ENERGY EFFICIENT COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

Ph.D. THESIS

by

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ABSTRACT

Cognitive or intelligent radio has emerged as a promising technology to ameliorate the spectrum utilization by exploiting the unused spectrum bands. Cognitive radio is proposed in literature as an intelligent wireless communication system that is aware of its surrounding environment. It allows unlicensed or secondary user, to utilize the vacant spectrum at any time with no or less interference to the licensed users. Generally, cognitive radio creates networks in order to better identify spectrum vacancies, avoid induced interference and accordingly, boost their revenue. One of the major challenge in cognitive radio communication, now a days, is high consumption of energy, resulting in limitation of implementation specifically in battery-powered devices.

The cognitive radio communication deals with three main steps such as spectrum sensing, allocation and reliable transmission. The initial step involves the detection of licensed user signals in order to determine the availability of a spectrum band for transmission. The spectrum sensing which deals with single primary and secondary node is known as single node spectrum sensing. It has been reported by previous studies that fading, shadowing and hidden node problem may affect the detection quality of single node sensing. It is therefore possible to improve the performance in such cases by employing multiuser diversity. In cooperative spectrum sensing (multiuser sensing), multiple secondary nodes work in collaboration with each other. The locally generated sensing results are exchanged in order to make a global decision regarding spectrum occupancy. However, due to overhead of multiple nodes, cooperative sensing consumes a significant amount of energy, which is a challenge for the cognitive users. Moreover, increasing number of sensing channels and periodicity of cooperative sensing further complicates the problem. Hence, energy efficiency in cooperative spectrum sensing have led to a proliferation of research in cognitive radio.

In this thesis, multiple energy efficiency maximization algorithms/schemes for cooperative spectrum sensing are proposed. There are three models of collaboration viz. centralized, distributed and hierarchical, here, we consider centralized model. The proposed work comprises of optimization of energy efficiency at local sensing, reporting and transmission stage. This includes the optimization of number of secondary users, sensing time and transmission time. The optimization is carried out in fading and non-fading environment and at different SNR levels. The performance of the proposed work is evaluated in terms of energy efficiency and detection accuracy.

The first objective of this dissertation is to optimize the sensing and transmission time to increase the bits transmitted per frame so as to achieve maximum energy efficiency for single cognitive radio. To maximize the energy efficiency a Sub Optimal Iterative Search Algorithm (SOISA) is proposed. This problem also considers the

interference occurred due to secondary user transmission to the primary user. The proposed algorithm shows the superiority in terms of complexity and high value of energy efficiency as compared to the other existing algorithms. The effects of change in sensing time, transmission time and transmission power on energy efficiency are shown by the simulation results.

Following this, the maximization of energy efficiency by optimizing the hard decision fusion in case of multiple users cooperative spectrum sensing is considered as another problem. A method to improve the energy efficiency by optimizing the number of secondary users is proposed and the results are compared in frequency selective fading and non fading environments. Three hard decision fusion rules viz. *OR* rule, *AND* rule, and *k-out-of-N* rule are compared with respect to energy efficiency and number of secondary users. It is clear after simulation that *k-out-of-N* rule outperforms others in term of energy efficiency and *Global probability-of-false-alarm*.

The above two problems optimized the sensing and transmission time and number of secondary users, separately. It is, however, possible to jointly optimize the above three parameters to achieve maximum energy efficiency in the cooperative spectrum sensing scenario. Therefore, joint optimization of sensing, transmission time and number of secondary users is proposed with the protection of primary user from secondary user transmission. In order to solve the problem, first the optimal expression for the number of secondary users is obtained and then an iterative sub optimal algorithm is proposed to achieve optimal sensing and transmission time. The effectiveness of this work is demonstrated by extensive simulation results and illustrations. Herein, comprehensive approaches for energy-efficiency maximization are proposed with different algorithms. The aim of these comprehensive approaches is to improve energy efficiency and provide consistency of the proposed algorithms. The simulation results reveal that the energy efficiency is achieved as high as 10.4957 bits/Hz/Joule, which is maximum as compared to other algorithms and methods.

The Non Orthogonal Multiple Access (NOMA) enabled cognitive radio technique will increase the application of cognitive radio into future 5 G systems. The NOMA enabled cognitive radio is proposed to improve the energy efficiency of single cognitive radio networks. Here, the energy efficiency maximization problem with down link NOMA technique is studied. A base station is assumed which is equipped with two antennas, one for primary user and another for secondary user. The energy efficiency maximization problem is formed as the ratio of maximum achievable sum rate and total power consumed. Further, the energy efficiency is maximized for the NOMA and compared with other existing conventional multiplexing techniques.

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(Meenakshi Awasthi)

To

my beloved family

List of Acronyms

ADM	Alternating Duration Method
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BS	Base Station
CDMA	Code Division Multiple Access
CMA	Conventional Multiple Access
CRN	Cognitive Radio Networks
CSS	Cooperative Spectrum Sensing
CU	Cognitive User
DSA	Dynamic Spectrum Access
EE	Energy Efficiency
FC	Fusion Center
FCC	Federal Communications Commission
FDMA	Frequency Division Multiple Access
GPD	Global Probability of Detection
GPFA	Global Probability of False Alarm
3Gpp	3Generation Partnership Project
IoT	Internet of Things
ISOA	Iterative Sub Optimal Algorithm
LTE	Long Term Evolution
MIMO	Multiple Input Multiple Output
NOMA	Non Orthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
PD	Probability of Detection
PDF	Probability Density Function
PFA	Probability of False Alarm
PU	Primary User
QAM	Quadrature Amplitude Modulation

QoS	Quality of Service
SE	Spectral Efficiency
SIC	Successive Interference Cancellation
SINR	Signal to Interference Noise Ratio
SOISA	Sub Optimal Iterative Search Algorithm
SNR	Signal to Noise Ratio
SU	Secondary User
TDMA	Time Division Multiple Access
WRANs	Wireless Regional Area Networks

Notation

N	Total number of sensing users
T	Time frame
t_s	Sensing time
t_t	Transmission time
P_t	Transmission power
P_s	Sensing power
P_r	Reporting power
P_{Int}	Interference probability to the primary user during the secondary user transmission
a_B	Mean values of busy period of primary user signal
a_I	Mean values of idle period of primary user signal
P_B	Probability of primary user busy channel state
P_I	Probability of primary user idle channel state
P_{fa}	Probability of false alarm
P_{de}	Probability of detection
P_{idle}	Perfect idle channel probability
E_t	Total energy consumed
R_0	Number of bits transmitted per unit time
R_t	Total throughput
ζ	Energy efficiency
α_q	Maximum interference level that occur in case of mis–detection, to the primary user by the transmission of secondary user
P_{de0}	Target probability of detection
Y	Primary user SNR due to secondary user data transmission
f_s	Sampling frequency
t_r	Reporting time
$H0$	Binary Hypotheses for primary user idle channel state
$H1$	Binary Hypotheses for primary user busy channel state
$y(m)$	Received signal
$z(m)$	Noise signal
J	Total number of samples or the sensing window size

ε	Sensing threshold
σ_x^2	Received primary user signal variance
σ_m^2	Noise variance
G_{de}^{OR}	Global probability-of-detection for OR rule
G_{fa}^{OR}	Global probability-of-false alarm for OR rule
G_{de}^{AND}	Global probability-of-detection for AND rule
G_{fa}^{AND}	Global probability-of-false alarm for AND rule
G_{de}^{koN}	Global probability-of-detection for k-out-of-N rule
G_{fa}^{koN}	Global probability-of-false alarm for k-out-of-N rule
Y_{SU}	Signal to noise ratio of secondary user
Γ	SNR gap
B	Channel bandwidth
P_{ber}	Bit error rate
$N_0/2$	Two sided power spectral density
N_f	Noise figure
G	Channel gain
M_l	Link margin
d^p	Transmission distance for path loss p
λ	Wavelength of the carrier
$\|h\|^2$	Fading gain
2^b	Constellation size for M-ary QAM
M	Number of users served by a single base station, simultaneously
$(.)^T$	Transpose of matrix
$(.)^H$	Hermitian transpose matrix
$E(.)$	Expectation operator
I_M	MxM identity matrix
$g_M \sim CN(0;I_M)$	g is a circular symmetric complex Gaussian random vector whose mean vector is 0 and covariance matrix is I_M
$Re(.)$	Real part of a complex number
$Im(.)$	Imaginary part of a complex number
$w_M x_M$	Linearly weighted message
h_M	Channel vector

d_M	Distance between base station and the Mth user
P_c	Circuit power consumption
L_1	Signal to interference ratio threshold for the decoding of first signal
P_{tot}	Total power requirement
a	Path loss exponent

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Chapter 1

Introduction

1.1 Cognitive Radio

Every country is having its own regulatory body that regulates the telecommunication services and frequency spectrum. The Federal Communications Commission (FCC) [3] regulates interstate and international communications by radio, television, wire, satellite, and cable in the District of Columbia and U.S. territories. An important observation has been reported by the FCC about the underutilization of some allocated spectrum. It has been observed that the actual utilization of allocated spectrum is less than 40 %. The observation has been confirmed by the other regulatory bodies as well. The two major issues have been highlighted, spectrum scarcity and spectrum underutilization, which means at one side spectrum is deficit due to heavy load of development in wireless communication while on the other side few spectrum bands are underutilized most of the time. In the Fig. 1.1, the United States frequency allocation chart is shown, it is clearly visible that some part of spectrum are highly loaded with application while few are rarely used [1]. It illustrates the over flooded spectrum usage of different applications. Further, the spectrum deficit is shown in Fig. 1.2, where a bar graph between capacity spectrum currently allocated and actual demand for spectrum by the year 2017, is illustrated [2]. It shows the yearly demand and supply of spectrum for United States country and spectrum deficit. It can be observed from the figure that the spectrum scarcity has already been started from 2017.

In order to ameliorate the above stated problems, a new paradigm of radio has been evolved, known as cognitive radio. Cognitive radio was first proposed by Joseph Mitola, that has the functionalities to think and act, learning the environment and gathering the intelligence with the corresponding decision making processes [4, 5]. This idea emerged as an opportunity for unlicensed user to access the free licensed user spectrum by the use of Dynamic Spectrum Access (DSA) [6], therefore, in this way increasing the spectrum utilization.

Here are some well known definitions of cognitive radio:

- Definition given by Joe Mitola [4]:

"A really smart radio that would be self-, RF- and user-aware, and that would include language technology and machine vision along with a lot of high-fidelity knowledge of the radio environment".

- Definition given by Simon Haykin [7]:

"Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment(i.e., outside world), and uses the methodology of understanding by building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:
- Highly reliable communications whenever and wherever needed;
- Efficient utilization of the radio spectrum".

Several studies investigating cognitive radio technology have been carried out and several cognitive radio standards have been developed by many standardization organizations [8–13]. In this way, a lot of attention is paid to cognitive radio, due to heavy demand of spectrum resources by high data rate devices. In this chapter, a brief introduction about cognitive radio, cooperative spectrum sensing (CSS) and energy efficiency (EE) of CSS, is presented.

1.1.1 Spectrum Access Techniques

There are different models for the spectrum access by which cognitive radio can be used for dynamic spectrum access [14, 15]. Different models for spectrum access can be classified as follows:

The Command and Control Model

This is one of the oldest model among all, that give complete usage rights to the spectrum user. But this model showed inefficient way of spectrum utilization.

The Exclusive-Use Model

In exclusive-use model, the spectrum is alloted to licensed user for exclusive usage with some set of rules. If the licensed user is not fully occupying the spectrum then access to the vacant spectrum may be granted to the unlicensed user or secondary user (SU) by the licensed user or primary user (PU).

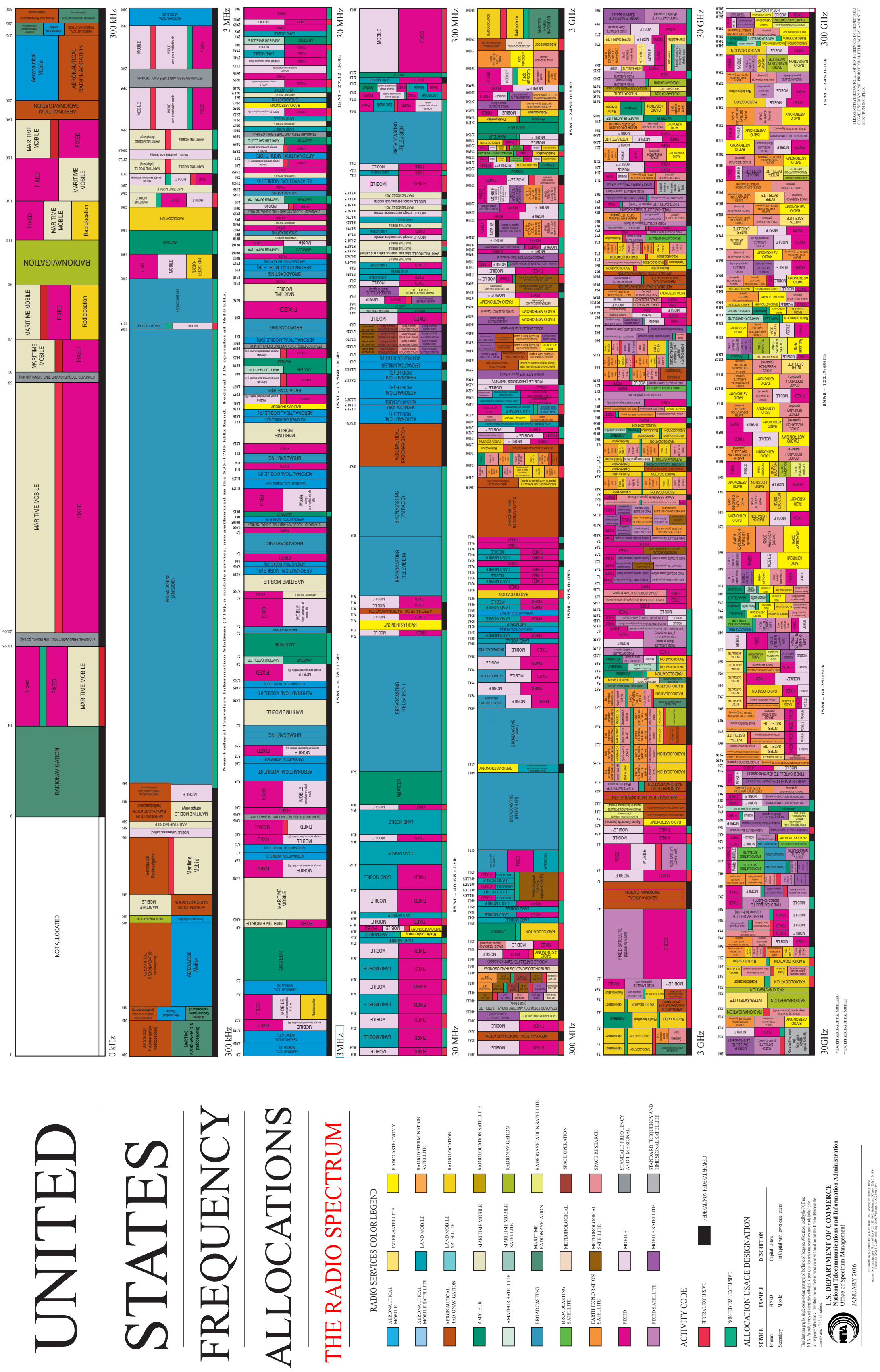

Fig. 1.1: Spectrum allocation chart of United States of January 2016 [1]

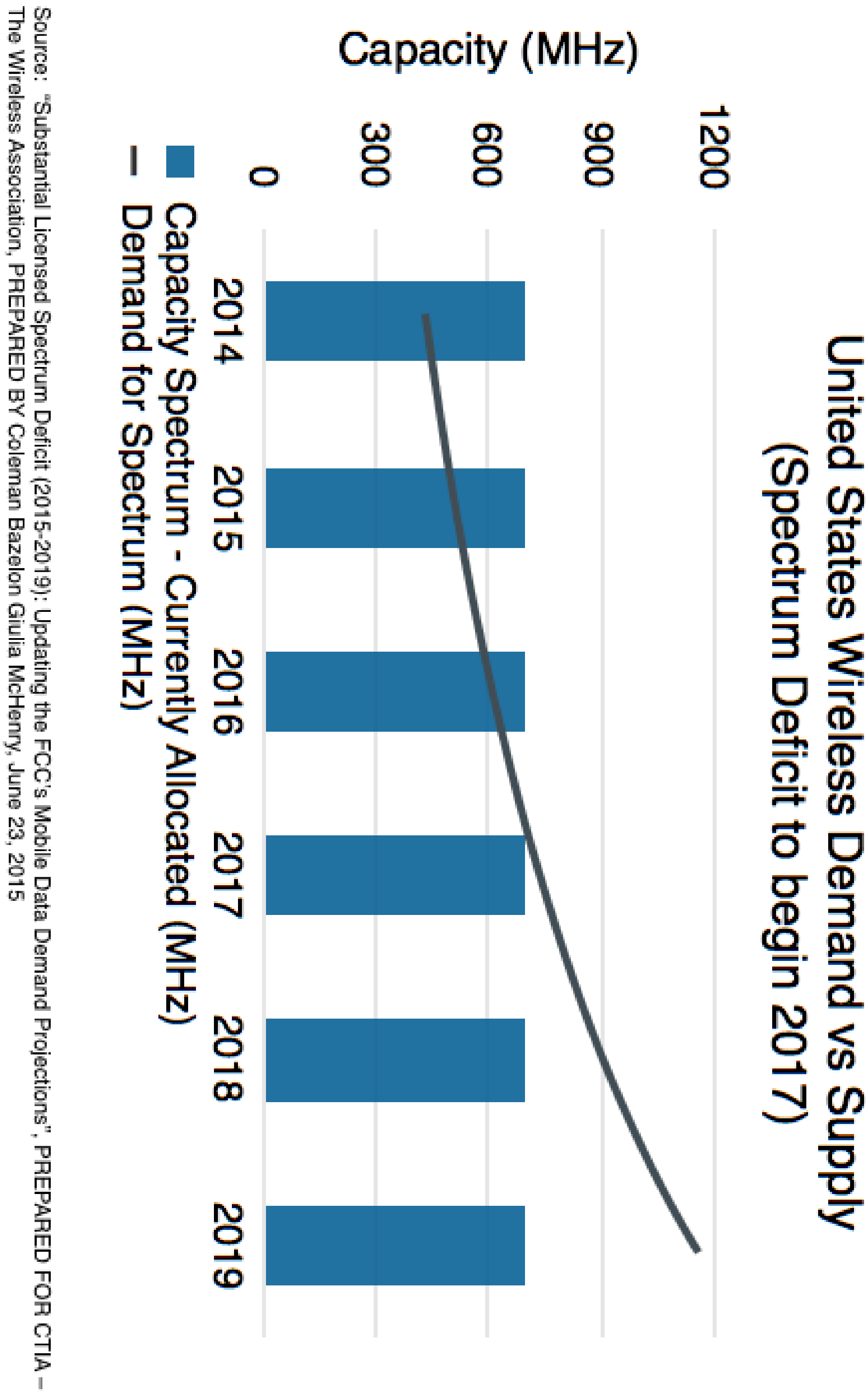

Fig. 1.2: United States demand versus supply bar graph of spectrum, showing spectrum deficit [2]

The Shared-Use Model

In this model, the spectrum is utilized on sharing basis and concurrently accessed by the PU and SU of the spectrum. Here, the SU will opportunistically access the spectrum without any interference to the PU of the same spectrum. This model can be implemented by spectrum underlay or spectrum overlay [16, 17]. In spectrum underlay strategy, the SU transmits simultaneously with the PU, with interference less than a pre-decided threshold. In spectrum overlay strategy, the SU occupy the spectrum in spatio-temporal domain when the spectral bands are not used. The vacant spaces or white spaces are identified by the spectrum sensing performed by the SU. If the white spaces are available then SU gain access to the channel. However, continuous monitoring by the SU is needed whether the PU have gain access to the spectrum again [15].

1.2 Cooperative Spectrum Sensing

Cooperation between secondary nodes, is proposed in the literature as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. Cooperative spectrum sensing or cooperative sensing decreases the probabilities of mis-detection and false alarm considerably. In addition, CSS can solve hidden PU problem and it can also decrease sensing time [18, 19].

The main goal of spectrum sensing is to identify the presence or absence of a PU at a certain location, at a given moment, and in a specified frequency band. Spectrum sensing in its simplest non-cooperative form is considered as single device (or single-node) sensing, where each node makes an independent decision on the availability of a frequency band, and acts accordingly (transmits in this band or not). Many researchers investigated that single node spectrum sensing is not accurate enough for the PU and SU transmission [20]. Hence, to increase the sensing reliability cooperation between secondary nodes is needed [21–23]. Therefore, in CSS, various SU nodes perform spectrum sensing in parallel and reports the sensing result to one pre designated fusion center (FC) node, which then take the global decision about the PU channel presence or absence and finally update the local sensing node with the final global decision. The schematics view of CSS is depicted in Fig. 1.3. The primary and secondary network is clearly visible in the figure. The licensed network connects the primary transmitter to the primary receiver, while using the CSS, SU are also connected with the primary transmitter. To further elaborate the model of cooperative scenario, Fig. 1.4 is illustrated. Figure shows the PU nodes, SU nodes and the FC. The working of CSS can be exhibited by four phases, which are clearly shown in Fig. 1.5 and 1.6 and listed below [19, 24]:

- Local spectrum sensing
- Local decision reporting
- Global decision fusion
- Global decision reporting

In local spectrum sensing phase, the spectrum sensing and detection of PU signal is performed. The sensing and detection of the PU is performed by many techniques such as, energy detection, cyclostationarity based detection, matched filter detection and few others [19, 25, 26]. The energy detection method is the most famous one because of its simplicity and less complexity. In CSS multiple nodes work in collaboration with each other. Sensing is performed at each secondary node. Sensing information is further send to the fusion node, which is the local decision reporting phase. Afterwards, global decision fusion is performed by soft scheme or hard scheme. In soft fusion, sensing data with a pre-decided level of accuracy is encoded and transmitted. Here, the data may be extended by additional beneficial information, e.g., quality of channel, sensing decision etc. Therefore, it can increase the global detection quality. However, few cons are also associated with it as this reporting scheme is burdened with large data overhead and computational complexity due to the large size of reporting messages. Additionally, large reporting messages introduce additional delay in transmission. Whereas, in hard-decision scheme just one bit is needed for the local decision representation (e.g., 1 represents busy channel, whereas 0 empty channel). The information is very concise and can be decoded easily, therefore, easily adopted. This hard decision fusion is made as per the rule of decision fusion i.e., *AND* rule, *OR* rule, $k-out-of-n$ rule. After the global decision is made by the FC, the secondary nodes are updated by this global decision. Finally, if the PU is found absent, the transmission of data is performed by the unlicensed user.

1.2.1 Cooperative Sensing Approaches

The cooperative spectrum sensing can be implemented in four different types of approaches, viz. Centralized, Cluster-based, Distributed/decentralized, and Relay-assisted as shown in Fig. 1.7. In this dissertation, the centralized approach is considered for the sensing and reporting.

Centralized Approach

In the centralized approach, total N sensing nodes, perform the sensing and detection process. The central node which is nearly at the same distance from other nodes are

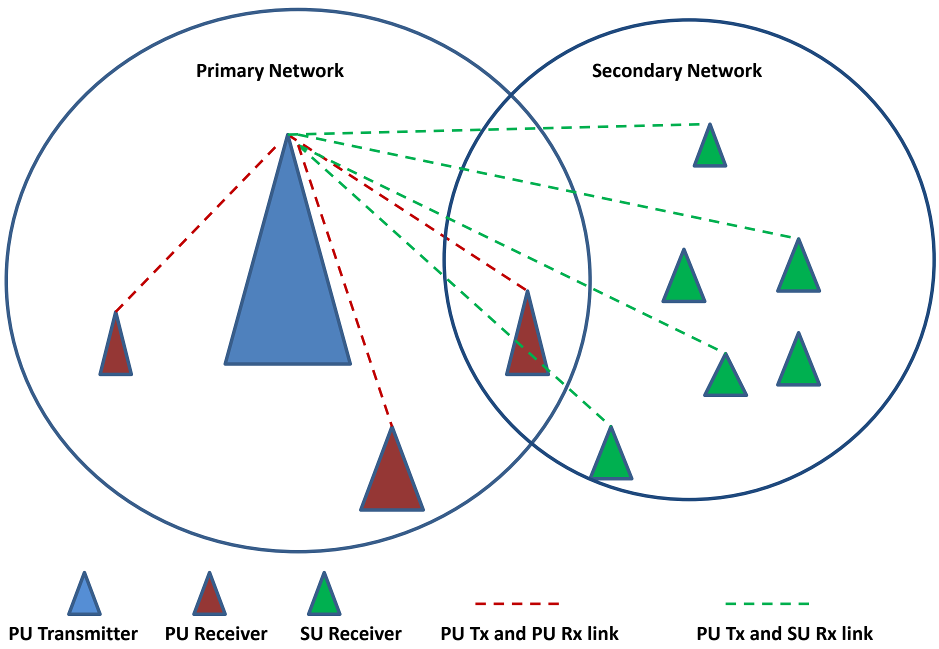

Fig. 1.3: Schematic view of cooperative spectrum sensing

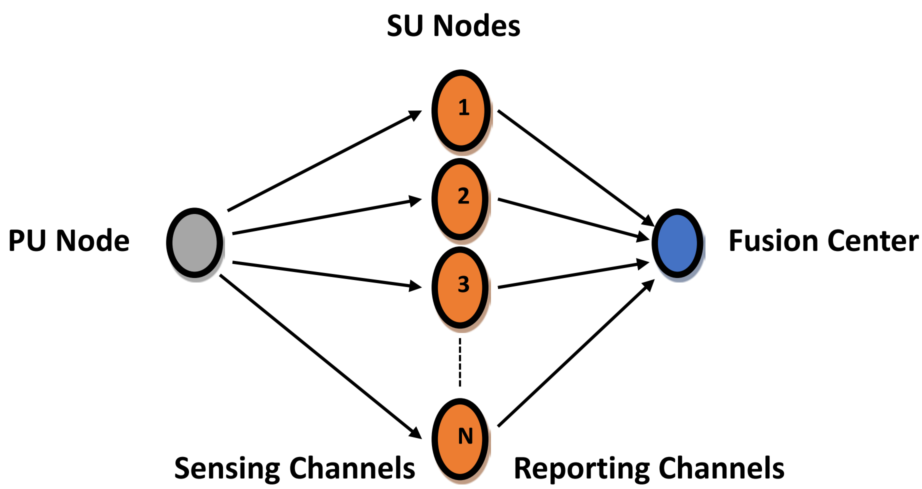

Fig. 1.4: Cooperative model of spectrum sensing and reporting

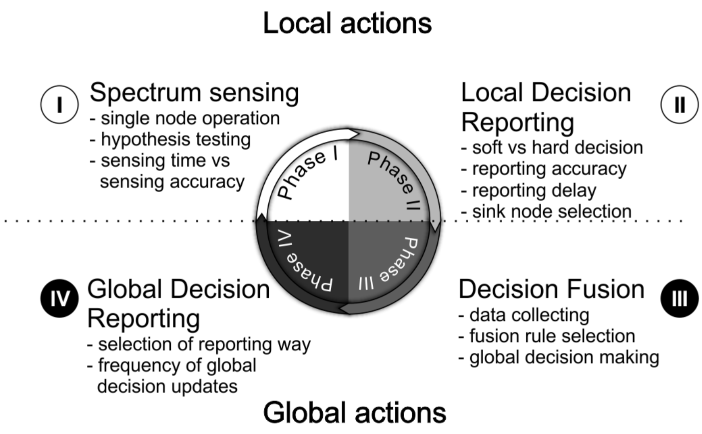

Fig. 1.5: Four phases of cooperative spectrum sensing

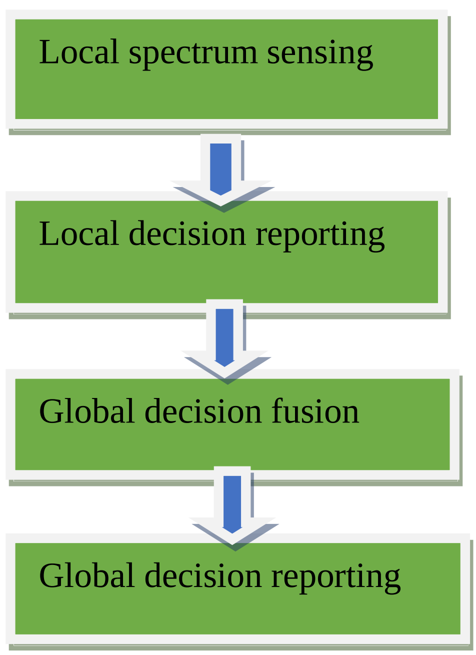

Fig. 1.6: Various stages of cooperative spectrum sensing

considered as the FC. The sensing is performed by the processing nodes and the result is reported to the FC. Then FC performs global decision by applying the hard/soft decision scheme. Afterwards, the global decision is returned back to the processing node for further transmission.

Cluster-Based Approach

In this approach, closed group is formed between neighboring nodes, which are geographically close to each other. This small closed group is known as cluster with one central node as a local cluster-head. This local cluster-head get the local sensing results from all the neighboring nodes. Then, it further reports that decision to the FC directly or may make the decision at the cluster level as illustrated in Fig. 1.7. However, this approach introduces some delay due to reporting of sensing information to cluster head and then from cluster head to FC. Moreover, selection of cluster head involves a specific procedure resulting in delay.

Decentralized/Distributed Approach

Dissimilar to the above approaches, in the decentralized scheme, there is not any selected/fixed FC that manages the process of sensing and reporting. Every node receives the sensing information from the surrounding node and makes the global decision in a determined order. It is clear from the Fig. 1.7 that due to heavy signaling messages, this approach is bit slower than the others.

Relay-Assisted Approach

In this scheme, cooperation between node is performed based upon the channel conditions, known as relay assisted. If the processing/sensing node has a weak channel, the node will cooperate with the neighboring nodes to improve the detection quality. This includes the relaying of the sensing node to the FC as illustrated in Fig. 1.7. It is to be noted here that relaying introduces delay in the whole network as the information is relayed by multiple nodes. In addition to that, complexity is also higher in relay scheme as compared to other approaches.

1.2.2 Energy Efficiency in Cooperative Spectrum Sensing

In the future 5^{th} Generation mobile radio communication, the EE of the overall network is considered as a key paradigm [27]. As the mobile data traffic is increasing rapidly hence resulting in significantly increase in energy consumption [28, 29]. Therefore, it

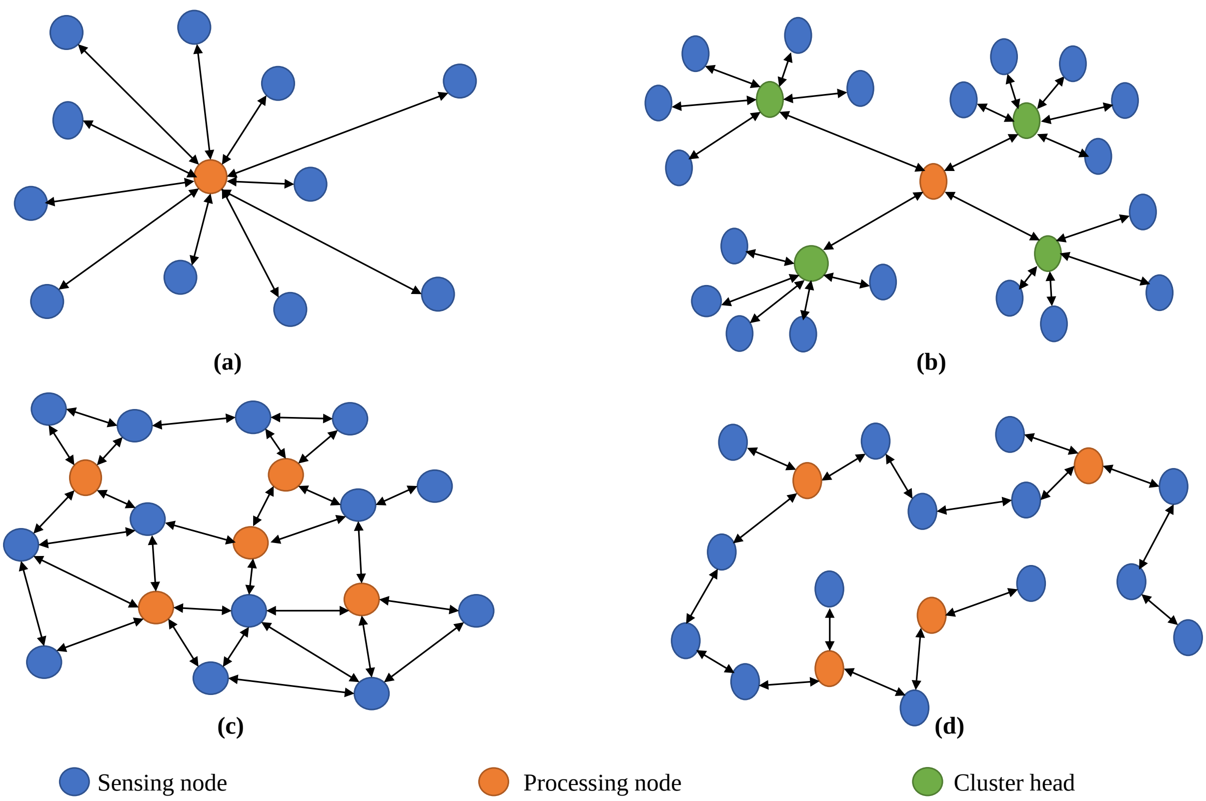

Fig. 1.7: Different cooperative spectrum sensing approaches (a) Centralized (b) Cluster-based (c) Distributed (d) Relay-assisted

is the need of wireless communication to increase the EE by manyfolds. For the systems, where cognition capabilities are present, PU protection by the SU transmission is required. Due to the sudden PU transmission at any moment of time, sensing is needed as a permanent process, results in large energy consumption. Therefore, EE in cooperative spectrum sensing is an important issue, and this issue has been reported by large number of literatures [30–35]. Hence, based upon the gaps identified after the literature survey, In this thesis, different EE maximization techniques/algorithms of CSS in CRNs are proposed and also compared with the state of art.

1.2.3 Introduction to Non Orthogonal Multiple Access

Non-orthogonal multiple access has emerged as the promising technique to improve SE of future 5G communication systems. In comparison to conventional multiple access (CMA) techniques, NOMA is empowered by the superposition coding, distinct power allocation and successive cancellation of interference [36–38]. That is why it has been emerged as more spectral efficient technique for future 5G systems [39]. In third Generation Partnership Project Long Term Evolution (3Gpp-LTE) NOMA was applied for downlink system [40–42].

Unlike NOMA, conventional orthogonal multiple access (OMA) techniques, such as time division multiple access (TDMA) and orthogonal frequency division multiple access (OFDMA), serve a single user in each orthogonal resource block. The spectral inefficiency of OMA can be illustrated with the following simple example. Consider a scenario, where one user with very poor channel conditions needs to be served for fairness purposes, e.g., this user has high priority data or has not been served for a long time [43, 44]. In this case, the use of OMA means that it is inevitable that one of the scarce bandwidth resources is solely occupied by this user, despite its poor channel conditions. Obviously, this has a negative impact on the spectrum efficiency and throughput of the overall system. In such a situation, the use of NOMA ensures not only that the user with poor channel conditions is served but also that users with better channel conditions can concurrently utilize the same bandwidth resources as the weak user. As a result, if user fairness has to be guaranteed, the system throughput of NOMA can be significantly larger than that of OMA. In addition to its spectral efficiency gain, academic and industrial research has also demonstrated that NOMA can effectively support massive connectivity, which is important for ensuring that the forthcoming 5G network can support the Internet of Things (IoT) functionalities [45–48].

1.3 Problem Statements and Description

The main objective of this research is to find the EE maximization techniques for the cooperative spectrum sensing in cognitive radio networks. The problem considered in this thesis may be broadly classified into two categories, viz. EE maximization in single SU cognitive radio system, and EE maximization in multiple SU cognitive radio system.

Under the first set of problem, single PU and single SU cognitive radio network is considered. The joint optimization of sensing and transmission time for EE is proposed by sub optimal algorithm. In this case, the cognitive radio quality metrics, *probability-of-detection*, *probability-of-false-alarm* and interference to the PU due to SU transmission, are considered as constraints.

However, many factors e.g., various noises, hidden node problem, multi-path fading and shadowing etc., affect the SU node which results in poor detection quality of single node sensing [21]. Therefore, collaboration between secondary nodes is needed to improve the reliability and detection quality of the cognitive radio system.

In the second set of problems, a cognitive radio network is considered with cooperative spectrum sensing scheme, where multiple SU nodes are working together in collaboration with each other. Firstly, the EE for the cooperative spectrum sensing by optimal fusion rule is investigated and maximized by minimizing the number of SU. The, decision fusion rule for the number of SUs, is optimized and compared for the fading and non-fading environment.

Following this, EE maximization by considering number of SUs, sensing time, and transmission time as design parameters with protection of PU from SU transmission is proposed. To achieve this, first the number of SUs are optimized and then optimal value of sensing and transmission time are obtained by proposing the iterative sub optimal algorithm.

Further, a brief introduction of EE maximization problem of cognitive radio is also investigated by Non Orthogonal Multiple Access (NOMA). Firstly, the cognitive radio inspired NOMA is generalized by multiple PUs. Then, EE is optimized for the proposed system.

1.4 Outline of Thesis

The second chapter investigates the literature survey and related research in the field of EE maximization in cognitive radios. In this chapter review of earlier work is shown and the gaps are identified. Based on the gaps, the problem is formulated on the EE maximization for cooperative spectrum sensing in cognitive radio networks.

In chapter 3, single cognitive radio network with one PU and one SU is considered. The EE maximization by optimizing the sensing and transmission time with PU protection from SU transmission is proposed. The parameters of optimal design problem are sensing, transmission time and transmission power. A Sub Optimal Iterative Search Algorithm (SOISA) is proposed to maximize efficiency by optimizing sensing time and transmitting time. The performance of the proposed algorithm is evaluated with the help of simulation in Matlab.

The maximization of EE by optimizing the hard decision fusion rule in fading and non fading environment is performed, in the chapter 4. In this chapter, N number of SU nodes are performing local spectrum sensing. Further, to reduce the overhead created by number of SU nodes, the optimization of fusion rule is performed along with improved detection quality. Here, *OR*, *AND*, and *k-out-of-N* rules are optimized and it is clear after simulation that *k-out-of-N* rule outperforms others in term of EE and *Global probability-of-false-alarm*.

In chapter 5, EE optimization for cooperative spectrum sensing in cognitive radio networks is proposed. Joint optimization of sensing time, transmission time and number of SUs has been considered with the protection of PU from SU transmission.

In order to solve the problem, first the optimal expression for the number of SUs is obtained and then an iterative sub optimal algorithm is proposed to achieve optimal sensing time and transmission time. The proposed algorithm decouples the problem into two parts (i.e., optimization of number of SUs and optimization of sensing time and transmission time) and solved the two problems till convergence. The effectiveness of this work is demonstrated by extensive simulation results and illustrations.

The Non Orthogonal Multiple Access (NOMA) enabled cognitive radio is discussed in chapter 6. In this chapter, the EE maximization problem with down link NOMA technique is studied. Here, base station equipped with two antennas, one PU and one SU is considered. CR-NOMA technique will further increase the application of cognitive radio into 5G systems. Further, the EE is maximized for the NOMA and compared with other existing conventional multiplexing techniques.

Finally, in chapter 7 conclusions of the whole thesis are drawn and directions for the future scope are displayed.

Chapter 2

Analysis of Techniques and Literature Survey

With the significant development of wireless communication networks and services, the need of spectrum is growing many-folds. The solution of spectrum scarcity is cognitive radio. A striking feature of cognitive radio is DSA, that allows the unlicensed user to utilize the spectrum while licensed user is absent, without low or no interference to the PU [4, 5, 19]. Hence, cognitive radio plays an important role in wireless communication networks now a days [49, 50]. The three main approaches to implement cognitive radio can be classified as, underlay, overlay, and interweave. In the first method i.e., underlay, SU can occupy the spectrum by simultaneously transmitting with the PU. In overlay approach, the SU of the spectrum is allowed to access the spectrum in spatio-temporal domain. However, in interweave approach SU will vacate the channel while PU reoccupy it [16, 17, 51, 52]. The sensing and detection can be performed by many techniques e.g., energy detection, matched filter detection, cyclostationarity based detection, feature detection, covariance matrix based detection, blind detection, filter bank based detection, wide-band spectrum sensing, and multi-band sensing [18, 53]. Among all, energy detection is less complex and mostly used [7, 24, 54–56]. However, there are many factors that may affect the single node spectrum sensing in terms of detection quality, such as hidden node problem, various types of noises, multi-path fading and shadowing etc., [21, 31, 57].

Cooperative spectrum sensing is assumed to be the most important function of CRNs [1]. By exploiting the spatial diversity, CSS improves the detection quality and gives solution of the above problems [58, 59]. The step by step process of CSS is explained as, first the state of PU channel is detected by local spectrum sensing at each

[1] This work has been published in the proceedings of 2017 IEEE CICT under the title "Energy-Efficiency Techniques in Cooperative Spectrum Sensing: A Survey"

sensing node and then local sensing result of each node is transmitted to FC for the global decision. Now, by using hard/soft fusion scheme the global decision is made by the FC. Afterwards, the global decision will be transmitted to all the SU nodes. Then, based on the global decision the PU channel will be occupied by the unlicensed user [60]. Unfortunately, collaborative users consume notable amount of energy due to communication overhead. Therefore, EE improvement is increasingly recognized as a very important aspect in CSS schemes in CRNs to overcome the overhead caused by multiple SU [61–66]. It is due to the restricted resources of energy at the cognitive radio, which is sometimes with huge requirement of data rates [67, 68]. This chapter offers an overview of available research activities that are aimed at maximization of energy efficiency in CSS of CRNs.

There are a number of diverse energy-efficient techniques that may be grouped according to various possible classifications. In this section, we review different techniques and approaches [69–71]. In [19], authors proposed four possible ways of energy savings, such as, energy reduction at local spectrum sensing, optimization of the number of secondary nodes, selection of fusion rule and energy-efficient network. An increase in EE is possible if the total power consumed at each stage of CSS is decreased [72, 73]. Hence the power at each stage of cooperative sensing is being minimized. The presented approaches/techniques at each stage of CSS can be broadly classified as:

- Energy efficiency at local sensing
- Energy efficiency at reporting
- Energy efficiency at fusion/decision making
- Energy efficiency at network level

At local spectrum sensing, EE can be implemented in three ways, by optimizing the sensing time, decision threshold and by optimizing the number of SUs. The consumed energy will be lower if the number of samples is less. Furthermore, with the use of automatic radio-frequency front-ends, in which the elements may be put at the ON/OFF/STANDBY mode may result in more energy efficient CSS even if the nodes used in sensing are more [74]. The optimization of number of SUs plays an important role in the EE maximization problem for CSS scenario in cognitive radio. For the optimization of number of SUs, various algorithms are proposed in the literature. Multiple authors have given the selection criterion of sensing nodes and find the optimal number of selected sensing nodes for various network configurations. Generally it is optimum to select the CRNs based on received SNRs [75]. In [33, 76, 77], authors discussed the effect of changing sensing-window size on the number of SUs for different hard decision fusion rules. However, few researches are also available, where the number of SU nodes were optimized for EE maximization [78–80]. Moreover, to optimize the number of SU nodes, optimum hard decision fusion schemes have been discussed in [78]. Further in [33], authors maximized the EE for different hard decision schemes in non fading environment.

At the reporting stage, energy may be improved by proper selection of SU nodes, who are reporting the local decision to the decision fusion [81]. To achieve this three ways may be opted: proper selection of active SU nodes, voting scheme or by censoring of SU nodes. Therefore, by lowering the number of active SU nodes, the energy consumption may be reduced. So, this will depends upon the criterion of selection of SU nodes and of course at the cost of detection performance. The other criterion for the selection of node is better signal to noise ratio that each node is experiencing. In the voting scheme a number of type of schemes are proposed in the literature e.g., confidence voting [82], collision detection scheme [83]. In [84], a cost function is produced which selects sensing nodes with the lowest energy consumption from those nodes which are fulfilling the detection quality criterion.

Further, at the decision fusion stage, any one of the hard or soft decision fusion scheme may be applied. In hard scheme, energy may be saved by optimizing the fusion rules. To optimize the number of SU nodes for fusion, optimum hard decision fusion schemes have been discussed in [78]. In [85], hard decision fusion rule and detection threshold are used as parameters to improve the EE. While, in [33], author discussed the effect of changing sensing-window size on the number of SUs for different hard decision fusion rules. However, few researches are also available, where the fusion rules were optimized for EE maximization [78, 79].

In [65], the transmission time and sensing time are optimized separately to achieve the maximum EE. In [86], authors proposed optimum sensing time and transmission time in frequency - flat fading environment. In the literature [87], optimal transmission time and transmission power are studied for EE maximization. Whereas in [88], authors proposed a hybrid protocol for the transmission so that SU can transmit data even when PU is present. Here, interference occurred due to SU transmission to the PU transmission is considered as one of the constraints. In [89], sub optimal algorithm is proposed to get the optimum sensor. The research in [90] reflects the joint optimization of sensing time and transmission power to improve EE. Literatures [63, 85], optimize either the detection threshold or sensing time to maximize EE. Many researchers have focused on the optimization of either the transmission parameter or the sensing parameter to improve the throughput of the CRNs [61, 91–93].

In [64], authors demonstrated the maximization of EE by optimizing the transmission parameters for the cooperative scenario of CRNs. Whereas in [65], authors optimized both sensing time and transmission time for a single PU and single SU case for a CRN. Authors in [94] examined the trade-off between sensing time and energy, and then carried out the optimization to improve EE of CRNs. It has been demonstrated by Liang in [53] that a trade-off exists between spectrum sensing and throughput for a cognitive radio. Authors in [95–97] investigated the relationship between transmission duration, sensing duration and energy. Specifically, [95], dealt with the sensing based spectrum sharing, whereas [96] presented optimal allocation of power for fading channels. Moreover, authors in [97, 98] analyzed the optimal allocation of power in CRNs for fading channels with PU outage constraints. In the analysis of EE, authors in [99,100] defined the cross layer optimization with partial knowledge of local sensing results. In [87,101–103] authors optimized the spectrum sensing duration to maximize the EE for homogeneous channel. In contrast with that, Erygit et. al. in [104] discussed the EE sensing scheduling for the heterogeneous case of CRNs.

In [105–108], authors considered the orthogonal frequency division multiple access (OFDM) and optimal power allocation on each sub carrier to enhance EE was investigated. Authors in [109], proposed Dinkelbachs iterative power adaptation based algorithm to increase the EE of CRNs. The optimum EE power allocation for OFDM based CRNs is examined in [91]. Moreover, in [30, 65] authors defined the EE as a ratio of throughput and energy consumed. In [86, 110, 111], joint optimization of the sensing and transmitting parameters were analyzed with respect to EE. Further, to improve the EE, the sensing time and transmission power in fading channel was optimized in [112]. Therefore, the EE of cognitive transmissions is largely affected by spectrum sensing duration, transmission duration, reporting duration and power associated with them, respectively [53,99]. Hence, the design of these parameters encounter significant impact on EE [100]. In the literature [113], optimization problem with parameters local sensing duration, number of SUs, bandwidth of the transmission and power, is formulated for the joint optimal sensing and transmission in CRNs. They have proposed a combined optimization algorithm of bi-level, Polyblock and Dinkelbach's for EE problem effectively. In [114], EE maximization of the CRNs is done subject to protection to the PU and also with the constraint of power. To achieve this, an algorithm is proposed by the author to optimize the power and sensing time of the SU transmitter. In [115, 116], authors proposed an energy efficient query processing protocol for wireless sensor network.

Nowadays, Non-orthogonal Multiple Access (NOMA) has emerged as the promising technique to improve spectral efficiency (SE) of future 5G communication systems [36–38]. In comparison to conventional multiple access techniques, NOMA is empowered by the superposition coding, distinct power allocation and successive cancellation of interference [39]. That is why, it has been emerged as more spectral efficient technique for future 5G systems. In third Generation Partnership Project Long Term Evolution (3GPP-LTE) NOMA was applied for down link system [43, 44]. The application of NOMA has been illustrated in [40–42]. Whereas, in [117] an analytical framework to analyze the gain achieved by NOMA in a heterogeneous cellular network consisting of a macro base station and a femto base station was modeled using repulsive point process. Moreover, cognitive radio is another approach to improve SE, proposed by [4, 7]. In CR networks multiple SUs opportunistically utilize the licensed spectrum by spectrum sensing, detection and allocation. Initially, NOMA inspired CR has been proposed by [39, 41, 118].

The research in [39] indicates that within multiple users, a user with a better channel conditions will be a SU and poorer channel will be PU. Here, the SU will try to occupy the channel of the PU. Further, NOMA for underlay CRNs of large scale was also applied in [118]. Apart from SE, EE is also drawing the attention of researchers as communication technology is responsible for 5% of the total world energy consumption [119]. As of now, very few researches are available in the field of NOMA with respect to EE in CRNs [43]. In [47, 48], authors proposed EE optimization for fading multiple input multiple output (MIMO) inspired by non-orthogonal multiple access. In the study [120], sub channel and power both are optimized jointly for a down link NOMA. They have considered a heterogeneous network in this case.

Energy efficiency may be done at the network organization stage also [44, 121]. Energy efficient clustering algorithm for wireless sensor network has been proposed in different studies [122–124]. Relay network topology for energy efficient cognitive radio is also proposed in various papers [125–128]. In [45,46], an energy efficient event monitoring framework for nano-IoT (Internet of Things) is proposed which enables nanosensors to update a remote base station about the location and type of the detected event using only a single short pulse.

Chapter 3

Optimization of Energy Efficiency for Single User Cognitive Radio Networks

3.1 Introduction

Cognitive Radio solves the spectrum paucity problem, by opportunistic transmission and dynamic spectrum allocation scheme. In the spectrum sensing process SU detects the PU presence or absence and accordingly access the vacant spectrum of PU. Hence, the spectrum sensing is a continuous process. The process of spectrum sensing consume a lot of energy due to its continuous nature. Therefore, in practical CRNs, EE concept is very essential. Both sensing and transmission parameters offer a great impact on power consumption. Energy efficiency has been identified as the key aspect of future mobile and wireless communication networks. Therefore, its measurement and assessment in effective, accurate and reliable manner, is much needed.

There are many sensing and transmission parameters which affect the consumption of energy. An increased transmission time increases the throughput but it also results in enhanced interference to PU and less probability of data. Also, increased sensing time results in high consumption of energy with improved detection accuracy. However, if sensing time is too short, it will give high false alarm probability. Based on this discussion, optimization of sensing time and transmission time to maximize energy efficiency is proposed in this chapter [1].

[1]This work has been published in the proceedings of 2017 IEEE INDICON under the title ”Energy Efficient Sensing, Transmitting Time and Transmission Power for Cognitive Radio Networks”

3.2 Background and Motivation

Some latest researchers are working on the EE in CRNs. In, [65] the transmission time and sensing time both are optimized separately. In [89], sub optimal algorithm is proposed to get the optimum sensor. The research in [90] reflects the joint optimization of sensing time and transmission power to improve EE. Literatures [63, 85], optimize either the detection threshold or sensing time to maximize EE. Many researchers have focused on the optimization of either the transmission or sensing parameters to improve the throughput of CRNs [61, 91–93].

Based upon the inspiration of past researches, in this chapter joint optimization of the transmission power, sensing and transmission time considering a single CR user environment, is proposed. Here, sensing and transmission time are considered as the variables of the optimization problem. In this chapter, the false alarm probability and interference to the PU occurred due to SU transmission is also considered. The optimal transmission time, sensing time and transmission power with respect to energy efficiency is exhibited. The main features of this research are as follows: Energy efficiency is maximized with respect to the sensing and transmission time by mathematically calculating the optimal sensing and transmission time . Afterwards, the proposed algorithm is applied to get the maximized value of EE by using the above optimized sensing and transmission time.

3.3 System Model

In this chapter, single PU and SU cognitive radio network is considered, which indicates that only one secondary/cognitive node is used to detect presence or absence of PU. The time frame of this network includes sensing and transmission time. For the total time frame of T sec, SU node will detect availability of PU channel. Here, the time frame T is given by, $T = t_s + t_t$, where, t_s and t_t are the sensing and transmission time, respectively. After each time frame T, the presence or absence of PU is detected and accordingly PU channel is occupied by the SU. However, during SU transmission, the channel can be reoccupied by the PU again. Then, due to SU transmission, interference may occur to the PU signal. Hence, the interference resulted by PU reoccupation has also been taken into account. The probability of interference to PU during the SU transmission time t_t, can be given by the following equation [102]:

$$P_{Int}(t_t) = \int_0^{t_t} p_I(t)dt = 1 - exp^{-t_t/a_I} \tag{3.1}$$

The pdf (probability density function) of the occupied and vacant PU channel is given by the following equation:

$$p_B(t) = a_B^{-1} exp^{-t/a_B} u(t) \tag{3.2}$$
$$p_I(t) = a_I^{-1} exp^{-t/a_I} u(t) \tag{3.3}$$

where P_{Int} is the interference probability, a_B and a_I are the mean values of busy and idle time of PU signal which are exponentially distributed, $u(t)$ is the unit step function. Hence, the respective probabilities of PU busy and idle state can be given by:

$$P_B = \frac{a_B}{a_I + a_B} \tag{3.4}$$
$$P_I = \frac{a_I}{a_I + a_B} \tag{3.5}$$

The quality metrics in cognitive radio can be specified by two types of probabilities, *probability-of-false-alarm* and *probability-of-detection*, denoted as $P_{fa}(t_s)$ and $P_{de}(t_s)$, respectively. These two probabilities depend upon the sensing time and detection threshold. Here, in this chapter we assume detection threshold as implicit variable. Now, as per detection of PU signal by the SU, four scenarios can be considered, which are as follows:

- First, the probability of correct detection of PU signals absence, $P_I(1 - P_{fa}(t_s))$. This means correct detection of vacant PU channel.

- Second, the probability of correct detection of PU signals presence, $P_B P_{de}(t_s)$. This gives the correct detection of occupied PU channel.

- Third, the probability of wrong detection of PU absence, $P_I P_{fa}(t_s)$. This implies the false detection of PU idle state.

- In the fourth scenario busy state of PU signal is falsely detected and the probability is given as $P_B(1 - P_{de}(t_s))$.

In the first case the probability that PU signal again uses the channel along with the transmission of SU is already given in equation (3.1). However, other definition of PU interference is also given in the literature [53]. In the scenario second and fourth, there is no SU data transmission exists and hence there is no PU interference.

3.4 Problem Formulation and Solution

The main objective of this research is to optimize the sensing time and transmission time to increase the bits transmitted per frame so as to achieve maximum energy efficiency. This problem also considers the interference occurred due to SU transmission. Also, the EE with respect to transmission power is shown by the graphs. Here, in this part, first the total energy consumed is calculated and then the total number of bits transmitted.

3.4.1 Total Energy Consumed

The energy consumed is calculated depending upon the total power for a given time. In this model, the sensing power and transmitting power are considered for the duration of t_s and t_t. The total energy consumption can be calculated for the four scenarios within a time frame. It is shown as follows:

$$E_t = P_s t_s + P_t t_t P_{idle} \tag{3.6}$$

where E_t is the total energy consumed, P_s is the sensing power, P_t is the transmission power and P_{idle} is the perfect idle channel probability, which is calculated as:

$$P_{idle} = P_I(1 - P_{fa}(t_s)) + P_B(1 - P_{de}(t_s)) \tag{3.7}$$

In the equation (3.7), P_I is the PU idle state probability and P_B is the PU busy state probability.

3.4.2 Total Throughput

In this model, Additive White Gaussian Noise (AWGN) channel is considered, hence the total number of bits transmitted for the duration of t_t is given by $t_t R_0$. Here, R_0 is the number of bits transmitted per unit time. By considering the four scenarios, successful data transmission can be occurred in the first scenario only if PU does not return again. In this model, whole frame is to be transmitted for a successful transmission. The total throughput of the CR system is given as:

$$R_t = R_0 P_I(1 - P_{fa}(t_s)) t_t (1 - P_{Int}(t_t)) \tag{3.8}$$

3.4.3 Energy Efficiency

The energy efficiency (EE) of the CRN for single CR case can be calculated as the ratio of total throughput and the total energy consumed, which is represented as follows [111]:

Energy Efficiency (EE) = Total throughput / Total energy consumed

$$\zeta(t_s,t_t) = \frac{R_t}{E_t} = \frac{R_0 P_I(1-P_{fa}(t_s))t_t(1-P_{Int}(t_t))}{P_s t_s + P_t t_t P_{idle}} \tag{3.9}$$

where ζ is the energy efficiency, R_t is the total throughput and E_t is total energy consumed. Further, to maximize EE, the problem for optimal sensing time and transmission time with varying transmission power can be formulated as:

$$\begin{aligned} & max\ \zeta(t_s,t_t) \\ s.t.\ & t_{s0} \le t_s \le t_{s1} \\ & t_{t0} \le t_t \le t_{t1} \\ & P_{de(t_s)} \ge P_{de0} \\ & P_{Int}(t_t) \le \alpha_q \end{aligned} \tag{3.10}$$

where P_{de0} is set to 0.9 as the target *probability-of-detection*, considering IEEE-802.22 standard and α_q is the maximum interference level that occur in case of mis–detection, to the PU by the transmission of SU. The *probability-of-false-alarm* for the energy detection based sensing can be defined as:

$$P_{fa}(t_s) = Q\sqrt{(2Y+1)}Q^{-1}(P_{de0}) + Y\sqrt{t_s f_s} \tag{3.11}$$

where f_s is the sampling frequency and Y is the PU signal to noise ratio (SNR) due to SU data transmission. If we increase the sensing time then $P_{fa}(t_s)$ will decrease. Therefore, to make $P_{fa}(t_s) \le 0.5$ [86], it should satisfy the condition of $t_s > (\frac{Q_{-1}(P_{de0})(2Y+1)}{Y\sqrt{f_s}})^2$. Hence, to satisfy probability of false alarm, the lower limit for sensing time is take as, $t_{s0} = (\frac{Q_{-1}(P_{de0})(2Y+1)}{Y\sqrt{f_s}})^2$. Next, for the transmission time, the lower and upper limits can be calculated based upon the interference constraint α_q. Hence, to fulfill this requirement the transmission time can be maximized as $t_{t1} = -a_I log(1-\alpha_q)$.

Now, the EE maximization problem can be rewritten as:

$$\begin{aligned} &max\, \zeta(t_s,t_t) \\ &s.t.\, t_{s0} \leq t_s \leq t_{s1} \\ &0 < t_t \leq t_{t1} \end{aligned} \tag{3.12}$$

3.4.4 Proposed Algorithm

In the preceding part of the chapter, we suggest the solution of the problem given above. The parameters for the problem considered here are, sensing, transmission time and transmitting power. First the relationship of energy and time is formed and then the maximization problem is solved. The values of sensing and transmission time to maximize EE are calculated and after that iterative sub optimal algorithm is proposed.

Step1: Take the partial differentiation of $\zeta(t_s,t_t)$ with respect to t_s and put it to zero keeping fix t_t [86].

$$\frac{\partial\zeta(t_s,t_t)}{\partial t_s} = \frac{\partial}{\partial t_s}\frac{R_0 P_I(1-P_{fa}(t_s))t_t(1-P_{Int}(t_t))}{P_s t_s + P_t t_t P_{idle}} = 0 \tag{3.13}$$

Let us take $P_{fa}(t_s)$, $P_{de}(t_s)$, and $P_{Int}(t_t)$ as P_{fa}, P_{de} P_{Int} for simplicity in equation (3.13). Now, the above equation is equivalent to:

$$P_s P_{fa} - (t_t P_t P_I(1-P_{de}) + P_s t_s)P'_{fa} - P_s = 0 \tag{3.14}$$

$$t_s^{opt} = -\frac{1}{P'_{fa}} - \frac{t_t P_t P_I(1-P_{de})}{P_s} + \frac{P_{fa}}{P'_{fa}} \tag{3.15}$$

The derivative of *probability-of-false-alarm* in the equation (3.14), P'_{fa} can be expressed as:

$$P'_{fa} = -\frac{1}{\sqrt{2\pi}}\frac{Y\sqrt{f_s}}{2\sqrt{t_s}}exp[-\frac{1}{2}Q^{-1}P_{de}\{(\sqrt{2Y+1})+Y\sqrt{t_s f_s}\}] \tag{3.16}$$

Here, for the range of sensing time $t_{s0} \leq t_s \leq t_{s1}$, $P_{fa}(t_s)$ is decreasing and $P'_{fa}(t_s)$ is increasing and negative, therefore $P_{fa}(t_s)$ is convex function and $P''_{fa}(t_s)$ is positive.

Step2: Take the partial differentiation of $\zeta(t_s,t_t)$ with respect to t_t and put it to zero keeping fix t_s :

$$\frac{\partial\zeta(t_s,t_t)}{\partial t_t} = \frac{\partial}{\partial t_s}\frac{R_0 P_I(1-P_{fa})t_t(1-P_{Int})}{P_s t_s + P_t t_t P_{idle}} = 0 \tag{3.17}$$

Algorithm 1 Pseudo Code for Iterative Sub-optimal Algorithm

Initialize $k=0$, $t_s(0)=(\frac{Q^{-1}(P_{de0})\sqrt{2Y+1}}{Y\sqrt{f_s}})^2$, $\zeta(0)=0$, $\triangle E$, $diff=inf$, $t_t(0)=0$.
while $diff >= \triangle E$ **do**
    $k=k+1$.
    Calculate $t_t(k)$ using (3.18) for $t_s(k-1)$.
    Compute $t_s(k)$ using (3.15) for $t_t(k)$
    Find $\zeta(k)$ for $t_s(k)$ and $t_t(k)$ using (3.9).
    Get the difference $diff=\zeta(k)-\zeta(k-1)$.
end while
    return $\zeta(k), t_s(k), t_t(k)$.

After solving the equation (3.17), we get:

$$t_t^{opt}=\frac{P_s t_s-\sqrt{P_s^2 t_s^2+4a_I P_t P_s t_s P_{idle}}}{-2P_t P_{idle}} \tag{3.18}$$

Hence, the above equation (3.18) gives the optimum value of transmission time. Here, for the range of $0<t_t\leq t_t^{opt}$, the EE shows a unique ζ_{max} value. If we further increase the value of transmission time, say, $t_t>t_t^{opt}$ then $\frac{\partial\zeta(t_s,t_t)}{\partial t_t}<0$, hence for the range of $0<t_t\leq t_t^{opt}$, $\zeta(t_s,t_t)$ has a unique maximum value for each fixed t_s.

Step 3: Optimization algorithm

An Sub Optimal Iterative Search Algorithm (SOISA), shown as Algorithm 1 is proposed to maximize the EE by calculating the optimization problem. Here, the efficiency can be calculated by using Algorithm 1. Here, in this algorithm, the EE, sensing time and transmission time are represented as $\zeta(k)$, $t_s(k)$and $t_t(k)$ for kth iteration. For the initialization purpose, let EE, transmitting and sensing time are considered as zero. All the values of $\zeta(k)$, $t_s(k)$and $t_t(k)$ are calculated for kth iteration, afterwards, the iteration will start with $k+1$. If the difference of $(k+1)th$ iteration and kth iteration is less than $\triangle E$ then the iteration process will stop and the optimized values are presented. Herein, $\triangle E$ is a pre-decided fix value.

Computational complexity: Generally, the proposed ISOA algorithm requires 3 iterations to converge, whereas Sub optimal algorithm needs 5 iterations to converge [86]. Additionally, the complexity of the proposed algorithm is much less than the complexity of exhaustive search method too [86].

3.5 Simulation Results

This section gives the results that have obtained through simulation in MATLAB. Different parameters used for simulation are given in Table3.1.

Table 3.1: Simulation parameters

Parameters	**Values**
Target probability of detection, P_{de0}	0.9
Threshold of interference probability, a_q	0.1
Sensing power, P_s	0.11 Watt
PU idle state, a_I	0.65 s
PU busy state, a_B	0.352 s
Sensing frequency, f_s	6 MHz
PU SNR, Y	-20 dB
Throughput, R_0	10 Mbps
Transmission power, P_t	0.1 Watt

Fig. 3.1 illustrates the effect of change in transmission power for the SOISA on EE. It can be observed that when transmission power is increased the EE will decrease. For the transmission power taken to be 0.1 W, the EE is 11.9321 Bits/Hz/Joule. Further increase in transmission power results in very low EE. The reason of this effect is, larger transmission power results in larger loss of throughput because of false alarm. That increases the consumed energy for a longer sensing time.

Fig. 3.2 shows the improvement of the proposed SOISA over exhaustive search method and sub optimal algorithm [86]. In this figure it is shown that at a fix transmission power the EE for the proposed algorithm is highest among all. For a transmission power of 0.1 W the EE for SOISA is 11.9321 Bits/Hz/Joule while for exhaustive and sub optimal algorithm it is 7.5092 Bits/Hz/Joule and 6.5285 Bits/Hz/Joule, respectively. The algorithm gives the optimal values for sensing, transmission time and accordingly EE as 0.0030 s, 0.0749 s and 11.9321 Bits/Hz/Joule respectively. The number of iterations required for the proposed algorithm is, 3 whereas for the sub optimal algorithm number of iteration required is, 5.

Fig. 3.3 exhibits the response of sensing time on the EE for three different values of transmission time. Here, it can be analyzed that the EE is maximum for $t_t = 0.06$s and $t_s = 0.002$s. Initially increase in sensing time results in increase in EE but after the optimal value it starts decreasing. Similarly, EE versus transmission time is shown in Fig. 3.4. This figure shows that increase in transmission time give rise in EE but after optimal transmission time EE falls rapidly. The three sensing time are taken as 0.001s,

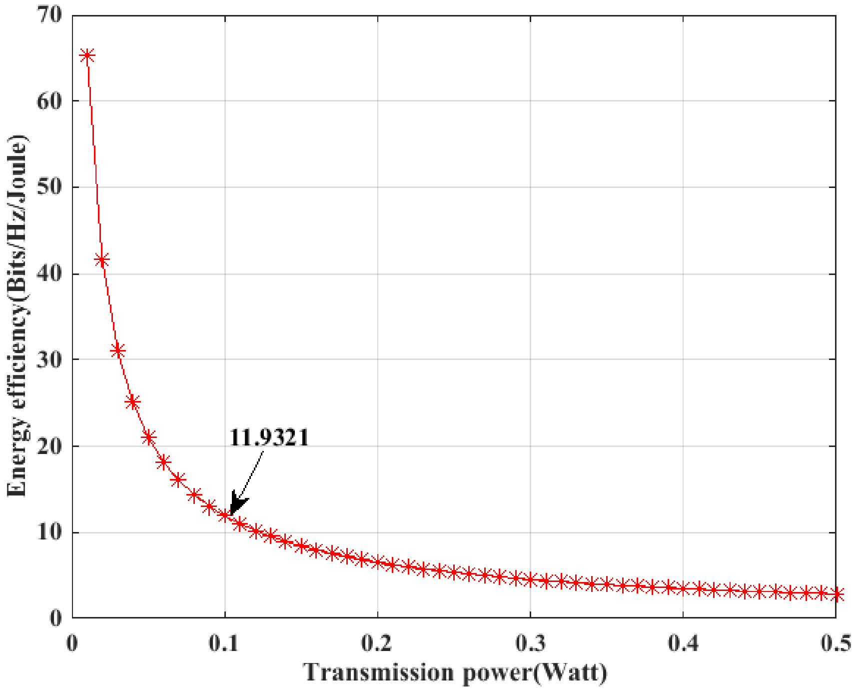

Fig. 3.1: Energy efficiency versus transmission power for the proposed SOISA algorithm

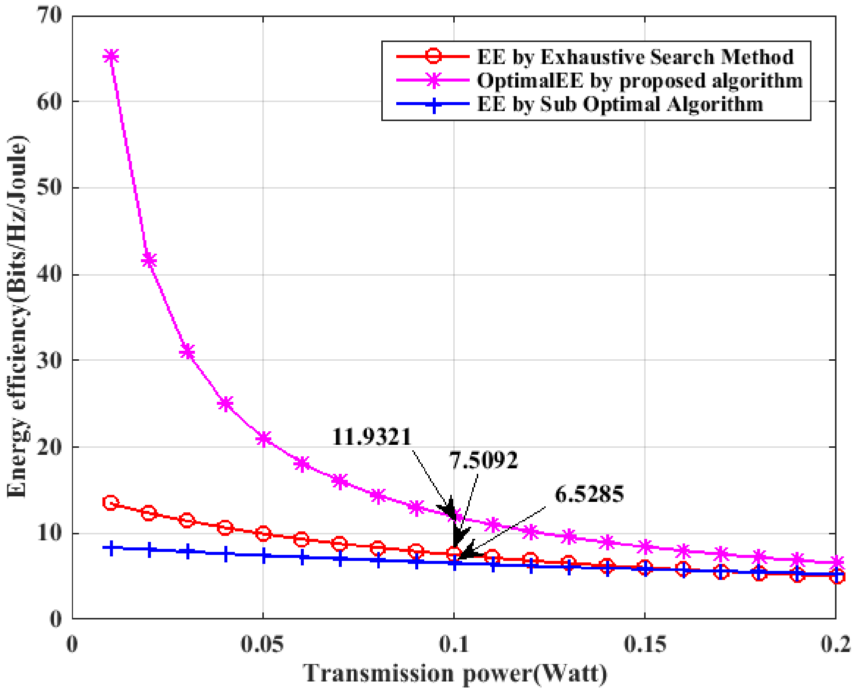

Fig. 3.2: Comparison of proposed SOISA algorithm with previous algorithms in terms of energy efficiency

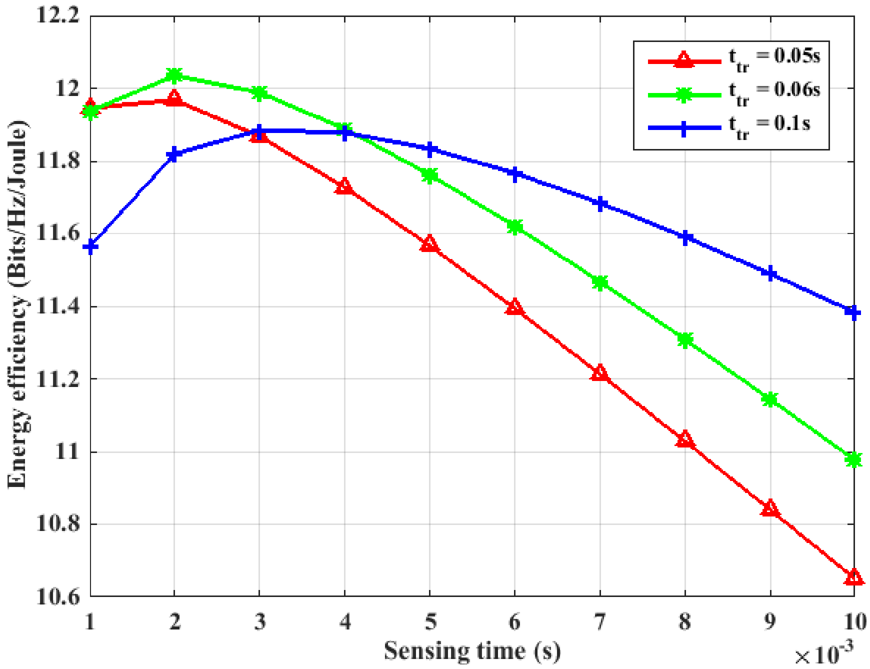

Fig. 3.3: Energy efficiency versus sensing time for different transmission times

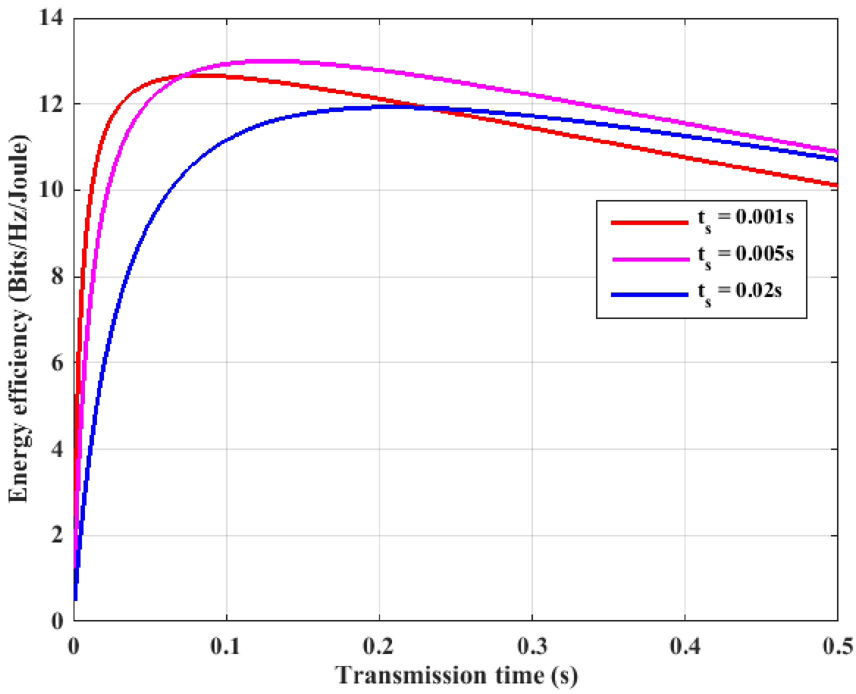

Fig. 3.4: Energy efficiency versus transmission time for different sensing times

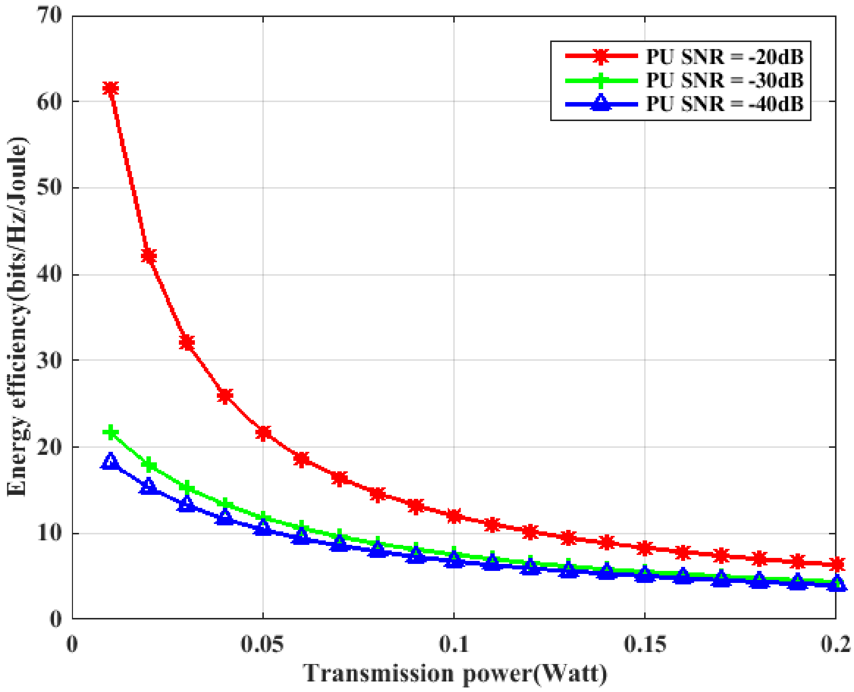

Fig. 3.5: Energy efficiency versus transmission power for different signal to noise ratio conditions

0.005s and 0.02s. Fig. 3.5 illustrates the EE plot against transmission power for three different PU SNR conditions. It is observed that decrease in PU SNR largely affects the EE. Here, PU SNR is considered as -20 dB. It can be observed that low PU SNR results in poor energy efficiency.

3.6 Conclusions

This chapter reflects the joint optimization of sensing and transmission time for energy efficiency in cognitive radio networks. A single primary user and single secondary user model to improve energy efficiency was considered in this chapter. The protection of licensed user from the unlicensed user's transmission was also taken into account. Simulation results show that for a unique point of both the sensing and transmission durations, energy efficiency is maximized under the constraint of primary user interference probability. Hence, the proposed algorithm shows superiority over sub optimal algorithm and exhaustive search method and outperforms both in terms of efficiency and complexity.

Chapter 4

Optimal Fusion Rule in Fading and Non-Fading Environment for Cooperative Spectrum Sensing

4.1 Introduction

It was shown in the previous chapter that optimizing the sensing, transmission time and transmission power, results in improved energy efficiency. This was shown for single-cognitive user in AWGN channels, in chapter 3. However, as discussed earlier, single cognitive user systems are susceptible to performance degradation due to fading, shadowing and the hidden node problem [19]. Accordingly, it has been proposed earlier that multiple SU should collaborate to counter these effects [21, 22]. Based on this idea, cooperative spectrum sensing was proposed in the literatures [58, 59]. However, multiple secondary nodes result in high energy consumption. Based on this idea, optimization of number of SUs to maximize EE is proposed in this chapter [1].

In this chapter, a CRN is considered with CSS, where multiple SU nodes are working together in collaboration with each other. Here, EE maximization problem is formulated with number of SU nodes is taken as system parameter and detection quality metrics are *probability-of-detection* and *probability-of-false-alarm*. First, maximum EE is calculated for different fusion rules and compared for AWGN channel. Then, EE is calculated for different fusion rules in flat fading environment. The EE, thus obtained for two scenarios are illustrated and compared for fading as well as non-fading. Such a comparison leads us to the conclusion that EE is higher for non-fading envi-

[1]This work has been published in the proceedings of 2017 IEEE Region Ten Conference (IEEE TENCON-2017, Malaysia) under the title "Energy Efficient Hard Decision Fusion Rules for Fading and Non-Fading Environment"

ronment as compared to the fading one. The novelty of this work is to compare and analyze the fusion rules on EE over AWGN with frequency-flat-fading environment.

This chapter seeks to remedy the above stated problem of energy by giving the following contributions:

- In this chapter, multiple SU nodes are considered and EE is maximized by optimizing different fusion rules. Three hard decision fusion rules are considered: *AND*, *OR*, and *k-out-of-N*. Here, EE is maximized firstly in the non-fading environment.

- The EE is then optimized for the same three fusion rules under the fading environment. Here, frequency flat-fading environment is considered.

- Afterwards, the EE obtained in the two different environments at different SNRs is compared by extensive illustrations. The simulation results reveal that the EE is high under the non-fading scenario as compared to the fading one. Along with EE, detection quality is also improved by enlarging the *probability-of-detection* (PD) and reducing the *probability-of-false-alarm* (PFA).

- The EE and number of SUs with respect to sensing window and sensing time are illustrated under various SNRs conditions. The comparison of EE for fading and non-fading environment by extensive simulation results is the novelty of this research.

4.2 Background and Motivation

Energy efficiency maximization has emerged as state of art in the field of cognitive radio [61–63]. Authors in [94] examined the trade-off between sensing time and energy, and then carried out the optimization to improve EE of CRNs. It has been demonstrated by Liang in [53] that a trade-off exist between spectrum sensing and throughput of a cognitive radio. Authors in [95–97] investigated the relationship between transmission duration, sensing duration and energy. Specifically, [95], dealt with the sensing based spectrum sharing , whereas [96] presented optimal allocation of power for fading channels. Moreover, authors in [97] analyzed the optimal allocation of power in CRNs for fading channels with PU outage constraints. In the analysis of EE, authors in [99, 100] defined the cross layer optimization with partial knowledge of local sensing results. In [87, 101], authors optimized the spectrum sensing duration to maximize the EE for homogeneous channel. In contrast with that, Eryigit et. al. in [104] discussed the EE sensing scheduling for the heterogeneous case of CRNs. In the literature [87], optimal transmission time and transmission power are studied for EE maximization. Whereas, the study in [88] proposed a hybrid protocol for the transmission so that SU can transmit data even when PU is present. Here, the interference produced by the transmission of SU to PU, is also considered. In [105–107], authors considered the orthogonal frequency devision multiple access (OFDM) and optimal power allocation on each sub carrier to enhance EE was investigated. Authors in [109], proposed Dinkelbachs iterative power adaptation based algorithm to increase the EE of CRNs. The optimum EE power allocation for OFDM based CRNs is examined in [91]. Moreover, in [30, 65] authors defined the EE as a ratio of throughput and energy consumed. In [86,110,111], joint optimization of the sensing and transmitting parameters were analyzed with respect to EE. Further, to improve the EE, the sensing time and transmission power in fading channel was optimized in [112]. In [90], authors formulated the problem with transmission power and sensing time as parameters, subject to PU protection.

The optimization of number of SUs plays important role in EE maximization problem for CSS scenario in cognitive radio. This number can be optimized based upon the selection of decision fusion rule. The decision fusion at the reporting stage can be performed by two schemes: soft scheme and hard scheme [19]. In hard decision fusion scheme, the information is transmitted in the form of 0 or 1. Here, 0 refers to the absence of PU signal whereas, 1 represents the presence of PU signal. However, sometimes the decision quality of sensing nodes is not good due to many reasons, hence soft scheme are used. In soft fusion, the SU may transmit all the samples or the total statistics, which results in improved quality of information. Eventually, soft scheme results in increased overhead due to large size of information samples. Therefore, quantized soft scheme is a better option, which is a trade-off between soft and hard schemes. In quantized soft scheme, the overhead is reduced by transmitting the quantized signal only [21, 24]. In [85], hard decision fusion rule and detection threshold are used as parameters to improve the EE. While, in [33], author discussed the effect of changing sensing-window size on the number of SUs for different hard decision fusion rules. However, few researches are also available, where the number of SU nodes were optimized for EE maximization [78, 79, 114]. Authors in [113], have presented joint optimization of sensing and transmission to maximize EE for a multichannel CR. They have proposed a combined optimization algorithm of bi-level, Polyblock and Dinkelbach's for EE problem effectively.

In addition to above work on EE, few researches have proposed hybrid architecture to improve the EE for 5G wireless networks. The research in [129] investigated the spectral efficiency (SE) of massive multiple input multiple output (MIMO) system based on discrete fourier transform (DFT) with hybrid architecture. The effects of number of radio frequency chains, SNR, and the number of users are also shown. The literature mentioned that optimal number of users could maximize SE. Further, to add more insight on SE, the literature [130] derived the achievable ergodic SE for a single-cell multi-user millimeter wave system with maximum ratio transmission precoding. The effect of the number of BS antennas, SNR, and crosstalk has also been evaluated. In [131] zero-forcing, minimum mean square error, and maximum ratio transmission precoding schemes are adopted to analyze the downlink multiuser massive MIMO system. It was analyzed in the literature that achievable rate increases with the increase in input SNR and the number of base station antennas. In the study of [132], parallel wireless power and information transfer were analyzed for the system that is multiuser information uplink and wireless powered downlink. Moreover, throughput maximization problem was studied in [133] for cloud radio access network by selecting the active remote radio heads. Additionally, in [134], SE and EE of massive MIMO with phase shifters for hybrid architecture were investigated. Further, to extend this work, in [135], authors proposed a low cost and hybrid architecture for massive MIMO with high SE and EE. However, none of the research have focused upon the comparison for EE maximization of CSS in CRNs in fading and non-fading environments.

4.3 System Model

In this chapter of dissertation, a CRN with N number of SUs and one fusion center is considered. Further, it is assumed that we have only one control and one PU channel. The PU channel is detected by using energy detection technique. The time slot of SU channel is synchronized with the PU channel. It is assumed that detection quality of all the SUs are same. Let, the time frame of the system is T sec. The time frame structure of CRN, is shown in Fig. 4.1. The total time frame is the sum of sensing time, reporting time and information transmission time of all the SUs. The local spectrum sensing is performed by N SUs at the same time, known as sensing time t_s. Further, all the SUs will report the local sensing results to the fusion center, hence the total reporting time is Nt_r . After the reporting stage, fusion center will perform the global decision making by using the fusion rule and the global result about the presence or absence of PU, is decided. Once, the SU declare that PU channel is vacant then data will be transmitted during the transmission time, t_t. Mathematically, the total time frame T can be represented as: $T = t_s + Nt_r + t_t$. The energy detection technique is used at the local spectrum sensing and detection phase. It can be easily implemented and less complex as compared to the other detection techniques. The local sensing and

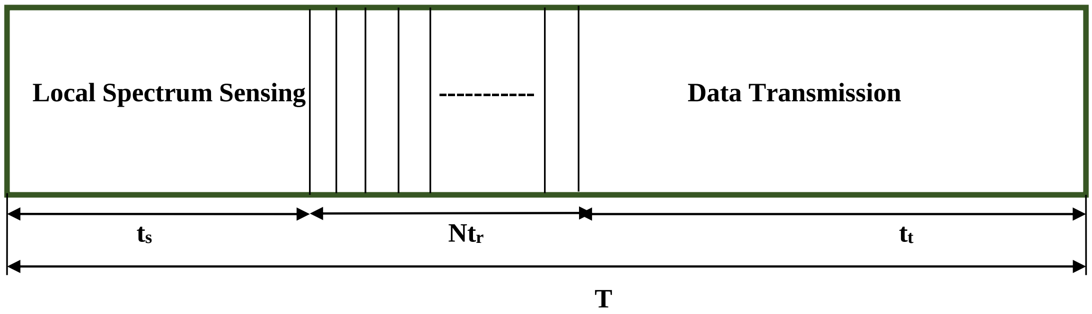

Fig. 4.1: Time frame structure of cooperative spectrum sensing

detection at each SU node is represented by binary Hypotheses as follows [113]:

$$\begin{aligned} &H0 \quad (idle \quad channel): \quad y(m) = z(m) \\ &H1 \quad (busy \quad channel): \quad y(m) = x(m) + z(m) \end{aligned} \tag{4.1}$$

where $H0$ represents the hypotheses of PU signal absence and $H1$ is the hypotheses of PU signal presence, $y(m)$ is the received signal, for $m = 1, 2.....J, x(m)$ is the PU signal and $z(m)$ is noise present. The total number of samples or the sensing window size is given as: $J = t_s f_s$, where J is the number of samples and f_s is the sampling frequency. Here, energy detection is used at each SU node for sensing and detection purpose and it can be given by the following energy statistics [113]:

$$\psi(y) = \Sigma_{m=1}^{J} |y(m)|^2 \tag{4.2}$$

The SNR of received signal is represented as: $Y = \frac{\sigma_x^2}{\sigma_z^2}$, where, σ_x^2 is the received PU signal variance and σ_z^2 is the noise variance. By assuming that all the N SUs have identical detection performance, the two probabilities of quality metrics, *probability-of-false-alarm* (PFA) and *probability-of-detection* (PD), can be defined as [113]:

$$\begin{aligned} &probability\text{-}of\text{-}detection: P_{de} = Q\left(\frac{\varepsilon - (1+Y)\sigma_z^2}{\sigma_z^2\sqrt{\frac{2(1+2Y)}{J}}}\right) \\ &probability\text{-}of\text{-}false\text{-}alarm: P_{fa} = Q\left(\frac{\varepsilon - \sigma_z^2}{\sigma_z^2\sqrt{\frac{2}{J}}}\right) \end{aligned} \tag{4.3}$$

where ε is the sensing threshold. The detection results from each SU node will be reported to the FC. Then FC performs the global decision by applying the hard decision fusion rule. The *global probability-of-detection* (GPD) and *global probability-of-false-alarm* (GPFA) for three fusion rules are as follows [33]:

OR

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{OR} &= 1-(1-P_{de})^N \\ \textit{Global probability-of-false alarm} : G_{fa}^{OR} &= 1-(1-P_{fa})^N \end{aligned} \tag{4.4}$$

AND

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{AND} &= P_{de}^N \\ \textit{Global probability-of-false alarm} : G_{fa}^{AND} &= P_{fa}^N \end{aligned} \tag{4.5}$$

k-out-of-N

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{koN} &= \Sigma_{i=k}^{N}\tbinom{N}{i}P_{de}^{i}(1-P_{de})^{N-i} \\ \textit{Global probability-of-false alarm} : G_{fa}^{koN} &= \Sigma_{i=k}^{N}\tbinom{N}{i}P_{fa}^{i}(1-P_{fa})^{N-i} \end{aligned} \tag{4.6}$$

4.4 Problem Formulation and Solution

The EE problem can be formulated as a ratio of total throughput to the total energy consumed. Hence, the problem can be set up as follows:

4.4.1 Throughput for AWGN Channel

In this system, for AWGN channel, it is assumed that data bits are transmitted after the successful detection of PU idle channel. Here, it is considered that there is no PU reoccupation during SU transmission. Therefore, for the given CRN, the data bits transmitted per frame is given as:

$$R_t = R_0 P_0 (1-G_{fa}) t_t \tag{4.7}$$

where, R_0 is the number of bits per transmission time t_t for AWGN channel, P_0 is the probability of PU idle channel state and R_t is the total throughput of the system.

4.4.2 Throughput for Frequency - Flat Fading Channel

In the frequency-flat fading channel, the number of bits that can be transmitted in the t_t transmission time, can be approximated as: $R_0 t_t$, where $R_0 = Blog_2(1+Y_{SU}/\Gamma), B$ is channel bandwidth, Y_{SU} is the SNR of SU receiver and Γ is the SNR gap and can be find as: $\Gamma = -ln(5P_{ber})/1.5$. The SNR at the receiver of SU can be calculated as: $Y_{SU} = P_t/(GBN_0N_f)$, where P_t is transmitted power, $N_0/2$ is power spectral density (two sided). The gain can be calculated as: $G = 4\pi M_l d^p/\lambda$, where d is transmission distance for path loss p, M_l is link margin and λ is wavelength of the carrier. Let, for this system, uncoded M-QAM (M-ary Quadrature Amplitude Modulation) is used, then the transmission power can be approximated as: $|h|^{-2}(2/3)GBN_0N_f ln(P_{ber}^{-1})(2^b - 1)$, where the constellation size for M-ary QAM is 2^b and fading gain is $|h|^2$.

4.4.3 Total Energy Consumed

In our model, the total power consumed is the sum of sensing, transmission and reporting power. Hence, the total energy consumed can be calculated by respective powers as follows:

$$E_t = NP_s t_s + NP_t t_r + P_t t_t P_{idle} \tag{4.8}$$

where, the sensing power is P_s, transmission and reporting powers are considered same as P_t.P_{idle} is the perfect idle channel probability and calculated as: $P_{idle} = P_0(1 - G_{fa}) + P_1(1 - G_{de})$. Here, P_0 and P_1 are the probabilities of PU idle and busy state, respectively.

4.4.4 Energy Efficiency

The energy efficiency for this system is defined as ratio of throughput and total energy consumed and denoted as [21]:

$$\zeta = \frac{R_t}{E_t} = \frac{R_0 P_0 (1 - G_{fa}) t_t}{NP_s t_s + NP_t t_r + P_t t_t P_{idle}} \tag{4.9}$$

It can be seen from above equation that increasing the number of SUs increases the sensing and reporting energy consumed, that ultimately results in less EE for the CSS system. Further, the impact of SU number depends on the type of fusion rule used. This leads us to minimize the number of SUs for different sensing time. Therefore, to improve the EE, the number of SUs must be optimized.

4.4.5 Proposed Method to Minimize the Number of SUs

The above stated problem of EE can be outlined in term of three decision fusion rules. The proposed strategy to achieve highest EE keeping the target quality of detection by minimizing the number of SUs, is as follows:

OR Case For *OR*, GPFA and GPD increases with the increase in N. Hence, N can be minimized for a fix PD and reduced PFA. It can be defined by the following problem:

$$\begin{aligned} & minN \\ s.t. \quad & t_{s,min} < t_s < t_{s,max} \\ & G_{de}^{OR} \geq a \\ & P_{fa} \leq b \end{aligned} \tag{4.10}$$

where, a is the constraint of GPD and b is the constraints of PFA for a single cognitive radio, whereas, $t_{s,min}$ and $t_{s,max}$ are the minimum sensing time and maximum sensing, respectively. However, the required threshold to keep G_{fa}^{OR} as minimum as possible can be calculated as:

$$\varepsilon = \left(\sqrt{\frac{2}{t_s f_s}} Q^{-1}(b) + 1 \right) \sigma_z^2 \tag{4.11}$$

The minimum number of SUs with minimum G_{fa}^{OR} and required detection quality can be expressed as:

$$N_m^{OR} = min\left(\lceil \frac{log(1-a)}{log(1-P_{de})} \rceil, N \right) \tag{4.12}$$

where, N is the total number of SU present in the CRN. The $t_{s,min}$ and $t_{s,max}$ can be calculated as follows:

$$\begin{aligned} t_{s,min} &= \frac{2(Q^{-1}(b_m) - G^{-1}(e_m)\sqrt{1+2Y})^2}{f_s Y^2} \\ t_{s,max} &= \frac{2(Q^{-1}(b) - Q^{-1}(e)\sqrt{1+2Y})^2}{f_s Y^2} \end{aligned} \tag{4.13}$$

In equation (4.13), b and e are the PFA and PD constraint for a single SU, while b_m and e_m are the minimum PFA and PD constraints, respectively.

AND Case The problem for *AND*, with minimum false alarm and better detection quality can be formulated by the following equation:

$$\begin{aligned} & minN \\ s.t. \quad & t_{s,min} < t_s < t_{s,max} \\ & G_{fa}^{AND} \leq c \\ & P_{de} \geq e \end{aligned} \tag{4.14}$$

In the above equation c constraint of GPFA. Here, to enlarge the GPD, sensing threshold can be calculated as:

$$\varepsilon = \left(\sqrt{\frac{2}{t_s f_s}(1+2Y)} Q^{-1}(e) + 1 + Y \right) \sigma_z^2 \tag{4.15}$$

Hence, the minimum number of SUs to meet the detection performance given above, for *AND* rule can be calculated as:

$$N_m^{AND} = min(\lceil \frac{log(c)}{log(P_{fa})} \rceil, N) \tag{4.16}$$

k-out-of-N Case As per [17], the *k-out-of-N* is a balance between the detection and false alarm quality. It enlarges the PD and reduce the PFA. Hence, to meet the target detection quality the problem can be formulated as:

$$\begin{aligned} & minN \\ s.t. \quad & t_{s,min} < t_s < t_{s,max} \\ & G_{de}^{koN} \geq a \\ & P_{fa} \leq b \end{aligned} \tag{4.17}$$

To achieve the required detection performance and to keep G_{fa}^{koN} as low as possible, the detection threshold can be computed by equation (4.11). Further, to solve for the minimum number of SU, the approximations of equation (4.6) can be achieved by Demoiver-Laplace Theorem and can be represented as:

$$\begin{aligned} G_{de}^{koN} &= Q\left(\frac{(k - 0.5 - NP_{de})}{\sqrt{NP_{de}(1-P_{de})}} \right) \\ G_{fa}^{koN} &= Q\left(\frac{(k - 0.5 - NP_{fa})}{\sqrt{NP_{fa}(1-P_{fa})}} \right) \end{aligned} \tag{4.18}$$

Hence, the minimum number of SUs to achieve the target performance $G_{de}^{koN} \geq a$ can be calculated as:

$$\begin{aligned} N_1 &= \frac{(2k-1+(Q^{-1}(a))^2(1-P_{de})) \pm Q^{-1}(a)\sqrt{(1-P_{de})(4k-2+(Q^{-1}(a))^2(1-P_{de}))}}{2P_{de}} \\ N_m^{koN} &= min(N, N_1) \end{aligned} \tag{4.19}$$

4.5 Simulation Results

The EE for each rule in fading and non-fading environment is illustrated by the simulation results. The results for both the environments are compared and analyzed. The simulation parameters are summarized in the Table 4.1.

Table 4.1: Simulation parameters

Parameters	Values
Sampling frequency, f_s	6 MHz
Total time frame, T	100 msec
Throughput for AWGN, R_0	10 Mbps
Sensing power, P_s	0.3 W
Transmission power, P_t	0.1 W
Probability of PU idle state, P_0	0.8
Constraint of detection probability, e	0.9
Number of SUs, N	30
Constraint of false alarm probability, b	0.1
Constraint of global detection probability, a	0.95
Constraint of global false alarm probability, c	0.05
Minimum probability of false alarm b_{min}	0.5
Minimum probability of detection, e_{min}	0.5
Reporting time, t_r	1 msec
Transmission distance, d	40 m
Link margin compensation, M_l	10 dB
Two sided power spectral density, $N_0/2$	-204 dBW/Hz
Path loss, p	4
Fading gain, h	1
Carrier frequency, f_c	700 MHz
Bit error rate, P_{ber}	10^{-5}

In the following explanation Fig. 4.2 illustrates the effects of varying sensing window on GPFA for OR at different SNR levels. It is apparent from the figure that as the size of window increases, G_{fa}^{OR} reduces. The effect of SNR level is very prompt on G_{fa}^{OR}. It can be observed that it is maximum at SNR of -12 dB and minimum at 0 dB. For a sensing window size under 50, the fall in GPFA is very fast, afterwards it reduces slowly. From the figures, Fig. 4.2, Gig. 4.4 and Fig. 4.14, it can be noticed that number of SUs decreases by increasing of sensing window, consequently, G_{fa}^{OR} decreases as well. Therefore, the spectrum efficiency consequently increases. Moreover, the decrease of both number of SUs and G_{fa}^{OR} results in improving EE with increasing window size as shown in Fig.4.4. Although, increase in sensing window size leads to increase in sensing energy, however, the impact of decreasing number of SUs and G_{fa}^{OR} on EE is greater than that of the impact of increasing window size. Furthermore, it can be seen from the figures that better SNR requires less cooperating SUs and enhances both the GPFA and EE.

The two sets of figures Fig. 4.3 and Fig. 4.4, compare and contrast the EE and sensing window for *AND* and *OR*, respectively. Here, the EE with respect to the size of sensing window is presented in Fig. 4.3 and taken at different SNR levels. From the above figure we can see that initially, for a window size of $0-50$ at SNR of 0 dB, the EE start increasing rapidly and then stabilize thereafter. Further, it is highest at 0 dB but lowest at -12 dB. Fig. 4.4 also illustrates the effect of window size on EE for *OR* rule at different SNRs. It is notable that *OR* gives the maximum EE 1.6431 bits/Hz/Joule while *AND* gives 1.6060 bits/Hz/Joule for 0 dB SNR. Interestingly, *OR* gives better EE as compare to *AND* rule.

In the text followed, the EE for *k-out-of-N* is analyzed at different parameters. In Fig. 4.5 EE with varying k at different SNR has represented. The analysis between EE and k has been done at the sensing window size of 100. Here, the maximum EE achieved for $k = 5$ at SNR of -2 dB is 2.3084 bits/Hz/Joule, which is the highest among the three fusion rules. It can be displayed graphically that the optimum k here is 5, at which we are getting the maximum EE.

The simulation results for EE in fading and non-fading environments are revealed in Fig. 4.6 and Fig. 4.7. By comparing, it can be realized that among the maximum EE can be achieved in non-fading environment. It is indicated by the figure that the effect of fading reduces the throughput which results in reduced EE. It is also notable here that *k-out-of-N* and *OR* are performing very close in terms of EE and outperform *AND*. It is evident from the graph that *OR* has a faster EE improvement as compared to *AND*. But, if we talk about the GPFA, Fig. 4.8 shows the better quality metric for *k-out-of-N* as compared to *OR* as the GPFA is lesser for *k-out-of-N*. Taken together the EE and GPFA, we can conclude that *k-out-of-N* outperforms *AND* and *OR* in terms of EE and GPFA.

The GPFA and EE with respect to the size of sensing window at different k values are displayed in Fig. 4.9 and 4.10. Fig. 4.9 indicates that higher the k lesser the G_{fa}^{koN}. This result may be explained by the fact that lowering the sensing window results in higher G_{fa}^{koN}. It can be seen from 4.10 that higher the sensing window, higher the EE. Here, EE are taken for different values of as k = 2, 3, 4, 5.

This section of figures, Fig. 4.11, Fig. 4.12, Fig. 4.13, Fig. 4.14, and Fig. 4.15 identified the impact of changing sensing time and sensing window on number of SUs. The effect of changing sensing time on number of SUs for different channel conditions is shown in Fig. 4.11. The result is this figure suggest that better SNR needs lesser number of SUs. However, it further reduces for higher sensing time. Furthermore, Fig. 4.12 unveils the impact of window size on number of SUs for k = 2, 3, 4, 5. Moreover, comparable performance for *AND* and *OR* in terms of number of SUs is shown in Fig.4.13 and Fig. 4.14, respectively.

Fig. 4.15 displays the performance evaluation of three hard decision fusion rules in terms of number of SUs with respect to change in sensing time. It is to be noted that for a particular sensing time the number of SUs required is maximum for *k-out-of-N*. It is least for the *OR* among all rules. However, the number reduces drastically with the increase in sensing time. Overall, these results suggest that increasing sensing time or sensing window reduces the requirement of number of SUs. However, for the large SNR condition the fall of number of SU is sharp as compared to low SNR.

For further comparison of the proposed method with other state of art, a comparison table is presented in Table 4.2. In [132], the EE is maximized by optimizing the time allocation for the downlink and traffic of multi-user uplink. The EE obtained after simulation is 2.55 bits/Hz/Joule at transmission power of 5 dB and target throughput of R_0 = 0.5 bits/s/Hz. In case of [134], the massive MIMO architecture based on phase shifter is proposed to improve the achievable SE and EE. The maximum EE achieved, is 0.054 bits/Hz/Joule for the proposed hybrid architecture with 300 base station antennas. The low cost with high SE and EE massive MIMO by applying the DFT processing is demonstrated in [135]. The achievable EE for the given system is 0.59 bits/Hz/Joule. For the comparison purpose the EE vs sensing time for three fusion rules have been illustrated in Fig. 4.16 at R_0 = 0.5 bits/s/Hz. The maximum EE is clearly illustrated by the graph which is, 4.925 bits/Hz/Joule.

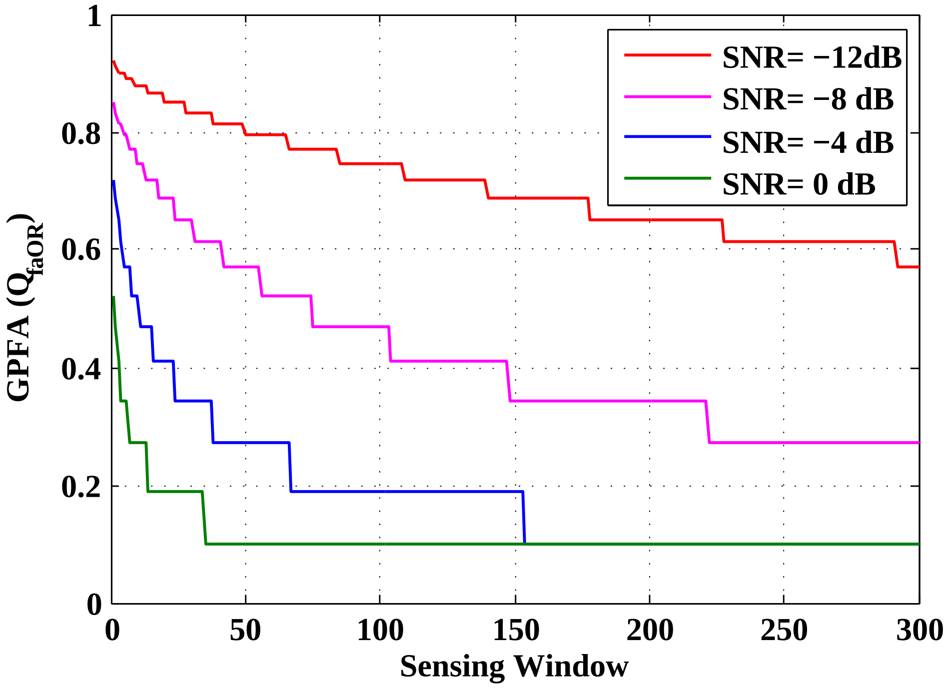

Fig. 4.2: Global probability of false alarm versus sensing window for *OR* rule

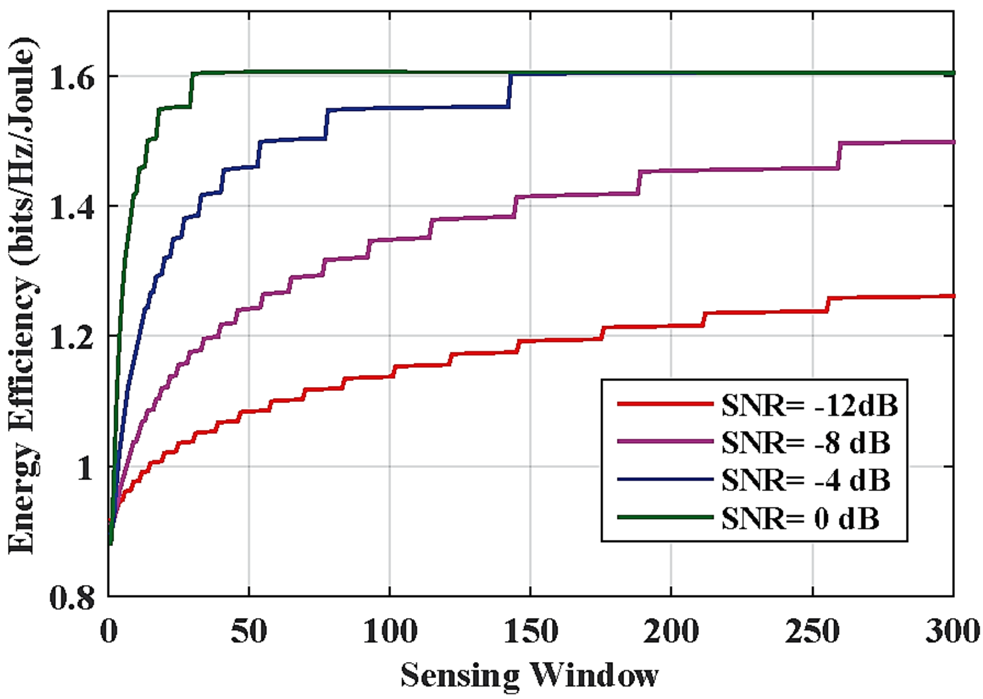

Fig. 4.3: Energy efficiency versus sensing window for *AND* rule

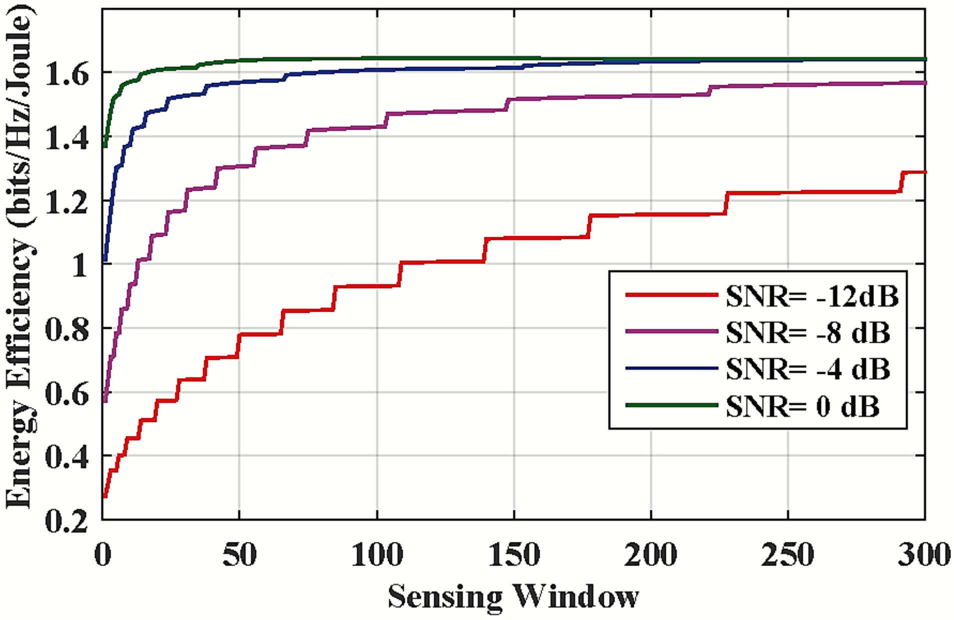

Fig. 4.4: Energy efficiency versus sensing window for *OR* rule

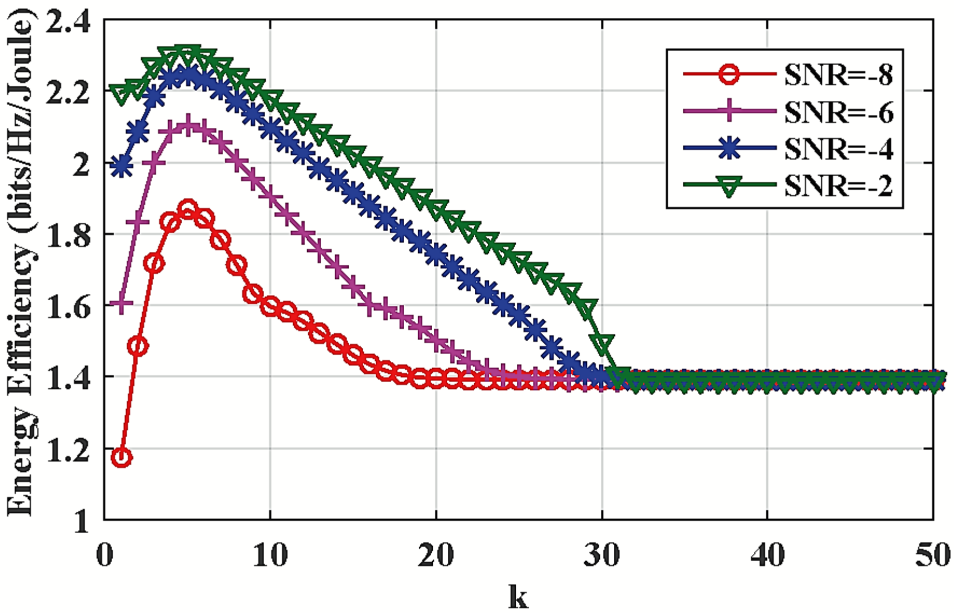

Fig. 4.5: Energy efficiency versus k at different signal to noise ratio conditions

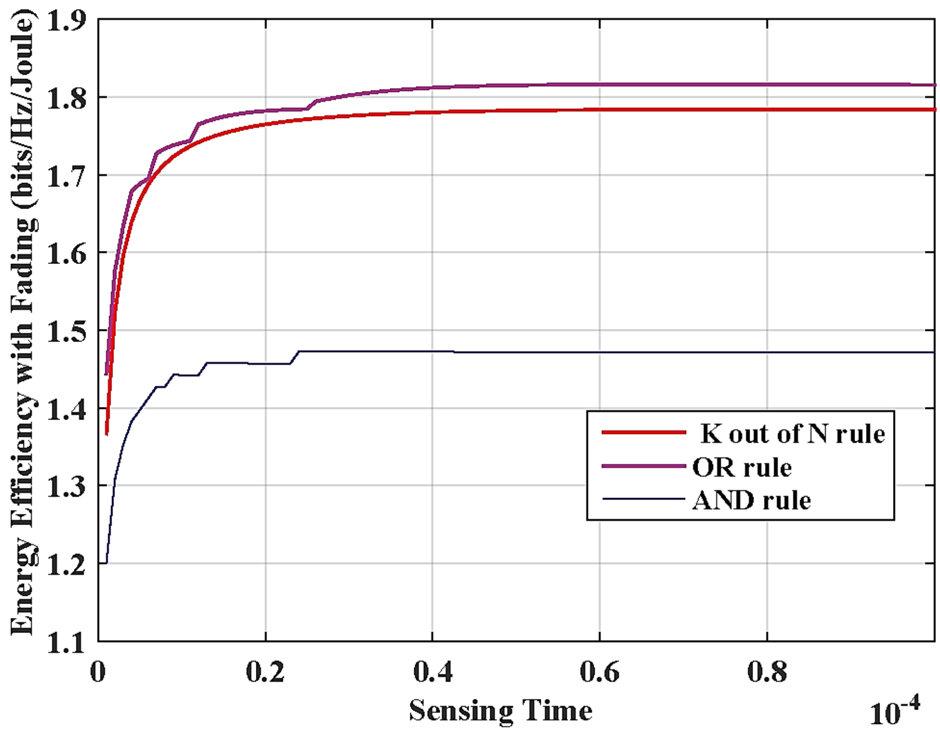

Fig. 4.6: Energy efficiency versus sensing time for three rules in frequency-flat-fading environment

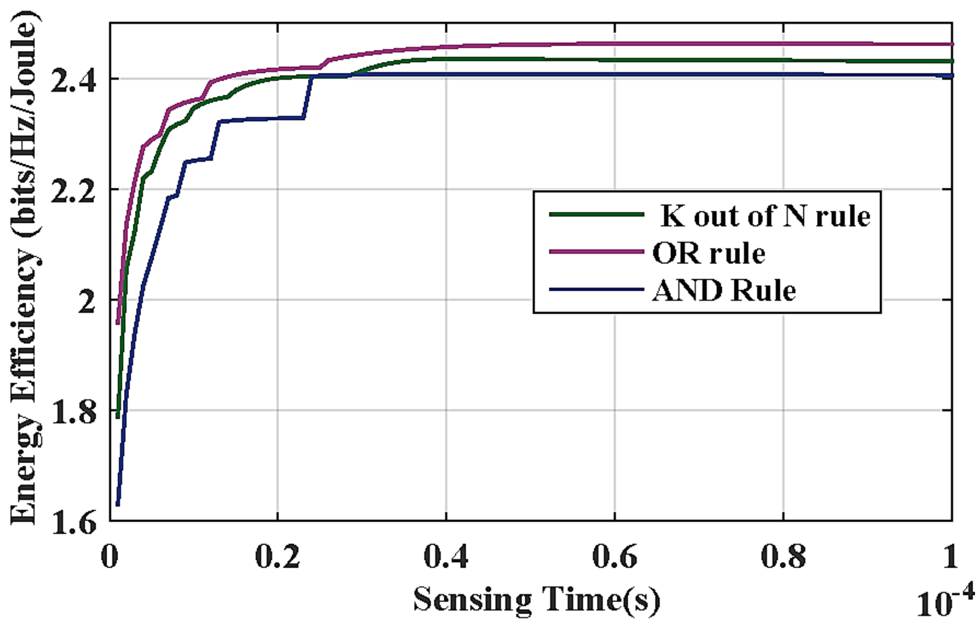

Fig. 4.7: Energy efficiency versus sensing time without fading

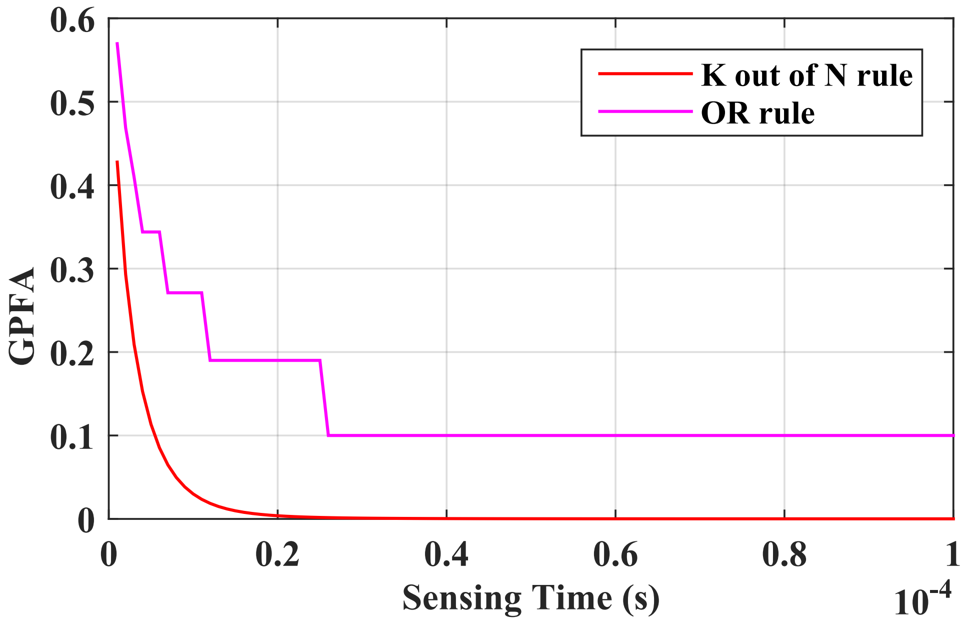

Fig. 4.8: Global probability of false alarm and sensing time for *k-out-of-N* rule and *OR* rule

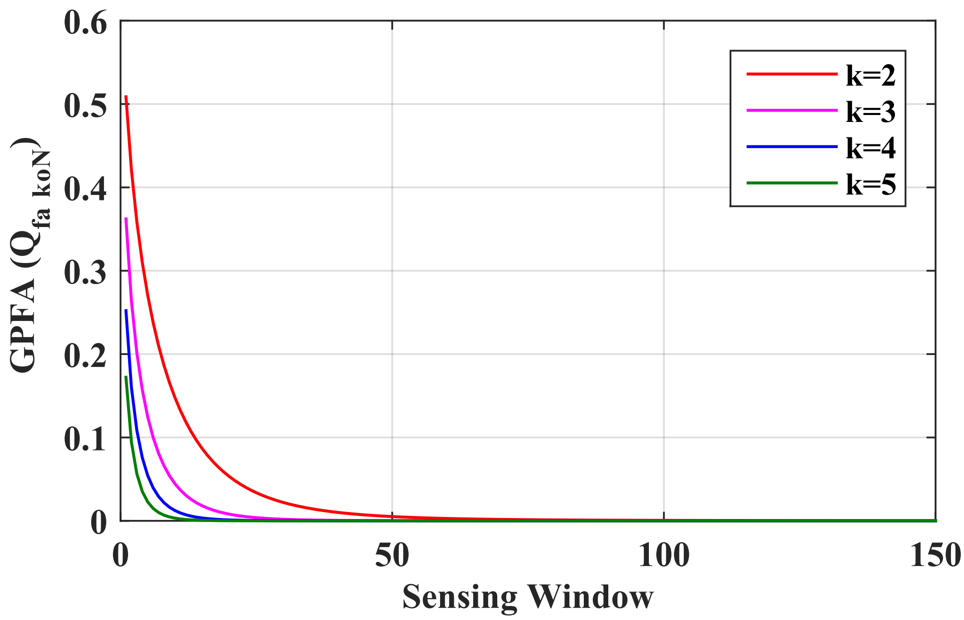

Fig. 4.9: Global probability of false alarm versus sensing window for *k-out-of-N* rule

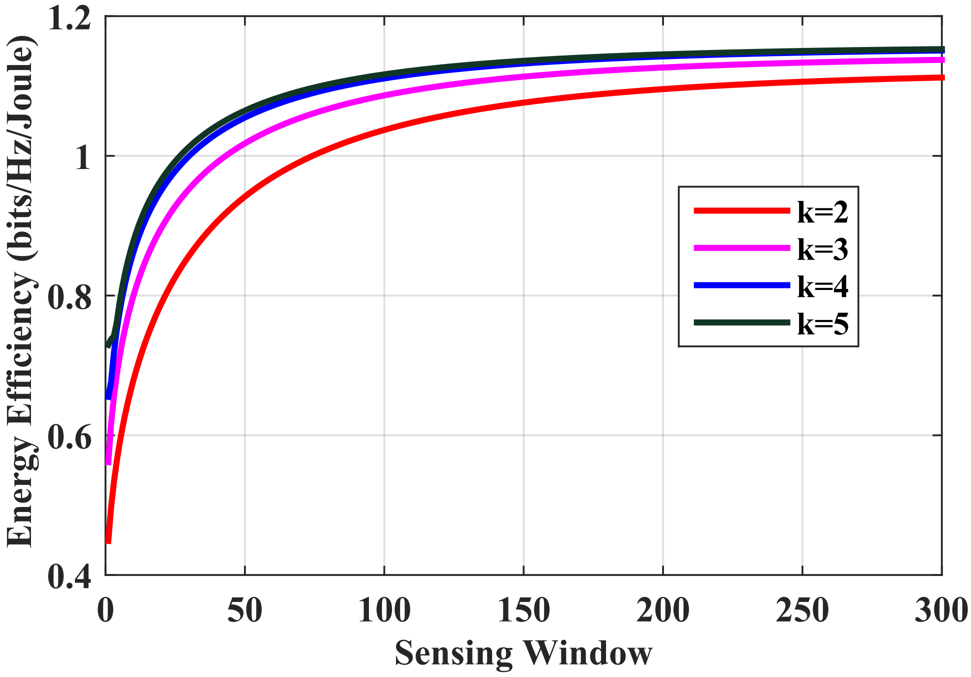

Fig. 4.10: Energy efficiency versus sensing window for *k-out-of-N* rule with fading

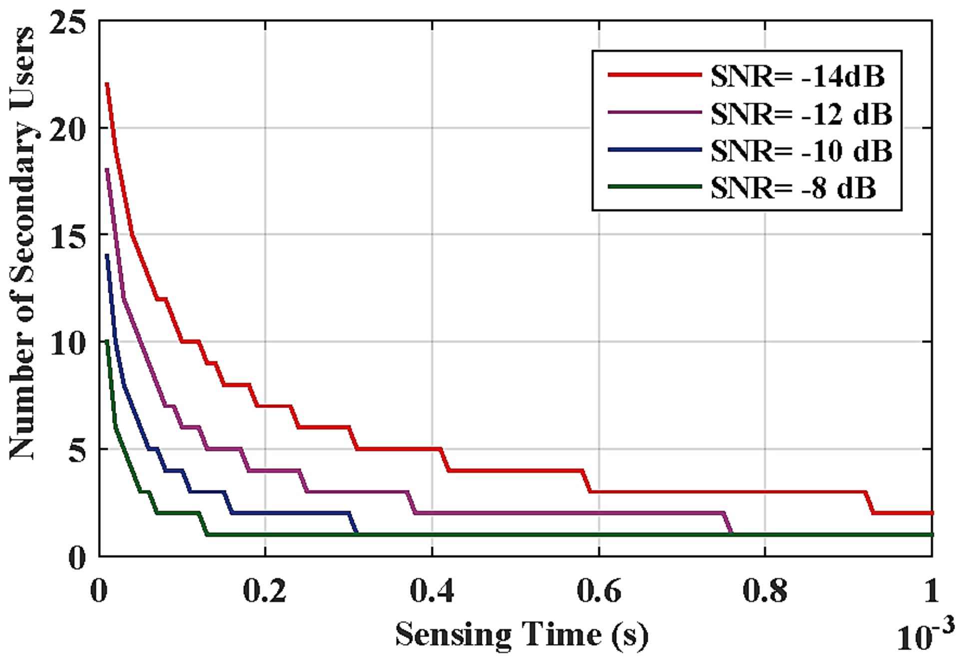

Fig. 4.11: Number of secondary users versus sensing time for *AND* rule at different signal to noise ratio conditions

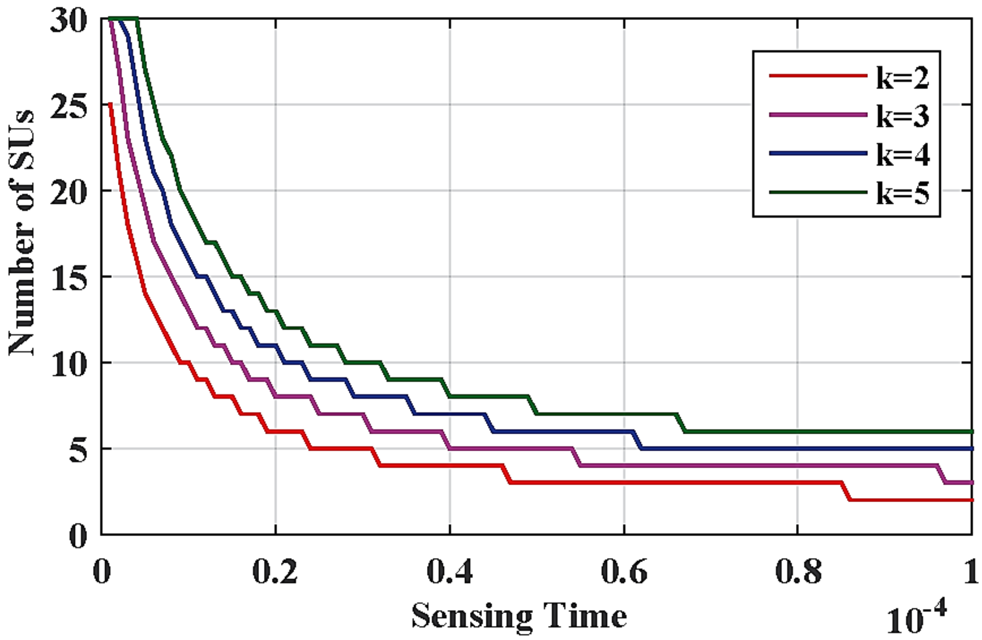

Fig. 4.12: Number of secondary users versus sensing time at different values of k

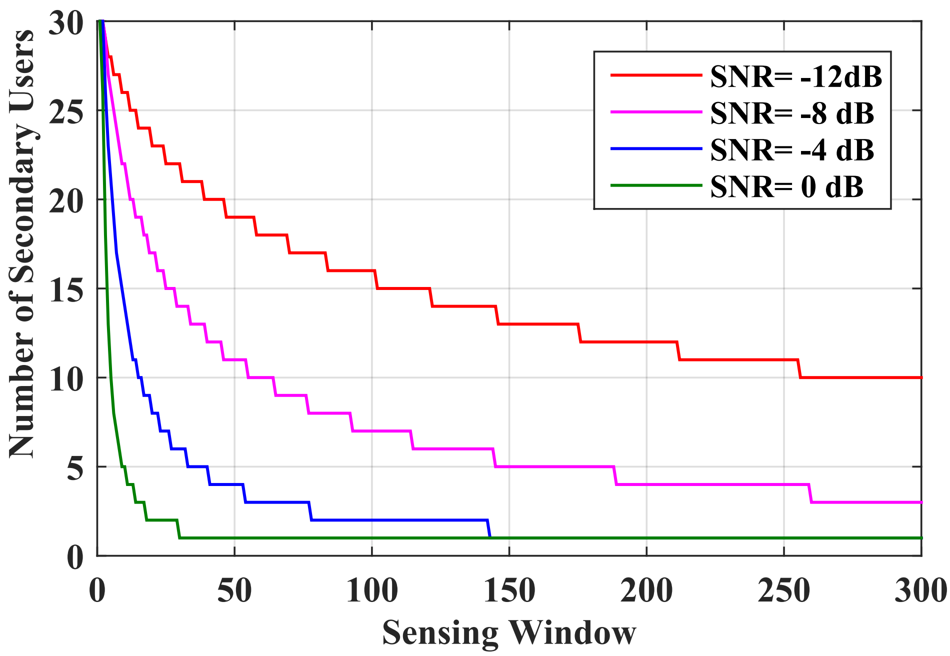

Fig. 4.13: Number of secondary users versus sensing window for *AND* rule at different signal to noise ratio conditions

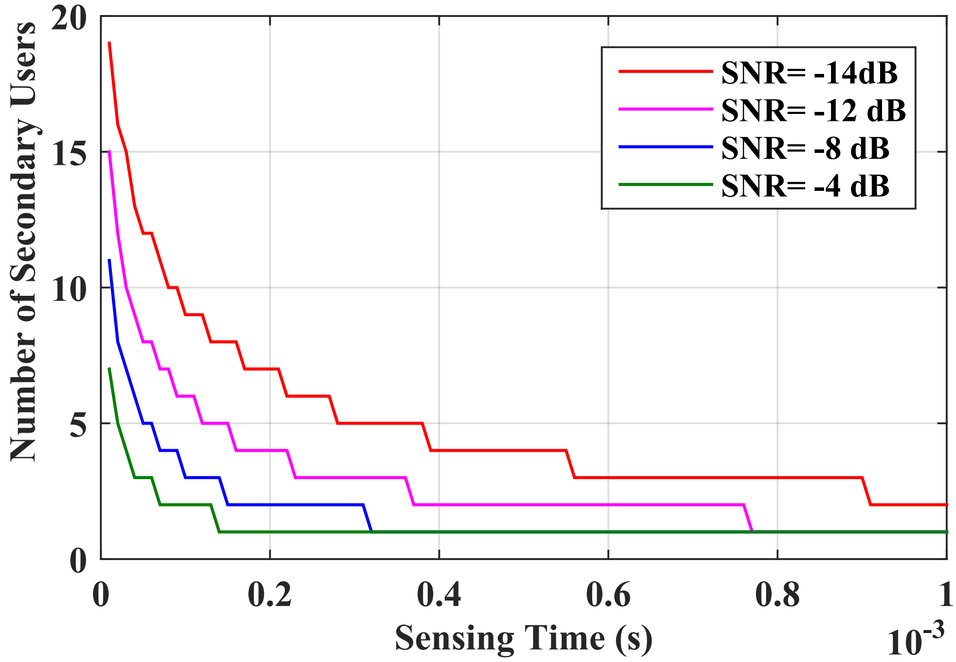

Fig. 4.14: Number of secondary users versus sensing time for *OR* rule at different signal to noise ratio

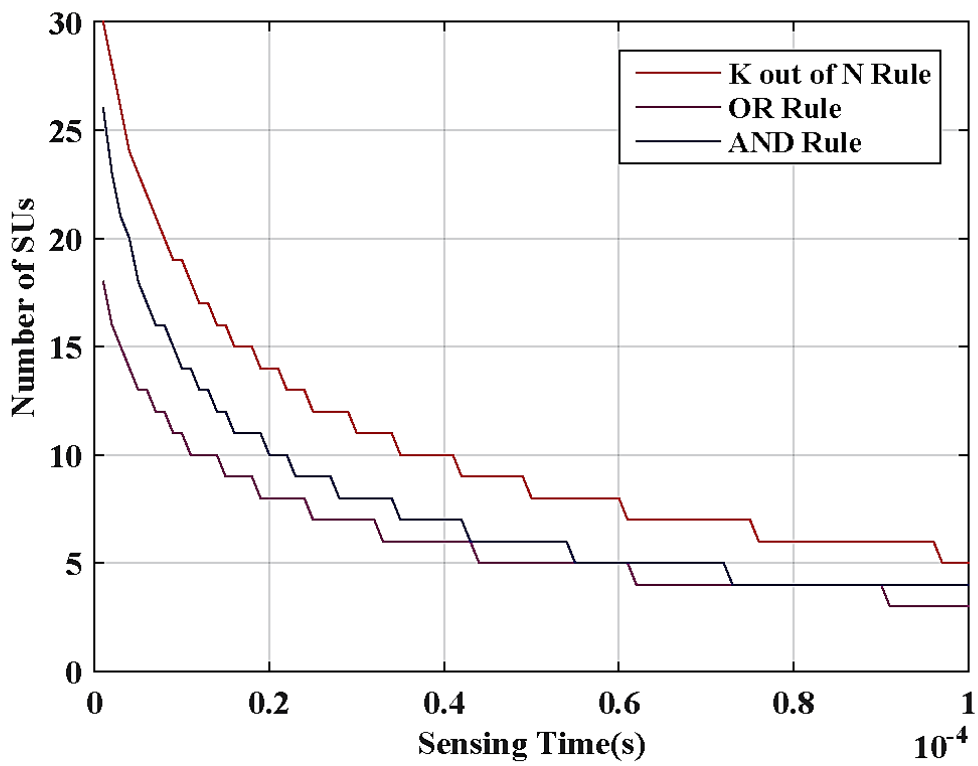

Fig. 4.15: Number of secondary users versus sensing time for three rules

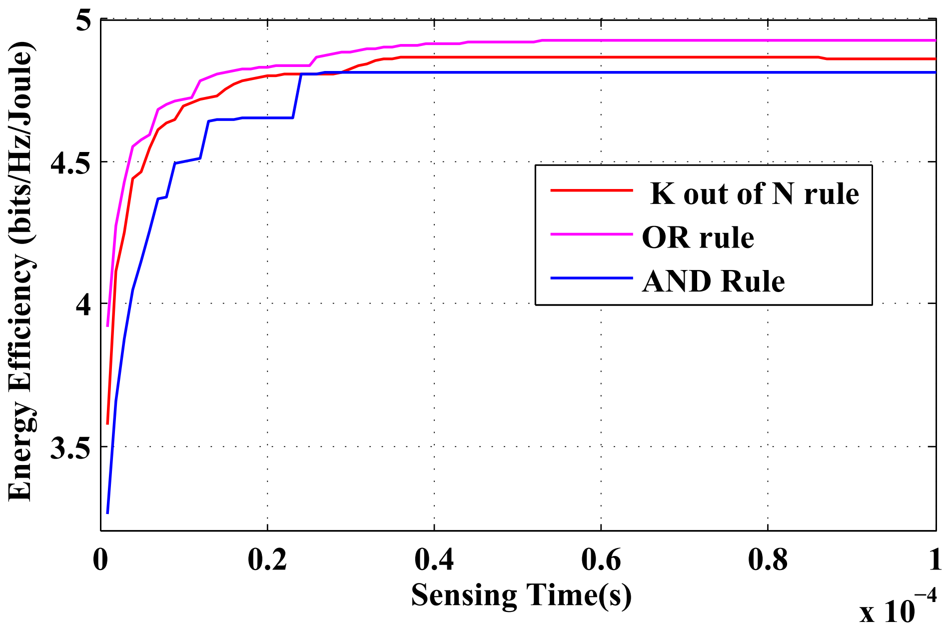

Fig. 4.16: Energy efficiency versus sensing time without fading for R_0 = 0.5 bits/s/Hz

Table 4.2: Comparison of proposed with state of art in terms of energy efficiency

System model, method/algorithm	**Parameters**	**Maximum EE (bits/Hz/Joule)**	**Remarks**
Wireless powered downlink and multiuser information uplink, Lagrangian multiplier approach [132]	Transmit power	2.55	Maximum EE is achieved for throughput R_0, 0.5 bits/s/Hz
Massive MIMO for hybrid architectures based on phase shifters [134]	Number of base station antenna and SNR	0.054	Hybrid architecture of massive MIMO, Maximum EE is achieved at 300 BS and 20 dB SNR
Hybrid analog/digital architecture in massive MIMO system [135]	Number of users, SNR	0.59	SE and EE are optimized, hybrid architectures with DFT processing, ideal phase shifters, and switch network
Proposed, EE maximization of cooperative cognitive radio in fading and non-fading environment	Number of secondary users, SNR	4.92	Maximum EE is achieved for *k-out-of-N* rule in non-fading at throughput R_0, 0.5 bits/s/Hz, SNR -4dB

4.6 Conclusions

This research has given an account of the three hard decision fusion rules, that were analyzed and compared exhaustively on the basis of energy efficiency, number of secondary users and detection quality. The overall detection performance of the cooperative spectrum sensing scheme in cognitive radio network is also considered. The energy efficiency maximization by optimizing the number of secondary user in fading and non fading environment has been illustrated graphically. The simulation results have revealed that increasing sensing time minimizes the number of secondary users and improves the energy efficiency keeping good quality of detection performance. The findings of this study suggest that *k-out-of-N* rule exhibits the best performance among three rules and shows the superiority over *AND* and *OR* rule in terms of energy efficiency and global probability of false alarm taken altogether.

Chapter 5

Optimizing Sensing and Transmission Parameters for Energy Efficiency Maximization

5.1 Introduction

The minimization of number of secondary users improves the energy efficiency in the case of cooperative spectrum sensing of cognitive radio networks. In the last chapter, the EE was improved by the optimization of hard decision fusion rules and compared in fading and non fading environments. However, EE depends on many other sensing and transmission parameters also, namely, sensing time, transmission time, transmission power, reporting time, type of multiple access techniques, and type of fusion rules etc. Therefore, in this chapter optimization of number of SUs, sensing time and reporting time is proposed to maximize EE [1].

There is a trade-off between sensing, transmission duration versus EE of CRNs [94, 97]. Therefore, the EE of cognitive transmissions is largely affected by sensing, transmission, reporting durations and power associated with them, respectively [53, 99]. Hence, the design of these parameters encounter significant impact on EE [100]. There is a lot of research published, in which EE is maximized by optimizing the sensing and transmission parameters [101, 105, 107, 109, 136].

In the literature [137], authors have investigated the mean EE maximization by hybrid spectrum sharing schemes. An iterative power adaptation algorithm was proposed to solve the optimization problem and *OR* fusion rule was adopted for the fusion

[1] This work has been published in (AEÜ) - International Journal of Electronics and Communications Elsevier, vol 98, issue 2019, as "Optimal Sensing, Fusion and Transmission with Primary User Protection for Energy-Efficient Cooperative Spectrum Sensing in CRNs"

purpose. Moreover, in the paper [138], EE is maximized by jointly optimizing the sensing, transmission durations, transmission power and fusion rule threshold. However, to find the global optimality, alternating duration method (ADM) was proposed. Although, authors have not considered reporting phase, which is very important phase in case of CSS. Moreover, no reporting time and reporting power is considered, even they have mentioned to optimize the fusion rule threshold. Further, EE maximization problem is formulated subject to detection performance constraints in [139]. In this research, first the optimal expression of detection threshold is formulated then iterative solution algorithm is proposed to get the optimal sensing time and modulated symbol sequence length. In the literature [140], joint optimization of sensing duration, detection threshold and selection of SUs for sensing and transmission time, is considered. Here, authors have proposed the improvement of throughput and reduction of consumption of energy. However, in this paper no effect on EE improvement is shown, only minimization of energy consumed is focused by the authors. In [114], EE maximization of the CRNs is done subject to protection to the PU and also with the constraint of power. The detail analysis of literature survey is mentioned in chapter 2.

The above discussion motivated us to formulate EE maximization model for multiple SU nodes CSS. To enhance the EE joint optimization of number of SU nodes, sensing and transmission duration is proposed. As the expression of EE for multiple SUs is complicated, the EE problem for global optimality is difficult to solve. To tackle this problem, we first optimize the number of SU nodes by optimizing the hard decision fusion rules and then propose an iterative sub optimal algorithm to obtain the optimal sensing and transmission durations by using optimized number of SU nodes. The interference due to SU transmission upon PU reoccupation is also considered in the sense that PU protection is also taken into account.

5.2 System Model

In this chapter, a cognitive radio network with N SUs, one fusion center, one control channel and one licensed channel of bandwidth B MHz is adopted. This CRN is considered as a single hop architecture and all the SU nodes are homogeneous. It is assumed that the reporting phase is performed by TDMA approach, in which each SU has its own time slot. The total time period can be partitioned into n frames and the fusion center node is synchronized with all the SU nodes. It is also assumed that the time frames operate with the periodic spectrum sensing.

Fig. 5.1 shows the time frame structure of CRN system. Total n time frames are considered in the system. Each time frame T consists of three phases, which includes

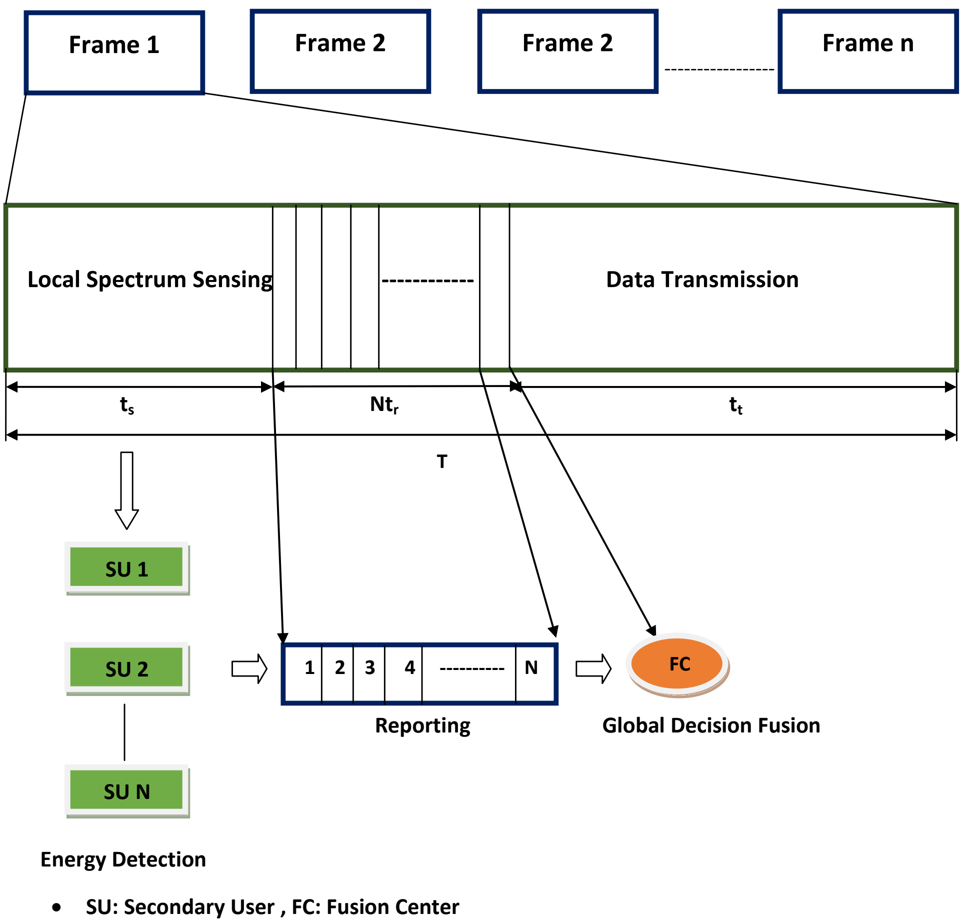

Fig. 5.1: Time frame structure of cooperative spectrum sensing

local spectrum sensing phase, reporting phase and the data transmission phase i.e. $T = t_s + Nt_r + t_t$. Where, t_s, t_r, t_t are sensing time, reporting time and transmission time, respectively.

5.2.1 Cooperative Spectrum Sensing

In local spectrum sensing phase, it is assumed that all the SU nodes use energy detection to detect the PU busy or idle stage. It is also assumed that all SU nodes are homogeneous. The sensing time for each SU node is t_s that works in parallel to each other independently with a sampling frequency of f_s. The PU signal detection mainly depend on the following hypotheses [113]:

$$\begin{aligned} H_0(\text{idle channel}) &: y(m) = z(m) \\ H_1(\text{busy channel}) &: y(m) = x(m) + z(m) \end{aligned} \tag{5.1}$$

where H_0 and H_1 are the hypotheses for PU vacant and busy channel, respectively and $m = 0, 1, 2, 3$ - - - - - J. In equation (5.1), $y(m)$ denotes the received signal, $x(m)$ is the PU signal, $z(m)$ is AWGN with zero mean and σ_z^2 variance and J is the total number of samples or the sensing window size, which can be computed as:

$$J = t_s f_s \tag{5.2}$$

The energy statistics of each SU, using energy detection can be given by:

$$\Omega(m) = \Sigma_{m=1}^{J} |y(m)|^2 \tag{5.3}$$

If σ_x^2 is the received PU signal variance and σ_z^2 is the noise variance then the received SNR $Y = \frac{\sigma_x^2}{\sigma_z^2}$.

The performance of CRN detection can be assessed by *probability-of-detection* and *probability-of-false-alarm*. Both the probabilities depend on the sensing time t_s and detection threshold ε. By assuming that all the N SUs have identical detection performance, both probabilities can be defined as [113] :

$$\begin{aligned} \textit{probability-of-detection} &: P_{de}(t_s, \varepsilon) = Q\left(\frac{\varepsilon - (1+Y)\sigma_z^2}{\sigma_z^2\sqrt{\frac{2(1+2Y)}{J}}}\right) \\ \textit{probability-of-false-alarm} &: P_{fa}(t_s, \varepsilon) = Q\left(\sqrt{(1+2Y)}Q^{-1}(P_{de}^b) + Y\sqrt{t_s f_s}\right) \end{aligned} \tag{5.4}$$

where ε is represented as sensing threshold and can be denoted as:

$$\varepsilon = \sigma_z^2 \sqrt{\frac{2}{J}(1+2Y)}Q^{-1}P_{de}^b + 1 + Y$$

As per the IEEE 802.22 WRAN (wireless regional area network) standards the target *probability-of-detection* must be equal to 0.9, therefore to analyze the EE P_{de}^b is set to be 0.9. For simplicity both the probabilities may be denoted as P_{fa} and P_{de} . Here, Y is the PU SNR and for AWGN channel the mean is considered as zero and variance σ_z^2 is taken as one.

The sensing results from each SU will be reported to the fusion center(FC). The FC then uses the hard decision fusion rule to compute the global decision. The *global probability-of-detection* and *global probability-of-false-alarm* for three rules are as follows:

OR Rule:

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{OR} &= 1-(1-P_{de})^N \\ \textit{Global probability-of-false alarm} : G_{fa}^{OR} &= 1-(1-P_{fa})^N \end{aligned} \tag{5.5}$$

AND Rule:

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{AND} &= P_{de}^N \\ \textit{Global probability-of-false alarm} : G_{fa}^{AND} &= P_{fa}^N \end{aligned} \tag{5.6}$$

k-out-of-N Rule:

$$\begin{aligned} \textit{Global probability-of-detection} : G_{de}^{koN} &= \Sigma_{i=k}^{N}\binom{N}{i}P_{de}^i(1-P_{de})^{N-i} \\ \textit{Global probability-of-false alarm} : G_{fa}^{koN} &= \Sigma_{i=k}^{N}\binom{N}{i}P_{fa}^i(1-P_{fa})^{N-i} \end{aligned} \tag{5.7}$$

The durations of PU busy period and idle period are assumed to be exponentially distributed with the mean of a_B and a_I respectively [86]. The pdf of these two periods can be determined by the equation (5.8):

$$\begin{aligned} p_B(t) &= a_B^{-1} exp^{-t/a_B} u(t) \\ p_I(t) &= a_I^{-1} exp^{-t/a_I} u(t) \end{aligned} \tag{5.8}$$

where $p_B(t)$ and $p_I(t)$ are the probability density functions(pdf) of PU busy and idle period respectively, and $t \geq 0$. Correspondingly, the stationary probabilities are $P_B = \frac{a_B}{a_I+a_B}$ and $P_I = \frac{a_I}{a_I+a_B}$. Here, the PU reoccupation is also considered and hence the PU re-occupation probability during transmission of SU is represented as in (3.1):

5.3 Problem Formulation and Solution

The main objective of this paper is to maximize EE by optimizing number of SUs, sensing time and transmission time considering the PU protection from SU transmission. Here, the problem can be set up as follows:

5.3.1 Number of Secondary Users

As discussed in chapter 4, it is noted that increase in number of SUs will further increase the consumption of energy. Therefore, by optimizing the hard decision fusion rule the EE can be improved. By considering the constraints of *global probability-of-detection* and *probability-of-false-alarm*, the problem of minimization of number of SUs can be defined as:

$$\begin{aligned} &minN \\ &s.t. t_s^{min} < t_s < t_s^{max} \\ &G_{de}^{koN} \geq P_{de}^{b} \\ &P_{fa} \leq 0.5 \end{aligned} \tag{5.9}$$

5.3.2 Throughput

In this system it is considered that data bits are transmitted when SU successfully detects the PU vacant state with a condition of non PU reoccupation. So, the data bits transmitted per frame for the given CR system is:

$$R_t = R_0 P_I (1 - G_{fa}) t_t (1 - P_{Int}(t_t)) \tag{5.10}$$

where R_0 is the number of bits per transmission time t_t and R_t is the total throughput of the system.

5.3.3 Energy Consumption

In the given system, EE improvement is measured with a consideration of reduction in consumed power. At the sensing node, total power consumed is taken as the addition of sensing power P_s, transmission power P_t and reporting power P_t. It is to be mentioned here that transmission power and reporting power are taken as P_t only. Hence, it may be represented as:

$$P_{total} = P_s + P_t + P_t \tag{5.11}$$

Therefore, to optimize EE, reduction of each component of total power from the equation (5.11) is required. The energy consumed during sensing process may be reduced by shortening the sensing time. The transmission power and reporting power depends on the transmission and reporting distance and the transmission environment. Finally, it can be observed that, energy should be considered in optimization process not the power. Moreover, it is the duration of each phase that is playing important role and accordingly, the total consumed energy can be calculated by respective powers as follows:

$$E_t = NP_s t_s + NP_t t_r + P_t t_t P_{idle} \tag{5.12}$$

where P_s is the sensing power, P_t is the transmission and reporting power and P_{idle} is the perfect idle channel probability, which is calculated as:

$$P_{idle} = P_I(1 - G_{fa}) + P_B(1 - G_{de}) \tag{5.13}$$

where P_I is the PU idle state probability and P_B is the PU busy state probability.

5.3.4 Energy Efficiency

In this research, our aim is to jointly optimize the design parameters i.e. number of SUs N, sensing time t_s and transmission time t_t. These design parameters have direct impact on EE. The EE is represented as a rate of volume of transmitted data / unit energy. Here, we are considering total throughput (calculated by equation (5.10)) and total consumed energy (calculated by equation (5.12)). By using the definition given in [111], EE is denoted by:

$$\zeta(t_s, t_t, N) = \frac{R_t}{E_t} = \frac{R_0 P_I(1 - G_{fa}) t_t (1 - P_{Int}(t_t))}{NP_s t_s + NP_t t_r + P_t t_t P_{idle}} \tag{5.14}$$

Here, it is necessary to avoid the interference to PU produced by SU while sensing and transmission. Two major issues causing interference to PU are: mis detection by SU and reoccupation of PU during SU transmission. Hence, there is a threshold for P_{de} and P_{int} to limit the interference and considered as constraints : $P_{de}(t_s) \geq P_{de}^b$ and $P_{int} \leq a_q$. Here, P_{de} is a function of t_s and P_{int} is a function of t_t. As given in equation (5.4) the *probability-of-false-alarm* P_{fa} is a function of t_s and decreases with respect to sensing time. In practical systems, the delay is needed and hence the upper limit of t_s is t_s^m and lower limit is $(\frac{Q^{-1}(P_{de}^b)\sqrt{2Y+1}}{Y\sqrt{f_s}})^2$ for the $P_{fa}(t_s) < 0.5$. To satisfy $P_{int} \leq a_q$, the maximum value of transmission time t_t is $-a_I log(1 - a_q)$. Therefore, the optimization problem for EE can be represented as:

$$
\begin{aligned}
& max\zeta(t_s,t_t) \\
s.t.(&\frac{Q^{-1}(P_{de}^{b})\sqrt{2Y+1}}{Y\sqrt{f_s}})^2 \leq t_s \leq t_s^m \\
& 0 < t_t \leq -a_I log(1-a_q)
\end{aligned}
\tag{5.15}
$$

5.3.5 Solution of the Problems

In this section the solution of above formulated problem mentioned in equation (5.15), is given. The key parameters to optimize EE are sensing time, transmitting time and number of SUs, which are also mentioned in literatures [110], [111], [65], [86]. However, to optimize all the three parameters at one go, by using exhaustive search method is really difficult and complex. Therefore, the method to find out the minimum number of SUs to maximize the EE is given first, later, the unimodal property of EE function with respect to sensing time and transmission time is given. Afterwards, the global optimality of three parameters for EE is being carried out by the proposed low complex iterative search algorithm. The local optimal number of SUs N, sensing time and transmission time are put together and optimized for a unique optimal value of EE. The proposed algorithm is represented by Algorithm 2.

5.3.6 Minimum Number of Secondary Users

As mentioned earlier, in cooperative spectrum sensing scenario, increased number of SUs results in good detection quality but with increased power consumption. Therefore, more energy is required in this case. Hence, to improve the EE, the number of SUs are minimized so as to improve the EE along with good detection quality. The first optimization problem can be solved to maximize EE by reducing the number of SUs i.e., N. The approximation of equation (5.7) by using Demoiver-Laplace theorem, is :

$$
G_{de}^{koN} = Q\left(\frac{(k-0.5-NP_{de})}{\sqrt{NP_{de}(1-P_{de})}}\right) \tag{5.16}
$$

After solving the equation (5.16) for *Global probability-of-detection*, the minimum number of SUs meeting the constraints for target *probability-of-detection*, and *probability-of-false-alarm* i.e. P_{de}^{b} and 0.5 respectively, can be calculated by the following equations [33]:

$$
\begin{aligned}
&N_1 = \frac{(2k-1+(Q^{-1}(P_{de}^b))^2(1-P_{de})) \pm Q^{-1}(P_{de}^b)\sqrt{O(4k-2+(Q^{-1}(P_{de}^b))^2 O)}}{2P_{de}} \\
&Hence, N_{min} = min(N, N_1) \\
&where\, O = (1-Pde)
\end{aligned}
\tag{5.17}
$$

Therefore, the minimum number of SUs for the CSS scenario for *k-out-of-N* rule is calculated by the above method, as shown in chapter 4.

5.3.7 Optimal Sensing Time

Lemma1 Now, to optimize the EE problem, first EE is calculated for fix transmission time t_t. For the N_{min} obtained above and fixed transmission time t_t, the optimal sensing time t_s to maximize the EE is calculated by partial differentiation of ζ with respect to t_s and equalizing it to zero. Mathematically, $\frac{\partial \zeta}{\partial t_s} = 0$, which means $\frac{E\dot{R}-\dot{E}R}{E^2} = 0$, where $\dot{E}$ and $\dot{R}$ are the first partial derivatives of E and R, respectively, with respect to t_s. After solving the equation, the optimal sensing time is given as (proof is given in Appendix A.1):

$$
t_s^{opt} = -\frac{1}{G'_{fa}} + \frac{G_{fa}}{G'_{fa}} - \frac{P_t(N_{min}t_r + P_B t_t - G_{de}P_B t_t)}{N_{min}P_s} \tag{5.18}
$$

As, we go with the range of t_s, given in equation(5.15), we see that P'_{fa} is negative and increasing. Hence, $\frac{\partial \zeta(t_s t_t)}{t_s} > 0$ for the range of t_s and has a unique maximum value at t_s^{opt} for a fixed t_t.

5.3.8 Optimal Transmission Time

Lemma2 For optimal transmission time, the partial differentiation of ζ with respect to t_t for a fixed t_s and N_{min} is being done. It can be denoted as $\frac{\partial \zeta}{\partial t_t} = 0$. The value of t_t that satisfies the previous statement and $t_t > 0$, is given by (proof is given in Appendix A.2):

$$
\begin{aligned}
&t_t^{opt} = \frac{-(N_{min}t_rP_t + N_{min}t_sP_s) + \sqrt{(S)^2 + 4P_tP_{idle}Sa_I}}{2P_tP_{idle}} \\
&where\, S = N_{min}t_rP_t + N_{min}t_sP_s
\end{aligned}
\tag{5.19}
$$

Algorithm 2 Pseudo Code for Iterative Sub-optimal Algorithm

1: Initialize $n = 0$, $t_s(0) = (\frac{Q^{-1}(P^b_{de})\sqrt{2Y+1}}{Y\sqrt{f_s}})^2$,$\zeta(0) = 0$,$\zeta_d$, $diff = inf$.
2: **while** $diff >= \zeta_d$ **do**
3: $n = n+1$.
4: Compute N_{min} using (5.17).
5: Calculate $t_t(n)$ using (5.19) for $t_s(n-1)$.
6: Compute $t_s(n)$ using (5.18) for $t_t(n)$
7: Find $\zeta(n)$ for $t_s(n)$ and $t_t(n)$ using (5.14).
8: Get the difference $diff = \zeta(n) - \zeta(n-1)$.
9: **end while**
10: return $\zeta(n), t_s(n), t_t(n), N_{min}$.

Here, we can see that $\frac{\partial \zeta}{\partial t_t} > 0$ for the range of t_t i.e. $0 < t_t < t_t^{opt}$ and it is less than 0 for the $t_t > t_t^{opt}$, hence ζ is having a unique maximum value for t_t^{opt} at each t_s.

5.3.9 The Proposed Algorithm

In this section, an algorithm is proposed to maximize the EE by optimizing the number of SUs, sensing time and transmission time. The symbols for n-th iteration are $t_s(n)$,$t_t(n)$,$N_{min}(n)$ and $\zeta(n)$. The initial value of t_s is set to be $(\frac{Q^{-1}(P^b_{de})\sqrt{2Y+1}}{Y\sqrt{f_s}})^2$. There is a fixed value of difference is initialized as ζ_d. Then accordingly, N_{min}, t_t and ζ are calculated. The difference of EE thus obtained with the previous one, is compared with the pre-decided ζ_d. Iteration continues if difference is more than some pre-assigned value, and stops if not. Finally, the optimal outputs are $\zeta(n), t_s(n), t_t(n), N_{min}$. The code of the proposed algorithm is given in Algorithm 2.

It is clear from the algorithm 2, that it significantly reduces the time to calculate the optimal sensing time and transmission time, provide an advantage to speed up the convergence rate. Hence, the proposed algorithm is less complex and needs less than 5 iteration to converge. Its complexity is much less than the exhaustive search approach. Therefore, the proposed algorithm provides an effective approach to find the optimal sensing and transmission time and EE. However, there are few limitations associated with the proposed algorithm. First, it provides the sub-optimal values and second, joint optimization of more than three parameters is little bit difficult and complex. Apart from the mentioned limitations, this algorithm is providing better results in case of three parameters. The results are illustrated in the coming section.

5.4 Simulation Results

Performance evaluation to validate the efficacy of this work is given in this section. All the parameters used for the simulation are summarized in the Table 5.1. Here, EE of the SU with the constraint of interference probability has also been taken into account.

Table 5.1: Simulation parameters

Parameters	**Values**
Target probability of detection P_{de}^{b}	0.9
Threshold of interference probability a_q	0.1
Sensing power P_s	0.11 W
PU idle state a_I	0.65 s
PU busy state a_B	0.352 s
Sensing frequency f_s	6 MHz
PU SNR Y	-20 dB
No. of CRs N_t	30
Reporting time t_r	10^{-3} s
Noise variance σ_z^2	1

Firstly, the performance analysis of first problem by optimizing the number of SUs to maximize the EE is given. Fig. 5.2 shows the results obtained from the preliminary analysis of three rules based on EE with respect to sensing time. Here, *OR* rule and *k-out-of-N* rule show comparative performance and surpasses *OR* rule in terms of EE. But for global false alarm probability *k-out-of-N* rule outperforms *OR* rule, which is clearly shown in Fig. 5.3. The figure clearly displays a lower false alarm for the *k-out-of-N* rule which improves the quality metric of the CRN.

Fig. 5.4, presents the number of SUs with respect to sensing time for different values of k. As we increase k, the requirement of SUs will also increase for a fix sensing time. This leads us to get the optimal k value graphically for maximum EE. Further, the result obtained by the above analysis on hard decision fusion rules are owned in the proposed algorithm to optimize EE.

Fig. 5.5, exhibits the optimal EE of second problem from the algorithm proposed and compared with other existing algorithms to validate the results. It illustrates that proposed algorithm outperforms the exhaustive search, sub optimal algorithm [86], alternating direction method (ADM) [138] and conventional scheme (represented as Conven.-CSS) [78] and achieve highest EE among all. The effect of transmission power on EE is shown in the figure. It is clearly exhibited that an increase in transmission power leads to decreased EE. The fact is that larger the transmission power indicates larger loss of throughput due to the probability of false alarm which exceeds the consumption of energy for a longer sensing time. The number of SUs are optimized by the equation (5.17), and *k-out-of-N* rule is adopted as fusion rule with optimum $k = 2$. Here, the optimal EE is obtained for the joint optimization of transmission time and sensing time. The detailed comparison of proposed algorithm with other existing algorithms is presented in Table 5.2.

In Fig. 5.6, a graph is plotted between EE and transmission power for different k values, justifying the optimality of k. The maximum EE is obtained at $k = 2$. It is clearly visible in the figure that EE is 35 bits/Hz/Joule at a transmission power of 0.02 Watt for $k = 2$, which is maximum among all.

Moreover, the simulation result showing EE versus sensing time is displayed in Fig. 5.7. The figure indicates effect of varying sensing time on EE. It can be observed that initially EE rises with the increase in sensing time but after the optimal value, it starts decreasing. Here, the maximum EE obtained is 8.3855 bits/Hz/Joule at a sensing time of at 0.0028 s. Whereas, the maximum EE that can be achieved for conven.- CSS is 7.8082 bits/Hz/Joule.

In addition to above discussions, Fig. 5.8 reflects the effect of varying transmission time on EE for three different sensing time. The effect is shown for conven.- CSS also. It is noticeable that plots presented in Fig. 5.7 and Fig. 5.8 are the results of separate optimization of sensing time and transmission time, hence the maximum EE obtained is lesser as compared to the results that we get by the joint optimization of the proposed algorithm. EE obtained by the joint optimization is the highest one, i.e., 10.4957 bits/Hz/Joule at a transmission power of 0.1 W, sensing time and transmission time of 0.0029 s and 0.1381 s, respectively.

For further analysis, the proposed algorithm is compared with other existing algorithms in Table 5.2. This table is quite revealing in multiple ways. First, it gives the analytical comparison of proposed method with other state of arts. Second, it shows various simulation parameters and different quality metrics. The algorithms SOA, exhaustive search used single SU and single channel CR, while ADM and conventional CSS used multiple SU and single channel CR. In [113], authors proposed multiple licensed channel and multiple SUs model. To compare the results of proposed method with, the system model of this research paper is approximated to one PU channel and multiple SUs. It is apparent from the table that the proposed method offers maximum EE among all compared algorithms and methods. There is a significant increase of 12.58 % in EE is noticed as compared to ADM of [138].

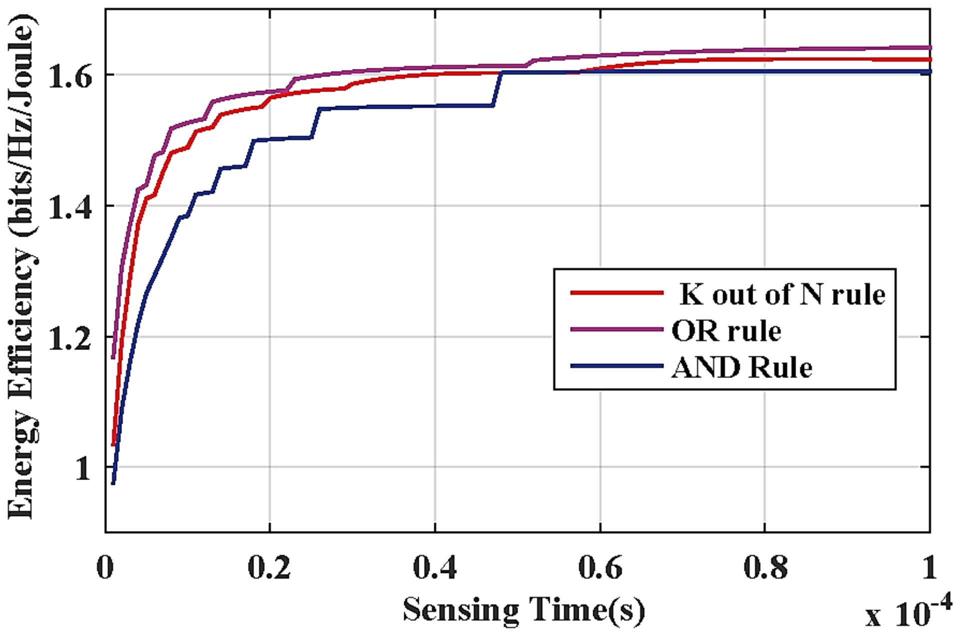

Fig. 5.2: Energy efficiency versus sensing time for three hards decision rules

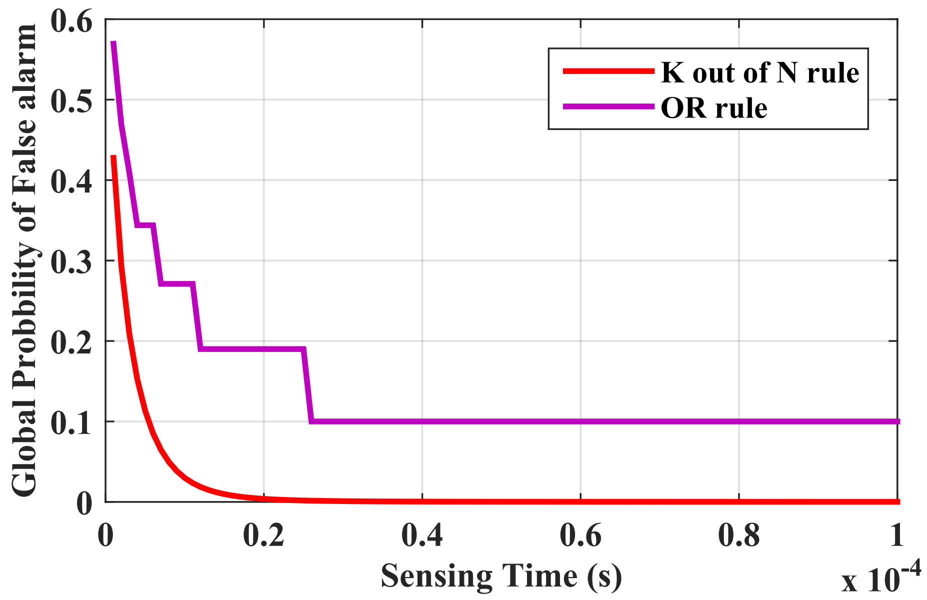

Fig. 5.3: Global probability of false alarm for *k-out-of-N* rule and OR rule

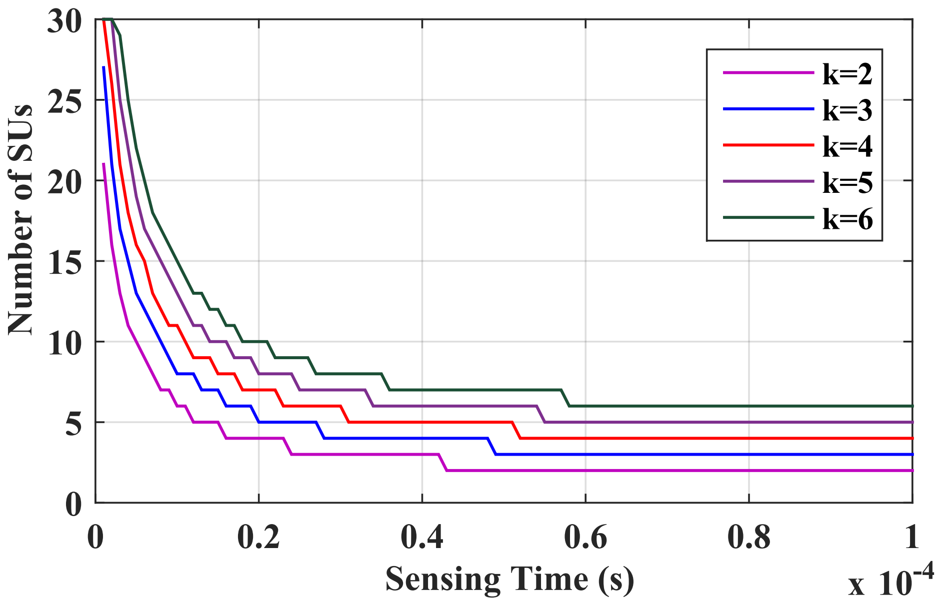

Fig. 5.4: Number of secondary users versus sensing time for different k

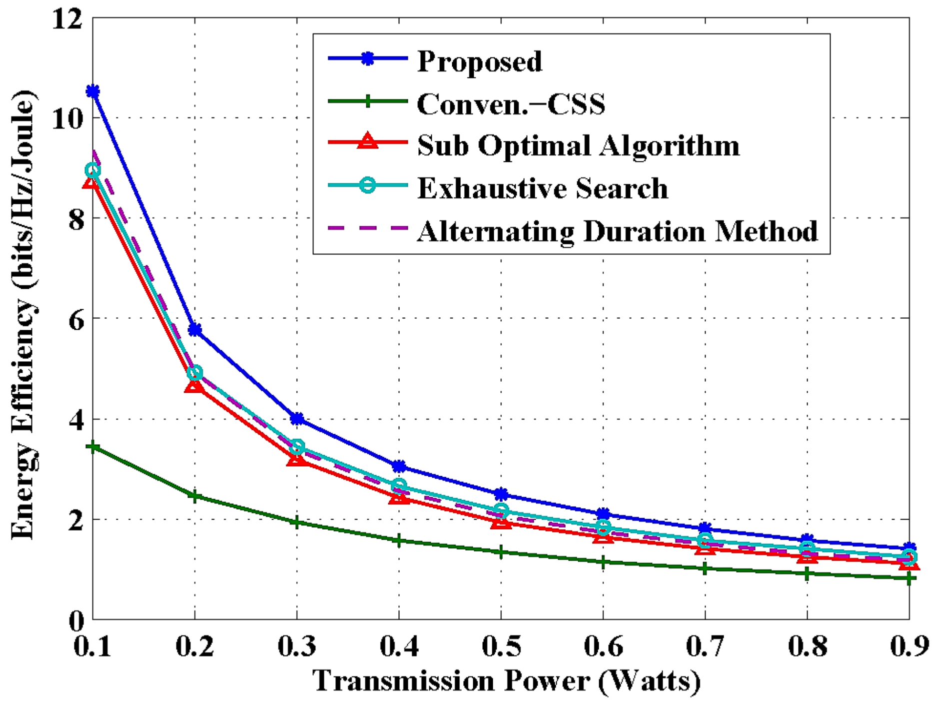

Fig. 5.5: Comparative analysis of energy efficiency versus transmission power

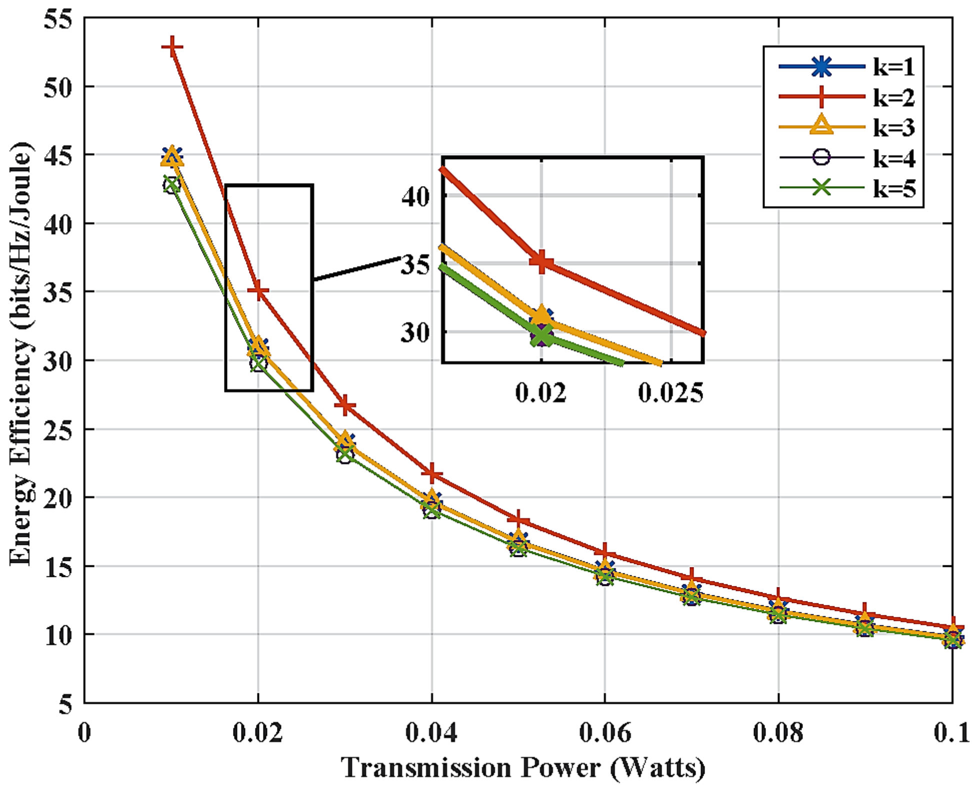

Fig. 5.6: Energy efficiency versus transmission power for different values of k

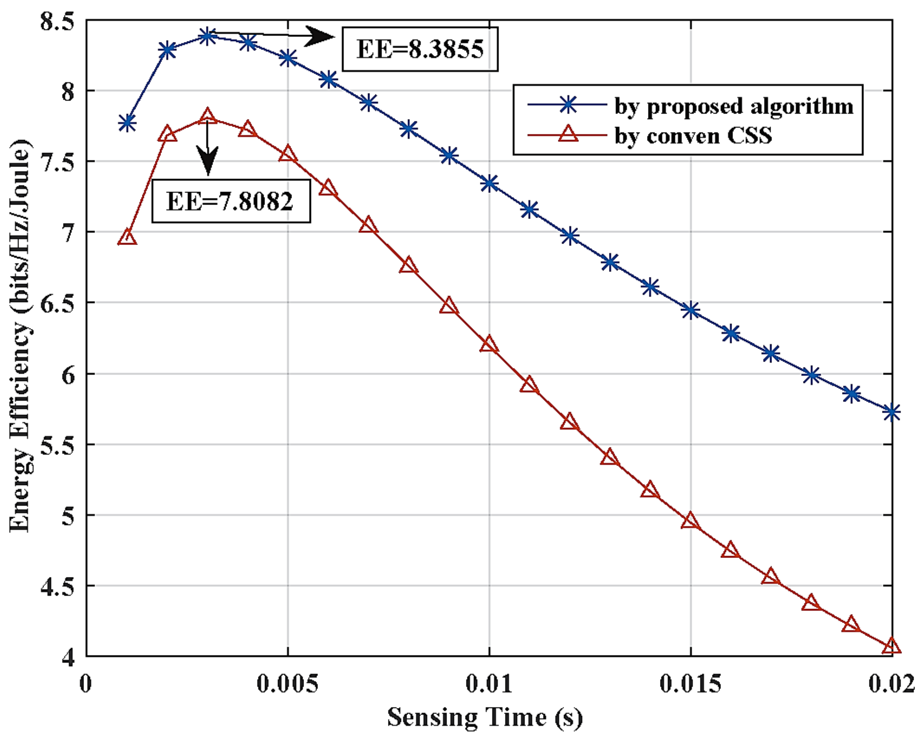

Fig. 5.7: Energy efficiency versus sensing time

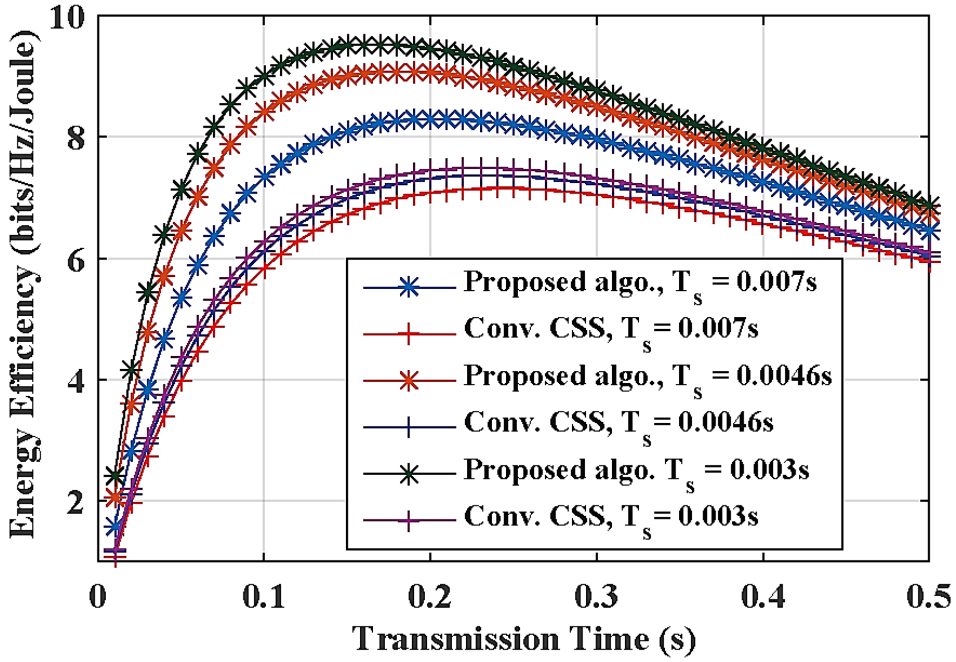

Fig. 5.8: Energy efficiency versus transmission time for different sensing times

Table 5.2: Comparison between the proposed and other existing energy efficiency maximization algorithms

Algorithms	**Parameters**	**Quality metric**	**Max. EE (bits/Hz/Joule)**	**Remarks**
Sub-optimal algorithm [86]	Sensing time, transmission time	Probability of PU reoccupation	8.7183	Single SU, single channel CR, less computational complexity as compared to Exhaustive search
Conven.-CSS [78]	Sleeping rate and censoring rate	False alarm probability	3.4280	Single channel CR, computational complexity is less, sensing and transmission time are not optimized
Exhaustive search [65]	Sensing time, transmission time	Average power capacity	8.9491	Single SU, Single channel CR, exhaustive search method is used
ADM [138]	Sensing time transmission time, fusion threshold, transmission power	Interference constraint, *Global probability-of-detection*, *Global probability of false alarm*	9.3226	Single channel CR, multiple SUs, No initial values of sensing, transmission time and power are taken
Dinkelbach's, Polyblock, k-Exhaustion [113]	Sensing time, number of SUs, transmission bandwidth	*Global probability-of-detection*, maximum transmission power	5.044	Energy efficiency maximization model is compared with Throughput maximization model, complex system with multi channel CR and multiple SUs.
Proposed	Number of secondary users, sensing time, transmission time, fusion threshold	*Global probability of false alarm*, *Global probability-of-detection*, PU reoccupation probability	10.4957	Maximum energy efficiency achieved, low computational complexity

5.5 Conclusions

This chapter has formulated a novel mathematical energy efficiency maximization problem for hard decision cooperative spectrum sensing scheme in cognitive radio networks. Joint optimization of sensing time, transmission time and number of secondary users has been considered with the protection of primary user from secondary user transmission. In order to solve the problem, first, the optimal expression for the number of secondary users was obtained and then an iterative sub optimal algorithm was proposed to achieve optimal sensing time and transmission time. The proposed algorithm decouples the problem into two parts (i.e., optimization of number of secondary users and optimization of sensing time and transmission time) and solved the two problems till convergence. The effectiveness of this work has been demonstrated by extensive simulation results and illustrations. Moreover, it shows that the proposed work outperforms the other existing works.

Chapter 6

Energy Efficiency Maximization in Cognitive Radio by Non Orthogonal Multiple Access

6.1 Introduction

In the previous chapters, we have applied the conventional time division multiple access (TDMA) technique but there is a revolution in wireless communication over the past few decades specially in the multiple access techniques. The multiple access techniques used in the first generation (1G), second generation (2G), third generation (3G), and fourth generation (4G) of mobile communication are, frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA), and orthogonal frequency division multiple access (OFDMA), respectively [141, 142]. These are commonly known as orthogonal multiple access (OMA), in which the wireless resources are orthogonally assigned to different users in time, frequency, and code domain or based on their combinations. However, due to the limited resources of OMA, the number of facilitated users is limited. Moreover, many a times the channel-induced impairments almost destroy the orthogonality of OMA techniques. Consequently, the requirements of massive connectivity and spectral efficiency (SE) in 5G is still a challenge of OMA techniques. The Fig. 6.1 reflects the different types of multiple access techniques [1].

Non-orthogonal multiple access has emerged as the promising technique to improve the SE of future 5G communication systems. In comparison to conventional multiple access (CMA) techniques, NOMA is empowered by the superposition cod-

[1]This work has been published in August 2018 issue of International Journal of Engineering & Technology as "Energy Efficiency Optimization in Cooperative Spectrum Sensing by NOMA"

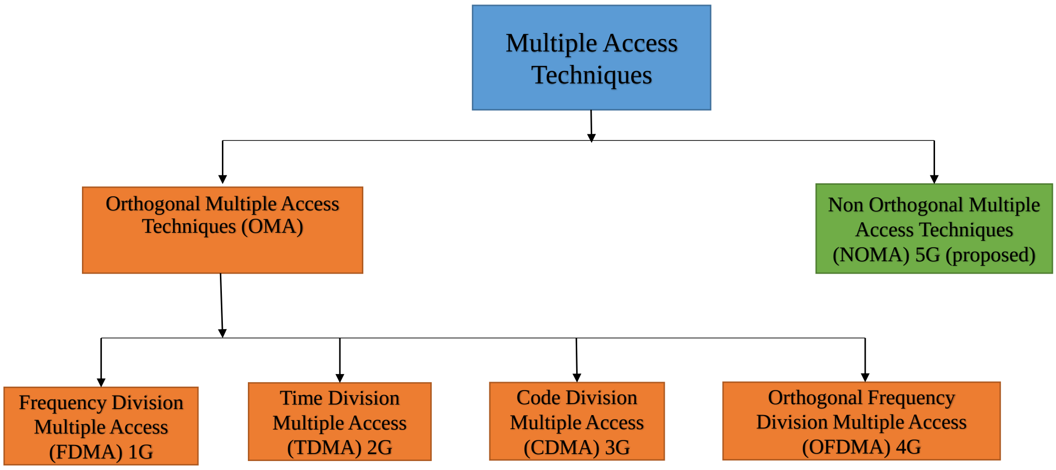

Fig. 6.1: Different types of multiple access techniques

ing, distinct power allocation and successive cancellation of interference. That is why, it has been emerged as more spectral efficient technique for future 5G systems. In third Generation Partnership Project Long Term Evolution (3 Gpp-LTE), NOMA was applied for down link system [43].

Moreover, cognitive radio (CR) is another approach to improve SE, proposed by [4, 7]. In CR networks multiple secondary users (SUs) opportunistically utilize the licensed or primary users (PUs) spectrum by spectrum sensing, detection and allocation. Initially, NOMA inspired CR has been proposed by [39, 41, 118].

The research in [39] indicates that within multiple users, a user with better channel will be unlicensed user or SU and poorer channel as PU or licensed user. The SU will try to occupy the channel of the PU. Further, NOMA for underlay cognitive radio networks of large scale was also applied in [118]. Apart from SE, EE is also drawing the attention of researchers as communication technology is responsible for 5 percent of the total world energy consumption [119]. As of now, very few researches are available in the field of NOMA with respect to EE in cognitive radio networks [43]. In [47,48] author proposed EE optimization for fading MIMO inspired by non-orthogonal multiple access. The aforementioned observations, leads us to motivate the study of EE improvement in NOMA inspired CRNs. The existing CR-NOMA proposed in [39] is generalized by considering one base station (BS), one PU and SU. A user, associated with strong channel is regarded as SU and PU with weak channel conditions. This unlicensed SU can take on the spectrum with the condition of less interference to PU. The main objective of this paper is to maximize the EE with the constraint of quality of service of PU or the licensed user. Here, the problem is formulated as the non-convex fractional programming problem.

6.2 System Model

In the system model, down link transmission with one BS with two antennas, working simultaneously for two users (PU and SU) is considered. Both the users are equipped with antennas. Let the channel from BS to PU and SU is flat with quasi-static fading. In this research, it is assumed that SU has better channel as compared to PU, hence it access the PU spectrum by NOMA with the constraint of non degradation of PU performance. The user 1 is PU and user 2 is SU. For a generalized CR-NOMA framework, the M users are served by a single base station simultaneously inspired by NOMA with the condition of providing quality of service to rest $M-1$ PU. Let the BS transmits the message $x1$ to PU and $x2$ to SU at the same frequency and same time slot but different power level. The BS is transmitting the superposition of weighted symbols $(w_M x_M)_{M=1}^2$. The received signal is a combination of the desired message plus interference plus additive noise. Mathematically, the observations received at the PU and SU can be represented, respectively as:

$$\begin{aligned} y_1 &= h_1^H w_1 x_1 + h_1^H w_2 x_2 + z_1 \\ y_2 &= h_2^H w_2 x_2 + h_2^H w_1 x_1 + z_2 \end{aligned} \tag{6.1}$$

where the first component of equation (6.1) is the message, the second component is interference produced by the other messages and the third one is noise i.e., z_1 and z_2 which are additive Gaussian noise with zero mean and variance σ_z^2. The channel vector, h_M can be represented as $h_M = g_M d_M^{-a/2}$, where $g_M \sim \mathbb{C}N(0, I_2)$, d_M is distance between BS and the Mth user, and a is the path loss exponent.

Further to implement NOMA in CRNs scenario, successive interference cancellation (SIC) is used so that the partial interference can be removed [47, 143]. Here, we have assumed that PU is far from the BS while SU is near to BS hence SU is strong user and PU is weak. In SIC decoding technique, PU will decode the message x_1 by taking SU interference as noise. While SU will first decode the message x_1 treating the interference by x_2 as noise then cancel the x_1 part from the received one. Thus, it will decode the x_2 from the remaining message. The user's decoding ability is given by its signal to interference - noise ratio (SINR) [144]. The general form of representation of SINR when, $M = 1, 2$and $1 \leq i \leq M$ is given by:

$$(SINR)_M^i = \frac{\mid h_M^H w_i \mid^2}{\Sigma_{j=i+1}^2 \mid h_M^H w_j \mid^2 + \sigma_2} \tag{6.2}$$

The above condition will be true, provided SU will decode the messages intended for the PU.

6.3 Problem Formulation and Solution

In this section first the EE maximization problem of NOMA inspired cognitive radio is formed and then the algorithm is proposed as the solution of the problem.

6.3.1 Energy Efficiency Maximization Problem

Here, the EE maximization problem is formed as the ratio of maximum achievable sum rate and total power consumed and represented as:

$$EE \triangleq \frac{R_t}{P_t + P_c} \tag{6.3}$$

where R_t is the sum rate in bits/sec/Hz, transmit power $P_t \triangleq \Sigma_{M=1}^{2} \|w_M\|_2^2$ and P_c is the circuit consumption power. The total achievable sum rate is the sum of PU rate and the SU rate. The PU sum rate is given by:

$$R_{PU} \triangleq log_2(1 + L_1) \tag{6.4}$$

where L_1 is the target SINR of message x_1 which is used as a threshold for the decoding of x_1. In the SU decoding, SIC and predefined order will be used so that the interference due to other user could be removed. Hence, the SU sum rate is formulated as:

$$R_{SU} = log_2(1 + \frac{|h_2^H w_2|^2}{\sigma_2}) \tag{6.5}$$

Accordingly, the problem of EE maximization can be formulated as:

$$\begin{aligned} & max_{w_1 w_2} EE \\ & s.t. SINR_1^1 \geq L_1, M = 2 \\ & \Sigma_{M=1}^{2} \parallel w_M \parallel_2^2 \leq P_{tot} \end{aligned} \tag{6.6}$$

Here, the first constraint will give the quality of service (QoS) required for successful transmission of PU and the second constraint will give the transmit power requirement. P_{tot} is the total power requirement. The problem defined in equation (6.6) is a non-convex fractional programming problem.

6.3.2 Solution of the Problem

To get the solution of the above formulated problem, first the problem is approximated by 1st order-Taylor's approximation and then the algorithm is proposed.

Proposed Algorithm The problem defined in (6.6) is further explored by putting the values of SINR and is given as :

$$\begin{aligned} &max_{w_1 w_2} EE \\ s.t. \mid h_1^H w_1 \mid^2 &\geq L_1(\mid h_1^H w_2 \mid^2 + \sigma_2), M = 1 \\ \mid h_2^H w_1 \mid^2 &\geq L_1(\mid h_2^H w_2 \mid^2 + \sigma_2), M = 2 \\ \Sigma_{M=1}^2 \parallel w_M \parallel_2^2 &\leq P_{tot} \end{aligned} \tag{6.7}$$

The above problem given in (6.7) is non-convex problem. This type of non-convex fractional programming problem can be solved by the Dinkelbach's algorithm [145]. But the computational complexity of this algorithm is very high. Hence, convex approximation is used to solve this problem. Further to explore the hidden convexity, the problem (6.7) can be rewritten in term of auxiliary variables s and u as:

$$\begin{aligned} &max_{w_1 w_2, s, u} s \\ s.t. R_{PU} + R_{SU} &\geq \sqrt{su} P_t + P_c \leq \sqrt{u} \end{aligned} \tag{6.8}$$

If v is taken as auxiliary variable which is used to indicate the target SINR for the Mth user and r is the data rate of v (data rate of SU), then $\frac{|h_M^H w_M|^2}{\sigma^2} \geq v$, and $1 + v \geq 2^r$. The squared EE can be interpreted by the s and squared power can be termed as u. With the explanations given above the original fractional programming problem can be approximated as convex by using Taylor's approximation with iterations and can be formulated for nth iteration as:

$$\begin{aligned} &max_{w_1 w_2, s, u, v, r} s \\ &s.t. \frac{yT(\phi_{M,M}, \phi_{M,M}^n)}{\sigma^2} \geq v \end{aligned} \tag{6.9}$$

where $\mid h_M^H w_i \mid^2 = \phi_R^2 + \phi_I^2, \phi_{M,i} \triangleq [\phi_{M,i}^R + \phi_{M,i}^I], y(\phi_{M,i})$ is the Euclidean norm of real vector and $yT(\phi_{M,M}, \phi_{M,M}^n)$ is th 1^{st} order-Taylor's approximation. Upon considering this, the approximations of the constraints are:

$$yT(\phi_{M,M}, \phi_{M,M}^n) \geq L_1(\mid h_1^H w_2 \mid^2 + \sigma_2), M = 1 \tag{6.10}$$

$$yT(\phi_{M,i}, \phi_{M,i}^n) \geq L_1(\mid h_2^H w_2 \mid^2 + \sigma_2), M = 2 \tag{6.11}$$

Algorithm 3 CR NOMA for EE optimization

1: Initialization: $w^{0\ 2}_{MM=1}, s_0, u_0, v_0, r_0$.
2: **while do**$n = 0$
3: Repeat.
4: Solve the equation (6.9).
5: $n = n + 1$.
6: Solve equations (6.12), (6.13) and (6.14).
7: Stop when reach the convergence.

$$\phi^n_{M,i} \triangleq [Re(h^H_M w_i)^{n-1}, Im(h^H_M w_i)^{n-1}]^T \tag{6.12}$$

$$u^n = (\Sigma^2_{M=1} \|w^{n-1}_M\|^2_2 + P_c)^2 \tag{6.13}$$

$$s^n = \frac{(R_{PU} + log_2(1 + \frac{|h^H_2 w_2|^2}{\sigma_2}))^2}{u^n} \tag{6.14}$$

The proposed algorithm shown in Algorithm 3, gives the EE optimization method. Firstly, the initial values of $w^{0\ 2}_{MM=1}, s_0, u_0, v_0, r_0$ are taken. Then, equation (6.9) is solved for $n = 0$. In step 5, update $n = n + 1$ and then solve the equations (6.12), (6.13) and (6.14) for the updated value of n. Lastly, the loop is terminated when it is converged. Further, the optimized values are obtained.

6.4 Results and Discussion

The performance of the system has been illustrated in this section by comparing the NOMA with the conventional TDMA technique. The simulation parameters used for MATLAB are given in table 6.1 :

In Fig. 6.2, EE versus transmission power is illustrated for NOMA and TDMA. Moreover, the comparison of NOMA and conventional TDMA (used in exhaustive search method and sub-optimal algorithm in [86]) is also presented. Fig. 6.2 shows the superior performance of the NOMA technique over the conventional TDMA in terms of EE. At the transmission power 0.2 W, the EE for NOMA is 0.998 bits/Hz/Joule, whereas 0.6 bits/Hz/Joule for sub-optimal. It is clearly visible from the graph that an increase in transmission power results in decrease of EE. However, the maximum EE for NOMA achieved at 0.1 W power.

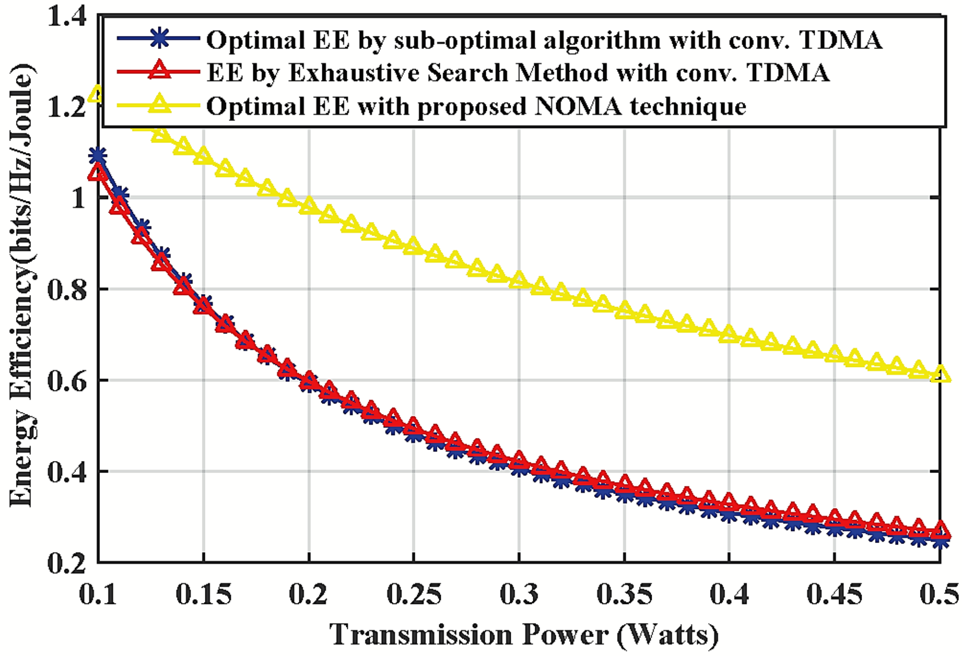

Fig. 6.2: Energy efficiency versus transmission power for TDMA and NOMA techniques

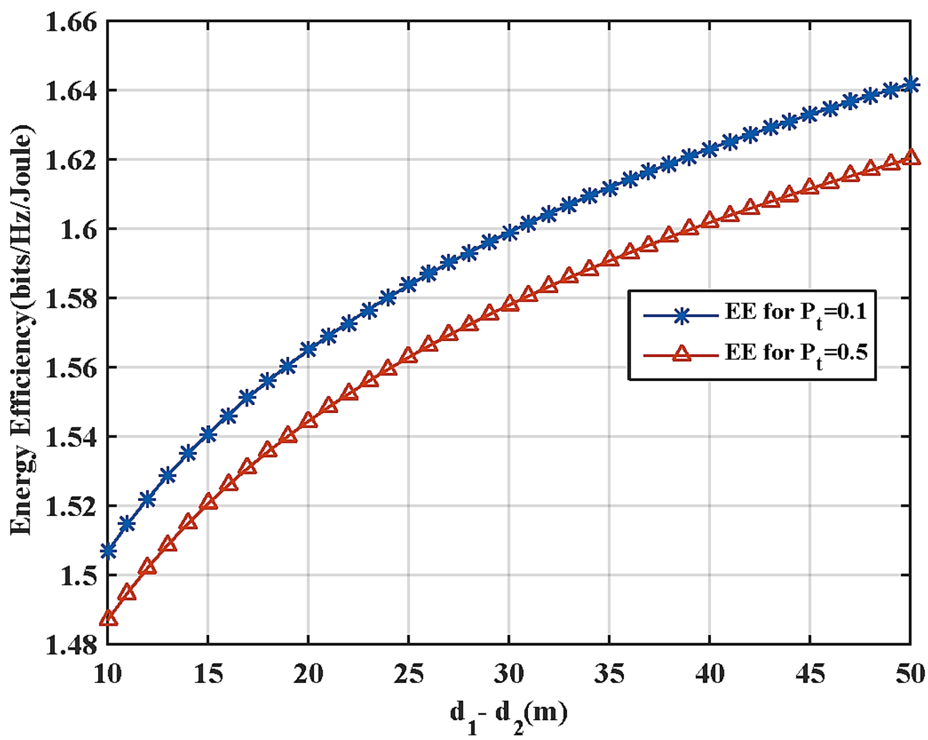

Fig. 6.3: Energy efficiency versus difference in distance of primary user and secondary user, to the base station

Table 6.1: Simulation parameters

Parameters	**Values**
Distance between transmitter and M^{th} base station d_M	40 m
Fix distance taken as reference d_1	50 m
Circuit power P_c	30 W
Path loss exponent a	3.5
Sensing frequency f_s	3 MHz
Throughput R_{PU}	2 bits/Hz/s
Noise variance σ^2	-80 dBm

Fig. 6.3, shows the impact of location of PU and SU from BS on EE. Here, it is assumed that the d1 is fixed and d2 is varying. Both the distances are calculated from the BS. It is depicted in the Fig. 6.3 that increase in the difference of distance results in increase in EE. It means, SU is going closer to the BS as difference is increasing. The important conclusion from the figure is, near–far-effect between PU and SU gives more benefit to the NOMA technique, which further increase its applications.

6.5 Conclusions

In this chapter, the energy efficiency maximization problem with down link non orthogonal multiple access technique is studied. Here, base station equipped with two antennas, one primary user and one secondary user, have been considered. Application of non orthogonal multiple access technique in cognitive radio is discussed. Cognitive radio - non orthogonal multiple access technique will further increase the application of cognitive radio into 5G systems. Further, the energy efficiency is maximized for the non orthogonal multiple access and compared with other existing conventional multiplexing techniques. The performance of the proposed method has an edge over the other methods. Energy efficiency maximization problem for multiple primary user and multiple secondary user with multiple input multiple output for different fading channels can be considered as future scope.

Chapter 7

Conclusions and Future Scope

In this dissertation, energy consumption problem of cooperative spectrum sensing in cognitive radio networks has been investigated. Energy efficiency maximization techniques have been developed. In the following sections, the key contribution of this dissertation is drawn and some open problems for the future scope are identified.

7.1 Conclusions

In the third chapter, single node spectrum sensing is performed and energy efficiency is maximized. The Sub Optimal Iterative Search Algorithm (SOISA) is proposed to maximize the energy efficiency by calculating the optimization problem. Here, sensing time and transmission time are taken as system parameters. Further, primary user protection from secondary user transmission is also considered. It is found that SIOSA algorithm reduces the number of iteration to 5 as compared to exhaustive search method and other algorithms, reducing the complexity of algorithm in this way.

In order to maximize the energy efficiency of cooperative spectrum sensing in cognitive radio network, the number of secondary users are optimized in the fourth chapter. Centralized cooperative model is adopted for the formulation of problem, where one fusion node (centrally located) and multiple secondary user nodes are randomly deployed. In this optimization problem, *Global probability-of-false alarm*, *Global probability-of-detection* are considered as constraints so as to improve the detection quality. Here, the decision fusion rules viz. *AND*, *OR* and *k-out-of-N* rules are considered and energy efficiency for each rule is calculated at different SNR levels. It is shown via simulations that *k-out-of-N* rule achieved higher energy efficiency with low *Global probability-of-false alarm* as compared to other fusion rules. Further, the effect of frequency selective fading on energy efficiency for three fusion rules is also illustrated and compared with non-fading environment.

Following the above problem, the energy efficiency is maximized by optimizing the number of secondary users, sensing time and transmission time, in the fifth chapter. Specifically, in the problem, joint optimization of sensing time, transmission time and number of secondary users has been proposed with the protection of primary user from secondary user transmission. In order to solve the problem, first the optimal expression for the number of secondary user was obtained and then an iterative sub optimal algorithm was proposed to achieve optimal sensing and transmission time. The effectiveness of this work has been demonstrated by extensive simulation results and illustrations. Moreover, it shows that the proposed work outperforms the other existing works.

Moreover, the energy efficiency problem of cognitive radio is also investigated with Non Orthogonal Multiple Access technique. In this case, single primary user and single secondary user network is considered. Non-orthogonal multiple access has emerged as the promising technique to improve spectral efficiency of future 5G communication systems. In comparison to conventional multiple access techniques, it is empowered by the superposition coding, distinct power allocation and successive cancellation of interference. That is why it has been emerged as more spectral efficient technique for future 5G systems. In the system model, down link transmission with one base station with two antennas, working simultaneously for two users (primary and secondary user) and is considered. Both the users are equipped with different antennas. Further, the energy efficiency is maximized for the Non Orthogonal Multiple Access and compared with other existing conventional multiplexing techniques. The performance of the proposed method has an edge over the other methods.

The simulation results of the above approaches/algorithms have shown: (i) a notable improvement in energy efficiency of single as well as cooperative spectrum sensing, (ii) a consistency among proposed algorithms/ schemes, and (iii) the significance of designing an energy-efficient cooperative spectrum sensing framework by optimizing energy at different stages.

7.2 Future Scope

Throughout the dissertation, several techniques that contributed to the efficient design of cooperative spectrum sensing schemes for cognitive radio networks are proposed. However, there are some relevant issues that warrant further consideration in the future work. In this dissertation, we have adopted the energy detector for local spectrum sensing at each secondary user node, which reduces the complexity compared to other detectors. However, it relies on the assumption that noise variance can be accurately estimated but difficult to obtain in practical. Therefore, a two-stage sensing scheme can be proposed wherein energy detection is performed as the first stage sensing and, if needed, cyclostationarity detection, can be performed at the second stage. In this work, we have assumed the energy efficiency maximization of cooperative spectrum sensing over the additive white Gaussian noise channel. However, it is suggested to extend this work of energy efficiency maximization in cooperative spectrum sensing over fading channels eg., Rayleigh, Rician (Ricean), Nakagami fading etc.

As most of the wireless communication research is leading towards 5G communication, energy efficiency maximization is playing vital role in this area. Hence, energy efficiency maximization problem for multiple primary user and multiple secondary user with multiple input multiple output (MIMO) for different fading channels can be considered as future scope.

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List of Publications

Journal Publications

1. Meenakshi Awasthi, M. J. Nigam and V. Kumar, “Optimal Sensing, Fusion and Transmission with Primary User Protection for Energy-Efficient Cooperative Spectrum Sensing in CRNs,” *(AEÜ) - International Journal of Electronics and Communications*, Elsevier, (SCI, IF - 2.115) vol. 98, no. 2019, pp. 95–105, 2019.

2. Meenakshi Awasthi, M. J. Nigam and V. Kumar, “Energy Efficiency Optimization in Cooperative Spectrum Sensing by NOMA,” *International Journal of Engineering & Technology*, vol. 7, no. 3, pp. 1125-1127, 2018.

3. Meenakshi Awasthi, M. J. Nigam and V. Kumar, “Energy Efficiency Maximization by Optimal Fusion Rule in Frequency-Flat-Fading Environment,” *AEÜ - International Journal of Electronics and Communications*, Elsevier, (SCI, IF - 2.115), pp. 1-23, Under Review, first revision submitted on 20 Nov 2018.

4. Meenakshi Awasthi, M. J. Nigam and V. Kumar, “Optimal Sensing and Transmission of Energy Efficient Cognitive Radio Networks,” *Wireless Personal Communication*, Springer (SCI, IF - 1.20), pp. 1-13, Under Review since January 2018.

5. Meenakshi Awasthi, P. J. Gaidhane, M. J. Nigam and V. Kumar,“Optimization of Energy Efficiency of Cognitive Radio Networks using GWO-ABC Algorithm,” to be communicated.

International Conference Publications

1. Meenakshi Awasthi, M. J. Nigam and V. Kumar , “Energy efficient hard decision fusion rules for fading and non-fading environment,” *TENCON 2017 - 2017 IEEE Region 10 Conference*, pp. 2056 - 2060, 2017.978-1-5090-1134-6/17/$31.00 ©2017 IEEE.

2. Meenakshi Awasthi, M. J. Nigam and V. Kumar, “Energy Efficient Sensing, Transmitting Time and Transmission Power for Cognitive Radio Networks,” *2017 14th IEEE India Council International Conference (INDICON)*, pp. 1-5, 2017, 978-1-5386-4318-1/17/$31.00 ©2017 IEEE.

3. Meenakshi Awasthi, V. Kumar and M. J. Nigam, "Energy - Efficiency Techniques in Cooperative Spectrum Sensing: A Survey," *3rd IEEE International Conference on "Computational Intelligence and Communication Technology" (IEEE-CICT 2017)*, pp. 1-6, 2017.

Appendix A

Basic Considerations for Sensing Time and Transmission Time

A.1 Proof of Lemma1

Proof For a given transmission time i.e., t_t and N_{min} (calculated priorly by using equation (5.17) there is an optimal sensing time that will maximize the EE. Therefore, the first partial derivative to obtain the optimal sensing time, of ζ with respect to t_s is to be calculated and afterwards set it to 0, i.e.,

$$\frac{\partial \zeta}{\partial t_s} = 0 \tag{A.1}$$

After putting all the values and doing partial differentiation, we get:

$$\frac{R_0 t_t e^{-\frac{t_t}{a_I}} P_I(-G^{'}_{fa})(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t) - R_0t_t(1-G_{fa})P_Ie^{-\frac{t_t}{a_I}}X_1}{(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t)^2} = 0 \tag{A.2}$$

$$where\, X_1 = (N_{min}P_s + P_I(-G^{'}_{fa})t_tP_t) \tag{A.3}$$

Now, the step by step solution of above equation is given as follows:

$$-G'_{fa}(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t) = (1-G_{fa})(N_{min}P_s + P_I(-G'_{fa}t_tP_t)) \tag{A.4}$$

$$-G'_{fa}N_{min}t_sP_s - G'_{fa}N_{min}t_rP_t - G'_{fa}P_{idle}t_tP_t = (1-G_{fa})N_{min}P_s - G'_{fa}P_It_tP_t(1-G_{fa}) \tag{A.5}$$

$$-G'_{fa}N_{min}t_sP_s - G'_{fa}N_{min}t_rP_t - G'_{fa}P_{idle}t_tP_t = N_{min}P_s - G_{fa}N_{min}P_s + X_2 \tag{A.6}$$

$$where\, X_2 = -G'_{fa}P_It_tP_t + G'_{fa}P_It_tP_tG_{fa} \tag{A.7}$$

$$-G'_{fa}N_{min}t_sP_s = G'_{fa}N_{min}t_rP_t + G'_{fa}P_{idle}t_tP_t + N_{min}P_s - G_{fa}N_{min}P_s + X_2 \tag{A.8}$$

Now, substituting the value of P_{idle} from equation (5.13), we get:

$$-G'_{fa}N_{min}t_sP_s = G'_{fa}N_{min}t_rP_t + G'_{fa}(P_I(1-G_{fa}) + P_B(1-G_{de}))t_tP_t + X_3 \tag{A.9}$$

$$where\, X_3 = N_{min}P_s - G_{fa}N_{min}P_s - G'_{fa}P_It_tP_t + G'_{fa}P_It_tP_tG_{fa} \tag{A.10}$$

$$-G'_{fa}N_{min}t_sP_s = G'_{fa}N_{min}t_rP_t + G'_{fa}(P_I - G_{fa}P_I + P_B - G_{de}P_B)t_tP_t + X_3 \tag{A.11}$$

$$-G'_{fa}N_{min}t_sP_s = G'_{fa}N_{min}t_rP_t + P_BG'_{fa}t_tP_t - P_BG_{de}G'_{fa}t_tP_t + N_{min}P_s - G_{fa}N_{min}P_s \tag{A.12}$$

Finally, calculating for the optimal t_s, for the maximum EE:

$$t_s = \frac{-t_rP_t}{P_s} - \frac{P_Bt_tP_t}{N_{min}P_s} + \frac{G_{de}P_Bt_tP_t}{N_{min}P_s} - \frac{1}{G'_{fa}} + \frac{G_{fa}}{G'_{fa}} \tag{A.13}$$

$$t_s^{opt} = -\frac{1}{G'_{fa}} + \frac{G_{fa}}{G'_{fa}} - \frac{P_t(N_{min}t_r + P_Bt_t - G_{de}P_Bt_t)}{N_{min}P_s} \tag{A.14}$$

Here, G'_{fa} and P'_{fa} can be calculated as:

$$G'_{fa} = -\frac{1}{\sqrt{2\pi}} exp\frac{-(k-0.5-N_{min}P_{fa})^2}{2A}\frac{N_{min}P'_{fa}}{2A\sqrt{A}}2A(1-2P_{fa})(k-0.5-N_{min}P_{fa}) \tag{A.15}$$

$$whereA = N_{min}P_{fa}(1-P_{fa}) \tag{A.16}$$

Now, $P^{'}_{fa}$, can be calculated with reference to [65], as:

$$P_{fa} = Q\left(\sqrt{(1+2Y)}Q^{-1}(P^{b}_{de}) + Y\sqrt{t_s f_s}\right) \tag{A.17}$$

$$Let,\, P_{fa} = Q\left(C + D\sqrt{t_s}\right) \tag{A.18}$$

$$P^{'}_{fa} = \frac{-1}{\sqrt{2\pi}}\frac{D}{2\sqrt{t_s}}exp\left(\frac{-1}{2}(C + D\sqrt{t_s})^2\right) \tag{A.19}$$

A.2 Proof of Lemma2

Proof Similarly, optimal transmission time for a fixed sensing time can also be evaluated be getting the first partial derivative of ζ with respect to t_t, and set it to zero i.e.,

$$\frac{\partial\zeta}{\partial t_t} = 0 \tag{A.20}$$

$$\frac{R_0(1-G_{fa})P_I(1-\frac{t_t}{a_I})e^{\frac{-t_t}{a_I}}(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t) - R_0t_t(1-G_{fa})P_Ie^{\frac{-t_t}{a_I}}P_{idle}P_t}{(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t)^2} = 0 \tag{A.21}$$

$$R_0(1-G_{fa})P_I(1-\frac{t_t}{a_I})e^{\frac{-t_t}{a_I}}(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t) = R_0t_t(1-G_{fa})P_Ie^{\frac{-t_t}{a_I}}P_{idle}P_t \tag{A.22}$$

$$(1-\frac{t_t}{a_I})(N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t) = P_{idle}t_tP_t \tag{A.23}$$

$$N_{min}t_sP_s + N_{min}t_rP_t + P_{idle}t_tP_t - \frac{N_{min}t_sP_st_t}{a_I} - \frac{N_{min}t_rP_tt_t}{a_I} - \frac{P_{idle}P_tt_t^2}{a_I} = P_tt_tP_{idle} \tag{A.24}$$

Let $F(t_t) = t_t^2(P_tP_{idle}) + t_t(N_{min}t_sP_s + N_{min}t_rP_t) - a_I(N_{min}t_rP_t - N_{min}t_sP_s) = 0$

Since, $F^{'}(t_t)$ is less than 0, for $t_t > 0$, we can say that $F(t_t)$ is a decreasing function. Hence, there is a distinctive optimum value of t_t^{opt}. Therefore, the optimum value of transmission time for fixed sensing time, to maximize EE is as follows:

$$t_t^{opt} = \frac{-(N_{min}t_rP_t + N_{min}t_sP_s) + \sqrt{(N_{min}t_rP_t + N_{min}t_sP_s)^2 + 4P_tP_{idle}(N_{min}t_rP_t + N_{min}t_sP_s)a_I}}{2P_tP_{idle}} \tag{A.25}$$

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A THESIS

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of

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **"ENERGY EFFICIENT COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS"** in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Electronics and Communication Engineering of the Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from July, 2015 to December, 2018 under the supervision of Dr. M. J. Nigam, Professor (Retired), and Dr. Vijay Kumar, Associate Professor, Department of Electronics and Communication Engineering, Indian Institute of Technology Roorkee, Roorkee, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institution.

(MEENAKSHI AWASTHI)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

(M. J. Nigam)
Supervisor

(Vijay Kumar)
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The Ph.D. Viva-Voce Examination of **Meenakshi Awasthi**, Research Scholar, has been held on ....

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Signature of External Examiner

This is to certify that the student has made all corrections in the thesis.

Signature of Supervisor (s)

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Dated:_____________