International Journal of Engineering

Journal Homepage: www.ije.ir

# Joint Sensing Times Detection Thresholds and Users Association Optimization in Multi-Channel Multi-Antenna Cognitive Radio Networks

M. Sadeghian Kerdabadi*[a], R. Ghazizadeh[b], H. Farrokhi[b], M. Najimi[c]

[a] *Department of Mechanic Engineering, Malek-e ashtar, University of Technology, Isfahan, Iran*
[b] *Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran*
[c] *Faculty of Electrical, University of Science and Technology of Mazandaran (USTM), Behshahr, Mazandaran, Iran*

*PAPER INFO*

*Paper history:*
Received 06 March 2023
Received in revised form 16 March 2023
Accepted 19 March 2023

*Keywords*:
*Cognitive Radio Network*
*Multi Channels*
*Multi Antennas*
*Throughput*
*Energy Consumption*

*ABSTRACT*

Energy consumption and throughput optimization in cognitive radio networks (CRNs) are two critical issues that have attracted more attention in recent years. In this paper, we consider maximization of the energy efficiency and improvement of the throughput as optimization metrics for jointly optimizing sensing times and energy detection thresholds in each sub-channel and selecting the spectrum sensing (SS) and data transmitting multi-antenna secondary users (SUs) in multi-channel multi-antenna CRN under constraints on the probabilities of false alarm and detection. The considered problem is solved based on the convex optimization method and the algorithm having less computational complexity compared to baseline approaches is proposed to achieve the optimal parameters and goals of the problem. The performance of the proposed scheme is evaluated by simulations and compared with the other methods. The results indicate that the proposed approach can achieve less energy consumption while the minimum required throughput is guaranteed.

***doi****: 10.5829/ije.2023.36.09c.15*

## 1. INTRODUCTION

Cognitive Radio (CR) has emerged as a practical approach to enhance spectrum efficiency (SE) by allocating the sensed bands as idle of the licensed users (primary users, PUs) to the unlicensed users (secondary users, SUs) [1]. Therefore, SS becomes a fundamental task in CR to quickly and reliably detect the presence of the Pus [2]. Energy detection is the most common technique for SS due to its simple implementation. In addition, it does not need prior knowledge of the PU's signal. However, reliable SS is not always guaranteed because of multipath fading and shadowing. Cooperative SS (CSS) approaches have been proposed to overcome these problems. CSS combines the local sensing decisions of multiple SUs or antennas in a fusion center (FC) for making a more reliable final decision on the absence/presence of the PU by achieving the advantage of the spatial diversity in wireless channels [3]. A lot of work has been done on sensing-throughput tradeoff and finding the optimum SS parameters such as detection threshold value for energy detection, SS time and power for data transmitting to guarantee the best performance on the probability of false alarm, $P_f$ , the probability of detection, $P_d$ , and as well as the throughput of CRN [4-13]. A sum-rate maximization strategy was proposed by Salari and Francois [14] to jointly obtain the optimal Energy Harvesting (EH) time allocation factor and distributed beamforming coefficients that achieve the best system performance for the secondary network under the individual EH power constraints at relays and an interference power constraint at the primary receiver. The sum throughput of SUs was maximized by Hameed et al. [15], while managing the interference constraint. For this goal, the uplink and downlink phase shift matrices of the IRS elements with optimal time slots for wireless energy transfer (WET) on downlink and wireless information transfer on uplink were optimized.

*Corresponding Author Email: mohammad.sadeghian@birjand.ac.ir (M. Sadeghian)

Please cite this article as: M. Sadeghian Kerdabadi, R. Ghazizadeh, H. Farrokhi, M. Najimi, Joint Sensing Times Detection Thresholds and Users Association Optimization in Multi-Channel Multi-Antenna Cognitive Radio Networks, ***International Journal of Engineering, Transactions C: Aspects***, Vol. 36, No. 09, (2023), 1704-1719

Most early research on SS has been primarily performed on sensing a single-band. However, multi-channel (multi-band) spectrum access has recently developed where multiple bands used by more than one PU are sensed and accessed to enhance the throughput and reduce data transmission interruptions due to the activities of the PUs. Many approaches have been presented to achieve the maximum throughput of the multi-channel CRN by optimizing the different sensing and transmission parameters [16-23].

The above-mentioned works only consider single-antenna CRNs. However, multi-antenna systems can provide many benefits for CRN such as multiplexing gain and diversity [24, 25]. In multi-antenna CSS, diversity leads to behave SUs virtually the same as systems having multiple sensing SUs. These benefits can be exploited to enhance the sensing and transmission capabilities of CRN that overcomes the fading problem and hence, increases the SUs' throughput. The optimal values of the SS times, sensing thresholds and transmit power were obtained for increasing the throughput in multi-antenna CRNs subject to constraints on transmit power, $P_d$ and $P_f$ [26]. In a cooperative multiple-input single-output (MISO) CR system was proposed by Liu et al. [27], some of the antennas are used to transmit the SU's data and the rest antennas for transmitting the PU's data. Kumar et al. [28] enhanced the SE by using multi antennas CSS and minimizing the spectrum sensing error. The problem of a joint robust transmission, reflection and reception strategy design at an active reconfigurable intelligent surface (RIS)-assisted underlay MIMO CRNs is solved in which a secondary transmitter serves multiple secondary receivers, simultaneously [29]. The energy and matched filter detectors were employed by Rauniyar and Shin [30] as cascades in each antenna of the multi-antenna CRN. Then the local sensing results of all antennas were combined to enhance the detection performance. A SS algorithm based on sample variance was proposed that significantly reduces the number of sampling points in MIMO schemes to achieve the optimum detection performance [31]. An energy harvesting-based multi-antenna CR scheme presented by Liu et al. [32] for powering SUs by harvesting energy from radio frequency (RF) signal of the PU and the noise. The performance of SS and throughput can be enhanced by using more cooperative SUs in the network. Nonetheless, this enhancement is at the cost of increasing the consumed energy and communication overhead of CRN [33]. Therefore, the selection of Sensing and data Transmitting SUs (SSUs & TSUs) has a significant impact on the throughput and energy consumption of CRN. Moreover, the frame structure of the opportunistic spectrum access CR networks consists of a spectrum sensing time slot (duration $\tau$) and a data transmission time slot (duration $T$-$\tau$), as shown in Figure 1. The longer sensing time increases the probability of detection and PU protection but decreases the transmission opportunity of the CR. Hence, the achievable throughput of the SUs is reduced. Therefore, a fundamental tradeoff exists between the duration of spectrum sensing and data transmission. Also, the more or less sensing times lead to more energy consumption because it takes more time for sensing and data transmitting, respectively.

The interplay between the above-mentioned components calls for jointly optimizing the sensing and data transmission parameters of CRN, which is the major issue of this paper. The aim is to share the advantages of multi-antenna and multi-channel CRN.

We solve the joint optimization problem of the detection thresholds, SS times, and the selection of multi-antenna SSUs and TSUs for each sub-channel to minimize the energy consumption and improvement of the throughput of CRN.

The main contributions of this paper are outlined as follows:

- Most of work done so far on CRNs just optimizes either the achieved throughput or consumed energy of CRN, but in this paper, we consider minimization of the energy consumption and enhancement of the throughput, simultaneously.
- We have considered the optimization problem of the sensing times, detection thresholds, and the selection of the multi-antenna SSUs and TSUs for each sub-channel of the multi-channel multi-antenna CRN jointly to improve the throughput and minimization of the consumed energy over all the sub-channels under constraints on the global $P_d$ and $P_f$ whereas most of the past done studies formulated an optimization problem without taking the joint optimization of the above-mentioned parameters for multi-channel multi-antenna CRN into consideration.
- The presence of the PU signal is detected by the multi-antenna CSS, in which each antenna employs energy detection to sense the PU signal. As a result, the sensing results of all the sensing antennas are combined to make the global decision with the goal of incrementing the CR throughput and improving the detection capability by obtaining the sensing diversity gain that overcomes the multi-path fading problem.
- We provide mathematical proofs for the proposed model. Then, convex optimization methods and Karush–Kuhn–Tucker (KKT) conditions are used

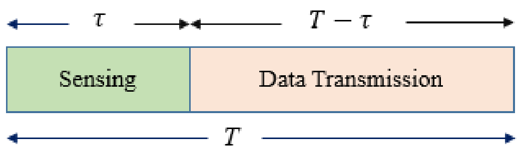



**Figure 1.** The time frame structure of the model

to solve our mix-variable optimization problem. Moreover, by using a convex-based iterative algorithm having less computational complexity compared to baseline approaches, the optimum sensing times and detection thresholds are achieved in each sub-channel. We also specify the sensing and data transmitting multi-antenna SUs on each sub-channel. Using the proposed algorithm, the sensing and data transmitting multi-antenna SUs for each suitable sub-channel are selected based on parameters such as detection probability, residual energy, and SNR such that the consumed energy is minimized and the constraints on the detection performance and the minimum required throughput are satisfied.

- Through simulations, we demonstrate that proposed scheme can significantly enhance the throughput and energy consumption of CRN when compared to structures using same sensing times or thresholds in all sub-channels or schemes, in which all single-antenna SUs are participated in SS and data transmitting.

The remainder of this paper is organized as follows. Section 2 describes the proposed system model. The problem formulation and analytical solution are also developed in this section. Section 3 provides the simulation results. The future prospect of the proposed approach are presented in section 4. Finally, conclusions are drawn in section 5.

## 2. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a cooperative CRN comprised of FC, $K$ PUs indexed by the set $\boldsymbol{\mathcal{K}}=\{1,2,\ldots,K\}$ and $M$ SUs indexed by the set $\boldsymbol{\mathcal{M}}=\{1,2,\ldots,M\}$ distributed uniformly and equipped with $L$ antennas as shown in Figure 2. The frequency band is assumed to be divided into $K$ non-overlapping channels. Every PU can use only one of the bands. Each SU receives the PUs' signal with an instant signal-to-noise ratio (SNR) within a particular time interval. Some channels might not be used by the PUs and are available for opportunistic spectrum access. We use energy detection as the SS method in proposed CR system. Let $f_s$ be the sampling frequency, $\tau_i$ and $\varepsilon_i$ the sensing time and detection threshold for the $i$th sub-channel, respectively. It is assumed the sensing time for all sensing SUs in one sub-channel is the same.

We assume two hypotheses $H_{0,i}$ and $H_{1,i}$ for receiving the signals in each antenna, which refer to the inactive and active state of the PU on $i$th sub-channel, respectively. Let $Y_{ijl}(k)$ denote the $k$th sample in the $i$th sub-channel (the $i$th PU signal) received by $l$th antenna of $j$th SU, $s_i(k)$ is the $k$th sample of the transmitted signal from the $i$th PU, $w_{jl}(k)$ is the independent identically distributed (i.i.d.) Gaussian random process with zero mean and the variance $\sigma_{n,j}^2$ received by $l$th antenna of $j$th SU. We assume a Rayleigh fading channel with gain $h_{ijl}$ between the $i$th PU and $l$th antenna of $j$th SU defined as:

$$h_{ijl} = 10^{-\frac{L_{ijl}}{20}}.g_{ijl} \tag{1}$$

where $g_{ijl}$ is a random process with complex Gaussian distribution having zero mean and unit variance [34]. $L_{ijl}$ has two components which are described as Equation (2): the first component is the path loss according to the free-space path loss model, and the second component expresses a real Gaussian random variable with zero mean and standard deviation of 3 based on large scale log-normal shadowing.

$$L_{ijl} = 20\log\left(\frac{d_{PS_{ijl}}4\pi f_c}{v}\right) + n_{jl} \tag{2}$$

where $d_{PS_{ijl}}$ expresses the distance of $l$th antenna of $j$th SU and $i$th PU. $f_c$ denotes the working frequency, and $v$ is the speed of light. Therefore, mathematically, the $k$th sample of the received signal of $l$th antenna of $j$th SU at the $i$th sub-channel, $y_{ijl}(k)$, can be written as two following hypotheses.

$$y_{ijl}(k) = \begin{cases} w_{jl}(k) & H_{0,i}\text{: PU is absent} \\ h_{ijl}s_i(k) + w_{jl}(k) & H_{1,i}\text{: PU is present} \end{cases} \tag{3}$$
$$k = 1,2,\ldots,\tau_i f_s$$

Therefore, the test statistic for $l$th antenna of $j$th SU on $i$th sub-channel is expressed as follows:

$$V_{ijl} = \frac{1}{\tau_i f_s}\sum_{k=1}^{\tau_i f_s}\left|y_{ijl}(k)\right|^2 \tag{4}$$

where $\tau_i f_s$ is the number of samples. By using the MRC technique as the diversity approach for combining the antenna's signal in $j$th SU, the test statistic of all antennas is accumulated to achieve the total received energy as follows [35]:

$$V_{ij} = \frac{1}{L\tau_i f_s}\sum_{k=1}^{\tau_i f_s}\left|\left(\sum_{l=1}^{L} y_{ijl}(k).\,h_{ijl}^*\right)\right|^2 \tag{5}$$

As a result, the following binary test is used to decide by the $j$th SU about the presence or absence of the PU in the $i$th sub-channel.

$$\text{Decide} = \begin{cases} H_{0,i} & \text{if } V_{ij} < \varepsilon_i \\ H_{1,i} & \text{if } V_{ij} > \varepsilon_i \end{cases} \tag{6}$$

The global $P_d$ and $P_f$ in $j$th SU for $i$th sub-channel can be expressed as follows:

$$P_{d_{ij}} = P\left(V_{ij} \geq \varepsilon_i \middle| H_{1,i}\right) = Q_{L\tau_i f_s}\left(\sqrt{2\,\gamma_{ij,MRC}}, \frac{\sqrt{\varepsilon_i}}{\sigma_{MRC}}\right) \tag{7}$$

$$P_{f_{ij}} = P\left(V_{ij} \geq \varepsilon_i \middle| H_{0,i}\right) = \frac{\Gamma\left(L\tau_i f_s, \frac{\varepsilon_i}{2\sigma_{MRC}^2}\right)}{\Gamma\left(L\tau_i f_s\right)} \tag{8}$$

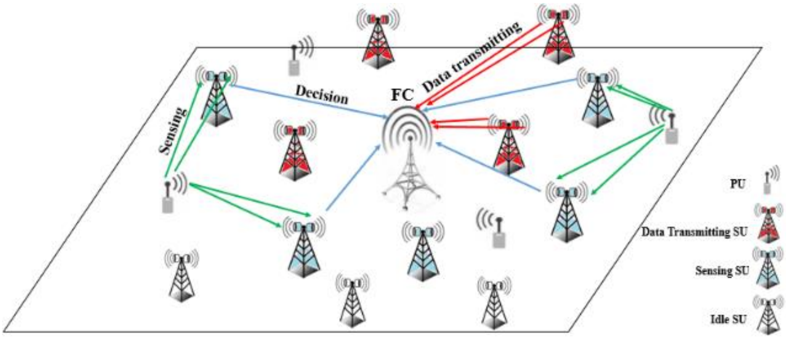



**Figure 2.** The multi-channel multi antenna CRN model

where $Q_m(a, b)$ denotes the generalized Marcum Q-function. $\Gamma(a)$ and $\Gamma(a,b)$ express the gamma and incomplete gamma functions, respectively. $\gamma_{ij,MRC}$ is the average SNR of $L$ antennas in $j$th SU and are defined as $\gamma_{ij,MRC} = \frac{(\sum_{l=1}^{L}|h_{ijl}|^2)^2 \cdot P_t}{\sigma_{MRC}^2}$ where $P_t$ denotes the transmit power of the PUs and $\sigma_{MRC}^2$ is the variance of effective noise defined as $\sigma_{MRC}^2 = \sum_{l=1}^{L}|h_{ijl}|^2\sigma_n^2$ .

It was shown that simultaneous participation of all SUs for sensing causes more energy consumption and higher $P_f$ while the $P_d$ will not increases significantly [22]. Therefore, we can select some SUs with the better $P_d$ for SS in $i$th sub-channel while some others are selected to send their data to the FC through $i$th sub-channel, and the rest are considered idle to enhance the consumed energy and throughput. OR fusion rule is employed in FC to fuse the local decisions of the SUs. Therefore, the global $P_d$ and $P_f$ for $i$th sub-channel are expressed as follows:

$$P_{d_i} = 1 - \prod_{j=1}^{M}\left(1 - \rho_{ij}P_{d_{ij}}\right) \quad (9)$$

$$P_{f_i} = 1 - \prod_{j=1}^{M}\left(1 - \rho_{ij}P_{f_{ij}}\right) \quad (10)$$

where $\rho_{ij} \in \{0,1\}$ is "1" if $i$th sub-channel is sensed by $j$th SU otherwise, it is considered as "0". Therefore, it should specify which SUs sense the $i$th sub-channel and which SUs transmit their data through $i$th sub-channel. If the SUs select transmitting the data on the $i$th sub-channel, the average throughput of the proposed CRN on all $K$ channels is given below:

$$C = \sum_{i=1}^{K}\frac{T_f - \tau_i}{T_f}\,(\sum_{j=1}^{M}(\,P(H_{0,i})(1-P_{f_i})\varphi_{ij}\log(1 + (SNR)_{ij}) + P(H_{1,i})(1-P_{d_i})\varphi_{ij}\log(1 + (SINR)_{ij})) \quad (11)$$

where $(SNR)_{ij} = \sum_{l=1}^{L}\frac{|h_{FS_{jl}}|^2 \cdot P_{tij}}{\sigma_n^2}$ and $(SINR)_{ij} = \sum_{l=1}^{L}\frac{|h_{FS_{jl}}|^2 \cdot P_{tij}}{p_{p,i}|h_{FP_i}|^2 + \sigma_n^2}$. $h_{FS_{jl}}$represents the channel gain between FC and $l$th antenna of $j$th SU and $h_{FP_i}$ is the channel gain between FC and $i$th PU. $P_{tij}$ and $p_{p,i}$ represent the transmitting power of the $j$th SU and $i$th PU on the $i$th sub-channel, respectively. The assignment index $\varphi_{ij} \in \{0,1\}$ is "1" if the $j$th SU is selected for transmitting the data on the $i$th sub-channel otherwise it is considered as "0". We assume that $P(H_{0,i})$ and $P(H_{1,i})$ denote the probabilities that the $i$th sub-channel is idle and busy, respectively. $T_f$ is the frame duration. The energy consumption of the proposed CRN is calculated by extending the considered model by Maleki et al. [36]. Therefore, the energy consumption of $j$th SU in each sub-channel at the sensing process can be written as follows:

$$E_{t_j} = \sum_{l=1}^{L} E_{s_{j,l}} + E_{t,dj} \quad (12)$$

where $E_{s_{j,l}}$ denotes the energy consumption by $l$th antenna of $j$th SU for sensing $i$th sub-channel. $E_{t,dj}$ represents the consumed energy for transmitting one decision bit from $j$th SU to the FC and is calculated as follows:

$$E_{t,dj} = E_{t-elec} + e_{amp}d_{FS_j}^2 \quad (13)$$

where $E_{t-elec}$ is the required energy for transmitter electronics and $e_{amp}$ denotes the required amplification such that a specified receiver sensitivity level is satisfied. $d_{FS_j}$ represents the distance between FC and $j$th SU. With respect to the selection of the SUs for sensing, data transmitting, or being idle, the total consumed energy can be expressed as follows:

$$E_T = \sum_{i=1}^{K}\sum_{j=1}^{M}\left[\rho_{ij}\left[\sum_{l=1}^{L} E_{s_{j,l}} + E_{t,dj}\right] + \varphi_{ij}E_{td_{ij}}\right] \quad (14)$$

where $E_{td_{ij}}$ denotes the consumed energy by $j$th SU to send one data bit to the FC through $i$th sub-channel. Assuming that $E_{s_{j,l}}$ is the same for all antennas and the SUs denoted as $E_s$, we have:

$$E_T = \sum_{i=1}^{K}\sum_{j=1}^{M}\left[\rho_{ij}[\,LE_s + E_{t,dj}] + \varphi_{ij}E_{td_{ij}}\right] \quad (15)$$

Now, we assume that $\alpha$ and $\beta$ denote the upper and lower bounds of $P_d$ and $P_f$ in each sub-channel, respectively, to have more opportunity for using the idle channels and satisfy the PU's signal protection requirements from the interference.

By increasing the number of SUs for data transmitting in the CR network, the energy consumption and the total throughput are increased. However, the main goal is to achieve the minimum energy consumption of CRN while keeping throughput above a certain value, $C_{th}$, and interference to the PUs below a certain threshold. In other words, our goal is to find the number of SUs and specify the SUs for each sub-channel that minimizes the energy consumption, and also satisfies the minimum required total throughput of the CR. Therefore, all SUs do not need to cooperate for data transmision. Thus, the selection of the data transmitting SUs is considered for minimization of the energy consumption of the network and satisfaction of the required throughput of SUs.

Therefore, we can achieve the minimum energy consumption by solving the following optimization problem.

$$\min_{\rho_{ij},\varphi_{ij},\tau_i,\varepsilon_i} \quad E_T \tag{16}$$

$$\textbf{s.t.} \quad P_{d_i} \geq \beta \quad \forall\, i\epsilon\mathcal{K} \tag{16.a}$$

$$P_{f_i} \leq \alpha \quad \forall\, i\epsilon\mathcal{K} \tag{16.b}$$

$$C \geq C_{th} \tag{16.c}$$

$$\textstyle\sum_{i=1}^{K} \rho_{ij} \leq 1 \quad \forall\, j\epsilon\mathcal{M} \tag{16.d}$$

$$\textstyle\sum_{j=1}^{M} \varphi_{ij} \leq 1 \quad \forall\, i\epsilon\mathcal{K} \tag{16.e}$$

$$\rho_{ij}\varphi_{ij} = 0 \quad \forall\, i\epsilon\mathcal{K}, j\epsilon\mathcal{M} \tag{16.f}$$

$$\rho_{ij}\epsilon\{0,1\} \quad \forall\, i\epsilon K, j\epsilon\mathcal{M} \tag{16.g}$$

$$\varphi_{ij}\epsilon\{0,1\} \quad \forall\, i\epsilon K, j\epsilon\mathcal{M} \tag{16.h}$$

The constraint (16.d) indicates that each SU can only sense one channel in the sensing time slot. The constraint (16.e) indicates that each channel should be allocated to maximum of one SU for data transmitting in the transmitting duration. The constraint (16.f) expresses that sensing and transmitting cannot be accomplished by $j$th SU on $i$th sub-channel, simultaneously. Using constraint (16.b) and Equation (10), $n_i \leq \frac{\ln(1-\alpha)}{\ln\left(1-\frac{\Gamma\left(L\tau_i f_s, \frac{\varepsilon_i}{2\sigma_{MRC}^2}\right)}{\Gamma(L\tau_i f_s)}\right)} = M_i$

where $n_i = \sum_{j=1}^{M} \rho_{ij}$ and $M_i$ represents the number of sensing SUs and maximum number of sensing SUs in the $i$th channel, respectively. Due to the discrete nature of $\rho_{ij}$ and $\varphi_{ij}$ the problem is a non-deterministic polynomial time (NP) problem, and the general solution will be the exhaustive search algorithm. Thus, all $n_i$ sensing candidates and $M$-$n_i$ transmitting candidates in the $i$th sub-channel should be examined such that it achieves the minimum energy consumption and the constraints on the required detection performance for each sub-channel is satisfied. This algorithm has a high exponential complexity in the order of $O((M!)^K)$ for large $M$. Therefore, to reduce the complexity of the solution, $\rho_{ij}$ and $\varphi_{ij}$ are assumed as continuous parameters so that $\rho_{ij}\epsilon[0,1]$ and $\varphi_{ij}\epsilon[0,1]$. After solving our problem, $\rho_{ij}$ and $\varphi_{ij}$ are matched to discrete space again. As a result, the optimization problem can be reformulated as follows:

$$\min_{\rho_{ij},\varphi_{ij},\tau_i,\varepsilon_i} \; E_T = \sum_{i=1}^{K}\sum_{j=1}^{M} \rho_{ij}\left[L\tau_i P_s + E_{t,dj}\right] + \varphi_{ij}(T_f - \tau_i)P_{tij} \tag{17}$$

$$\textbf{s.t.} \quad P_{d_i} \geq \beta \quad \forall\, i\epsilon\mathcal{K} \tag{17.a}$$

$$\textstyle\sum_{j=1}^{M} \rho_{ij} \leq M_i \quad \forall\, i\epsilon\mathcal{K} \tag{17.b}$$

$$C \geq C_{th} \tag{17.c}$$

$$\textstyle\sum_{i=1}^{K} \rho_{ij} \leq 1 \quad \forall\, j\epsilon\mathcal{M} \tag{17.d}$$

$$\textstyle\sum_{j=1}^{M} \varphi_{ij} \leq 1 \quad \forall\, i\epsilon\mathcal{K} \tag{17.e}$$

$$\rho_{ij}\varphi_{ij} = 0 \quad \forall\, i\epsilon\mathcal{K}, j\epsilon\mathcal{M} \tag{17.f}$$

$$\rho_{ij}\epsilon[0,1] \quad \forall\, i\epsilon\mathcal{K}, j\epsilon\mathcal{M} \tag{17.g}$$

$$\varphi_{ij}\epsilon[0,1] \quad \forall\, i\epsilon\mathcal{K}, j\epsilon\mathcal{M} \tag{17.h}$$

where $P_s$ is the sensing power of the SUs assumed to be the same for all SUs. $P_{tij}$ represents the power for transmitting the data of $j$th SU on $i$th sub-channel. The above problem is not a standard convex optimization problem. However, the convex optimization approach can be employed to achieve a local solution instead of a global. For this purpose, the convex method based on the Lagrangian multiplier is used to solve the problem. We use Karush–Kuhn–Tucker (KKT) conditions to prioritize the SUs for SS and data transmitting in each sub-channel. Thus, the Lagrangian function is given by:

$$\begin{aligned} L\left(\varphi_{ij},\rho_{ij},\zeta,\Upsilon,\phi_i,\psi_i,\chi_i,\omega_j\right) = {} & \sum_{i=1}^{K}\sum_{j=1}^{M} \rho_{ij}\left[L\tau_i P_s + E_{t,dj}\right] + \varphi_{ij}\left(T_f - \tau_i\right)P_{tij} + \\ & \zeta(C_{th} - C) + \sum_{i=1}^{K} \phi_i\left(\beta - P_{d_i}\right) + \Upsilon\rho_{ij}\varphi_{ij} + \\ & \sum_{i=1}^{K} \psi_i\left(\sum_{j=1}^{M} \rho_{ij} - M_i\right) + \sum_{i=1}^{K} \chi_i\left(\sum_{j=1}^{M} \varphi_{ij} - 1\right) + \sum_{j=1}^{M} \omega_j\left(\sum_{i=1}^{K} \rho_{ij} - 1\right) \end{aligned} \tag{18}$$

where $\zeta$, $\Upsilon$, $\phi_i$, $\psi_i$, $\chi_i$ and $\omega_j$ represent the Lagrangian multipliers. Therefore, we have:

$$\frac{\partial L}{\partial \rho_{ij}} = L\tau_i P_s + E_{t,dj} - \phi_i \left(P_{d_{ij}}\right)\prod_{n\neq j}\left(1 - \rho_{in}P_{d_{in}}\right) + \psi_i + \omega_j = 0 \tag{19}$$

$\forall i\epsilon\mathcal{K}$ and $\forall j\epsilon\mathcal{M}$

$$\frac{\partial L}{\partial \varphi_{ij}} = (T_f - \tau_i)P_{tij} - \zeta \frac{T_f - \tau_i}{T_f}\Big[P\big(H_{0,i}\big)\Big(1 - P_{f_i}(\tau_i, \varepsilon_i)\Big) \log\big(1 + (SNR)_{ij}\big) + P\big(H_{1,i}\big)\Big(1 - P_{d_i}(\tau_i, \varepsilon_i)\Big) \log\big(1 + (SINR)_{ij}\big)\Big] + \chi_i = 0 \quad (20)$$

For notation simplicity, we assume that $C_{ij}^{0} = P\big(H_{0,i}\big)\log\big(1 + (SNR)_{ij}\big)$ and $C_{ij}^{0} = P\big(H_{0,i}\big)\log\big(1 + (SNR)_{ij}\big)$. Therefore, we rewrite Equation (20) as:

$$\frac{\partial L}{\partial \varphi_{ij}} = (T_f - \tau_i)P_{tij} - \zeta \frac{T_f - \tau_i}{T_f}(\Big(1 - P_{f_i}(\tau_i, \varepsilon_i)\Big) C_{ij}^{0} + \Big(1 - P_{d_i}(\tau_i, \varepsilon_i)\Big) C_{ij}^{1}) + \chi_i = 0 \quad (21)$$

The goal is to prioritize the selection of the SUs as sensing or data transmitting in each sub-channel. Thus, the quantity of $\rho_{ij}$s and $\varphi_{ij}$s for the $i$th sub-channel is not essential. Instead, we compare the ratio of $\rho_{ij}/\rho_{ik}$ for any pair of SUs. As a result, the SUs are prioritized for sensing and data transmitting on $i$th sub-channel by using the cost functions Equations (22) and (23) in which the SUs with smaller cost functions are selected as sensing and transmitting SUs, respectively.

$$\mathrm{cost}(i,j) = L\tau_i P_s + E_{t,d_j} - \phi_i\left(P_{d_{ij}}\right) + \psi_i + \omega_j \quad (22)$$

We assume $\psi_i$ and $\omega_j$ are identical for all SUs in all sub-channels. Therefore,

$$\mathrm{cost}(i,j) = L\tau_i P_s + E_{t,d_j} - \phi_i\left(P_{d_{ij}}\right) \quad (23)$$

and for data transmitting SUs, we have:

$$\mathrm{cost}(i,j) = E_{td_{ij}} - \zeta \frac{T_f - \tau_i}{T_f}(C_{ij}^{0} \prod_{j=1}^{M}\Big(1 - \rho_{ij}P_{f_j}\Big) + C_{ij}^{1} \prod_{j=1}^{M}\Big(1 - \rho_{ij}P_{d_j}\Big)) \quad (24)$$

We use the complimentary slackness conditions to specify the optimum Lagrangian multipliers as follows:

$$\sum_{i=1}^{K} \phi_i\,(P_{d_i} - \beta) = 0 \rightarrow \begin{cases} \phi_i = 0\,, P_{d_i} > \beta & (25\text{-}1) \\ \text{or} & \\ \phi_i \neq 0\,, P_{d_i} = \beta & (25\text{-}2) \end{cases}$$

$$\sum_{i=1}^{K} \psi_i\big(\sum_{j=1}^{M} \rho_{ij} - M_i\big) = 0 \rightarrow \begin{cases} \psi_i = 0\,, \sum_{j=1}^{M} \rho_{ij} < M_i & (25\text{-}3) \\ \text{or} & \\ \psi_i \neq 0\,, \sum_{j=1}^{M} \rho_{ij} = M_i & (25\text{-}4) \end{cases}$$

$$\zeta(C - C_{th}) = 0 \rightarrow \begin{cases} \zeta = 0\,, C > C_{th} & (25\text{-}5) \\ \text{or} & \\ \zeta \neq 0\,, C = C_{th} & (25\text{-}6) \end{cases}$$

$$\sum_{i=1}^{K} \chi_i\big(\sum_{j=1}^{M} \varphi_{ij} - 1\big) = 0 \rightarrow \begin{cases} \chi_i = 0, \sum_{j=1}^{M} \varphi_{ij} \neq 1) & (25\text{-}7) \\ \text{or} & \\ \chi_i \neq 0, \sum_{j=1}^{M} \varphi_{ij} = 1) & (25\text{-}8) \end{cases}$$

$$\sum_{j=1}^{N} \omega_j\big(\sum_{i=1}^{K} \rho_{ij} - 1\big) = 0 \rightarrow \begin{cases} \omega_j = 0, \sum_{i=1}^{K} \rho_{ij} < 1 & (25\text{-}9) \\ \text{or} & \\ \omega_j \neq 0, \sum_{i=1}^{K} \rho_{ij} = 1 & (25\text{-}10) \end{cases}$$

$$\Upsilon \rho_{ij}\varphi_{ij} = 0 \rightarrow \begin{cases} \Upsilon = 0, \rho_{ij}\varphi_{ij} \neq 0 & (25\text{-}11) \\ \text{or} & \\ \Upsilon \neq 0, \rho_{ij}\varphi_{ij} = 0 & (25\text{-}12) \end{cases}$$

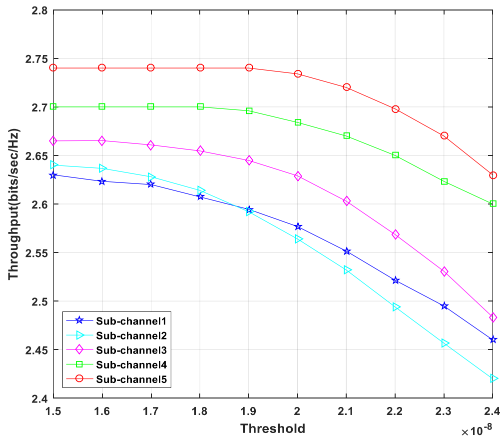
We note that $P_{d_i}$, $P_{f_i}$, and $E_T$ are the increasing functions of $\rho_{ij}s$ for the $i$th sub-channel. Therefore, we can decrease $\rho_{ij}$ so that $P_{d_i} = \beta$ is satisfied for $i$th sub-channel. As a result, we can achieve smaller $P_{f_i}$ and $E_T$. Therefore, $\phi_i \neq 0$ is considered a true condition. If the detection performance on $i$th sub-channel is satisfied by less sensing SUs, condition (25-3) will be optimal otherwise, (25-4) will be true. In other words, conditions (25-3) and (25-4) determine the maximum number of sensing SUs in each sub-channel. We consider $C = C_{th}$ as the optimal condition because $E_T$ is an increasing function of $\rho_{ij}$s. Therefore, we can achieve less energy consumption when $\rho_{ij}$s decreases while satisfying the constraint on the minimum required throughput. Since the SUs cannot use more than one channel for transmitting their data and thus condition (25-8) is considered optimum. Conditions (25-9) and (25-10) indicate that the SUs can sense up to one sub-channel in the sensing duration. The last condition expresses that the data transmitting and sensing cannot be performed by one SU, simultaneously, so $\rho_{ij}\varphi_{ij} = 0$ is a true condition. To achieve the optimum SS time and detection threshold in each sub-channel and selecte the suitable SSUs and TSUs, an iterative algorithm as shown in the following flow chart, based on the bisection method [37] called STDTST, is proposed. First, we determine the priority of the sub-channels by computing the average SNR of the SUs over each sub-channel and sorting them in ascending order. Then, we select the sub-channels having the highest priority, $i = 0$. In the next step, $P_d$ and $P_f$ are computed for all SUs in $i$th sub-channel. At each iteration in which $\phi$, $\zeta$, $\tau$, and $\varepsilon$ are updated by the bisection algorithm, the cost function in Equation (23) for all SUs over selected sub-channel is computed and sorted in ascending order, then the SUs with the lowest cost are considered to be participate in SS until the global $P_{d_i} \geq \beta$ on the $i$th sub-channel is met, and the maximum number of selected SUs on $i$th sub-channel becomes less than $M_i$. Then, the cost function (24) is calculated for the remaining SUs on $i$th sub-channel and sorted in ascending order. We select the SUs having the lower cost for data transmitting on $i$th sub-channel while guaranteeing the required throughput. The values $\tau$, $\varepsilon$, $\phi$ and $\zeta$ are updated by using bisection search approach according to the following rule. If $P_{d_i} \geq \beta, \tau$ is decreased; otherwise is increased. As a result, we can achieve the optimum $\tau$ by this algorithm. The same approach is employed simultaneously to obtain the optimum $\zeta$, $\phi$. Now, for finding the optimum $\varepsilon$, we employ the same algorithm to the one used to obtain the optimum $\tau$. However, the difference lies in updating, where $\varepsilon$ increases if $P_{d_i} \geq \beta$ and vice versa. The condition for stopping the algorithm is that its accuracy becomes less than a small predetermined threshold. The complexity of our proposed algorithm to find the solutions is linear in the order of $O(MK)$, since, only the cost functions should be computed for all SUs over the sub-channel in each iteration which is much less than the computational complexity of the exhaustive search algorithm.

## 3. SIMULATION RESULTS

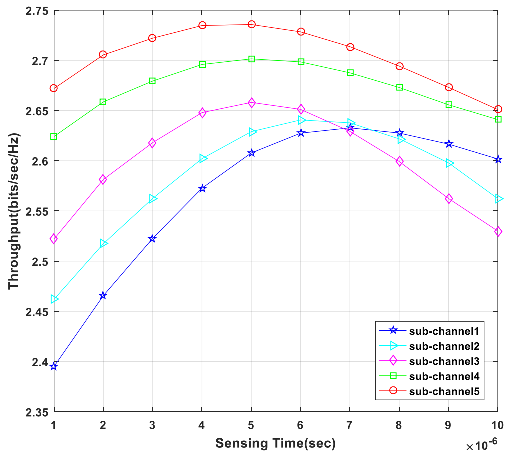
For simulations, we consider a cooperative CRN consisting of the SUs and PUs located randomly with a uniform distribution in the square area with a variable length between 100 m to 500 m in which FC is located in the center of the square. The 2.4 GHz IEEE 802.15.4/ZigBee is used as the communication technology in the network. We assume that the channel model from the PUs to the FC and each SU to the FC, is as Equation (1) [38]. We employed MATLAB 2015a for simulations and each point in the results is obtained by averaging over 10000 independent random experiments. The simulation parameters are listed in Table 1. Let us first analyze the optimality of average achievable throughput versus the sensing time and detection threshold over the five sub-channels, as shown in Figure 3. We would like to maximize the throughput over the five sub-channels.

**TABLE 1.** The simulation parameters

| Parameter | Value |
|---|---|
| The number of SU ($M$) | 50 ~500 |
| The number of PU ($K$) | 5 |
| The number of antenna ($L$) | 2 ~ 4 |
| $\alpha$ | 0.1 |
| $\beta$ | 0.9 |
| $f_c$ | 2.4 MHz |
| $P(H_0)$ | 0.6 |
| $P(H_1)$ | 0.4 |
| $T_f$ | 100 ms |
| $f_s$ | 1 MHz |
| $v$ | $3 \times 10^8$ m/s |
| $E_s$ | 190 nJ |
| $E_{t-elec}$ | 80 nJ |
| $e_{amp}$ | 40.4 pJ/m$^2$ |
| $p_P$ | 20 mW |
| $C_{th}$ | 10 bits/sec |
| Data rate | 250 Kb/s |
| Receiver sensitivity | -90 dBm |




(a)




(b)

**Figure 3.** The average throughput vs. (a) Detection threshold (b) Sensing times for different sub-channels when $K$ = 5, $M$ = 100 and $L$=2

It can be clearly seen that there is an optimal $\tau$ and $\varepsilon$ for each sub-channel that maximizes the throughput. The throughput for each sub-channel is low in very short sensing time because the detection performance is low, and therefore, $P_f$ is high while, in a long sensing time, the throughput is low because the data transmitting time is very short. Therefore, there is a tradeoff between the sensing time and throughput over each sub-channel. In Figure 4, the consumed energy in different sub-channels versus different sensing times and detection thresholds has been obtained. The energy consumption is high in small and large $\tau$ because, in small $\tau$ the more time is used for data transmitting, while in large $\tau$ more time is used for sensing. From Figures 3(a) and 4(a), we can also see that there are optimal detection thresholds for each sub-channel that maximizes the throughput and achieve the minimum energy consumption over each sub-channel.

The more significant thresholds achieve less throughput and more energy consumption.

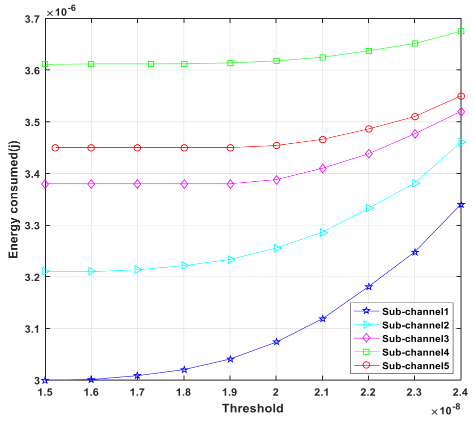
In Figure 5(b), $P_d$ in each sub-channel versus different sensing times is evaluated. We can see that increasing the sensing time leads to an increment in the global $P_d$ in each sub-channel until it reaches to 1. Therefore, the signal quality of the PUs can be sufficiently maintained. We also can see that $P_d$ for different sub-channels is almost identical and close to each other. That's due to the fact that the optimal selection of the SUs can compensate the low SNR or non-optimal sensing time or detection threshold for the different sub-channels. Although the average global $P_d$ constraint for all sub-channels is maintained, however according to Figure 4, it increases energy consumption. By decreasing the detection threshold, the global $P_d$ and $P_f$ for each sub-channel increase, and the desired detection performance is obtained by using fewer SUs. Therefore, the consumed energy over the sub-channels is reduced.

Table 2 shows the average SNR, optimal sensing times, and detection thresholds obtained with Algorithm 1 for each sub-channels when $K$ = 5, $M$ = 100 , and $L$=2. Since all $K$ sub-channels can be used by CR users for transmission, thus the objective is to achieve the minimum sum of the energy consumption, and improve the sum of the throughput of all sub-channels by optimizing the sensing times, detection thresholds and the selection of the SSUs and TSUs in all frequency bands.

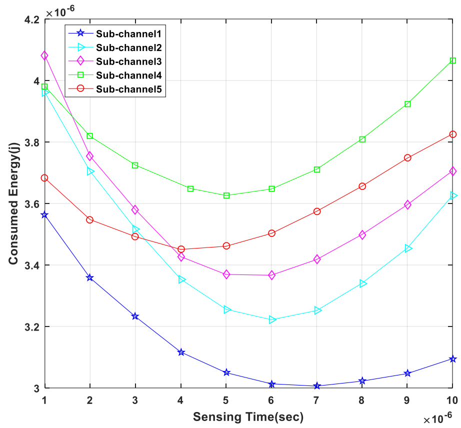
Note that in the multi-channel scenario, the global $P_d$ and $P_f$ requirements and the minimum required throughput of CRN in different sub-channels may differ.

**Algorithm 1.** The algorithm to find the optimum detection thresholds and sensing times and to select the SSUs and TSUs on each sub-channel for a multi-channel multi-antenna CRN.

**Initialization:**
$\tau_{max}$ = a large enough number
$\tau_{min} = 0$
$\varepsilon_{max}$ = a large enough number
$\varepsilon_{min} = 0$
$\zeta_{min} = 0$
$\zeta_{max}$ = a large enough number
$\phi_{min} = 0$
$\phi_{max}$ = a large enough number
$\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4$ are the small numbers
Compute average SNR of all SUs on all sub-channel
$i$=0 % index of sub-channel
Sort all $SNR_i$ in an ascending order so $SNR_0$ has maximum value
**WHILE** ($i < K$ % number of sub-channel) **do**
**WHILE** ($|\tau_{max} - \tau_{min}| > \epsilon_1$) **do**
$\tau_i = (\tau_{max} + \tau_{min})/2$
**WHILE** ($|\varepsilon_{max} - \varepsilon_{min}| > \epsilon_2$) **do**
$\varepsilon_i = (\varepsilon_{max} + \varepsilon_{min})/2$
Compute $P_{d_{ij}}$ and $P_{f_{ij}}$ for all SU
**WHILE** ($|\phi_{max} - \phi_{min}| > \epsilon_3$) **do**
$\phi_i = (\phi_{max} + \phi_{min})/2$
**WHILE** ($|\zeta_{max} - \zeta_{min}| > \epsilon_4$) **do**
$\zeta = (\zeta_{max} + \zeta_{min})/2$
Compute $\text{cost}(i,j) = L\tau_i P_s + E_{t,d_j} - \phi_i \left(P_{d_{ij}}\right)$ for all SUs
Sort cost functions (23) in an ascending order
$m$=0 % The number of SSUs with higher priority
Compute $M_i$ (maximum number of SU for sensing)
**WHILE** ($m < M_i$) **do**
Compute $P_{d_i} = 1 - \prod_{j=1}^{m}(1 - P_{d_{ij}})$
**IF** $P_{d_i} > \beta$ **THEN** **BREAK**
**ELSE** $m = m + 1$
**END IF**
**END WHILE**
Compute $E_T$ according to (15 )
$N_t = M - m$ % The remaining SUs which can be selected as TSU
Compute cost function (24) for all SUs
Sort cost functions (24) in an ascending order
$t = 0$ % The number of selected TSUs
**WHILE** ( $t < N_t$)
Compute $C$ % total throughput
**IF** $C \geq C_{th}$ **THEN** **BREAK**
**ELSE** $t = t + 1$
**END IF**
**END WHILE**
**IF** $P_{d_i} > \beta$ **THEN** $\zeta_{max} = \zeta$
**ELSE** $\zeta_{min} = \zeta$
**END IF**
**END WHILE**
**IF** $P_{d_i} > \beta$ **THEN** $\phi_{max} = \phi_i$
**ELSE** $\phi_{min} = \phi_i$
**END IF**
**END WHILE**
**IF** $P_{d_i} > \beta$ **THEN** $\varepsilon_{min} = \varepsilon$
**ELSE** $\varepsilon_{max} = \varepsilon$
**END IF**
**END WHILE**
**IF** $P_{d_i} > \beta$ **THEN** $\tau_{max} = \tau$
**ELSE** $\tau_{min} = \tau$
**END IF**
**END WHILE**
$i = i + 1$
**END WHILE**
**Output:** The optimal $\tau$ , $\varepsilon$ , TSUs, SSUs for each sub-channel and optimum energy efficiency and throughput

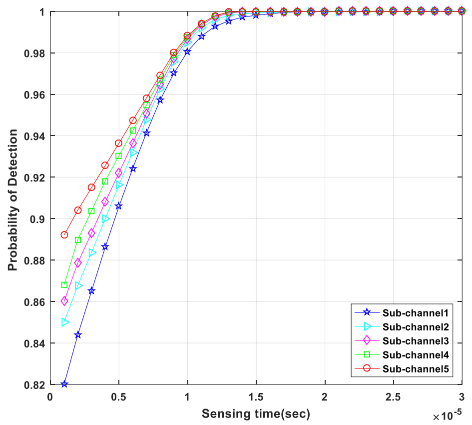



(a)




(b)

**Figure 4.** The consumed energy vs. (a) Detection threshold (b) Sensing times for different sub-channels

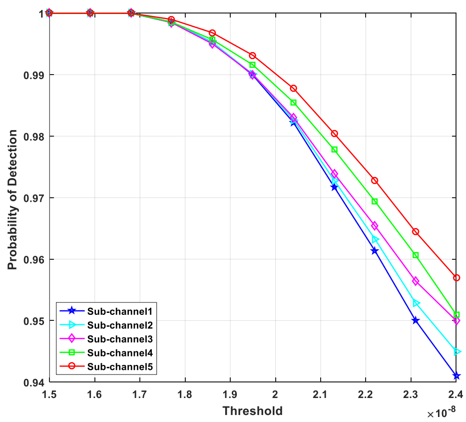



(b)

**Figure 5.** The probability of detection vs. (a) Detection thresholds and (b) Sensing times in each sub-channel

However, we consider the sum of the throughput over all sub-channels. Now, we compare the proposed algorithm with the following schemes in the simulations.

1. Joint optimization scheme of the Sensing Time and Detection Threshold and selection of SSUs and TSUs called STDTTS: This scheme is similar to STDTST, the difference is that the TSUs over each sub-channel are selected based on Equation (24) so that the energy consumption and the throughput constraints are satisfied then, according to Equation (23) the SSUs over each sub-channel are determined while satisfying the constraints on the maximum number of SSUs and $P_{d_i}$.
2. Random Selection of the SUs scheme (RSMA): In this algorithm, TSUs and SSUs are randomly selected over each sub-channel until the constraints on the $P_{d_i}$ is satisfied. In this approach, none of the sensing times and detection thresholds for sub-channels are optimized.




(a)

**TABLE 2.** Average SNR, optimal sensing times and detection thresholds for a multi antenna multi-channel CR network with 5 sub-channels, 100 SUs with 2 antennas

| Sub-Channel | Average SNR | Optimum sensing time (s) | Optimum threshold |
|---|---|---|---|
| Sub-channel1 | 6.4134 | 0.7116e-5 | 0.1524e-7 |
| Sub-channel2 | 6.5876 | 0.6153e-5 | 0.1587e-7 |
| Sub-channel3 | 6.6943 | 0.5059e-5 | 0.1623e-7 |
| Sub-channel4 | 7.5441 | 0.4960e-5 | 0.1788e-7 |
| Sub-channel5 | 7.7238 | 0.4235e-5 | 0.1865e-7 |

3. Joint optimization scheme of the Detection Threshold, the selection of SSUs and TSUs (DTST): The SSUs and TSUs are selected similar to the STDTST algorithm while the sensing times are considered the same and predetermined for all sub-channels.
4. Joint optimization scheme of the Sensing Time and the selection of SSUs and TSUs (STST): In this method, after determining the priority of sub-channels based on their average SNR for each sub-channel, the cost function in Equation (23) is computed and sorted in ascending order. Then, the SUs with the lowest cost is considered to participate in SS until the global $P_{d_i} \geq \beta$ on the $i$th sub-channel is met, and the constraint on the maximum number of selected SSUs is satisfied. After that, from the remaining SUs, the SUs with the lowest cost in Equation (24) are selected for data transmitting so that the minimum required total throughput is satisfied. The values of the sensing times are updated for each sub-channel by using the following rule: If the $P_{d_i} \geq \beta$, the sensing time will decrease otherwise, it will increase. This algorithm

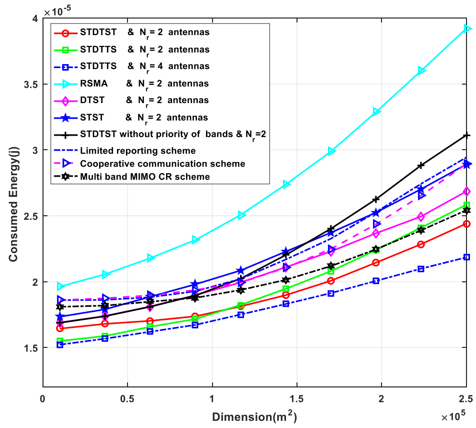
allocates equal detection thresholds to all sub-channels.

5. STDTST without priority of bands: This scheme is similar to STDTST the difference is that the prioritization of sub-channels is not performed.
6. The limited reporting scheme [22].
7. The cooperative communication scheme between CRN and the primary network [24].
8. The presented multi-band MIMO CR scheme reported by Moghimi et al. [26].

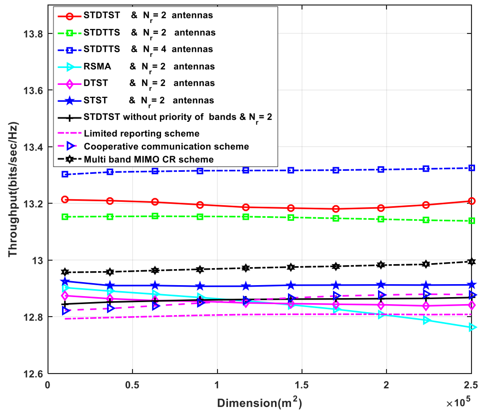
We consider a CRN with 5 PUs and 100 SUs equipped with 2 or 4 antennas. The detection threshold levels and the sensing times are set according to Table 2 for each sub-channel. The total throughput threshold is fixed at 10. The sampling time ratio and the reporting time ratio for the limited reporting scheme are set to 0.15e$^{-4}$ and 0.4e$^{-4}$, respectively. We consider a multi-band 4 x 4 MIMO CR system for the presented scheme by Moghimi et al. [26]. In Figure 6, the average throughput and consumed energy of all the schemes are compared in different dimensions of the network. It can be seen that all algorithms satisfy the constraint on the minimum required throughput in different dimensions. It is clear that in large dimensions, the difference between the throughput of STDTTS with 4 antennas and other algorithms becomes greater, which is due to the enhancement of the diversity gain. It can be seen that the prioritization of sub-channels leads to the increment of throughput and reduction of the energy consumption of CRN, especially in large dimensions. Moreover, because of the random selection of the SSUs and TSUs over each sub-channel, RSMA scheme has more energy consumption and less throughput in comparison to other schemes.

Figure 7 indicates $P_d$ of different algorithms for the first sub-channel with the lowest SNR in different dimensions when the number of the SU is $M$=100 and the detection threshold for STST and RSMA algorithms is fixed to 0.18e$^{-7}$. The sensing time for DTST and RSMA algorithms is set to 0.7e$^{-5}$. The detection threshold and the sensing times for STDTST and STDTTS schemes are set according to Table 1. It can be seen that increasing the dimension of the network decreases the $P_d$ for all schemes because the network obtains higher chances to distribute more SUs far from the PUs. However, the minimum required $P_d$ constraint for all algorithms, $P_{d_1} \geq \beta$ , is satisfied. We can also see that selecting the non-optimal detection threshold for the first sub-channel would have a very negative effect on detection performance.

In Figure 8, we investigate the impact of the number of SUs on the total throughput and energy consumption of CRN when the dimensions of the network are set to 100 m x 100 m. We can see STDTTS with 4 antennas has more throughput and less energy consumption than other schemes. We also see that, compared with STDTTS




(a)




(b)

**Figure 6.** The impact of the dimension of the network on the (a) Consumed energy (b) Total throughput of CRN

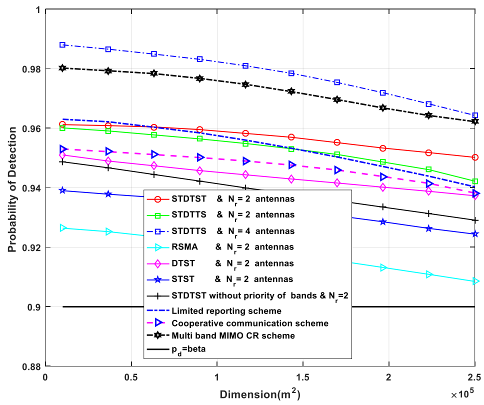
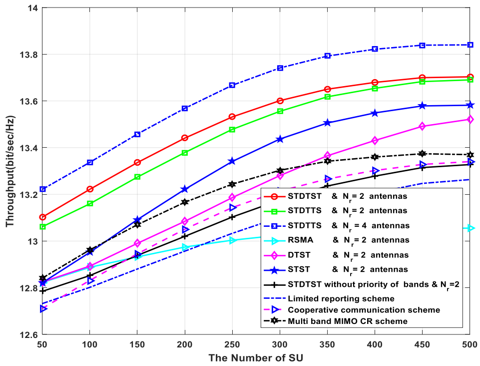
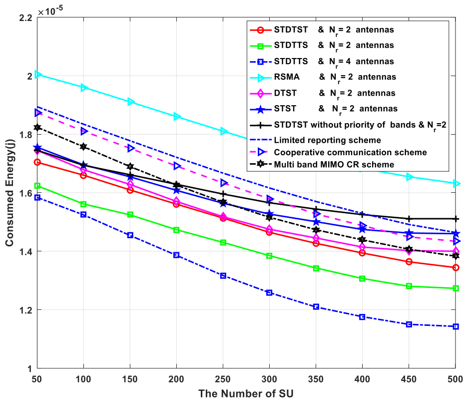



**Figure 7.** $P_d$ versus dimension of the network for first sub-channel

with 2 antennas, the 4 x 4 multi-band MIMO CR approach achieve more throughput. Figure 9 depicts $P_d$ versus the number of SUs for different algorithms in




(a)




(b)

**Figure 8.** (a) The total throughput (b) Energy consumption of CRN vs the number of the SU

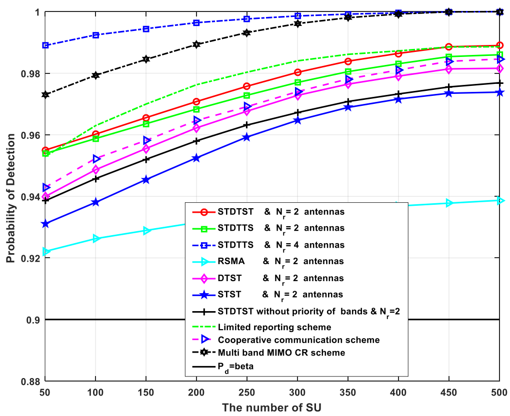


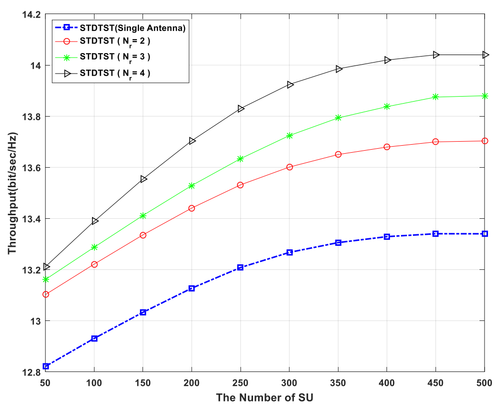

**Figure 9.** The impact of the number of the SU on $P_d$ in first sub-channel

the first sub-channel. It can be observed that the $P_d$ of all schemes increases by increasing the number of SUs until reaches to the maximum value.Thus, when the number of the SUs is large enough, it has little effect on the detection performance. Considering Figure 8 and the results illustrated in Figure 9, it can be concluded that the increment of the number of antennas increases $P_d$ especially when the dimensions are small. For example, when the dimensions of the network are 100 m x 100 m and the desired $P_d$ for the first sub-channel using the STDTTS scheme is considered as 0.99, at least 250 SUs with 2 antennas must be distributed in the network while the above detection performance can be satisfied by 80 SUs with 4 antennas. We can also see that the STDTTS scheme can achieve approximately 13.4 bits/s/Hz total throughput by 125 SUs with 4 antennas or 205 SUs with 2 antennas in 100 m x 100 m network dimensions. Therefore, when the minimum total throughput can be achieved by SUs having the fewer numbers of antenna, it is more appropriate to exclude employing more antennas since it will be useless and has more cost. However, it is possible to consume more energy because the more SUs must be applied to achieve the minimum required total throughput.

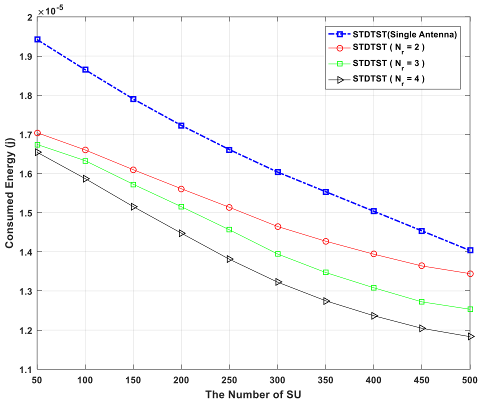
A a result, the final decision about the number of antennas should be obtained based on the tradeoff between implementation cost and consumed energy.

In Figure 10, the impact of the number of SUs having different numbers of antenna on the total throughput and consumed energy is evaluated when the STDTST algorithm is used. The SUs with 1, 2, 3 ,and 4 antennas are considered ,while the dimensions of the network are 100 m x 100 m. From Figure 10(b), we can see that the STDTST with more antennas consumes less energy than other cases. Therefore, the number of antenna used for the STDTST scheme depends on the difference in the implementation cost and complexity between adding antennas and adding SUs with less antennas for energy saving.

Finally, the convergence of the STDTST algorithm is analyzed in Figure 11, when $M$=100, $K$=5, $L$=2 and the dimensions of the network are 100 m x 100 m. The energy consumption decreases in each iteration and converges to a fixed and minimum point in the 69th iteration.




(a)




(b)

**Fugure 10.** (a) The joint influence of the number of the SU and number of antennas on the (a) throughput (b) energy consumption

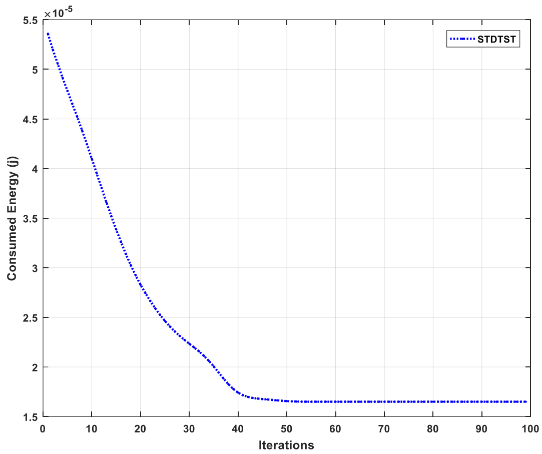



**Figure 11.** The convergence performance of STDTST algorithm for different iterations

**3. 1. Results Analysis** In Figures 3(a), 4(a) and 5(a) we investigated the impact of detection threshold on the average throughput, energy consumption and probability of detection for different sub-channels in the multi-antenna multi-channel CR network, resectively. It can be seen that when the threshold is less than a unique optimal value the average throughput can attain almost the maximum and constant value for each sub-channel while more threshold leads to less throughput. Figure 4(a) shows that as the threshold increases, the energy consumption increases.That's due to the fact that as the threshold increases, the probability of detection for each SU in each sub-channel decreases and the selection of more SUs is required to satisfy detection performances. Figures 3(b), 4(b) and 5(b) show the influence of the sensing time on the throughput, energy consumption and probability of detection for different sub-channels, respectively. We can see, the probability of detection increases with the increasing of the sensing time until it reaches to 1. In Figure 3(b), the achievable throughput for each sub-channel is less at a small or large sensing time, that's due to the fact that the small sensing time decreases the detection performance, whereas large sensing time reduces the data transmitting time and therefore, we see the tradeoff between the sensing time and achievable throughput of the CR network.

Form Figure 4(b), we can clearly see that there exist an optimal sensing time for minimizing the energy consumption over the five sub-channels. It can be seen that at the unique optimal sensing times for each subchannel, the energy consumption can attain almost the minimum value, while the more or less sensing times leads to more energy consumption because it gets more times for sensing and data transmitting, respectively.

Therefore, according to Figures 3 to 5, the minimum threshold and sensing time should be achieved, such that the throughput of the secondary network is maximized and the total energy consumption is minimized, while detection constraints can be satisfied. Thus, We see that $P_{d_j}$ increase by increasing the time sensing and by decreasing the threshold. As a result, the fewer number of SUs participating in the spectrum sensing is required to satisfy the detection constrains and reduce the total energy consumption. Figure 6 shows the influence of dimensions of the network on the throughput and energy consumption of all the schemes. As can be observed, all schemes maintain the throughput threshold constraint for all dimensions. It can be seen when the dimension increases the more energy is consumed because the detection performance will be decreased by increasing the length of network as shown in Figure 7. Therefore, it should be selected more SUs for satisfying the detection performance and transmitting their data to the FC to satisfy the constraint (17.c). When the dimension of the network is small, the SUs will have a high density in the area. Therefore, the constraint on the detection performance can be satisfied by selecting less SUs. In addition, by increasing the dimension of the network the average distance from the PUs to the SUs and from the SUs to the FC increases. Thus, it consumes more energy to guarantee the minimum sensitivity of the receivers.

The influence of the number of SUs on the total throughput, energy consumption, and probability of detection of all the schemes is shown in Figures 8 and 9. We see that the average throughput increases monotonically by increasing the number of SUs, however it grows slowly when the quantity of SU is large until it reaches to the maximum value and then is fixed. It can be clearly seen from Figure 8(b) that the total consumed energy of CRN decreases with the increasing number of SUs. This can be expressed by the fact that as the number of SUs increases, there will be a greater chance for more SSUs or TSUs be near the PUs or FC. Therefore, the total throughput and $P_d$ increase while the located SUs near to FC leads to less energy consumption. It is also shown that the throughput enhances by increasing the number of antenna because of the enhancement of the diversity gain.

The impact of changing the number of antenna on the total throughput and consumed energy of STDTST scheme is shown in Figure 10. It can be observed that the multi-antennas strategy outperforms the one using single antenna. We analyzed the convergence of proposed algorithm in Figure 11. We can see that the algorithm correctly converges to the minimum value after several iterations.

## 4. FUTURE PROSPECT OF THE PROPOSED APPROACH

We anticipate that CR technology will soon emerge from early-stage laboratory trials and vertical applications to become a general-purpose programmable radio that will serve as a universal platform for wireless system development, much like microprocessors fulfill that role for computation. The evolution of CR toward CR networks is underway; the concept of CR networks is to intelligently organize a network of CRs. Applications of spectrum-sensing CR include emergency-network and WLAN higher throughput and transmission-distance extensions. The CR technology will be used commercially in the 5G and 6G cellular networks. 6G networks will be able to use higher end of the radio spectrum than 5G networks and provide substantially higher capacity and much lower latency. While reliable spectrum sensing techniques are pivotal, the CRN's throughput, energy efficiency ,and channel maintenance are important considerations for the SUs. This has primarily motivated the employment of multi-channel multi-antenna CR paradigm. Multi-antenna SUs to sense and access multiple channels, simultaneously promised significant enhancements to the network's throughput and energy efficiency. In addition, it provids seamless handoff from band to band, which improves the link maintenance and Quality of Service (QoS) and reduces data transmission interruptions.

Moreover, cooperative networks were analyzed, and a possible extension to integrate such a powerful paradigm into multi-channel CRN was suggested. Particularly, cooperative multi-channel CR provided a desirable compromise between spatial diversity and sampling complexity. In addition, some of the most common performance measures that help evaluate the network's performance in terms of spectrum reliability and network's throughput have been presented.

However, there are fundamental limits and tradeoffs among several critical design parameters in multi-channel multi-antenna CRNs that must be carefully investigated. The most common considerations are the sensing time, detection threshold, network throughput, data combination methods, detection reliability, number of cooperating SUs, power control, and channel assignment. Some of these cases, such as sensing time, and detection threshold were discussed in this paper. The rest will be explained in the following.

1. One of the key issues in cooperative communications is how to combine the collected information from the participating SUs. There are three main techniques, namely: hard combining, soft combining, and hybrid combining. 1) Hard Combining: In this technique, the SU merely sends its final one-bit decision to the other SUs. In this technique, the SU shares its original sensing information (or original statistics) with the other SUs without locally processing them. Hard combining requires less overhead compared to soft combining. However, since the statistics at each SU are reduced to one bit, there is an information loss that propagates to the other SUs. Therefore, the final decision is less reliable compared to soft combing. The soft combination techniques such as MRC, EGC, OC, SC, SLS, SLC, and hard combination methods consist of AND, OR and MAJORITY for CRs with and without multiple antenna. Therefore, the selection of the optimal combination technique is essential, which was not discussed in this paper, and it can be considered as an effective research case in future works when it is added to the proposed model of this paper.
2. Optimum power allocation is vital for improving the network's throughput and protecting PUs. It becomes even more important when the underlay scheme is used, since power adaptation becomes necessary. Therefore, our future works include adding transmit power and interference bounds as constraint functions.
3. While increasing the number of cooperating SUs improves the reliability of detection and reduces sensing time, it incurs a long delay due to the time required to collect the information from all the SUs. To tackle this issue, the SUs can simultaneously send their decisions on orthogonal frequency bands, yet this requires larger bandwidth. Thus, an effective scheme should be proposed to obtain the minimum number of SUs to maintain the desired performance, which was not considered in this paper, and can be investigated in future works.
4. One can presume that accessing all available bands would theoretically increase the throughput. However, when a SU accesses all these bands, there is a higher probability that a PU returns to at least one of them. Thus handoff becomes necessary, which consequently increases the network's overhead. Therefore, optimizing the number of sub-channels for spectrum access becomes essential. To

guarantee that each SU picks the best channels, frequent channel reselections become inevitable, and hence high overhead is incurred. To reduce the overhead, a proper approach is required where the SU selects a channel as long as it can support the least possible transmission rate. Otherwise, an alternative channel is randomly selected. This algorithm has a lower throughput, yet it reduces the frequency of channels' reselections. The future work advises using of adaptive bandwidth selection for the proposed multi-channel multi-antenna CRN to further maximize the network's throughput.

5. Recently, energy harvesting (EH) from ambient radio frequency (RF) signal sources has been proposed as a promising solution to address the energy shortage problem. In an Energy Harvesting Cognitive Radio (EHCR) network, a CR transmitter collects energy from RF signals by EH when a PU is present in the channel and employs it for data transmission when the spectrum is idle. Therefore, the SU should search for not only a vacant channel of PUs for its data transmission, but also an occupied channel for EH. In future works, we can use an energy harvesting-based multi-channel multi-antenna CR network to execute cooperative SS, data transmission, and RF energy harvesting by a secondary transmitter from PU's signal and the ambient noise, simultaneously.

## 5. CONCLUSION

In this paper, we studied the problem of designing the optimal sensing times and detection thresholds in each sub-channel and selecting the multi-antenna SSUs and TSUs in the multi-channel multi-antenna CRNs for improvement of both throughput and energy efficiency so that the constraints on the global $P_d$ and $P_f$ in each sub-channel are satisfied. Our problem formulated, and the priority of SUs for sensing and data transmitting in each sub-channel determined. We proposed the algorithm having less computational complexity than baseline approaches to achieve the optimal parameters and goals of the problem. Furthermore, simulation results have shown that the proposed structures and algorithms can consistently achieve an improvement on the throughput and energy consumption in comparison to the structures using the same sensing times or thresholds in all sub-channels or schemes in which all single-antenna SUs have participated in spectrum sensing and data transmitting on all sub-channels.

## 5. REFERENCES


1. Mergu, K. and 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***, Vol. 34, No. 6, (2021), 1468-1474. https://doi.org/10.5829/IJE.2021.34.06C.10
2. Asif, H.M., "F.: Spectrum sensing challenges & their solutions in cognitive radio based vehicular networks int", ***J. Commun. Syst.(02)***, (2021), 23-25. https://doi.org/10.1002/dac.4748
3. Zhao, H., Tan, Y., Pan, G., Chen, Y. and Yang, N., "Secrecy outage on transmit antenna selection/maximal ratio combining in mimo cognitive radio networks", ***IEEE Transactions on Vehicular Technology***, Vol. 65, No. 12, (2016), 10236-10242. https://doi.org/10.1109/TVT.2016.2529704
4. Kishore, R., Gurugopinath, S., Muhaidat, S., Sofotasios, P.C., Dobre, O.A. and Al-Dhahir, N., "Sensing-throughput tradeoff for superior selective reporting-based spectrum sensing in energy harvesting hcrns", ***IEEE Transactions on Cognitive Communications and Networking***, Vol. 5, No. 2, (2019), 330-341. https://doi.org/10.1109/TCCN.2019.2906915
5. Sarala, B., Devi, S.R. and Sheela, J.J.J., "Spectrum energy detection in cognitive radio networks based on a novel adaptive threshold energy detection method", ***Computer Communications***, Vol. 152, (2020), 1-7. https://doi.org/10.1016/j.comcom.2019.12.058
6. Jiang, H., Yu, Z., Yang, J. and Kang, K., "Throughput-oriented full-duplex cognitive radio network parameter optimization", ***International Journal of Antennas and Propagation***, Vol. 2022, (2022), 1-8. https://doi.org/10.1155/2022/4056645
7. Ahmed, A., Mishra, D., Prasad, G. and Baishnab, K.L., "Cognitive radio timing protocol for interference-constrained throughput maximization", ***IEEE Transactions on Cognitive Communications and Networking***, Vol. 8, No. 2, (2021), 989-1004. https://doi.org/10.1155/2022/4056645
8. Kumar, A., Thakur, P., Pandit, S. and Singh, G., "Hsa-spc: Hybrid spectrum access with spectrum prediction and cooperation for performance enhancement of multiuser cognitive radio network", ***Computer Networks***, Vol. 203, (2022), 108596. https://doi.org/10.1016/j.comnet.2021.108596
9. Liu, X. and Tan, X., "Optimization algorithm of periodical cooperative spectrum sensing in cognitive radio", ***International Journal of Communication Systems***, Vol. 27, No. 5, (2014), 705-720. https://doi.org/10.1002/dac.2377
10. Sadeghian Kerdabadi, M., Ghazizadeh, R., Farrokhi, H. and Najimi, M., "Energy consumption minimization and throughput improvement in cognitive radio networks by joint optimization of detection threshold, sensing time and user selection", ***Wireless Networks***, Vol. 25, (2019), 2065-2079. https://doi.org/10.1007/s11276-018-1797-x
11. Liu, X., Xu, B., Wang, X., Zheng, K., Chi, K. and Tian, X., "Impacts of sensing energy and data availability on throughput of energy harvesting cognitive radio networks", ***IEEE Transactions on Vehicular Technology***, Vol. 72, No. 1, (2022), 747-759. https://doi.org/10.1109/TVT.2022.3204310
12. Das, D., Khadanga, R.K. and Rout, D.K., "A matching game framework for users clustering and resource allocation with wireless power transfer in a cr-noma network", ***International Journal of Communication Systems***, Vol. 36, No. 2, (2023), e5376. https://doi.org/10.1002/dac.5376
13. Bokobza, Y., Dabora, R. and Cohen, K., "Deep reinforcement learning for simultaneous sensing and channel access in cognitive networks", ***IEEE Transactions on Wireless Communications***, (2023). https://doi.org/10.1109/TWC.2022.3230872
14. Salari, S. and Chan, F., "Maximizing the sum-rate of secondary cognitive radio networks by jointly optimizing beamforming and energy harvesting time", ***IEEE Transactions on Vehicular Technology***, (2023). https://doi.org/10.1109/TVT.2023.3238347
15. Hameed, I., Camana, M.R., Tuan, P.V. and Koo, I., "Intelligent reflecting surfaces for sum-rate maximization in cognitive radio

enabled wireless powered communication network", ***IEEE Access***, Vol. 11, (2023), 16021-16031. https://doi.org/10.1109/ACCESS.2023.3243848

16. Singh, J.S.P., "Apc: Adaptive power control technique for multi-radio multi-channel cognitive radio networks", ***Wireless Personal Communications***, Vol. 122, No. 4, (2022), 3603-3632. https://doi.org/10.1007/s11277-021-09103-w
17. Gutierrez del Arroyo, J.A., Borghetti, B.J. and Temple, M.A., "Considerations for radio frequency fingerprinting across multiple frequency channels", ***Sensors***, Vol. 22, No. 6, (2022), 2111. https://doi.org/10.3390/s22062111
18. Huang, X.-L., Tang, X.-W. and Hu, F., "Dynamic spectrum access for multimedia transmission over multi-user, multi-channel cognitive radio networks", ***IEEE Transactions on Multimedia***, Vol. 22, No. 1, (2019), 201-214. https://doi.org/10.1109/TMM.2019.2925960
19. Tamaddondar, M. and Noori, N., "Hybrid massive mimo channel model based on edge detection of interacting objects and cluster concept", ***International Journal of Engineering, Transactions B: Applications***, Vol. 35, No. 2, (2022), 471-480. https://doi.org/10.5829/IJE.2022.35.02B.23
20. Thanh, P.D., Hoan, T.N.K. and Koo, I., "Joint resource allocation and transmission mode selection using a pomdp-based hybrid half-duplex/full-duplex scheme for secrecy rate maximization in multi-channel cognitive radio networks", ***IEEE Sensors Journal***, Vol. 20, No. 7, (2019), 3930-3945. https://doi.org/10.1109/JSEN.2019.2958966
21. Gharib, A., Ejaz, W. and Ibnkahla, M., "Enhanced multiband multiuser cooperative spectrum sensing for distributed crns", ***IEEE Transactions on Cognitive Communications and Networking***, Vol. 6, No. 1, (2019), 256-270. https://doi.org/10.1109/TCCN.2019.2953661
22. So, J. and Kwon, T., "Limited reporting-based cooperative spectrum sensing for multiband cognitive radio networks", ***AEU-International Journal of Electronics and Communications***, Vol. 70, No. 4, (2016), 386-397. https://doi.org/10.1016/j.aeue.2015.12.017
23. Alhamad, R., "Nonorthogonal multiple access with adaptive transmit power and energy harvesting using intelligent reflecting surfaces for cognitive radio networks", ***Signal, Image and Video Processing***, Vol. 17, No. 1, (2023), 83-89. https://doi.org/10.1007/s11760-022-02206-2
24. Liu, X., "A new sensing-throughput tradeoff scheme in cooperative multiband cognitive radio network", ***International Journal of Network Management***, Vol. 24, No. 3, (2014), 200-217. https://doi.org/10.1002/nem.1859
25. Contreras, A., "Objective functions for the optimization of an ultra wideband antenna", ***International Journal of Engineering, Transactions A: Basics***, Vol. 34, No. 7, (2021), 1743-1749. https://doi.org/10.5829/IJE.2021.34.07A.19
26. Moghimi, F., Mallik, R.K. and Schober, R., "Sensing time and power optimization in mimo cognitive radio networks", ***IEEE Transactions on Wireless Communications***, Vol. 11, No. 9, (2012), 3398-3408. https://doi.org/10.1109/TWC.2012.081312.112278
27. Liu, X., Jing, Q., Jia, Y., Zhong, W. and Guan, Y.L., "Sensing-throughput tradeoff for cooperative multiple-input single-output cognitive radio", ***International Journal of Communication Systems***, Vol. 28, No. 5, (2015), 848-860. https://doi.org/10.1002/dac.2709
28. Kumar, A., Pandit, S., Thakur, P. and Singh, G., "Optimization of fusion center parameters with threshold selection in multiple antenna and censoring-based cognitive radio network", ***IEEE Sensors Journal***, Vol. 22, No. 5, (2022), 4709-4721. https://doi.org/10.1109/JSEN.2022.3142197
29. Allu, R., Taghizadeh, O., Singh, S.K., Singh, K. and Li, C.-P., "Robust beamformer design in active ris-assisted multiuser mimo cognitive radio networks", ***IEEE Transactions on Cognitive Communications and Networking***, Vol. 9, No. 2, (2023), 398-413. https://doi.org/10.1109/TCCN.2023.3235788
30. Rauniyar, A. and Shin, S.Y., "Multiple antenna-aided cascaded energy and matched filter detector for cognitive radio networks", ***International Journal of Distributed Sensor Networks***, Vol. 11, No. 9, (2015), 175943. https://doi.org/10.1155/2015/175943
31. Ren, X. and Chen, C., "Spectrum sensing algorithm based on sample variance in multi-antenna cognitive radio systems", ***AEU-International Journal of Electronics and Communications***, Vol. 70, No. 12, (2016), 1601-1609. https://doi.org/10.1016/j.aeue.2016.09.013
32. Liu, X., Li, B. and Liu, G., "Simultaneous cooperative spectrum sensing and energy harvesting in multi-antenna cognitive radio", ***Mobile Networks and Applications***, Vol. 23, (2018), 263-271. https://doi.org/10.1007/s11036-017-0946-2
33. Vahedian, B. and Mahmoudi-Nasr, P., "Toward energy-efficient communication protocol in wban: A dynamic scheduling policy approach", ***International Journal of Engineering, Transactions A: Basics,*** Vol. 35, No. 1, (2022), 191-200. https://doi.org/10.5829/IJE.2022.35.01A.18
34. Ebrahimzadeh, A., Najimi, M., Andargoli, S.M.H. and Fallahi, A., "Sensor selection and optimal energy detection threshold for efficient cooperative spectrum sensing", ***IEEE Transactions on Vehicular Technology***, Vol. 64, No. 4, (2014), 1565-1577. https://doi.org/10.1109/TVT.2014.2331681
35. Song, Z., Zhang, Z., Liu, X., Liu, Y. and Fan, L., "Simultaneous cooperative spectrum sensing and wireless power transfer in multi-antenna cognitive radio", ***Physical Communication***, Vol. 29, (2018), 78-85. https://doi.org/10.1016/j.phycom.2018.04.022
36. Maleki, S., Pandharipande, A. and Leus, G., "Energy-efficient distributed spectrum sensing for cognitive sensor networks", ***IEEE Sensors Journal***, Vol. 11, No. 3, (2010), 565-573. https://doi.org/10.1109/JSEN.2010.2051327
37. Monemian, M., Mahdavi, M. and Omidi, M.J., "Optimum sensor selection based on energy constraints in cooperative spectrum sensing for cognitive radio sensor networks", ***IEEE Sensors Journal***, Vol. 16, No. 6, (2015), 1829-1841. https://doi.org/10.1109/JSEN.2015.2503324
38. Hojjati, S.H., Ebrahimzadeh, A., Najimi, M. and Reihanian, A., "Sensor selection for cooperative spectrum sensing in multiantenna sensor networks based on convex optimization and genetic algorithm", ***IEEE Sensors Journal***, Vol. 16, No. 10, (2016), 3486-3487. https://doi.org/10.1109/JSEN.2016.2535862

## Persian Abstract

**چکیده**

بهینه‌سازی مصرف انرژی و گذردهی در شبکه‌های رادیوشناختگر (CRN) دو موضوع مهمی است که در سال‌های اخیر توجه زیادی را به خود جلب کرده است. در این مقاله، بهینه‌سازی توام زمان‌های طیف‌سنجی و آستانه‌های آشکارساز انرژی در هر زیرکانال و انتخاب کاربران ثانویه چندآنتنه طیف‌سنج و ارسال‌کننده داده با هدف بیشینه‌سازی بازده انرژی و بهبود گذردهی در CRN چندآنتنه چندکاناله و تحت محدودیت احتمالات هشدار غلط و آشکارسازی در نظر گرفته می‌شود. مسئله تعریف شده مبتنی بر مدل پیشنهادی، بر اساس روش بهینه‌سازی محدب حل شده و الگوریتمی با پیچیدگی محاسباتی کمتر در مقایسه با رویکردهای مبنا پیشنهاد شده است. عملکرد طرح پیشنهادی با شبیه‌سازی‌ها ارزیابی و با سایر طرح‌ها مقایسه می‌شود. نتایج نشان می‌دهد که روش پیشنهادی می‌تواند به مصرف انرژی کمتری دست یابد در حالی که حداقل گذردهی مورد نیاز تضمین شده است.