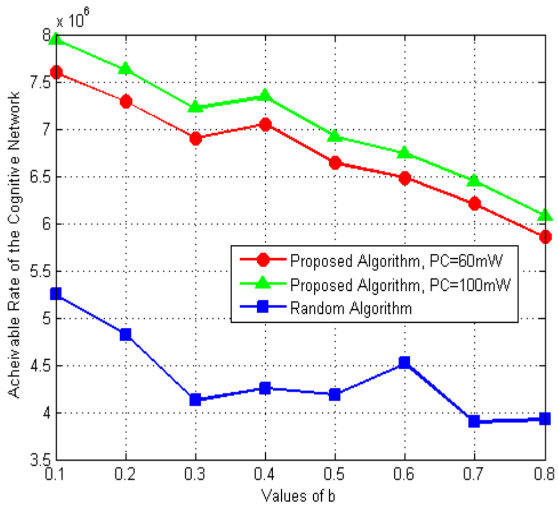

Fig.10. Available rate of the cognitive network versus different values of b

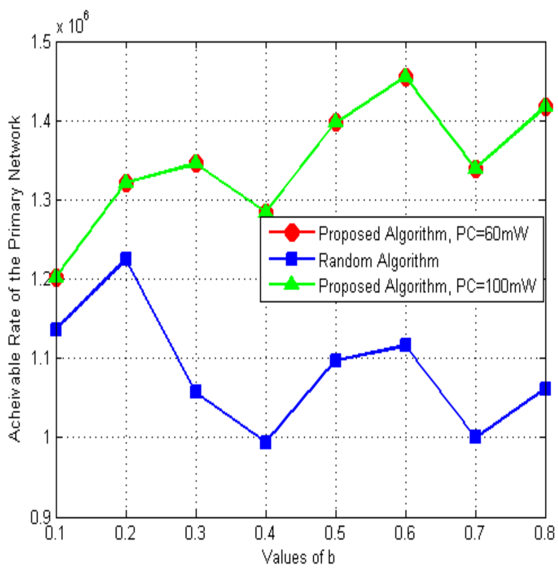

Fig.11. Available rate of the primary network versus different values of b

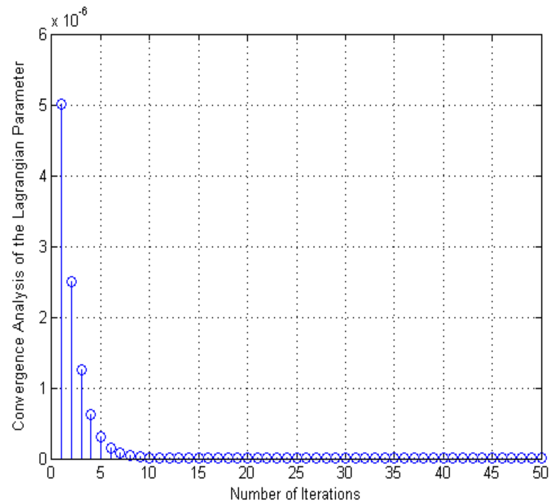

Fig.12. Convergence analysis of the Lagrangian parameter versus different iterations

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 ($\boldsymbol{P_C}$). Fig.5, Fig.9 and Fig.10 show the available rate of the cognitive network in different dimensions of the environment, values of $\boldsymbol{\alpha}$ 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 $\boldsymbol{\alpha}$, 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 bench mark algorithms.

References

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: Making software radios more personal, " IEEE Pers. Commun., Vol. 6, No. 4, pp. 13-18, Aug. 1999.

[2] M. Najimi, A. Ebrahimzadeh, S. M. H. Andargoli, and A. Fallahi, "A novel sensing nodes and decision node selection method for energy efficiency of cooperative spectrum sensing in cognitive sensor networks," IEEE Sensors J., Vol. 13, No. 5, pp. 1610-1621, May 2013.

[3] A. Ebrahimzadeh, M. Najimi, S. M. H. Andargoli, and A. Fallahi, "Sensor selection and optimal energy detection threshold for ef_cient cooperative spectrum sensing, " IEEE Trans. Veh. Technol., Vol. 64, No. 4, pp. 1565-1577, Apr. 2015.

[4] A. Bagheri, A. Ebrahimzadeh, and M. Najimi, "Sensor selection for extending lifetime of multi-channel cooperative sensing in cognitive sensor networks " Phys. Commun., Vol. 26, pp. 96_105, Feb. 2018.

[5] S. Kisseleff, X. Chen, I. F. Akyildiz, and W. H. Gerstacker, "Efficient charging of access limited wireless underground sensor networks," IEEE Trans. Commun., Vol. 64, No. 5, pp. 2130-2142, May 2016.

[6] A. Mehrabi, K. Kim, "General framework for network throughput maximization in sink-based energy harvesting wireless sensor networks, " IEEE Trans. Mobile Computing, Vol. 16, No. 7, pp. 1881-1896, July,2017.

[7] G. Zheng, Z. Ho, E. A. Jorswieck, and B. Ottersten, "Information and energy cooperation in cognitive radio networks," IEEE Trans. Signal Process., Vol. 62, No. 9, pp. 2290-2303, May 2014.

[8] J. Yan, Y. Liu, "A dynamic SWIPT approach for cooperative cognitive radio networks," IEEE Trans. Vehicular Technology, Vol. 66, No. 12, pp. 1122-1136, Dec., 2017.

[9] J. R. Birge and F. Louveaux, Introduction to Stochastic Programming 2nd ed. New York, NY, USA: Springer, Jun. 2011.

[10] R. Caballero, E. Cerda, M. M. Muñoz, and L. Rey, "Analysis and comparisons of some solution concepts for stochastic programming problems, " Top, Vol. 10, No. 1, pp. 101_123, Jun. 2002.

[11] H. Kaschel, K. Toledo, J. Torres Gomez and M. Julia Fernandez- Getino Garcia, "Energy-efficient cooperative spectrum sensing base on stochastic programming in dynamic cognitive radio sensor networks, " IEEE Access Journal, Vol.9, pp.720-732, Dec.2020.

[12] W. Lu, T. Nan, Y. Gong, M. Qin, X. Lui, Zh. Xu and Zh. Na, " Joint resource allocation for wireless energy harvesting enabled cognitive sensor networks, " IEEE Access Journal, Vol.6, pp.22480-22488,2018.

[13] M. Karimi, S.M.S. Sadough and M.Torabi, "Improved joint spectrum sensing and power allocation for cognitive radio networks using probabilistic spectrum access, " IEEE Syst. Journal, Vol.13, No.4, pp. 3716-3723, Jan.2019.

[14] A. Pakmehr and A. Ghaffari , "Coverage improving with energy efficient inwireless sensor networks, "Journal of Information Systems and Telecommunication (JIST), Vol.5, No.1, 2017.

[15] M.R. Thaghva, R. Hamlbarani Haghi, A. Hanifi and K. Feizi, "Clustering for reduction of energy consumption in wireless sensor networks by AHP method," Journal of Information Systems and Telecommunication (JIST), Vol.6, No.1, 2018.

[16] M. Bavaghar, A. Mohajer and Sara Taghavi Motlagh, "Energy efficient clkustring algorithm for wireless sensor networks," Journal of Information Systems and Telecommunication (JIST), Vol.7, No. 4 , 2019.

[17] Zh. Liu, M. Zhao, Y. Yuan and X. Guan, "Subchannel and resource allocation in cognitive radio sensor network with wireless energy harvesting , " Computer Networks, Vol.167, Feb. 2020.

[18] M.Sharifi and M. Mohassel Feghhi, "Joint energy and throughput optimization in energy harvesting cognitive sensor networks, " 29th Iranian Conference on Electrical Engineering (ICEE), Tehran, Iran, May 2021.

[19] S. Ebrahimi Mood and M.M. Javadi, "Energy-efficient clustering method for wireless sensor networks using modified gravitational search algorithm, "Evolving Systems Journal, Vol.11, pp.575-578, 2020.

[20] J-C Charr , K. Deschinkel, R. Haj Mansour and M. Hakem, " Lifetime optimization for partial coverage in heterogeneous sensor networks, " Ad hoc Networks, Vol. 107, 2020.

[21] X. Deng, P. Guan, C. Hei, F. Li, J. Liu and N. Xiong, "An intelligent resource allocation scheme in energy harvesting cognitive wireless sensor networks, "IEEE Transactions on Network Science and Engineering, Vol.8, No.2, 1900-1912, 2021.

[22] X. Yan, Ch. Huang, J. Gan and X. Wu, "Game theory-based energy efficient clustering algorithm for wireless sensor networks, " Sensors Journal, Vol. 22, No.2, 2022.

[23] A. Bagheri, A. Ebrahimzadeh and M. Najimi, "Lifetime maximization by dynamic threshold and sensor selection in

multi-channel cognitive sensor networks, " Journal of Information Systems and Telecommunication (JIST), Vol.5, No.4, pp.225-235, 2017.

[24] M.Najimi, " Cooperative game approach for mobile primary user localization based on compressive sensing in multi-antenna cognitive sensor networks, " Journal of Information Systems and Telecommunication (JIST), Vol.7, No.2, pp.134-143, 2019.

[25] M. Monemian and M. Mahdavi, "Analysis of a new energy-based sensor selection method for cooperative spectrum sensing in cognitive radio networks, " IEEE Sensors J., Vol. 14, No. 9, pp. 3021_3032, Sep. 2014.

[26] B. Sklar, "Rayleigh fading channels in mobile digital communication systems part1:Characterization, " IEEE Commun. Mag., Jul. 1997.

[27] Y. Ma, D. I. Kim, Zh. Wu, "Optimization of ofdm-based cellular cognitive radio networks, " IEEE Trans. on Communications. Vol. 58, No.8, Aug.2010.

[28] S. Maleki, A. Pandharipande, and G. Leus, "Energy-efficient distributed spectrum sensing for cognitive sensor networks, " in Proc. 35th Annu. Conf. IEEE Ind. Electron. Soc., Nov. 2009, pp. 2642–2646.

[29] S. Maleki, A. Pandharipande, and G. Leus, "Energy efficient distributed spectrum sensing with convex optimization, " in Proc. 3rd Int. Workshop Comput. Advances in Multi-Sensor Adaptive Processing, Nov.2009, pp. 396–399.