IJE TRANSACTIONS B: Applications Vol. 37, No. 05, (May 2024) 833-841

International Journal of Engineering

Journal Homepage: www.ije.ir

Optimal Node Selection for Cooperative Spectrum Sensing in Cognitive Radio Sensor Networks with Energy Harvesting

A. Al-bosham[a], A. Ebrahimzadeh[b]*, A. Bagheri[c]

[a] *Department of Electronic and Communication, Engineering Collage, Al-Qadisiya University, Al-Diwaniya, Iraq*
[b] *Faculty of Electrical and Computer Engineering, Babol Noshirvani University of Technology, Babol, Mazandaran, Iran*
[c] *Department of Electrical Engineering, Esfarayen University of Technology, Esfarayen, North Khorasan, Iran*

PAPER INFO

Paper history:
Received 22 August 2023
Received in revised form 30 October 2023
Accepted 04 November 2023

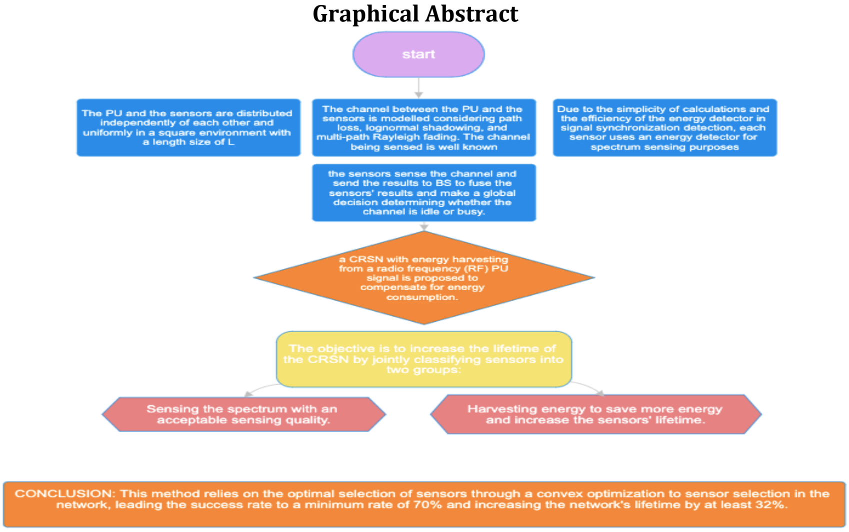
Keywords:
Cognitive Radio
Energy Harvesting
Fifth Generation Communication
Mathematical Optimization
Spectrum Sensing
Wireless Sensor Network

ABSTRACT

5G communication technology supports the Internet of Things, remote health care centers, and cloud computing by tuning their communication services over a very wide range of frequency bands with low-cost, low-battery consumption, and low latency. However, the development of such wireless technology is highly dependent on radio frequency spectra. The Cognitive Radio Sensor Network (CRSN) is an excellent candidate to improve radio spectrum utilization and manage the heavy communication data traffic in 5G wireless networks. CRSN can sense the frequency channels, making it possible for secondary users (who are denied service) to use the free channels. Despite the outstanding features of CRSNs, some limitations overshadow their performance. The most critical limitation is energy and its optimal consumption to increase the network's lifetime. Recent research has shown that energy harvesting can be an effective way to increase the lifetime of CRSNs. However, the sensors should sense the frequency spectrum with a high success rate. In this paper, several optimal sensor nodes using energy harvesting with the approach of increasing the network's lifetime are proposed to solve the mentioned challenge. This way, the sensor nodes are divided into two independent groups for simultaneous spectrum sensing and energy harvesting in each time frame. We will solve this problem based on mathematical optimization and the use of proposed solutions for convex problems. Finally, simulations are developed to evaluate the ability of the proposed solution, assuming the systems use IEEE802.15.4/Zigbee and IEEE802.11af.

doi: *10.5829/ije.2024.37.05b.02*

Graphical Abstract



*Corresponding Author Email: e_zadeh@nit.ac.ir (A. Ebrahimzadeh)

Please cite this article as: Al-bosham A, Ebrahimzadeh A, Bagheri A. Optimal Node Selection for Cooperative Spectrum Sensing in Cognitive Radio Sensor Networks with Energy Harvesting. International Journal of Engineering, Transactions B: Applications. 2024;37(05):833-41.

1. INTRODUCTION

Advances in wireless communication systems have led to challenges such as very high data rates and dense congestion of users, with higher requirements on end-to-end performance and user experience. Challenges arising from new application areas are ultra-low latency, energy, and cost (1). 5G uses mmWave access technology where a spectrum above 6 GHz and networks should address emerging needs such as wide bandwidth, lower latency, and higher capacity (2). More capacity requires more spectrum, which leads to the integration of Cognitive Radio (CR) into 5G networks. CR focuses on enabling much more efficient use of the spectrum. CR can improve the utilization of dense spectrum in a wireless network because some parts of the spectrum allocated to a licensed user often need to be utilized, ultimately enabling more dynamic and flexible spectrum access (3).

A Cognitive Radio Sensor Network (CRSN) consists of a large number of sensor nodes with various facilities to sense the frequency spectrum and detect the free channels. These scattered frequency sensors can process their sensing results and send them to a final node or data fusion center to cooperatively decide about the busy state of under-sensed frequency channels. The Secondary Users (SUs) can use the free detected channels (4, 5). Spectrum sensing, as the first and most crucial activity in CRSNs, requires the highest possible degree of accuracy and speed, and the limited energy of sensors must be used optimally in spectrum sensing. Therefore, it improves radio spectrum utilization and helps manage the heavy communication data traffic in 5G wireless networks (6). However, each node in a CRSN has limitations due to its small size and lightweight. The sensors' first and most important limitation is their limited power and battery. If the battery runs out, the sensor will not survive in the network, limiting the lifetime of the CRSN (7). Due to environmental and economic issues, reducing energy consumption and increasing energy efficiency in these systems have become particularly important.

On the other hand, CRSNs often use batteries as a source of energy; hence, the amount of energy consumed and the battery life is significant in these networks. In addition, in some applications of CRSNs, such as spectrum sensing in military or remote areas, it is difficult or sometimes impossible to recharge the sensors (8). Therefore, network lifetime is a significant challenge in the design of CRSNs, and energy efficiency is one of the main goals of academic and industrial research centers. One of the methods to overcome this challenge in CRSNs is to recharge the battery of sensor nodes using energy harvesting (EH) techniques. The purpose of energy harvesting is to supply energy for the sensor networks. There are different types of EH, such as solar, wind, thermal, and mechanical (9).

In this paper, to increase the lifetime of CRSNs, we present an electromagnetic energy harvesting method that divides the sensors into two categories: energy harvesters and spectrum sensors in a time frame. By this method, the sensors that do not sense the spectrum in each time frame harvest energy from the spectrum to extend its lifetime by increasing the total energy of the sensor network. The proposed method uses convex optimization to select the network nodes according to the measurement of the accurate spectrum sensing and the amount of remaining energy. Choosing the duty of each node according to these two parameters will increase the network's lifetime along with the network's efficiency and accurate spectrum sensing to an acceptable level. Because in the existing methods in other similar works, the optimization of the network is not done correctly according to the energy and brightness. On the other hand, relying on convex optimization, the proposed method can be used for other cognitive radio networks and significantly reduce the volume of calculations compared to other algorithms.

The rest of the paper is as follows: Section 2 contains an overview of recent related works. In section 3, we have first introduced the proposed network model and then energy harvesting in it, and finally, we have formulated the proposed method for this model. The simulation results are included in section 4, and according to this section, we conclude in section 5.

2. RELATED WORKS

In the literature, the ability to harvest energy in the sensors of the CRSNs has been used to optimize various network parameters. For example, based on the Markov chain model introduced by Ercan et al. (10) for energy-efficient and spectrum-efficient slot-synchronized IoT cellular networks, these networks perform RF energy harvest, transfers, and share their spectrum opportunistically among other cellular networks. However, this research uses energy harvesting for cellular network efficiency. Nevertheless, the selection of energy harvester nodes, which PU randomly selects, is modeled in the Markov chain. With this random selection, the maximum lifetime of the network cannot be achieved because the network's energy is not considered a critical parameter in the algorithm. In other words, to share the spectrum with other networks, energy harvesting will happen in a limited and random manner to balance the amount of energy in the network.

Halima and Boujemâa (11) derived a new expression for Packet Error Probability (PEP) of several relay techniques when unlicensed users harvest licensed user RF signals and also presented the use of adaptive power to avoid interference. In this method, the proposed model adds several intermediary decision-making relays to the network; in each time frame of information transmission, one part of a slot is dedicated to harvesting energy and the other to sensing the network. With the increase in the number of nodes in the network, the number of intermediate relays also increases, and the problem of relay energy is also expressed as a challenging factor. The division of each time slot to harvest energy and sense the spectrum makes the energy harvesting and sensing of the network be done in a limited and constant manner in each time frame. As a result, the probability of correct detection of the cooperative spectrum sensing, as well as the lifetime of the network, is optimized in a limited way.

Alsharoa et al. (12) addressed the RF multi-band energy harvesting using a Support Vector Machine (SVM); using this method, the secondary user senses the spectrum to decide on harvest and communication geographical regions of primary users. In this approach, complexity increases with the training data set. Relying on a multi-class SVM in this method requires a large amount of training data to implement the method for each network. Also, in this method, the energy harvesting in each SU is limited to a specific region of the network, and the need to check the area by the SU causes additional energy consumption in the network, which can reduce the network's lifetime by transmitting additional packets to sense the region.

Due to dynamic channel availability, limited node transmission range, and position-dependent energy arrival, an EH-based multi-hop clustering routing protocol (RFMCRP) was proposed by Wang and Ge (13). In this method, the main focus was on the routing and clustering of nodes so that the energy harvesting is limited to each cluster, and in the cases where the clustering becomes uneven, the energy consumption is out of the optimal state, and the network lifetime is reduced.

Due to the uncertainty of the energy harvesting process and the behavior of the primary user (PU), allocating and managing limited network resources is a crucial problem. Deng et al. (14). proposed a Q-learning-based channel selection method for energy harvesting and the randomness of the PU's behavior in the sensor network. By continuously interacting and learning with the environment, the method guides the secondary user (SU) to select the better-quality channel. In this method, energy harvesting is implemented by optimizing channel selection to sense the radio network, and due to the uncertainty of energy harvesting in this method, the network's lifetime will not reach the maximum achievable level.

Zheng et al. (15) proposed a hybrid active-passive communication scheme in which the SU adaptively makes channel selection and specific action decisions based on its knowledge of the channel availability and the amount of available energy. The decision to harvest energy or sense each node in this method has not been made for each time frame slot, and non-RF energy sources have been used to compensate for the amount of energy required in the problem of energy harvesting and in environments where energy sources are limited to RF sources, will lose its efficiency.

Salehi et al. (16) introduced a new multilevel inverter configuration that can harvest the unused energies and return them to another output which leads to the harvest of the maximum input energy. The multilevel inverter with a focus on harvesting maximum energy (HME) comprises two terminals: one connected to an AC load and the other linked to a DC load or rechargeable batteries. Additionally, this inverter boasts a relativity low number of switches when compared to alternative configurations that do not harness unused energy.

A wideband planar monopole antenna design was put forth (17). This design incorporates fractal geometry and integrates a slender slot on the radiation patch, intended for energy harvesting purposes. The optimization of the antenna occurs at multiple stages throughout its development.

3. PROPOSED WORK

In this section, we first introduce the desired system model and formulate the energy harvesting for this model, and at the end, we describe the proposed optimization method.

3. 1. System Model The single channel 5G CRSN consists of a Base Station (BS), N sensor nodes distributed randomly, and a primary user (PU) with a random position. Other assumptions considered are:

- The PU and the sensors are distributed independently of each other and uniformly in a square environment with a length size of L.
- The channel between the PU and the sensors is modelled considering path loss, lognormal shadowing, and multi-path Rayleigh fading. The channel being sensed is well known.
- Due to the simplicity of calculations and the efficiency of the energy detector in signal synchronization detection, each sensor uses an energy detector for spectrum sensing purposes.
- We assume a centralized cooperative spectrum sensing scheme, i.e., the sensors sense the channel and send the results to the centrally-located BS to fuse the sensors' results and make a global decision determining whether the channel is idle or busy.

Figure 1 shows the overview of the introduced network model. The objective is to specify the cooperating nodes to sense the channel and the nodes that harvest energy in such a way that:

$$\forall n_s, n_h \subset \{1,2,...,N\} \qquad \begin{cases} n_h \cap n_s = \varnothing \\ n_h \cup n_s = n \end{cases} \tag{1}$$

where n_h is the set of energy harvester sensors, and n_s is the set of channel sensing sensors. In other words, each sensor can be selected to perform one task at any time as shown in Figure 2, so the similarity of two sets of n_h and n_s must be empty, and their sum must be the total set of sensors n .

3. 2. Energy Harvesting CRSN may consume high energy due to sensing the spectrum. Hence, a CRSN with energy harvesting from a radio frequency (RF) PU signal is proposed to compensate for energy consumption. Here we assume each sensor node of the CRSN has both spectrum sensing and energy harvesting abilities, which can sense the PU channel or harvest the RF energy of the PU signal. The energy harvester model is specified in Figure 3.

Here spectrum sensing by a sensor n is modeled as a test of a binary hypothesis in which $H_{0,n}$ and $H_{1,n}$ are the absence and presence of the PU signal in the under-sensed channel, respectively. As a result, the channel can be used by SUs who are denied services when it appears. Therefore, we will have:

$$\begin{cases} H_{1,n}; \ X(k) = H_n.S(k) + V_n(k) \\ H_{0,n}; \ X(k) = V_n(k) \end{cases} \tag{2}$$

where $V_n(k)$ is the k_{th} sample of additive white Gaussian noise with zero mean and variance σ_v^2. $S(k)$ is the k_{th} sample of the PU signal, a random process with zero mean and variance σ_s^2. It is assumed that $S(k)$ and $V_n(k)$ are independent. The random variable H_n denotes the channel gain between the PU and the sensor n. However, the channel is modeled considering path-loss attenuation, lognormal shadowing, and multi-path Rayleigh fading, which is assumed to be well-known

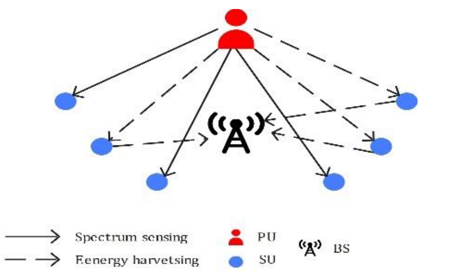


Figure 1. The desired model of CSRN

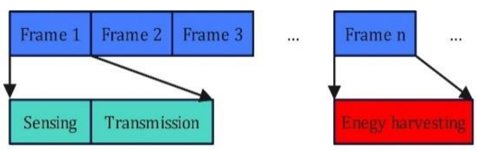


Figure 2. The frame structure of the proposed CSRN

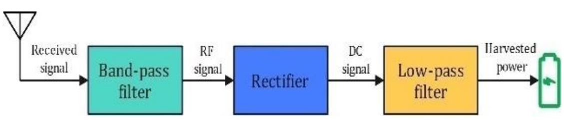


Figure 3. Energy harvesting model

(18). Accordingly, $X_n(k)$ denotes the k_{th} sample of the received signal from the under-sense channel observed by the sensor n.

The Energy Detector (ED) is used in the receiver of sensors due to its low complexity (19). Hence, the received signal energy is measured by the sensor n as:

$$RS_n = \frac{1}{K}\sum_{k=1}^{K} \left| X_n(k) \right|^2 \tag{3}$$

in which K is the number of samples calculated by:

$$K = \delta f_s \tag{4}$$

where δ and f_s are sensing time and sampling frequency, respectively. Then, the signal energy is compared with a threshold γ to generate a decision bit D_n. This bit shows the detected status of the channel by the sensor n, as follows:

$$\begin{cases} if \ \ RS_n \geq \gamma; \ D_n = 1 \\ if \ \ RS_n \geq \gamma; \ D_n = 0 \end{cases} \tag{5}$$

Therefore, the probabilities of correct detection in spectrum sensing for each sensor n can be calculated as follows:

$$P_{d_n} = P\left(H_{1,n} \middle| H_{1,n}\right) = P\left(RS_n \geq \gamma \middle| H_{1,n}\right)$$
$$= Q\left(\left(\frac{\gamma}{\sigma_v{}^2} - SNR_n - 1\right)\sqrt{\frac{\delta f_s}{2SNR_n + 1}}\right) \tag{6}$$

in which SNR_n is the received signal-to-noise-ratio from the under-sensed channel in the sensor n due to reported data by Bagheri et al. (20). According to a similar process, false alarm probability is defined by:

$$P_{f_n} = P\left(H_{1,n} \middle| H_{0,n}\right) = P\left(RS_n \geq \gamma \middle| H_{0,n}\right)$$
$$= Q\left(\left(\frac{\gamma}{\sigma_v{}^2} - 1\right)\sqrt{\delta f_s}\ \right) \tag{7}$$

Due to fading or shadowing effects and a limited sensing range of sensors, sensing the channel by only a single sensor may fail to detect the PU signal correctly. Any lost detection leads to a secondary transmission that interferes with unidentified active PU, and more false alarm leads to less frequency reuse opportunities for the SUs. Then if spectrum sensing is performed only by one sensor node, a more complicated and reliable detector (than an energy detector) is needed which may consume more energy. Therefore, this paper proposes centralized cooperative spectrum sensing to increase the sensing quality. On the other hand, the participation of all sensors in spectrum sensing could be more optimal. Because if all sensors participate in sensing, it leads to high energy consumption and false alarm without increasing significant correct detection. Thus, energy consumption can be saved by determining the appropriate nodes for spectrum sensing. At the same time, the remaining sensors can be involved in energy harvesting, which is an excellent way to increase the network's lifetime.

In the sensing section, a group of sensor nodes cooperatively detect the presence of PU by sensing the channel. In contrast, the other nodes use simultaneous energy harvesting to collect the RF energy of the PU signal, and the frame structure of a CRSN for energy harvesting through spectrum sensing is shown in Figure 2. The harvested energy is then stored in the rechargeable batteries of the harvested nodes. Sensor and harvester nodes can change their modes in each frame to achieve energy balance. The figure shows the structure of energy harvesting that the RF energy of wireless signals is converted to DC energy with a rectifier circuit. The harvested energy for each sensor is denoted by EH_n and calculated as follows:

$$EH_n = \mu\left(1+SNR_n\right)\sigma_n^2 \tag{8}$$

where μ is the efficiency of energy harvesting. The energy consumption of the sensor nodes can be divided into two parts. The first part of the consumption energy is used in ED to make a decision bit about the idle or busy state of the channel, which is denoted by ESn The second part of the energy is used to safely send the decision bit to BS, which is denoted by E_{tn}. Therefore, the total energy consumption of each sensor E_{cn} involved in cooperative spectrum sensing is calculated as follows:

$$E_{cn} = E_{sn} + E_{tn} \tag{9}$$

We assume that all sensors have the same structure and, therefore, all sensors are the same but can differ for different sensors that are calculated for each sensor as follows:

$$E_{tn} = E_{t-elec} + e_{amp}.d_n^2 \tag{10}$$

where E_{t-elec} is the energy consumption of the electronic circuits of the transmitter sensor, e_{amp} is the amplifier coefficient, the gain required to satisfy the database receiver's sensitivity, and d_n is the distance between the sensor n and the BS.

3. 3. Optimization Algorithm

The objective is to increase the lifetime of the CRSN by jointly classifying sensors into two groups:

- Sensing the spectrum with an acceptable sensing quality.
- Harvesting energy to save more energy and increase the sensors' lifetime.

For the first group, we select suitable sensors for cooperative spectrum sensing, considering the conditions on the maximum probability of false alarm denoted by α and the minimum probability of correct detection denoted by β. To model the object as an optimization problem, we use an allocation index φ_n which determines whether a sensor is selected for the cooperative spectrum sensing or performs EH. According to the mentioned model for energy and also assuming the initial energy $E_{0,n}$ for the sensor n, the residual energy of the sensor after each period of sensing or harvesting is calculated by the following equation:

$$E_n = E_{0,n} + \left(1-\varphi_n\right)EH_n - \varphi_n EC_n \tag{11}$$

If sensor n is selected for the cooperative channel sensing, $\varphi_n = 1$, and if it performs EH, $\varphi_n = 0$. Also, according to the proposed allocation index, we will have the global probability of false alarm and the global probability of correct detection, based on the OR fusion rule in the BS, as follows:

$$P_d = 1 - \Pi_{n\in n_s}\left(1-\varphi_n P_{d_n}\right) \tag{12}$$

$$P_f = 1 - \Pi_{n\in n_s}\left(1-\varphi_n P_{f_n}\right) \tag{13}$$

Now, we can mathematically define the problem as an optimization problem as follows:

$$\max_{\varphi_n}\{lifetime\} \tag{14}$$

Subject to:

$$P_f \le \alpha \tag{14-1}$$

$$P_d \ge \beta \tag{14-2}$$

$$\varphi_n \in \{0,1\} \tag{14-3}$$

Equations 14-1 and 14-2 show the cooperative spectrum sensing efficiency constraints in this definition. Precisely, the smaller value of α provides probably more opportunities for the 5G SUs to use the free channel, and the larger β leads to less probability of interfering with the PU signal in the channel. However, there is no precise formula for a sensor network lifetime, and different related research has proposed different formulas based on their subject. In this paper, we propose the network lifetime as the time until the number of active sensors drops below $L.N$ where $0 < L \le 1$ (21).

Also, we propose energy harvesting to extend the network lifetime. We define an active sensor as a node that its remaining energy is upper than lower bound, denoted as E_{min}. This proposed solution causes balanced energy use in the CRSN and extends the network lifetime. Upon the formulization, we can use the "max-min" method for optimizing the network lifetime. By this method, the minimum remaining energy of sensors will be maximized. Thus, the sensors that have the lower remaining energy are not selected for sensing, and they perform EH. It leads to the remaining energy level of sensors keep balanced, consequently extending the network lifetime. The remaining energy and the minimum remaining energy of sensors are denoted by E_n and E_{th}, respectively. Now, the problem can be written as follows (22):

$$\max_{\varphi_n}\{\min\{E_n\}=E_{th}\} \tag{15}$$

Subject to:

$$E_n \geq \varphi_n.E_{th} \tag{15-1}$$

$$E_{th} \geq E_{\min} \tag{15-1}$$

$$P_f \leq \alpha \tag{15-1}$$

$$P_d \geq \beta \tag{15-2}$$

$$\varphi_n \in \{0,1\} \tag{15-3}$$

We added the first constraint to emphasize that all sensors must have a residual energy level above to be selected for spectrum sensing. This constraint balances the energy consumption in the network and keeps the remaining energy of sensors at an almost balanced level. The second constraint is added to satisfy that a sensor harvests energy if it has less remaining energy and it is not selected to cooperate in spectrum sensing. Also, Equation 15-3 can be replaced with an equivalent condition. A short note on Equations 7 and 13 reveals that the false alarm probability for a sensor is independent of the SNR received by that sensor. Therefore, the global probability of a false alarm can be converted to another form, as follows:

$$P_f = 1-\prod_{n\in J}\left(1-\varphi_n.Q\left(\left(\frac{\gamma}{\sigma_v^{\,2}}-1\right)\sqrt{\delta f_s}\right)\right) \leq \alpha \tag{16}$$

Then:

$$\sum_{n\in J} ln\left(1-Q\left(\left(\frac{\gamma}{\sigma_v^{\,2}}-1\right)\sqrt{\delta f_s}\right)\right) \leq ln(1-\alpha) \tag{17}$$

Finally, with the following definition, Equation 17 can be replaced with an equivalent condition that is easy to attend to:

$$|J| \leq J_{max} \triangleq \left|\frac{ln(1-\alpha)}{ln\left(1-Q\left(\left(\frac{\gamma}{\sigma_v^{\,2}}-1\right)\sqrt{\delta f_s}\right)\right)}\right| \tag{18}$$

where $|J|$ denotes the number of sensors participating in the sensing, and J_{max} shows the maximum number of sensors that can participate. If more sensors are selected for cooperative spectrum sensing, the condition for the probability of a false alarm will not be met. However, the global probability of correct detection for cooperative spectrum sensing is met with fewer sensors. In that case, it is unnecessary to choose more sensors because it causes more energy consumption, while it has no advantage. Now, the problem can be rewritten as follows:

$$\max_{\varphi_n}\{E_{th}\} \tag{19}$$

Subject to:

$$E_{th}-\varphi_n.E_n \leq 0 \tag{19-1}$$

$$E_{th} \geq E_{min} \tag{19-2}$$

$$\sum_{n=1}^{N}\left(\varphi_n - J_{max}\right) \leq 0 \tag{19-3}$$

$$\beta-\left(1-\prod_{j\in J}\left(1-\varphi_j.P_{d_j}\right)\right) \leq 0 \tag{19-4}$$

$$\varphi_n \in \{0,1\} \tag{19-5}$$

Equation 19 cannot be considered a convex optimization problem because condition in Equation 19-4 is not convex. Therefore, using the Lagrange method (23), the priority of each sensor is obtained through the following:

$$PR_n \triangleq \frac{\rho_n\left(E_{0,n}-E_{th}\right)+\lambda.P_{d_n}}{2\rho_n.E_{c,n}} \tag{20}$$

where ρ_n and λ are Lagranges multipliers. Finally, the pseudocode of algorithm is shown in Table 1.

TABLE 1. Pseucode of optimization algorithm

```
Compute J_max
While off_sensors < (1-L)N
    λ = (λ_min + λ_max)/2 , ρ_n = (ρ_n,min + ρ_n,max)/2
    While error > ε
        For j = 1:J_max
            for n = 1:N
                if E_n >= E_n^c : Compute the PR_n and add
                sensor to selected sensors, counter =
                counter + 1
                Else: PR_n = 0
            end
            Sort selected sensors
            P_dm = 1
            if counter < J_max & P_dm < β_m
                sl = selected from selected sensors
```

$$P_{d_m} = 1 - \left(P_{d_m} \times \left(1 - P_{d_{m,sl}}\right)\right)$$

end

end

end

Update E_n

$\lambda = max\left(min\left(\lambda_{max}, \lambda\right), \lambda_{min}\right)$, $\rho_n = max\left(min\left(\rho_{n,max}, \rho_n\right), \rho_{n,min}\right)$

end

4. SIMULATION AND RESULTS

In this section, the proposed algorithms are numerically evaluated using MATLAB computer simulations. We use the Monte Carlo method with 1000 iterations. It is assumed that a region with 400 * 400 (m^2), a sink node located in the center, N sensors, and one PU are distributed identically in this region. Here, the cognitive sensors use the IEEE 802.15.4/Zigbee (24). The simulation parameters are presented in Table 1. The sampling frequency of the sensor's energy in the detector equals the Nyquist frequency.

We compare our proposed method with two benchmark methods, detection based and random. In the detection base method, sensors are selected based on the probability of correct detection in the network sense, and this method increases its efficiency in meeting the optimization conditions. In the random method, the selected sensors for sensing the network are randomly selected, and the reason for the presence of this method in this comparison is its low complexity.

One of the critical parameters in the algorithm's efficiency is its success rate, which refers to the ratio of successful iterations of the algorithm to the total number of iterations. This parameter is shown in Figure 4 for a network with a different number of sensors. The success rate from the point of view of changing the network area is also compared in Figure 5.

TABLE 2. Simulation parameters

$f_s = 2.45GHz$	$E_{0,n} = 0.2mJ$
$e_{amp} = 40.4\, pJ/m^2$	$E_s = 190nJ$
$E_{t-elec} = 80nJ$	$\sigma_s^2 = 10^{-11}W$
$\alpha = 0.1$	$\sigma_z^2 = 3dB$
$\beta = 0.9$	$\mu = 0.8$
$p_t = 20mW$	$L = 0.25$

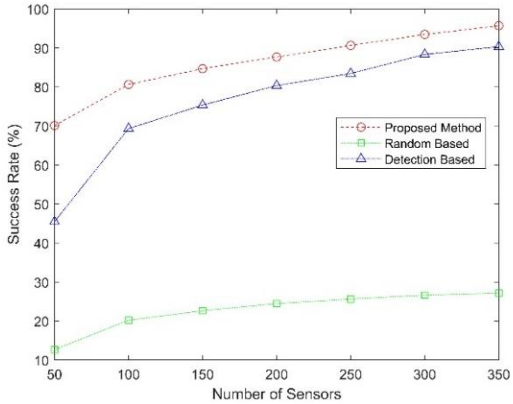


Figure 4. Success rate for different sensor numbers in a square area with 200 m length

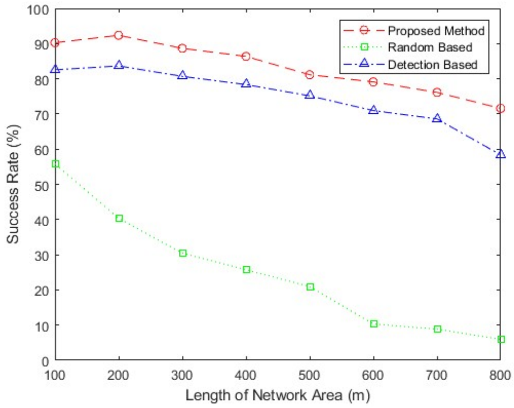


Figure 5. Success rate for different area with 200 sensors

The number of successful iterations as the network's lifetime, as shown in Figure 6. This figure shows that the proposed algorithm can perform better by increasing the number of sensors due to more optimal energy harvesting, which is superior to the detection-based method. Because by optimally choosing sensors based on the remaining energy and the probability of correct detection, it meets the optimization constraints in more iterations.

Figure 7 shows the simulation results for the minimum remaining energy in each iteration. This figure shows that according to the selection of sensors based on energy consumption and correct detection, the proposed algorithm performs more efficiently. Because in the other two methods, the amount of remaining energy is not checked.

The results in Figure 8 show that the number of alive sensors is more in the proposed algorithm. This is because energy harvesting is done according to the amount of remaining energy and correct detection by that sensor. In the other two methods, the energy harvester sensor is selected regardless of its priority regarding remaining energy.

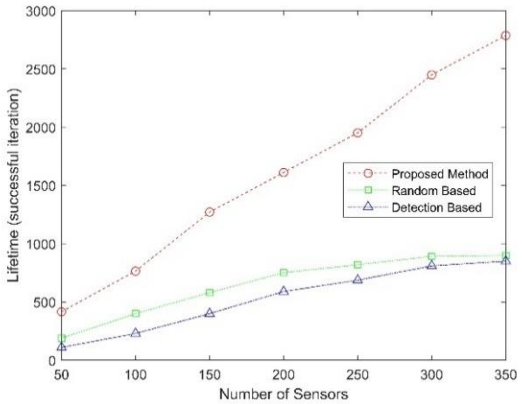


Figure 6. Lifetime for a CSRN in square area with 200m length

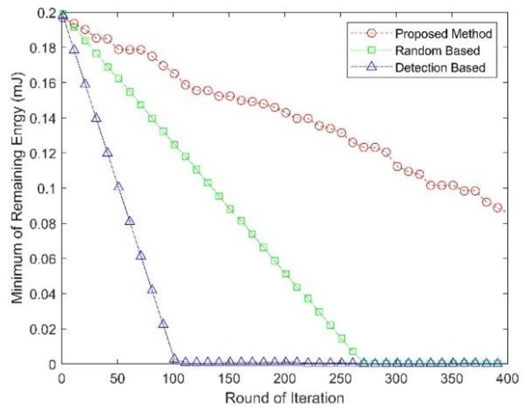


Figure 7. Minimum remaining energy in a CSRN with 200 sensors and 200m length

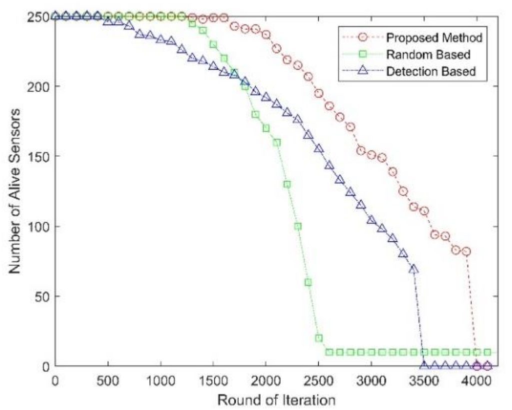


Figure 8. Number of alive sensors in a CSRN with 250 sensors and 200m length

5. CONCLUSION

Energy efficiency and lifetime are considered the main challenges of CRSN. In this paper, we improved the performance of these networks by relying on convex optimization and providing an optimal method to harvest energy in the above networks. The results show that the proposed algorithm has a significant advantage over other methods in increasing the network lifetime and success rate.

This method relies on the optimal selection of sensors through a convex optimization to sensor selection in the network, leading the success rate to a minimum rate of 70% and increasing the network's lifetime by at least 32%. On the other hand, this method can be used in networks with more nodes because increasing the number of sensors does not limit the network's lifetime. Additionally, the amount of remaining energy in the network is reduced at a lower rate, which can improve the reliability of the network, and, due to the survival of a larger number of nodes, accurate sensing along with the optimal lifetime of the network can be achieved.

However, the convergence of this algorithm may decrease with the increase in the network size and the number of sensors. Also, in multi-channel networks, the selection of the channel used by each sensor to harvest energy can be added as an additional optimization factor to the proposed method. These issues considered one of the research focuses in the future to optimize the convergence rate of this optimization compared to the network size.

6. REFERENCES

1. Salina JL, Salina P. Next Generation Networks: perspectives and potentials: John Wiley & Sons; 2008.
2. Uwaechia AN, Mahyuddin NM. A comprehensive survey on millimeter wave communications for fifth-generation wireless networks: Feasibility and challenges. IEEE Access. 2020;8:62367-414. https://doi.org/10.1109/ACCESS.2020.2984204
3. Adigun O, Pirmoradian M, Politis C. Cognitive radio for 5G wireless networks. Fundamentals of 5G Mobile Networks. 2015:149-63. https://doi.org/10.1002/9781118867464.CH6
4. Setoodeh P, Haykin S. Fundamentals of cognitive radio: John Wiley & Sons; 2017.
5. Mergu K, Khan H. Mitigation of spectrum sensing data falsification attack in cognitive radio networks using trust based cooperative sensing. International Journal of Engineering, Transactions C: Aspects. 2021;34(6):1468-74. https://doi.org/10.5829/IJE.2021.34.06C.10
6. Tseng F-H, Chao H-c, Wang J. Ultra-dense small cell planning using cognitive radio network toward 5G. IEEE Wireless Communications. 2015;22(6):76-83. https://doi.org/10.1109/MWC.2015.7368827
7. Suraweera HA, Smith PJ, Shafi M. Capacity limits and performance analysis of cognitive radio with imperfect channel knowledge. IEEE Transactions on Vehicular Technology. 2010;59(4):1811-22. https://doi.org/10.1109/TVT.2010.2043454
8. Zheng K, Liu X, Zhu Y, Chi K, Li Y. Impact of battery charging on spectrum sensing of CRN with energy harvesting. IEEE Transactions on Vehicular Technology. 2020;69(7):7545-57. https://doi.org/10.1109/TVT.2020.2994005

9. Guo J, Hu H, Da X, Liu J, Li W. Optimization of energy efficiency for cognitive radio with partial RF energy harvesting. AEU-International Journal of Electronics and Communications. 2018;85:74-7. https://doi.org/10.1016/J.AEUE.2017.12.030
10. Ercan AÖ, Sunay MO, Akyildiz IF. RF energy harvesting and transfer for spectrum sharing cellular IoT communications in 5G systems. IEEE Transactions on Mobile Computing. 2017;17(7):1680-94. https://doi.org/10.1109/TMC.2017.2740378
11. Halima NB, Boujemâa H. Energy harvesting with adaptive transmit power for cognitive radio networks. Telecommunication Systems. 2019;72(1):41-52. https://doi.org/10.1007/S11235-019-00548-W/METRICS
12. Alsharoa A, Neihart NM, Kim SW, Kamal AE, editors. Multi-band RF energy and spectrum harvesting in cognitive radio networks. 2018 IEEE International Conference on Communications (ICC); 2018: IEEE.
13. Wang J, Ge Y. A radio frequency energy harvesting-based multihop clustering routing protocol for cognitive radio sensor networks. IEEE Sensors Journal. 2022;22(7):7142-56. https://doi.org/10.1109/JSEN.2022.3156088
14. Deng X, Guan P, Hei C, Li F, Liu J, Xiong N. An intelligent resource allocation scheme in energy harvesting cognitive wireless sensor networks. IEEE Transactions on Network Science and Engineering. 2021;8(2):1900-12. https://doi.org/10.1109/TNSE.2021.3076485
15. Zheng K, Wang J, Liu X, Yao X-W, Xu Y, Liu J. A Hybrid Communication Scheme for Throughput Maximization in Backscatter-aided Energy Harvesting Cognitive Radio Networks. IEEE Internet of Things Journal. 2023. https://doi.org/10.1109/JIOT.2023.3267453
16. Salehi SJ, Shmasi-Nejad M, Najafi HR. A new multilevel inverter based on harvest of unused energies for photovoltaic applications. International Journal of Engineering, Transactions C: Aspects. 2022;35(12):2377-85. https://doi.org/10.5829/ije.2022.35.12c.14
17. Fakharian M. A wideband fractal planar monopole antenna with a thin slot on radiating stub for radio frequency energy harvesting applications. International Journal of Engineering, Transactions B: Applications. 2020;33(11):2181-7. https://doi.org/10.5829/ije.2020.33.11b.08
18. Bagheri A, Ebrahimzadeh A, Najimi M. Game-theory-based lifetime maximization of multi-channel cooperative spectrum sensing in wireless sensor networks. Wireless networks. 2020;26(6):4705-21. https://doi.org/10.1007/S11276-020-02369-1/METRICS
19. Maleki S, Chepuri SP, Leus G. Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks. Physical Communication. 2013;9:193-8. https://doi.org/10.1016/J.PHYCOM.2012.07.003
20. Bagheri A, Ebrahimzadeh A, Najimi M. Energy-efficient sensor selection for multi-channel cooperative spectrum sensing based on game theory. Journal of Ambient Intelligence and Humanized Computing. 2021;12:9363-74. https://doi.org/10.1007/S12652-020-02651-2/METRICS
21. Noori M, Ardakani M. Lifetime analysis of random event-driven clustered wireless sensor networks. IEEE Transactions on mobile computing. 2010;10(10):1448-58. https://doi.org/10.1109/TMC.2010.254
22. Najimi M, Ebrahimzadeh A, Andargoli SMH, Fallahi A. Lifetime maximization in cognitive sensor networks based on the node selection. IEEE sensors Journal. 2014;14(7):2376-83. https://doi.org/10.1109/JSEN.2014.2311154
23. Boyd SP, Vandenberghe L. Convex optimization: Cambridge university press; 2004.
24. Han D-M, Lim J-H. Smart home energy management system using IEEE 802.15. 4 and zigbee. IEEE Transactions on Consumer Electronics. 2010;56(3):1403-10. https://doi.org/10.1109/TCE.2010.5606276

Persian Abstract

چکیده

فناوری ارتباطی 5G از اینترنت اشیا، مراکز مراقبت بهداشتی از راه دور و محاسبات ابری با تنظیم خدمات ارتباطی آنها در طیف بسیار وسیعی از باندهای فرکانسی با هزینه، مصرف باتری و تأخیر کم پشتیبانی می کند. با این حال، توسعه چنین فناوری بی سیم به شدت به طیف فرکانس رادیویی وابسته است. شبکه حسگر رادیویی شناختی (CRSN) یک پیشنهاد عالی برای بهبود استفاده از طیف رادیویی و مدیریت ترافیک داده های ارتباطی سنگین در شبکه های بی سیم 5G است. CRSN می‌تواند با سنجش کانال‌های فرکانسی استفاده از کانال‌های رایگان را برای کاربران ثانویه (که از خدمات محروم هستند) ممکن سازد. با وجود ویژگی های برجستهCRSN ، برخی محدودیت ها بر عملکرد آنها سایه می اندازد. مهم ترین محدودیت، مسئله انرژی و مصرف بهینه آن برای افزایش طول عمر شبکه است. تحقیقات اخیر نشان داده است که برداشت انرژی می تواند راه حل موثری برای افزایش طول عمر CRSN باشد. از طرفی، حسگرها باید طیف فرکانس را با نرخ موفقیت بالا سنجش کنند. در این مقاله انتخاب چندین گره حسگر بهینه برای برداشت انرژی با رویکرد افزایش طول عمر شبکه برای حل چالش مذکور پیشنهاد شده است. به این ترتیب که گره های حسگر به دو گروه مستقل برای سنجش همزمان طیف و برداشت انرژی در هر بازه زمانی تقسیم می شوند. این مسئله را بر اساس بهینه سازی ریاضی و استفاده از راه حل های پیشنهادی برای مسائل محدب حل خواهیم کرد. در نهایت، شبیه‌سازی‌ها برای ارزیابی توانایی راه‌حل پیشنهادی، بر پایه IEEE802.15.4/Zigbee و IEEE802.11af توسعه داده می‌شوند.