Optimal Threshold Selection of Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks

Thesis submitted in fulfillment of the requirements

for the Degree of

Doctor of Philosophy

by

ALOK KUMAR

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY

WAKNAGHAT, SOLAN – 173234, INDIA

DECEMBER, 2019

TABLE OF CONTENTS

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY
(Established by H.P. State Legislative vide Act No. 14 of 2002
P.O. Waknaghat, Teh.Kandaghat, Distt. Solan-173234 (H.P.) INDIA
Website: www.juit.ac.in
Phone No. +91-01792-257999 (30 Lines)
Fax : +91-01792-245362

DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the Ph.D. thesis entitled "**Optimal Threshold Selection of Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks"** submitted at **Jaypee University of Information Technology, Waknaghat, Solan (H.P.), India** is an authentic record of my work carried out under the supervision of **Dr. Shweta Pandit & Dr. Ghanshyam Singh**. I have not submitted this work elsewhere for any other degree or diploma. I am fully responsible for the content of my Ph.D. thesis.

Alok Kumar

Alok Kumar

(Enrollment No.: 156001)

Department of Electronics and Communication Engineering

Jaypee University of Information Technology, Waknaghat, Solan (H.P.), India

Date: 29 / 06 /2020

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY
(Established by H.P. State Legislative vide Act No. 14 of 2002
P.O. Waknaghat, Teh.Kandaghat, Distt. Solan-173234 (H.P.) INDIA
Website: www.juit.ac.in
Phone No. +91-01792-257999 (30 Lines)
Fax : +91-01792-245362

SUPERVISOR'S CERTIFICATE

This is to certify that the work presented in the thesis entitled "**Optimal Threshold Selection of Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks"** submitted by **Alok Kumar** in fulfilment of the requirement for the award of the degree of **Doctor of Philosophy** in Electronics and Communication Engineering and submitted in the Department of **Electronics and Communication Engineering of Jaypee University of Information Technology, Waknaghat (H.P), India** is an authentic record of candidates' own work carried out by him under our supervision.

The matter presented in this thesis has not been submitted by him for the award of any other degree in this Institute or any other Institute/University.

Dr. Shweta Pandit
Assistant Professor (SG),
Department of Electronics and Communication Engineering
Jaypee University of Information Technology, Waknaghat, Solan (H.P.), India
Date: 29 / 06 /2020

Professor Ghanshyam Singh
Department of Electrical and Electronics Engineering Science
Auckland Park Kingsway Campus,University of Johannesburg, Johannesburg 2006 , S. Africa
Date: 29 / 06 /2020

Dedicated to my Parents, my wife Dimpal and son Pratyush Garg.

ACKNOWLEDGMENT

"Love the life you live. Live the life you love"

First of all, I express my sincere gratitude to my supervisors, Dr. Shweta Pandit, Jaypee University of Information Technology (JUIT) Waknaghat, Solan (H.P.), India and Dr. Ghanshyam Singh, University of Johannesburg, Auckland Park Kingsway Campus, S. Africa, for their guidance and encouragement. Their vast experience and deep understanding of the subject proved to be an immense help to me.

My sincere thanks to Vice-Chancellor and Dean (Academic and Research) of Jaypee University of Information Technology (JUIT), Waknaghat, Solan (H.P.), India for providing me all the needed support to complete the research work. I am sincerely thankful to my Doctoral Program Monitoring Committee (DPMC) members, Professor Dr. P. B. Barman, Dr. Shruti Jain and Dr. SunilDatt Sharma for their constructive feedback and comments that have helped me in improving my thesis. I am grateful to Professor & Head of Electronics and Communication Engineering, Professor M. J. Nigam, and my colleague Dr. Vikas Baghel for their valuable suggestions and moral support. Their profound view-points and motivation enlightened me in many ways. I sincerely thank every member of the ECE Department of the JUIT Solan for their kind support.

I give my greatest gratitude to my parents, wife and my child who have been offering all around support during the period of my studies and research. It is the tremendous blessings of my parents and endless sacrifice of my wife and child. They have shown immense patience and supported me in every possible way. I owe everything to them.

I am thankful to my friends Dr. Prabhat Thakur and Dr. Sujit Kumar Patel for their valuable suggestions, motivation and good discussion on problem related to the current issue. I would like to thank all those people from the core of my heart those who have directly or indirectly helped me during my research.

(Alok Kumar)

ABSTRACT

Recent progress in various wireless services such as device-to-device (D2D) communication, anytime anywhere access to multimedia content on smart phones, have driven explosive demand of data traffic. In addition, new frequency spectrum is required to provide these different wireless services to the end users resulting inadequacy of required radio spectrum. However, as per the Federal Communication Committee (FCC) report, the allocated spectrum is not utilized efficiently due to fixed spectrum assignment policy which has resulted the spectrum scarcity problem. In the fixed spectrum assignment policy, the dedicated spectrum (licensed channel) is allocated to the users called licensed/primary users and other unlicensed users are not allowed to access that dedicated spectrum. Therefore, the demand of dynamic spectrum allocation (DSA) strategy has been developed, which also allows the unlicensed users to access the licensed channel without affecting the communication of licensed users. Cognitive Radio (CR) technology is a promising technology which has the potential to address frequency requirements by employing DSA and improve spectrum efficiency. Various spectrum sensing techniques can be employed by CR in order to sense the status of licensed channels being active/busy or idle. The energy detector spectrum sensing (EDSS) is one of the potential spectrum sensing technique, majorly employed by various researchers due to its low computation complexity and easy implementation over other techniques. Further, it is a blind spectrum sensing method which does not require prior knowledge of the primary user (PU) signal. Due to its inherent advantages, we have employed EDSS based CR system in this thesis. The spectrum sensing decision in energy detector spectrum sensing relies on the sensing threshold consequently, the computation and selection of sensing threshold is a very prominent aspect. In addition, the key spectrum sensing performance metrics of CR are the false-alarm and detection probabilities. For the maximum utilization of channel, the low false-alarm probability is required while to provide sufficient protection to PU from CU transmission, the significantly higher value of detection probability is needed. For example, as per the CR Wireless Regional Area Network (WRAN) standard, minimum 90% detection probability and maximum 10% false-alarm probability is permitted for the licensed TV signal detection with maximum sensing time of 25ms.

Since the spectrum sensing threshold plays a major role in EDSS for detection of licensed user, therefore its proper selection is needed for minimizing false-alarm and maximizing detection

performance. However, both the false-alarm and detection probabilities decrease with increase in the sensing threshold. Therefore, there is tradeoff between the false-alarm and detection probabilities for the selected sensing threshold. Further, the sensing performance of CU is degraded under the multipath fading, shadowing and non-line-of-sight communication therefore, various researchers have employed cooperative spectrum sensing (CSS) technique to improve the spectrum sensing performance of CU under the fading environment. In CSS technique, the spectrum sensing decision of each CU is sent to the fusion center (FC) via the reporting channels where FC apply different cooperative rules (OR, AND, Majority and *K*-out-of-*M* rules) to take the overall decision about the status of licensed or primary user channel. In practice, the reporting channels are imperfect which leads to inaccurate sensing decisions by the FC. Further, the multiple antennas can be employed at each CU to improve the sensing decision by employing spatial diversity. However, in CSS technique, the energy consumption increases due to cooperation overhead bits, therefore to reduce the energy consumption and to save the bandwidth of reporting channels, hard reporting, sleeping, censoring approaches, and selection of optimal fusion rule are employed.

In this thesis, we have precisely overviewed the state-of-the-art of various spectrum sensing techniques. In addition to this, we have presented detailed study of threshold computation methods employed by different researchers and their breakthrough contribution. The threshold selection is mostly performed with constant false-alarm rate (CFAR), constant detection rate (CDR), minimizing error probability (MEP) in EDSS.

In CFAR approach, the sensing threshold (λ_f) is computed for desired or targeted value of false-alarm probability ($\overline{P_f}$) while in CDR approach the sensing threshold (λ_m) is computed for targeted or desired detection probability ($\overline{P_d}$). However in MEP approach, the sensing threshold (λ_e) is computed by differentiating the sensing error probability (P_e) with respect to the threshold. Further, for the fixed value of number of samples (*N*), individual consideration of CFAR/CDR/MEP threshold selection approach agrees to meet either the target/desired false-alarm or detection probability values individually but is not achieved simultaneously at all the signal-to-noise ratio (SNR) which is a challenging issue.

In this context, we have developed an algorithm to achieve the single spectrum sensing threshold in the additive white Gaussian noise (AWGN) with the non-cooperative environment, which has achieved the desired values of false-alarm and detection probabilities, simultaneously at all (low as well as high) SNR. The existence of this single threshold is made possible by finding and satisfying the optimality condition. In addition to this, we have also analyzed the effect of various threshold selection approaches on the throughput of CU. We have demonstrated that at low SNR, the proposed optimal threshold selection approach has provided improved throughput as compare to that of CDR and MEP threshold selection approaches.

Furthermore, we have considered practical wireless communication scenario that is fading channels which leads to low received SNR at CUs. Under the fading channels, the spectrum sensing performance of CU also decreases therefore, we have employed centralized cooperative spectrum sensing to improve the sensing performance with the perfect reporting (PR) channels. Further, we have shown the comparison of spectrum sensing performance of non-cooperative and different cooperative rules scenario at low SNR by analyzing receiver operating characteristic (ROC) curve under AWGN and fading channels. In addition, we have also shown the variation in throughput and sensing error probability with SNR while employing different sensing threshold selection approaches under the non-cooperative and cooperative spectrum sensing scenario. With the observation, we have concluded that the throughput is maximized by CFAR with cooperative spectrum sensing rule at some SNR while it is maximized with MEP approach at other, inthe non-cooperative scenario. In addition, the sensing error probability has decreased after cooperation, however in the Rayleigh and Nakagami-*m* fading environment, MEP and CFAR approaches have provided least sensing error probability at different SNRs.

Further, it is observed for fading channels that the single threshold selection approach is not suitable to provide significantly higher throughput and less sensing error probability under the non-cooperative or cooperative spectrum sensing scenario. Therefore, we have introduced the concept of critical SNR (γ_c) and have proposed the algorithms to select an appropriate sensing threshold to achieve significantly higher throughput and minimum sensing error probability at different SNR (γ). From the obtained results, we have accomplished that the proposed approach has outperformed the other approaches in terms of throughput and sensing error probability in different fading environments.

Subsequently, we have considered more realistic wireless communication scenario of imperfect spectrum sensing and imperfect reporting channels and have analyzed its consequences on the CU communication system performance (sensing error probability and throughput) at different SNR while employing different threshold selection approaches. Since in CSS, the energy consumption increases with increases in the number of cooperative CUs, resulting energy inefficient CUs communication and one of the possible solutions to improve the energy efficiency is the censoring approach in which only few CUs report their sensing decision to the fusion center. With this context, we have applied censoring approach in proposed communication system to analyze the system performance and have compared its effect with the non-censoring based cognitive radio network (CRN) system under the perfect and imperfect reporting (IR) channels.

Further,the spectrum sensing error probability and energy efficiency are the key performance parameters in CRN which are affected by the threshold selection techniques, number of antennas employed at CU, reporting error probability and cooperative fusion rule applied at the fusion center (FC). Therefore, we have derived the mathematical expression for sensing error probability by considering the effect of all these parameters and have optimized the cooperative fusion rule at FC. The optimal cooperative rule at different SNR is decided by formulating the mathematical expression for number of cooperative CUs to minimize the sensing error probability. In addition, we have also illustrated the sensing error and energy efficiency (EE) improvement achieved with the censoring approach when different threshold selection approaches are employed at each CU. From the results, significant enhancement in energy efficiency is achieved with censoring approach in comparison to that of the non-censoring approach while employing particular threshold selection technique.

LIST OF ACRONYMS

Acronym	Meaning
D2D	Device to Device
FCC	Federal Communication Committee
DSA	Dynamic Spectrum Allocation
CR	Cognitive Radio
CU	Cognitive User
SS	Spectrum Sensing
EDSS	Energy Detector Spectrum Sensing
PU	Primary User
WRAN	Wireless Regional Area Network
CSS	Cooperative Spectrum Sensing
FC	Fusion Center
CFAR	Constant False Alarm Rate
CDR	Constant Detection Rate
MEP	Minimizing Error Probability
SNR	Signal-to-Noise Ratio
AWGN	Additive White Gaussian Noise
PR	Perfect Reporting
IR	Imperfect Reporting

ROC	Receiver Operating Characteristic
CRN	Cognitive Radio Network
EE	Energy Efficiency
RF	Radio Frequency
IoT	Internet-of-Things
IIoT	Industrial Internet of Things
IWNs	Industrial Wireless Networks
IoVs	Internet of Vehicles
IoMT	Internet of Medical Thing
WSN	Wireless Sensor Network
CR-WSN	Cognitive Radio-based Wireless Sensor Network
VANETs	Vehicular Ad hoc Networks
CR-VANETs	CR based Vehicular Ad hoc Networks
C-RAN	Cloud based Radio Access Networks
HetNets	Heterogeneous Networks
SP	Service Provider
DOSA	Dynamic and Opportunistic Spectrum Access
ED	Energy Detection
FD	Feature Detection
MFD	Matched Filter Detection
CBD	Covariance Based Detection

EVD	Eigen Value Based Detection
CAF	Cyclic Autocorrelation Function
CSD	Cyclic Spectral Density
CFN	Covariance Frobenius Norm
CAV	Covariance Absolute Value
C-CSS	Centralized Cooperative Spectrum Sensing
MRC	Maximal Ratio Combining
SLC	Square Law Combining
SC	Selection Combining
SLS	Square Law Selection
QoS	Quality of Service
BER	Bit Error Rate
NP	Neyman-Pearson
BD	Bayesian Detection
FD	Full-Duplex
FDC-MAC	Full Duplex Cognitive Medium Access Control
FT	Fixed Threshold
DT	Dynamic Threshold
LLR	Log-Likelihood Ratio
DT-LLR-HSC	Double Threshold-based Log-Likelihood Ratio Hard-Soft Combining
GDOP	Geometric Dilution of Precision

KKT	Karush– Kuhn–Tucker
SINR	Signal-to-Interference Noise Ratio
WCD	Weighted-Covariance-based Detection
LB	Ljung-Box
Tx	Transmitter
Rx	Receiver
IID	Independent and Identically Distributed
CSCG	Circularly Symmetric Complex Gaussian
PSK	Phase Shift Keying
FNS	Fixed Number of Samples
ONS	Optimal Number of Samples

LIST OF SYMBOLS

Symbol	Notations
λ	Threshold \Sensing threshold
λ_{CFAR} or λ_f	Threshold with CFAR approach
λ_m or λ_{CDR}	Threshold with CDR approach
λ_{MEP} or λ_e	Threshold with MEP approach
$\overline{P_f}$/ P_{f_fixed}	Targeted value of false-alarm probability /Desired false-alarm probability
$\overline{P_d}$/ P_{d_fixed}	Targeted value of detection probability / Desired detection probability
P_f	False-alarm probability
P_d	Detection probability
P_e	Probability of error / Sensing error probability
Q_f	False-alarm probability after cooperation
Q_d	Detection probability after cooperation
Q_e	Sensing error probability after cooperation / Total sensing error probability
N	Number of samples
γ	PU SNR
γ_s	CU SNR
γ_c	Critical SNR
H_1	Hypothesis for PU channel being busy

H_0	Hypothesis for PU channel being idle
$X(n)$	Received Signal
$S(n)$	Transmitted PU Signal
$W(n)$	Noise Signal (Additive White Gaussian Noise)
h	Channel Gain Coefficient
$T(x)$	Test Statistics for the Energy Detector
D	Sensing Data
T	CU Frame Duration
T_s	Sensing Time
T_R	Reporting Time
C or R	Throughput
E_{Total}	Average Energy Consumed
$P(H_0)$	Probability of PU Channel being Idle
$P(H_1)$	Probability of PU Channel being Active
Erfc(.)	Error Function
σ_n^2	Noise Variance
$N*$	Optimal Number of Samples
$Q^{-1}(.)$	Inverse Complementary Distribution Function of the Standard Gaussian Distribution
R or R(T_s)	Throughput
R_c	Throughput after Cooperation

$\overline{P_d^f}$	Average Detection Probability over Fading Channel
$\overline{P_d^{ray}}$	Average Detection Probability over Rayleigh Fading Channel
$\overline{P_d^{Naka}}$	Average Detection Probability over Nakagami-*m* Fading Channel
f_{ray}	Probability Density Function of Rayleigh Fading Channel
f_{Naka}	Probability Density Function of Nakagami-*m* Fading Channel
$\bar{\gamma}$	Average SNR value
m	Shape Parameter in Nakagami Fading Channel
$\lambda_e(Ray)$	Threshold with MEP Approach for Rayleigh Fading Channel
$\lambda_e(Naka)$	Threshold with MEP Approach for Nakagami-*m* Fading Channel
M	Total Number of CUs
k	*N*umber of CU Terminals Employed for Cooperation who give Sensing Decision in Favor of Busy Licensed Channel
λ^*	Normalized Threshold
Q_f^M	False Alarm Probability after Majority Rule
Q_d^M	Detection Probability after Majority Rule
P_e^r	Reporting Error Probability
T_{sr}	Sensing plus Reporting Time
L_a	Number of Antennas
M_c	Number of CUs Reporting to FC in Censoring Approach
P_f^r , P_d^r	Received False-alarm, Detection Probability of CU at FC with Imperfect Reporting in Non- censoring Approach

$P_{f_i}^{rc}$ or $P_{d_i}^{rc}$	Received False-alarm, Detection Probability of ith CU at FC with Imperfect Reporting in Censoring Approach
Q_f^r, Q_d^r, Q_e^r	False-alarm, Detection, Sensing Error Probability at FC after Cooperation with Imperfect Reporting in Non-censoring Approach
Q_f^{rc}, Q_d^{rc}, Q_e^{rc}	False-alarm, Detection, Sensing Error Probability at FC after Cooperation with Imperfect Reporting in Censoring Approach
R_I	Throughput of CU after Cooperation with Imperfect Reporting Channels
R_{IC}	Throughput of CU after Cooperation in Censoring with Imperfect Reporting Channels
$P_{f_i}^{SLS}$	False-alarm Probability of the i^{th} CU when CU employed L_a Number of Antennas.
$P_{d_i}^{SLS}$	Detection Probability of the i^{th} CU when CU employed L_a Number of Antennas
$P_{f_i}^{r,SLS}$	False-alarm Probability of i^{th} CU received at FC under Imperfect Reporting Channel with Non-censoring Approach when CU employed L_a Number of Antennas
$P_{d_i}^{r,SLS}$	Detection Probability of i^{th} CU, received at FC under Imperfect Reporting Channel with Non-censoring Approach when CU employed L_a Number of Antennas
$P_{f_i}^{rc,SLS}$	False-alarm Probability of i^{th} CU received at FC under Imperfect Reporting Channel with Censoring Approach when CU employed L_a Number of Antennas
$P_{d_i}^{rc,SLS}$	Detection Probability of i^{th} CU, received at FC under Imperfect Reporting Channel with Censoring Approach when CU employed L_a Number of Antennas
M_c^{SLS}	Number of CUs reporting to FC in Censoring Approach when CU employed L_a Number of Antennas

$Q_f^{rc,SLS}$, False-alarm, at FC after Cooperation with Imperfect Reporting in Censoring Approach when CU employed L_a Number of Antennas

$Q_d^{rc,SLS}$ Detection Probability at FC after Cooperation with Imperfect Reporting in Censoring Approach when CU employed L_a Number of Antennas

$Q_e^{r,SLS}$ Sensing Error Probability at FC after Cooperation with Imperfect Reporting in Non-censoring Approach when CU employed L_a Number of Antennas

$Q_e^{rc,SLS}$ Sensing Error Probability at FC after Cooperation with Imperfect Reporting in Censoring Approach when CU employed L_a Number of Antennas

E_S, E_R, E_T Energy consumed in the Spectrum Sensing, Reporting and Transmission

P_S, P_R, P_T Power consumed in the Spectrum Sensing, Reporting and Transmission

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Motivation

Recent reports [1] revealed that at the end of 2018, globally 5.1 billion people subscribed to the mobile services, which is approximately 67% of the global population. However, with the introduction of 5G which is now with us, carries exciting new services and new telco-business opportunities: internet-of-things (IoT), media convergence, artificial intelligence (AI) and new milestones in connected devices. Further, these new opportunities have the potential to increase mobile operator revenue over the coming years, with an expected annual average growth rate of 1.4% between 2018 and 2025. Therefore, an increase in spectrum-hungry radio applications over mobile and wireless devices, as well as its inefficient static assignment, which is accompanied by an uneven distribution of wireless traffic across the radio spectrum and the proliferation of unlicensed wireless technology, has led to a problem of spectrum scarcity. Further, the demand of wireless radio frequency (RF) spectrum has been increased to provide various services e.g. accessing high speed internet, seamless connectivity between devices everywhere at all time, internet-of-things (IoT), multimedia applications (video streaming in Netflix, YouTube, Skype etc) [2]–[4]. Further, the RF spectrum is partitioned into different frequency bands which are allocated to numerous applications and usage. The spectrum assignment process organized by regulatory bodies (International and/or National/Local), allows some of these frequency bands to be used openly (unlicensed bands) by the public community without any permission while the other frequency bands are allocated to the primary users (PUs) called licensed users [5]. The primary users have full-authority to use the licensed bands wherever needed but in unlicensed band, the interference issue may rise due to the uncoordinated usage of the band by different kind of users [6]. However, as per the report of Federal Communications Committee (FCC), the vast amount of PU frequency bands are not used efficiently, indeed, they are unutilized or underutilized [7]. Further, this problem arises due to fixed spectrum allocation policy therefore, there is a demand of dynamic spectrum allocation (DSA) technique to utilize the radio frequency spectrum efficiently [8], [9]. In DSA, the unutilized/underutilized available spectrum (spectrum hole) is dynamically allocated to unlicensed users in spatial as well as temporally manner. One of the technologies which employ DSA is cognitive radio (CR) in which the cognitive user called as unlicensed user has the capability to access the licensed band and can successfully provide the solution for this era of spectrum demand [10]–[13].

Further, recent technologies such as industrial internet of things (IIoT) [14], industrial wireless networks (IWNs) [15], big data [16], cloud computing [17], Internet-of-vehicles (IoVs) [18],internet-of-medical-thing (IoMT) [19], [20], etc. have brought enormous opportunities for encouraging industrial upgrades and has allowed the introduction of the fourth industrial revolution, namely Industry 4.0 [21], [22]. In the context of Industry 4.0 which uses IoT, all kinds of intelligent equipment supported by the wired or wireless networks are widely adopted. The wireless sensor network (WSN) is one of the key enablers for the Internet-of-Things (IoT), where WSNs will play an important role in future internet for several application scenarios, such as healthcare, agriculture, environment monitoring, and smart metering [23]. However, as we have already discussed that radio spectrum is very crowded for the rapid increasing popularities of various wireless applications [23] hence, WSN can utilize the advantages of cognitive radio technology, namely, the cognitive radio-based WSN (CR-WSN). Further, CR-WSN leads to a promising solution for spectrum scarcity problem of IoT applications in Industry 4.0. One of the major challenges in CR-WSN is the efficient detection of the unutilized licensed spectrum in the practical wireless scenario which motivated us to work in this direction [24]. Further in recent era, the mobile wireless sensor network has many applications in IoT and it is a universal network of interconnected objects which are uniquely addressable, and allows people and things to be connected any-time, anyplace, any path/network and any service. Conversely, it is anticipated that large number of IoT objects will grow up and will increase the data traffic on the network resulting in shortage of frequency spectrum for IoT objects. Moreover, it is presented by various researchers [4], [25] that IoT objects consisting of spectrum sensing block have the capability to separately search for existing available frequency channel in cloud servers and it is also possible to combine IoT with 5G network [26]. Moreover, in the vehicular ad hoc networks (VANETs), demand of wireless applications is increasing therefore shortage of frequency spectrum has occurred for coordination between different services. Implementation of sensing operation of CR for searching new available frequency bands can be a potential solution of this frequency shortage for VANETs.

Further, the spectrum sensing is also employed under battlefield surveillance system to monitor the attack of enemy missile or other aircrafts [27]. In addition to this, the spectrum sensing has great importance for utilization of the new technologies such as, internet of medical thing (IoMT), CR based vehicular ad hoc networks (CR-VANETs), cloud based radio access networks (C-RAN), etc. The C-RAN is widely employed in heterogeneous networks (HetNets) to resolve the complexity of broadband wireless services and provide better coverage along with high data rates concurrently. The HetNets are placed by service provider (SP) which requires cautious frequency planning such that the interference between overlapping and adjacent cell is avoided. Therefore, the spectrum sensing block can be used to perform the efficient utilization of spectrum in HetNets [28]. As a result, the spectrum sensing is considered as a foundational technology for better spectrum efficiency in the next generation networks and has received a persistent attention from the communication and signal processing community. Its fundamental task is to obtain the awareness about the licensed spectrum usage and existence of PU in a geological area and this knowledge can be obtained by various local spectrum sensing techniques [29]. In this context, CR-VANETs have employed spectrum sensing in cooperative manner to resolve the frequency spectrum scarcity issue. However, the location of vehicle and vehicular speed are the key challenges in spectrum sensing performance of CR-VANETs [30]. From the above discussion it is clear that spectrum sensing has great advantage for different application of industry 4.0 therefore efficient SS has the major role for its proper functioning.

1.2 Cognitive Radio

Cognitive radio (CR) is a technological advancement that envisions giving solution to static spectrum allocation problem by employing DSA in the wireless communication systems. Its core objective is to provide the provision of PU spectrum access through dynamic and opportunistic spectrum access (DOSA), as long as there is no harmful interference to the primary user (PU). [31], [32]. The cognition and reconfiguration ability of CR enables it to adapt easily in the dynamic radio frequency environment. Further, the cognitive capability of CR is defined as the interaction with its RF environment in real time to determine appropriate communication parameters. While the reconfigurability is the capability of adjusting operating parameters (e.g. Transmission power, modulation type, operating frequency) for the transmission without any modifications in the hardware systems[8]. Further, CR devices are developed with an in-built capacity to sense and predict the surroundings in which they operate. Apart from spectrum sensing, CR is also characterized by three other distinct operations namely: spectrum decision, spectrum mobility and spectrum sharing and the association of all these four operations of CR is shown in Fig. 1.1 [32], [33].

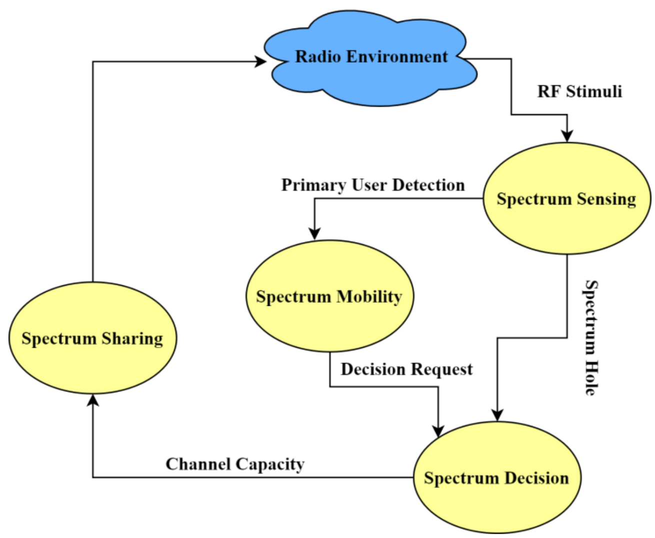


Figure 1.1: Cognitive cycle [32].

1.2.1 Spectrum sensing

In the spectrum sensing (SS), cognitive user (CU) identify the idle and underutilized licensed frequency band either in time/frequency/space/code/angle domain etc [29]. Initially, the CU receives the signal in the desired frequency band and employ any of the suitable spectrum sensing technique (which is discussed later in Section 1.2.3 of this thesis) to detect the presence or absence of the PU in the channel. The absence or presence of PU are considered to be related with binary hypothesis H_1 and H_0; where H_1/H_0 are the hypothesis for PU channel being active/idle respectively. In general, the spectrum sensing detection problem analyzed as a binary hypothesis model, is defined as follows:

$$X(n) = \begin{cases} W(n) & : H_0 \\ h.S(n) + W(n) & : H_1 \end{cases} \tag{1.1}$$

where, $X(n)$, $S(n)$, $W(n)$ and h are the received signal, transmitted PU signal, additive white Gaussian noise (AWGN), channel gain coefficient, respectively. n =1, 2, …. N and N is the total number of samples of received signal. Further, the SS is most crucial part of CU whose high accuracy is highly desired. Since if the sensing results are not accurate e.g. wrong predication of the busy licensed channel can create interference to PU and inaccurate sensing decision of idle licensed channel cause the transmission opportunity deprivation of CU in the available idle/free frequency band. Therefore, further we have elaborated about the spectrum sensing task of CR.

1.2.2 Spectrum sensing classification

In this section, we have presented the spectrum sensing classification employed by various researchers and this classification is also shown in Fig. 1.2 [34], [35]. On the basis of signal processing techniques, SS can be classified as: Energy Detection (ED), Feature Detection (FD), Matched Filter Detection (MFD), Covariance Based Detection (CBD), and Eigen Value Based Detection (EVD). The detailed description of these techniques has been presented further in Section 1.2.3. where it is elaborated to show how the received signal is processed by the CU device to obtain the status of licensed channel (idle or free). In addition, on the basis of bandwidth of licensed channels to be sensed, it is classified as narrowband and wideband SS [3]. Here, the term narrowband entails that the frequency range is adequately narrow such that the channel frequency response can be treated as flat. In other words, the bandwidth of interest is less than the coherence bandwidth of the channel. Moreover, in case the bandwidth of interest is greater than the coherence bandwidth of the channel, it can be considered as wideband spectrum sensing. Afterwards on the basis of the need of the prior information of the PU signal, SS is classified as blind and non-blind. In the blind SS, the PU information is not required to detect the licensed channel while in non-blind SS some or full information of PU signal (i. e. PU signature and noise power estimation) is required. Moreover, on the basis of spectrum sensing frequency, it may be classified as proactive and reactive; where the proactive sensing employ continuous spectrum sensing after a fixed interval of time while reactive sensing is performed on demand basis [34]. In addition to this,the SS can be also classified as non-cooperative and cooperative on the basis of decision of individual sensing result sharing between multiple CUs. Moreover, the detailed discussion of CSS is presented in Section 1.2.4.

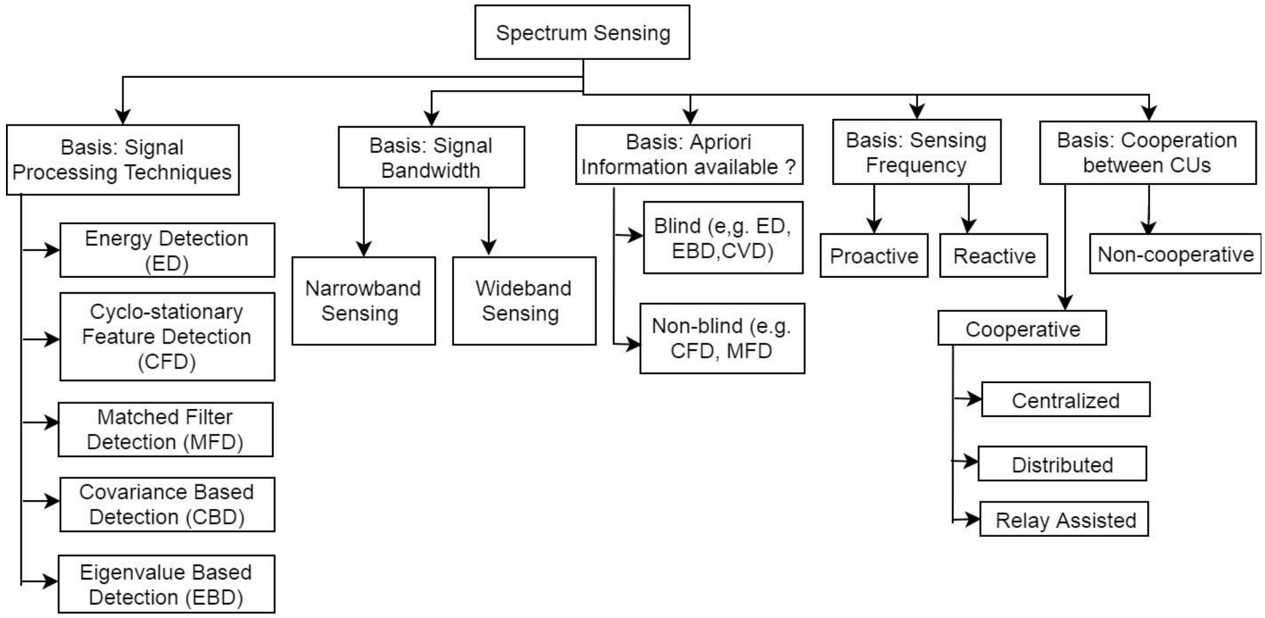


Figure 1.2: Classification of spectrum sensing (SS).

1.2.3 Spectrum sensing classification based on signal processing

This section presents the methodology of various spectrum sensing techniques which are described as follows.

1.2.3.1 Energy detection

The energy detector identifies the presence or absence of PU in the channel by computing the energy of the received signal as shown by the block diagram of the energy detection spectrum sensing (EDSS) in Fig. 1.3. In EDSS, the received signal is passed from the band pass filter (bandwidth of filter depends on the spectrum of interest) and then the filter output signal $X(t)$ is converted to discrete signal $X(n)$ with the help of analogue-to-digital (A/D) converter. Further, the energy of sampled signal $X(n)$ is computed over N samples which acts as a test statistics ($T(x)$) for the energy detector. The test statistics ($T(x)$) is then compared with the predefined sensing threshold (λ) to achieved the status of PU channel being either active/idle and then accordingly the hypothesis H_1/H_0 become true [36][37], [38].

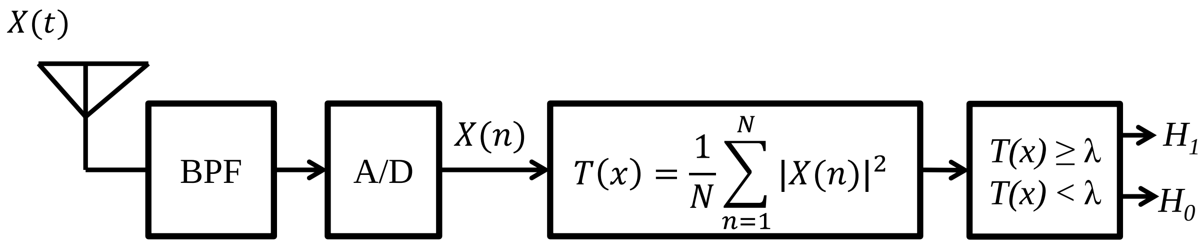


Figure 1.3: Basic block diagram of EDSS.

1.2.3.2 Feature detection

The principle of feature detection is based on acquiring the some specific signature of PU signal. In the wireless communication systems, some features such as cyclic prefix, preamble, hopping sequence, pilots, beacon frames etc. are added in the transmitted signal for synchronization or signaling purpose and hence the transmitted signal show periodicity which can be employed for sensing purpose. Therefore, to detect the PU signal transmission in background of noise, this built-in periodicity of received signal at CU is helpful for PU signal detection in feature detection [39], [40]. For example, when the mean and correlation replicate after regular interval of time in PU signal then received signal show high correlation which is employed in cyclic autocorrelation function (CAF), or cyclic spectral density (CSD) based feature detection (FD) technique [31]. This technique has the capability to differentiate among different types of PUs and PU signal from interference and noise since noise is in general (white) uncorrelated. Moreover, FD achieve high accuracy but at the cost of large sensing time and implementation complexity.

1.2.3.3 Matched filter detection

The matched filter based detection perform processing by correlating a known signal with an unknown received signal which is comparable to convolving the anonymous signal with a conjugated time-reversed version of the template. The matched filter designing is performed such that it maximizes the signal-to-noise ratio (SNR) at the output in the presence of noise. However, the matched filter based spectrum sensing can be employed only when CU has the perfect knowledge about the PU signal and physical structure e.g. (preambles, pilot, spreading codes, modulation type, pulse shape, frame format etc.). After correlating the template and received signal, wherever peak occurs, CU detect the presence of PU on that band otherwise PU is not present [41], [42].

1.2.3.4 Covariance based detection

The covariance is used to determine the variation in two random variables and generally the statistical covariance matrices of noise and signal are different. In this method of detection, the receiving filter determines the statistical covariance matrix of noise with the help of its structure and make new covariance matrix of the received signal. The finding of non-diagonal elements zero in the covariance matrix of the received channel signal leads to the conclusion of PU absence on that channel, however, in other case PU presence will be detected [43], [44].The covariance frobenius norm (CFN) and covariance absolute value (CAV) detectors, take the advantage of difference between the covariance matrices of noise and primary signals, and it has lower computational complexity in comparison to the eigen value based detection [45]. Further, the covariance-based detection technique is also considered with multi-antenna based CU by exploiting spatial correlation and it is concluded that performance of covariance based spectrum sensing is good when there is high correlation between multiple antennas. In addition, a weighted correlation-based detector [46] has been presented which requires the knowledge of correlation coefficients that may not be available in practice. Further, both the spatial and temporal correlations have been exploited in [47] for spectrum sensing, which achieves good performance with apriori knowledge of noise power and signal temporal correlation function.

1.2.3.5 Eigen value based detection

This SS method is based on the received signal's covariance matrix which can be built by utilizing the receiver diversity such as multiple antennas, cooperation among multiple users, and oversampling [48]. Further, the ratio between the largest and the smallest eigen value in covariance matrix is considered as decision threshold to predict the busy or idle state of licensed channel. The eigen value based detection (EVD) is a blind SS and provides better performance under noise uncertainty[48]–[50]. In the minimum EVD algorithm [51], the relation between the least eigen value and the power of the noise signal can be used to detect the presence of the PU. This spectrum sensing approach provide higher sensing performance as compare to maximum EVD at low SNR [51] however, different types of eigen value based SS is discussed in [52].Moreover, in Table 1.1 comparison among different SS approaches are presented.

Table 1.1: Comparison among different SS techniques.

Spectrum Sensing Approach	Pros.	Cons.	References
Energy Detection (ED)	Implementation easy. Computational complexity is low. Blind. Suitable for detecting the PU signal who are independent identical distributed (IID).	Unable to detect spread spectrum signal. Unable to differentiate between different types of signal. Poor performance under noise uncertainty and at low SNR.	[31], [53]–[59]
Feature Detection (FD)	Able to differentiate between different types of signal (e.g. PU signal from noise and interference signal). Robust to noise uncertainty. Less prone to hidden node problem. Fast sensing as compare to ED.	Implementation complexity. Non-blind. Bad performance when noise is stationary. Poor performance under fading. For higher accuracy demand, longer duration of known sequence is needed resulting in less spectrum utilization.	[60]–[66]
Matched Filter Detection	Detection time is less Maximized the SNR	Perfect knowledge of PU signal features are required (e.g. frame format, pulse shaping, modulation type, operating frequency, bandwidth). Implementation complexity is high. Large power consumption.	[41], [42], [67]–[69]
Covariance Based Detection	Low computational complexity. Blind High accuracy	Performance degrades when signals are not independent identical distributed (IID). Sensing performance degrades when antenna correlation is relatively low.	[44], [45], [70]–[74]
Eigen Value Based Detection	Non-coherent Suitable at low SNR Robust to noise uncertainty	High computational complexity Poor threshold accuracy for less number of samples.	[49], [75]–[79]

Moreover, due to the promising advantages of EDSS such as its simplicity, low implementation complexity and blind nature of sensing (no information is requires about the PU signal), various researchers have worked on EDSS technique under different channel conditions and have analyzed the performance of CRN [31], [58], [80].

1.2.4 Cooperative spectrum sensing

The key goal of any spectrum sensing approach is to identify the absence or presence of a PU in a specified frequency band at a given moment in a certain location. When each node makes an autonomous decision on the availability of a licensed frequency band, and acts accordingly then SS is considered as non-cooperative spectrum sensing. However, the sensing results in non-cooperative spectrum sensing may be inaccurate under real wireless scenario (multipath and shadowing). Therefore, to increases the reliability under real wireless scenario, individual sensing results of multiple CUs are shared among each other. The cooperative communication and networking allows different users or nodes in a wireless network to share resources and to create collaboration through distributed transmission/processing. The cooperative communication and networking is a new communication paradigm that promises significant capacity and increased multiplexing gain of wireless networks. It also realizes a new form of space diversity to reduce the harmful effects of severe fading, shadowing and the receiver uncertainty problem [81], [82]. In Fig. 1.4, we have shown the multipath fading, shadowing and receiver uncertainty scenario under the non-cooperative cognitive radio network.

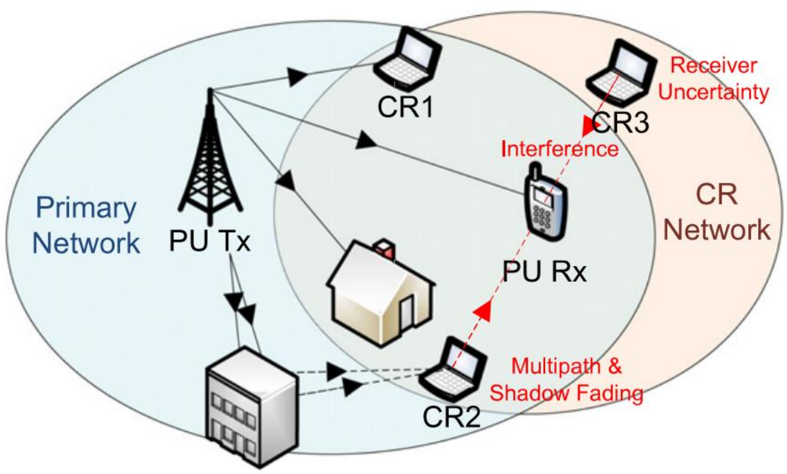


Figure 1.4: Multipath and shadowing effect in non-cooperative SS [83].

From Fig. 1.4, it is clear that CR2 suffers multiple signals from building and comes in the shadow of house, therefore CR2 suffers multipath fading and shadow fading which results degradation of the sensing decision of CR2 even though CR 2 is within the range of PU transmission. In addition, CR 3 is outside the PU transmitter range hence cannot detect the transmission of PU and it is allowed to access the channel in spite of PU transmission so suffers receiver uncertainty problem. As a result, the transmission from CR3 may interfere with the reception at PU Rx. Therefore to deal with all these issues, multiple CRs can be intended to cooperate with each other in spectrum sensing results to employ spatial diversity [84]. Since due to spatial diversity, it is unlikely for all spatially distributed CR users in a CR network to concurrently experience the fading or receiver uncertainty problem, hence the cooperative spectrum sensing can greatly increase the sensing performance of CR in the real wireless scenario [85]. Further, on the basis of sharing the sensing results between CUs, CSS can be classified in to three groups [81], [83]: a) Centralized, b) Distributed, and c) Relay-assisted and these CSS are described below:

Centralized: In the centralized CSS, all CUs/CRs sense the licensed frequency band using sensing channels and report the local sensing results to one central entity called fusion center (FC) using reporting channels which is also shown in Fig. 1.5(a). Further, FC combines all local sensing results using different fusion rules and take global final decision about the status of licensed channel being busy or idle. Afterwards, the global decision taken by FC is broadcasted to all CR in the network. The detailed description of reporting and fusion rules employed in centralized based cooperative spectrum sensing (C-CSS) is presented further in Section 1.2.5.

Distributed: In the distributed CSS, all CUs share the sensing results from each other and converge to single decision about the status of PU channel by iterations. Fig. 1.5(b) illustrates the distributed CSS in which all CRs sense the transmission of PU signal in the desired frequency band on the sensing channel and these sensing results are shared with each CR in the network. Afterwards, each CR combines its own sensing results with the received sensing results and employs some local criteria to make a decision about the PU presence or absence. When the local criteria is satisfied, CR will take unanimous cooperative decision, however in case of ambiguity, CR user will send its combined result to other users again in the network and this process is repeated until the criteria is not satisfied and unanimous cooperative decision has not come [83].

Relay-assisted: Since in a CRN, the sensing and reporting channels are not perfect therefore, it might be the possibility that some CR have good sensing channel and weak reporting channel while some CRs may have weak sensing and good reporting channels. Consequently, due to imperfect sensing or imperfect reporting channel, the sensing decision is affected. Therefore, the relay assisted SS employs the advantage of that CR having strong sensing and/or reporting channel by considering CR as a relay. Further, the relay assisted CSS can be employed either in centralized or distributed manner, however Fig. 1.5(c) illustrated the centralized based relay assisted CSS. In Fig. 1.5(c) it is shown that CR1 and CR5 have good sensing channels but weak reporting channels while other CR in the network i.e. CR2, CR3 and CR4 have good reporting channels, in that case later CRs (i.e. CR2, CR3 and CR4) can act as relays to help in forwarding the sensing results of CR1, and CR5 to the FC [83].

In addition, the comparison among different CSS approaches has been presented in Table 1.2.

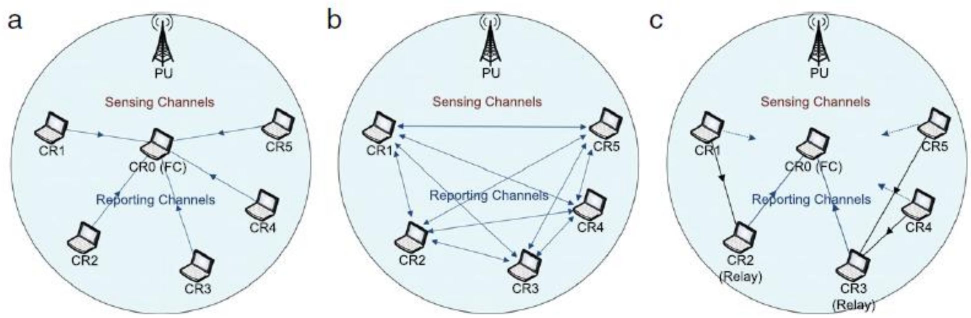


Figure 1.5: Classification of CSS (a) centralized (b) distributed (c) relay assisted [83].

Table 1.2: Comparison among CSS approaches

Topology	Pros.	Cons.	References
Centralized	More reliable decision Detailed information acquired by the FC Cooperation overhead bits are less than the distributed	Energy consumption and delay in sensing decision increases with increase in cooperative CUs. Quality of reporting channels must be good. Sensing decision highly depends on the FC. Selection of FC is crucial.	[86]–[89]
Distributed	Sensing decision does not depend on one central device. Each CU collects the sensing results from the surrounding CUs.	It may take a number of iterations to reach the common cooperative decision. It may be inefficient in terms of energy efficiency.	[90]–[92]
Relay Assisted	Suitable when either sensing or reporting channel of CU is weak and other CUs channel/s are strong.	Requires fast and accurate route selection algorithm Energy consumption is high.	[93]–[96]

1.2.5 Reporting and fusion rules in C-CSS

The centralized CSS (C-CSS), one of the majorly deployed methods for cooperation, has three phases, in which first phase is sensing which is followed by reporting and fusion decision phases. In the sensing phase, each CU senses the licensed channel and takes the sensing decision by employing spectrum sensing technique. The reporting and fusion decision phases have been detailed further where the type of reported sensing results to FC and different fusion rules employed by FC to take global final decision, has been presented.

1.2.5.1 Reporting phase

In the reporting phase, the sensing results of each CU is reported to FC either in hard, soft or quantized soft reporting manner in CRN which is discussed as follows.

a) Hard decision reporting

In the hard decision reporting, individual sensing result of each CU about the status of licensed channel being busy or idle is sent in single bit (D). D=1 represents the sensing decision in favor of licensed channel being busy while D=0 represents idle channel, which is shown in Fig. 1.6(a). In the hard reporting, it is considered that when the decision variable (such as the received signal power, the presence of periodicity in the received signal, etc.) is above a specified sensing threshold (λ), the CU will decide the sensing decision in favor of hypothesis H_1 and only bit 1 is sent to FC otherwise sensing decision comes in favor of hypothesis H_0 and only bit 0 is sent. Since in the hard decision reporting, sensing decision is sent with single bit only therefore, it is bandwidth efficient, easy for decoding and decision making. However this type of reporting also has some drawback such as sensing results may be imprecise, and the decision made by the CU is not replicated in its binary representation [97].

b) Soft decision reporting

In the soft decision reporting, the spectrum sensing result of each CU is sent in the form of multiple bits which represents the useful information, such as sensing-channel quality, a dedicated metric describing the CU's previous decisions etc. Since in the soft decision reporting, all important information regarding the sensing decision is sent therefore, the global detection probability increase however at the cost of large overhead reporting bits and delay in transmission and computational complexity [98], [99]. In Fig. 1.6(b) shows the soft decision reporting where the sensing data (D) is sent in the vector form of long sequence of 0 and 1. The sensing data (D) reported by the CU can be used to someway replicate the degree of uncertainty of the CU's decision, e.g., the vector of 1's which is represented as D = [111 . . . 1] will correspond to the belief of the accuracy of hypothesis H_1. The higher the number of bits in vector D, the higher the accuracy of the decision [81], [100].

c) Quantized soft reporting

In the quantized soft reporting, combination of the hard and soft reporting is employed where two or more bits are used to report the sensing decision. In Fig. 1.6(c), two bit quantized soft reporting is presented which has total four possible cases. To differentiate among these four cases, CR consider three thresholds, namely,λ_1, λ_2, and λ_3. When decision variable is below λ_1, the sensing decision of CU is highly probable of channel being free and report 00 to FC, whereas, if the decision variable lies between λ_1 and λ_2, CU reports a weak sensing decision for the channel being idle by sending bits 01. Further, if the decision variable lies between $\lambda_2$and λ_3, then CR reports weak sensing decision in favor of licensed channel being occupied and bits 10 are reported to the FC. In the final scenario, where decision variable is greater than λ_3, a strong sensing decision will be reported by the CU in favor of licensed channel being occupied and bits 11 is sent to the FC. Further, in depth analysis of the aforesaid schemes (quantized soft reporting) are presented in [101]–[103].

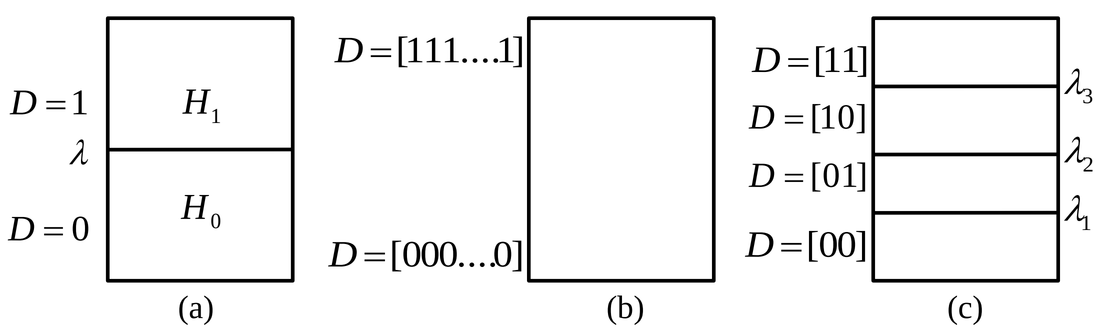


Figure 1.6: Reporting schemes (a) hard decision (b) soft decision (c) quantized decision (two bits).

1.2.5.2 Fusion rules

In this section, we have presented various fusion rules employed by FC in the cooperative communication to take global final decision about the status of licensed channel (active/idle). The FC may employ either soft or hard fusion rules whereas in the soft fusion rules, each CU forward the soft or quantized soft reporting results while in hard fusion rules, the CU forward the hard reporting results to the FC [104], [105]. For the soft fusion, FC may apply maximal ratio combining (MRC), square law combining (SLC) or selection combining (SC) [106]–[108] etc rules while in hard fusion, OR, AND, Majority, or K-OUT of M [109]–[111] rules are mostly employed by the researchers.

In this context, the weighted sum of sensing results are added at the FC in MRC to yield the status of licensed channel, where the weight assigned to the sensing result is decided according to their SNR. However, in the Square Law Combining (SLC), FC combines all the sensing results received from each CU and compares this summation value with the predefined threshold to decide the idle or busy status of licensed channel while in the selection combining (SC), FC only process the strongest sensing data out of all CUs. Further, in K-out of M hard decision fusion rule, FC takes the sensing decision in favour of licensed channel being active only when K out of M CUs report to the FC in the favor of active licensed channel. Further, OR, AND and Majority rules of hard fusion are the special case of K-out of M rule, when K=1, M, and M/2, respectively. Moreover, the hard fusion rule provides better performance than soft fusion rule in terms of less overhead bits, energy consumption, reporting channel bandwidth, at the cost of less sensing performance [112].

1.3 CRN Performance Parameters

In the CRN, various performance parameters such as reliability, throughput and energy efficiency etc. are considered and presented in Fig 1.7. Various approaches are employed by different researchers to enhance the performance of these parameters (Reliability, Throughput and Energy Efficiency) in CRN which are presented further.

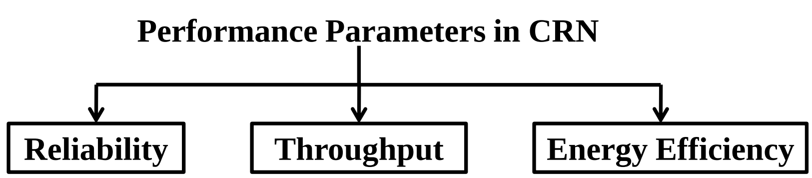


Figure 1.7: QoS parameters in CRN.

1.3.1. Reliability

The reliability of CR can be defined as the trustworthiness and can be considered in terms of minimizing call outage (false-alarm or miss-detection) probability [113], [114], the sensing error probability [113], call dropping probability[115], call blocking probability [116], collision probability [117], [118], and bit error rate (BER) [119]. The false-alarm probability (P_f) is defined as the probability of falsely detecting the presence of PU and in context of EDSS is given as $T(x) \geq \lambda / H_0$; i.e. the result of test statistics is higher than sensing threshold value (λ) giving the sensing decision in favour of H_1while actually PU channel is free (H_0). However, the miss-detection probability is defined as the probability of missing the detection of active PU channel given as $T(x) < \lambda / H_1$; i.e. the result of test statistics $T(x)$ is less than the sensing threshold value providing the sensing decision in favour of H_0 while actual status is active (H_1). Therefore, the spectrum sensing error probability is the combination of false-alarm and miss-detection probability given as $P_e = P_f + P_m$. However, the maximum utilization of channel and sufficient protection of PU need low numerical values of P_f and P_{m}. Since the reliability can be improved by reducing the sensing error probability therefore, in Fig.1.8, we have presented various approaches available in the literature to minimize the spectrum sensing error and is detailed below:

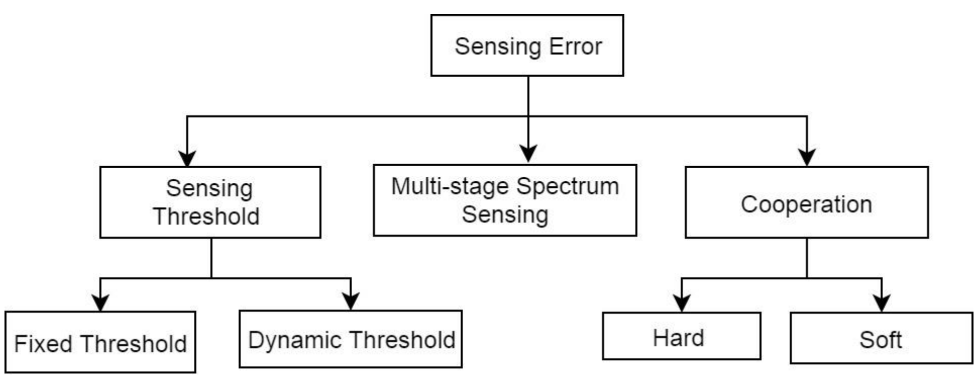


Figure 1.8: Techniques affecting sensing error.

a) Sensing threshold

The spectrum sensing error is the function of false-alarm and miss-detection probability and these parameters are affected with sensing threshold value which influences the sensing decision of CU (idle or active state of licensed channel). For higher value of sensing threshold, false-alarm probability is reduced but at the same time miss-detection probability is increased therefore, the selection of threshold is an important parameter to minimize the spectrum sensing error. In the reported literature, the fixed as well as dynamic threshold methods are commonly employed by researchers [120]–[122]; whereas in former, the sensing threshold value remains constant while in later its value is varied with change in SNR to minimize the probability of error (P_e) in sensing results which is also shown in Fig.1.9 and Fig. 1.10.

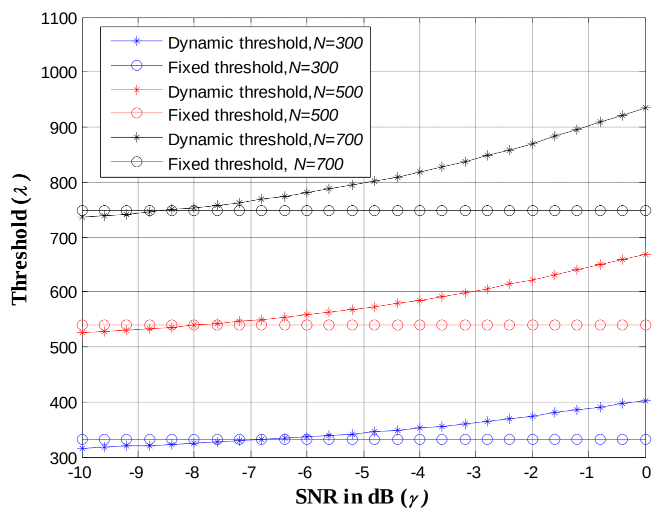


Figure 1.9: Threshold versus SNR at different N [121].

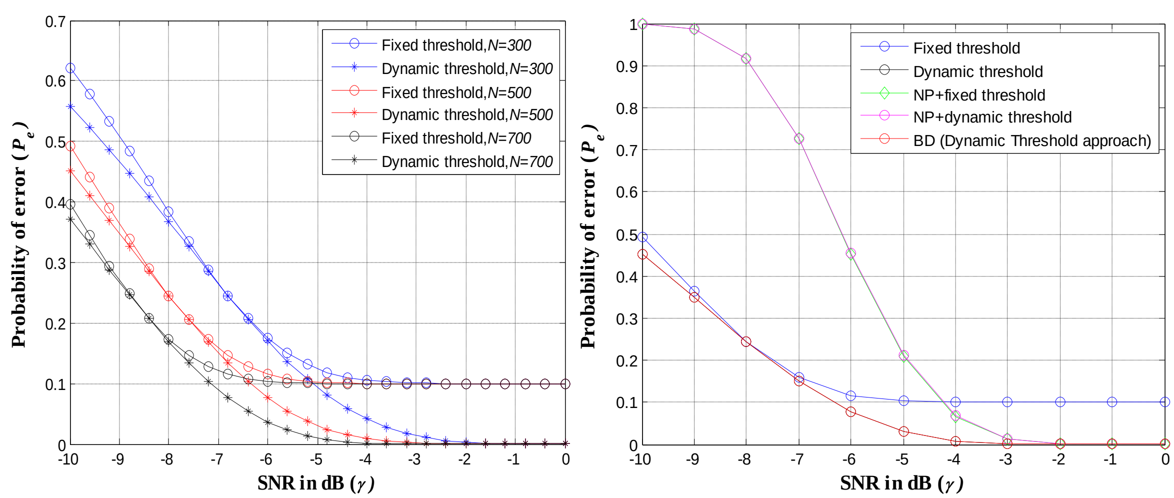


Figure 1.10: Probability of error versus SNR (a) at different N (b) various threshold selection approaches at N=500; NP: Neyman-Pearson, BD: Bayesian Detection [121], [122].

It has been demonstrated by various researchers [120]–[122] that the threshold selection with dynamic threshold, gives better sensing result as compare to that of the fixed threshold method.

Further, detailed discussion of fixed and dynamic threshold selection approaches is presented in Chapter 2 of the thesis.

b) Multi-stage spectrum sensing

The implementation of single spectrum sensing technique can taint the performance of CR as we have already discussed in Section 1.2.3, e.g. the energy detector (ED) has low sensing performance in noise uncertainty, feature detector (FD) requires a priori information about the PU signal etc. Therefore to mitigate the drawbacks of single stage spectrum sensing, various researchers [123]–[125] have employed two stage instead of single stage spectrum sensing to improve the sensing performance. With this context, most of the researchers have employed ED at first stage for coarse sensing while other SS techniques (e.g. FD, EVD etc) for fine sensing at the second stage [32], [123]–[126].

c) Cooperation

The cooperative can improve the sensing performance of CRN by increasing the detection probability to a great extent with space diversity, by means of which other CUs also involve in PU detection process for the case when individual CU may not be able to detect it due to fading or shadowing. The CU positioned in the neighborhood of PU can also function as relay for forwarding the sensing data in CSS. Detection probability can also be improved [127]. Further in [128], the fusion rules (hard and soft) effect on the C-CSS performance has been presented, where the soft reporting (multi-bit combination rule) has shown better sensing performance than hard (one-bit) combination rules at the cost of increased reporting overhead bits [129].

1.3.2. Throughput

The throughput of CRN is the average number of successful bits transmitted by the CU. In the reported literature, various parameters available to maximize the throughput and the work done in this direction are presented further.

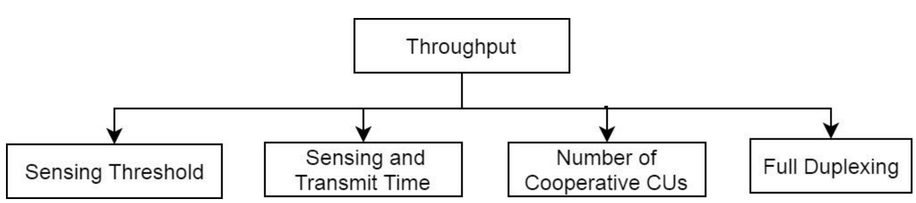


Figure 1.11: Techniques affecting throughput.

a) Sensing threshold

The spectrum sensing threshold is one of the critical parameter which affects the sensing error as presented in Section 1.3.1 and also the throughput of CU is dependent on this parameter. It is because the sensing threshold has an effect on the sensing parameters, P_f as well as on P_d, which has direct impact on the throughput of CRN. One of the threshold selection approach provided by Verma and Sahu [130], which has fixed the false-alarm probability, provides higher throughput however at the cost of increased probability of interference to PU. However, by fixing the detection probability in the other approach [130], has sufficiently avoided PU interference from CU with reduction of throughput. In addition, Jafarian and Hamdi [131] have employed double threshold based SS and maximized the throughput by minimizing the difference between two threshold values. Further, in [132] Shi et.al. have jointly optimized the sensing threshold and resource allocation schemes (i.e. power allocation and sub-channel assignment) to maximize the throughput. Moreover, Table 1.3 presents the additional major work on the throughput of CR by considering the sensing threshold parameters.

b) Sensing and transmission time

The spectrum sensing and transmission time of CU is another parameter affecting the throughput of CU; larger the transmission time, more is the transmitting opportunity that CU gets and hence higher will be the throughput as is clear from Fig.1.12. Fig. 1.12 has presented the frame structure of CU having frame duration *T*.

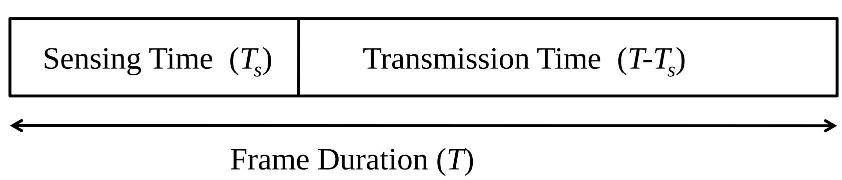


Figure 1.12: CU frame structure without CSS *[133]*.

Further, the frame duration T comprises T_s sensing time and remaining (T-T_s) time will be allotted for data transmission. For the fixed frame duration T, the less sensing time although provides more data transmission time to increase the throughput but at the same time will increase the sensing error. However, the longer sensing time will lead to more accurate sensing results by reducing the throughput. This is a major problem called sensing-throughput tradeoff, on which various researchers have worked to provide a solution. In this context, authors in [134] have computed the optimal sensing time and threshold to maximize the CU throughput while providing adequate protection to the PU. However, the optimal sensing time and power allocation strategies are obtained by Pei et. al [135] to maximize the throughput.

c) Cooperative CUs

In CSS, the number of cooperative CUs also affects the throughput as described in Fig. 1.13 which presents the frame structure of CRN in C-CSS. The total frame duration is considered to be of T units of time, which has T_s time allotted to multiple CUs to sense the channel. Further, each CU takes T_R time to report the individual sensing results to the FC and the total number of reporting CUs are considered to be M, therefore total reporting time will be $M * T_R$ and consequently, the data transmission time is: T-T_s-MT_R. As the number of reporting CUs (M) increases, the transmission time will reduce and cooperation overhead bits from large number of CUs will also increase resulting in reduced throughput of CRN. In this context, Liu and Tan [136] have jointly optimized the sensing time and the cooperative CUs to enhance the throughput of CRN and has minimized the overall sensing time to get the free licensed channels. In addition, by considering minimum sensing error, Bhowmick et.al [137] have computed the optimal number of CUs for cooperation to maximize the throughput.

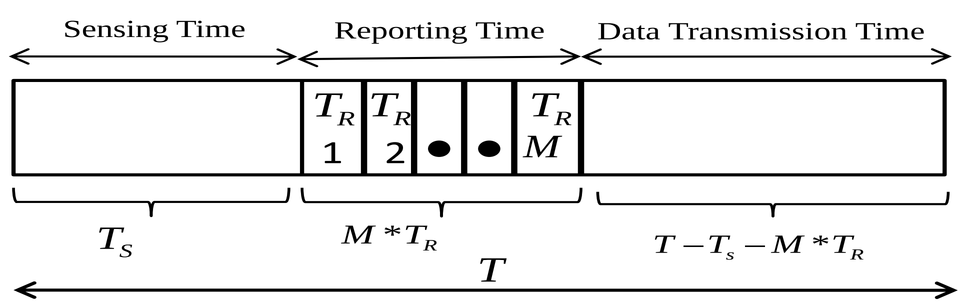


Figure 1.13: Frame structure in C-CSS.

d) Full Duplexing

In the full-duplex (FD) technology, generally CUs are equipped with two antennas, one antenna employed for sensing operation and other for transmission. This result in additional transmission time to CU than the system employing only single antenna for both operations and hence has increased the throughput of CU. However, the self-interference is the critical issue for the implementation of full-duplex technology therefore, different self-interference suppression techniques such as active analogue cancellation, null-steering beam forming, passive suppression, antenna polarization diversity etc. are readily employed in FD-CRN [138]–[140]. Further, in [141], Tan and Le have employed full-duplex cognitive medium access control (FDC-MAC) protocol and have analyzed the throughput performance by considering the effects of self-interference, PU activity and imperfect sensing. Moreover, the CU equipped with full-duplex transceivers has maximized the throughput with constraints on energy consumption [142]. Further, Table 1.3 presents the key approaches employed by various researchers and their contribution to improve the sensing error and throughput of CRN.

Table 1.3: Literature survey for improvement in sensing error and throughput of CR.

References	**Key Approaches**	**Major Contribution**
[143]	• Dynamic Threshold (DT)	• A filter bank approach is used for spectrum sensing. • Gradient descent based algorithm is proposed for threshold adaptation in dynamic scenarios to minimize the sensing error.
[144]	• Two stage sensing (Multistage)	• Spectrum sensing time is minimized. • Based on the received signal sample strength, switching between ED and CAV sensing approach is performed. • Their proposed approach has achieved better performance as compare to single stage in terms of hardware area and reconfiguration time.
[145]	• Two stage sensing (Multistage)	• Energy consumption is minimized for optimizing the reliability. • Achieved good detection performance along with energy efficiency. • Energy efficiency is achieved with two stage sensing which has employed energy detection and cyclostationary feature detection, jointly.
[146]	• Two stage sensing	• Minimized the sensing time with respect to the one stage sensing, to detect the idle channel when bandwidth of the coarse sensing unit is less.
[147]	• Optimal threshold	• Illustrated the trade-off between detection and false alarm probability.
[148]	• Double threshold	• Proposed the combination of hard plus soft reporting and demonstrated the trade-off between sensing performance and communication overhead.
[149]	• Two stage sensing • Double threshold	• ED is employed at both stages for which fixed threshold is used at first stage and dynamic threshold at the second stage. • The proposed approach has achieved higher detection probability and less sensing time at low SNR.
[131]	• Sensing time • Double Threshold	• Shown the sensing-throughput trade-off. • Optimized the difference between two threshold values and sensing time, simultaneously to achieve higher throughput at CU.
[150]	• Double Threshold	• Employed dynamic double thresholds to achieve desired Pd and Pf by limiting sensing overhead bits.
[151]	• Weighted hard-soft	• DT-LLR-HSC schemes is employed to sense the spectrum under fading

	combining scheme	channels. • Achieved higher performance than LLR-SC scheme in fading scenario.
[152]	• Threshold	• Derived the methods to calculate the Pd as a function of range from the sensing node to the object of interest. • This kind of function is important as it enables optimal positioning of multiple sensors over a region of interest.
[153]–[155]	• Sensing and transmission time	• Showed sensing-throughput tradeoff problem. • Computed optimal sensing duration to maximize the achievable throughput. • Tang et al. found optimal sensing time to maximize the achievable throughput by considering different traffic patterns of PUs.
[156]–[158]	• Sensing time • CU transmission power	• Proposed the strategy to maximize the throughput by jointly optimizing sensing time and power allocation to CU.
[159], [160]	• Full Duplex	• Applied a partial relaying scheme in CRN and improved the network throughput significantly of full-duplex CU.
[136]	• Sensing time • Number of CUs	• Jointly optimized the sensing time and number of the cooperative CUs to maximize the throughput.

1.3.3. Energy efficiency

The energy efficiency (EE) is defined as the ratio of average number of bits transmitted successfully (throughput, i.e. C) to the average energy consumed (E_{Total}). The CRN performance can be improved by enhancing the energy efficiency by throughput maximization and/or by minimizing energy consumption [161] as is clear from following equation:

$$EE = \frac{C}{E_{Total}} \tag{1.2}$$

Since, the work and methods of throughput improvement has already been presented in Section 1.3.2, therefore in this section, we have focused only for the energy consumption reduction to improve the energy efficiency. Various methods available for minimizing the energy consumption in CRN are presented in Fig. 1.14.

a) Sleeping and censoring schemes

In [162], the researchers have employed dynamic censored spectrum sensing scheme in which each CU compares the received signal power with predefined censoring threshold to decide the termination of sensing by the CU. Therefore, each CU turns off its sensing module with a specific sleeping rate to decrease the energy consumption. In addition, Wang et al. in [163] have considered censoring to send the informative sensing observations of some particular CUs to FC which has reduced the energy consumption of the overall CRN. Further, the sleeping scheme implementation in sensing phase along with censoring in the transmission has been performed in [164], [165] for minimizing the energy consumption of each CU. Moreover, Akhila and Priya in [166] have proposed the schemes for intra- and inter-cluster data transmission along with sleep and wake schemes to reduce the energy consumption, however Lunden et.al. in [167] used censoring in CSS.

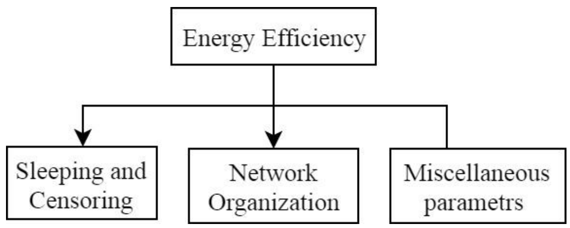


Figure 1.14: Approaches affecting energy efficiency.

b) Network organization

Generally, the CSS techniques enhance the spectrum efficiency of CRN by effectively combating the fading and shadowing effects at the cost of higher overhead bits, power consumption, and complexity [168]. In CSS, the cluster- based network architecture consists of local information sensing clusters distributed throughout the network. A cluster head is allocated for each cluster which is accountable for receiving sensing information from each CU belonging to the cluster and forward their sensing result to the fusion center. The energy consumption in this scenario increases with increase in distance between cluster head and FC and the amount of sensing data to be transmitted. Therefore, the network organization for cluster formation and proper cluster head selection is important parameter to reduce the energy consumption [169]. Further, minimizing the overall energy consumption with minimum geometric dilution of precision (GDOP) method, employed for the optimal placements of the CUs is presented by Saeed and Nam in [170]. However, Monemian et.al. in [171] have proposed the CU node selection strategy for spectrum sensing to minimize the energy consumption.

c) Miscellaneous parameters

Some other major parameters affecting the EE of CRN are the sensing and transmission time, number of cooperative CUs, fusion rule, transmitted power etc. As per the frame structure of the centralized CSS CU shown in Fig.1.13, consisting of sensing, reporting and transmission period, the power consumption in the frame can be minimized by optimizing their duration. In addition, the power consumed in the spectrum sensing phase also depends on the complexity of selected sensing technique. Further, the proper selection of number of cooperative CUs is required in the reporting phase to get the least energy consumption with appropriate performance of the network. In this context, Najimi et.al. in [172] have presented the optimal number of cooperative CUs by proposing the algorithm which has satisfied the Karush– Kuhn–Tucker (KKT) condition. While Xu et. al.[173] have derived the optimal number of cooperative relays in the cooperative spectrum sensing for minimizing the energy consumption. Further, in [174], the authors have dynamically selected the appropriate CUs for CSS with insight of their energy constraints. Since, the fusion rule (hard or soft) employed at the FC also affects the energy consumption therefore, Maleki et.al. in [175] have chosen the hard fusion over soft fusion rule to make energy and bandwidth efficient CRN. Further, it is shown for the hard fusion scheme that energy efficiency of AND rule is less with respect to the OR and Majority rule.

In summary, Table 1.4 has presented the key approaches employed by the various researchers and their significant contribution in the direction of energy efficiency improvement.

Table 1.4: Literature survey on improvement in energy efficiency of CR.

References	Key Approach	Major Contribution
[176], [177]	• Active and sleep mode	• Decreased the energy consumption by dividing each cluster into disjoint subsets with overlapped sensing coverage of PU activity and activates only one subset at certain period. • Selected the nodes from the active subset to perform sensing and schedules the switching of subsets for sleeping.
[164]	• Censoring • Sleeping	• Combined censoring and sleeping scheme to achieve significant energy saving. • Computed the lower and upper limit of energy consumption on each CU under AND and OR rule • Minimized the energy consumption on each CU
[89], [178]	• Network organization (Clustering)	• Presented survey on clustering approach by minimizing the number of clusters, cluster size, and efficient clustering. • Energy efficiency is achieved by dynamic clustering.
[179]	• Fusion rule (*K*-out-of-*M*)	• Achieved significant improvement in energy efficiency by optimizing K in K out of M rule for predefined threshold.
[175]	• Hard fusion rule	• Derived the optimal number of CUs for energy efficient optimization. • OR and Majority rule has outperformed the AND rule in terms of energy efficiency.

		• OR rule gives higher throughput than AND rule with a smaller number of CUs.
[180]	• Number of cooperative CUs	• Derived the closed-form expressions for determining the optimum number of cooperative CUs to optimize the average sensing energy efficiency.
[181]	• Optimal sensing interval • Number of CUs	• Derived the bounds for the number of CUs to achieve the desired P_f and P_d, simultaneously • Computed optimal sensing interval and the optimal CUs to minimize the energy consumption.
[182]	• Sensing and transmission durations	• Sensing and transmission time computation for energy-efficiency. • Proposed the condition to balance the energy consumption in sensing and transmission phase.
[183]	• Transmit power	• Maximized the ergodic capacity and minimized the average transmission power. • Iterative algorithm based sub-gradient method is proposed to obtain the minimum transmit power. • Minimum power allocation approach for spectrum sensing is presented under perfect and imperfect sensing.
[134]	• Sensing time • Sensing threshold	• Maximized the throughput and minimized the energy consumption jointly in CSS by optimizing the sensing time, sensing threshold and the sensing and data transmitting CUs.
[184]	• Sensing Threshold	• Jointly selected the sensing CUs, sensing threshold and decision CU nodes for minimizing the energy consumed in distributed sensing.

1.4 Literature Survey, Problem Formulation and Contribution

In this section we have presented the literature survey and from there formulated the research gaps. Verma and Sahu [130], which has fixed the false-alarm probability, provides higher throughput however at the cost of increased probability of interference to PU. However, by fixing the detection probability in the other approach [130], has sufficiently avoided PU interference from CU with reduction of throughput. In addition, Jafarian and Hamdi [131] have employed double threshold based SS and maximized the throughput by minimizing the difference between two threshold values. Further, in [132] Shi et.al. have jointly optimized the sensing threshold and resource allocation schemes (i.e. power allocation and sub-channel assignment) to maximize the throughput. Authors in [134] have computed the optimal sensing time and threshold to maximize the CU throughput while providing adequate protection to the PU. However, the optimal sensing time and power allocation strategies are obtained by Pei et. al [135] to maximize the throughput. Moreover, the detailed literature survey for improvement in sensing error, throughput and improvement in energy efficiency of CR is presented in Table 1.3 and Table 1.4 of this chapter.

As per the above presented literature in Table 1.3 and Table 1.4, there exist different challenges in the implementation of spectrum sensing methods of CRN which are discussed further in this section. The practical wireless communication scenario has been considered that is affected by the fading which degrades the received SNR and sensing and reporting channels. Therefore, the major challenge of spectrum sensing in practical wireless communication scenario lies in the selection of threshold for improving particular spectrum sensing detector performance. In this context, the researchers in [185] have analyzed the effect of threshold on the false-alarm and detection probabilities and have tried to achieve the desired P_f and P_d. However, since the attainment of both P_f and P_d values at low SNR is a challenging task, therefore in this thesis, we have presented the optimum results for the aforementioned sensing parameters. Further, in the literature presented in [130], [185], the researchers have analyzed the system performance for only non-cooperative CRN. However due to the significant advantages of cooperation over non-cooperation we have analyzed the CUs cooperation for the spectrum sensing to enhance the sensing performance of CRN.

However, there is very limited work on the effect of threshold approaches to maximize the throughput and minimize the sensing error in CRN for practical wireless cooperative communication scenario. Therefore, the analysis of threshold approaches in cooperative scenario is another major contribution of this thesis. In addition, the throughput and spectrum sensing error performance comparison for perfect and imperfect reporting channels with different threshold selection approaches is also provided in details, which is an important factor to be included in cognitive network design. Moreover, the cooperation increases the energy consumption of the network, therefore various researchers have worked on different methods which has minimized the energy consumption. One of the methods to do so for reducing the energy consumption due to the requirement of sensing results reporting by the large number of CUs, is the censoring method. In the censoring method, only the informative sensing results of limited CUs are sent to the FC. Further, the fusion rule applied at the FC also plays an important role in the energy consumption. However, the researchers in [186] have optimized the number of CUs whose decision is to be considered to yield the channel status while minimizing the sensing error for particular considered range of thresholds, without analyzing its effect on the energy efficiency. Moreover, the researchers study in [186] have presented for high SNR. However in this thesis, we have described the analysis at low SNR for threshold selection in the censoring and non-censoring scenario. Further, it is shown that there is significant improvement in the energy efficiency with censoring approach over that of the non-censoring while implementing different threshold selection approaches.

Based on the aforementioned potential challenges of the threshold selection and its effect, the contributions of this thesis is as follows:

- In this thesis, we have analyzed the condition for a single optimal threshold to achieve the desired probability of false alarm (P_f) and probability of detection (P_d) simultaneously under AWGN in the non-cooperative scenario. Further, we have proposed the approach to satisfy the optimality condition for a single optimal threshold at all SNR. Afterwards, for the proposed approach we have computed the closed-form expressions of various sensing performance metrics (P_f, P_d, and P_e) and achieved throughput and compared with the state-of-the-art work.
- Further, the sensing performance of CRN is analyzed under different fading channels in terms of ROC curve with different cooperation rules at low SNR and selected the Majority cooperative rule. We have also explored the effect of selection of various threshold selection approaches (using fixed (CFAR) and dynamic (MEP)) on throughput and sensing error in non-cooperative and cooperative (Majority rule) CRN under AWGN, Rayleigh and Nakagami-*m* fading channels.
- We have computed the value of critical SNR (γ_c) which provided the efficient threshold selection approach at different SNR to optimize the throughput and sensing error. In addition, algorithms to maximize the throughput and reduce the sensing error probability at all SNR are proposed for Rayleigh and Nakagami-*m* fading channels.
- The imperfect reporting channel is employed which has affected the sensing decision at FC and two scenarios are considered in such a manner where the sensing decision of CUs is sent to the FC with and without the censoring approach. Further, we have derived the expressions of sensing error and throughput for the fading channels while employing perfect/imperfect

reporting channel in the censoring and non-censoring approaches. The comparison between censoring and non-censoring approach is also presented.

- It is shown that by employing the optimal rule at FC, the sensing error is minimized with respect to Majority fusion rule. Further, the censoring approach is employed to improve the energy efficiency, and the closed-form expressions are derived for the optimal number of CUs at FC. Moreover, the energy efficiency comparison is also illustrated under the non-censoring and censoring scenario for CFAR and MEP threshold selection approaches when the respective optimal value of K is employed at the FC to reduce the sensing error. Further, from the results, it is depicted that the energy efficiency is significantly higher in the censoring scenario as compare to that of the non-censoring scenario.

1.5 Research Objectives

Our contribution in the thesis is categorized under three research objectives which are as follows:

Objective 1: Optimal threshold selection in AWGN channel under non-cooperative scenario such that both the sensing requirement parameters (P_f and P_d) achieved simultaneously.

Objective 2 : Optimal threshold selection in fading channels under cooperative scenario and its effect on performance of CR.

Objective 3: Optimization of Cooperative rule at FC to minimize the sensing error probability under different threshold selection in AWGN channel.

We have attained Objective 1 in Chapter 2 of the thesis, in which we provided an approach for optimal selection of threshold under AWGN channel and achieved the desired values of false and detection probabilities, simultaneously. However, Objective 2 is achieved in Chapter 3, 4 and 5 in which we have selected the optimal threshold under fading channel in cooperative spectrum sensing scenario. The Chapter 3 provides the analysis of different threshold selection approaches for AWGN and fading channels and illustrated the effect of threshold selection on throughput and sensing error probability in the considered scenarios. Moreover, in the Chapter 4, we have commenced the critical SNR concept to choose the appropriate threshold approach at different SNR to reduce the spectrum sensing error probability and improved the throughput of CRN for fading channels while considering perfect reporting channels. In Chapter 5, we have considered more realistic scenario of wireless CRN system consisting of imperfect spectrum sensing and imperfect reporting channels in all considered channels. Further, we have employed the censoring approach in CRN system and have analyzed the effect of different threshold selection in the non-censoring and censoring under cooperative scenario. Moreover, the Objective 3 is achieved in Chapter 6, in which we have optimized the number of cooperative users at FC in AWGN channel to minimize the sensing error probability. Further we have also analyzed the effect of multiple antennas, reporting error probability and probability of idle – or active – state of the licensed channel on the spectrum sensing performance in Chapter 6.

1.6 Thesis Organization

The remainder of the thesis is organized as follows. Chapter 2 provides the optimal threshold selection approach in AWGN channel under non-cooperative spectrum sensing to achieve the desired values of probability of false alarm (P_f) and probability of detection (P_d), simultaneously at all SNR. Further, we have also shown the effect of optimal threshold selection on sensing error probability and throughput of CRN.

Chapter 3 provides the analysis of different threshold selection approaches for AWGN and fading channels in the non-cooperative as well as cooperative scenario. Further, we compared the detection performance of CU under the non-cooperative and cooperative environment for different threshold selection approaches. In addition, we have also illustrated the effect of threshold selection on throughput and sensing error probability in fading channels.

Moreover in Chapter 4, we have commenced the critical SNR concept to choose the appropriate threshold approach at different SNR to reduce the sensing error probability and to improve the throughput of CRN for fading channels while considering perfect reporting channels. Further the analysis performed in this chapter has shown the trade-off between sensing error probability and throughput.

In Chapter 5, we have considered more realistic scenario of wireless CRN system consisting of imperfect spectrum sensing and imperfect reporting channels in AWGN, Rayleigh and Nakagami-*m* fading channels. Further, we employed the censoring approach in CRN system and have analyzed the effect of different threshold selection in the non-censoring and censoring scenario.

In Chapter 6, we have optimized the number of cooperative users at FC to minimize the sensing error probability. Further we have considered the effect of multiple antennas, reporting error probability and probability of free or active state of the licensed channel. In addition, we have also employed censoring approach in CSS and achieved significant improvement in the energy efficiency over non-censoring.

Finally, the Chapter 7 concludes the thesis and recommends its future scope.

CHAPTER 2

THRESHOLD SELECTION APPROACHES IN EDSS

2.1 Introduction

The comparison of different spectrum sensing approaches has been already presented in Chapter 1 and it is observed that energy detector spectrum sensing (EDSS) is commonly used for sensing the licensed spectrum. This sensing technique has significantly fewer computations and low complexity to implement. In EDSS, the energy of the received signal is presented in terms of test statistics ($T(x)$) and compared with the sensing threshold (λ) at CU to decide the sensing decision. When the $T(x) \geq \lambda$, the sensing decision of CU comes in favor of licensed channel being active otherwise idle. Since the sensing decision of CU is affected by the chosen value of threshold therefore, selection of threshold is crucial in EDSS. In addition, the key spectrum sensing performance metrics are the false-alarm and detection probabilities and these values are affected with the selection of threshold [120], [121], [185]. This effect of selection of threshold on false-alarm and detection probabilities is also shown in Fig. 2.1, e.g. if the threshold (λ) increases, both P_d and P_f decreases while these parameters increases with reduction in threshold (λ).

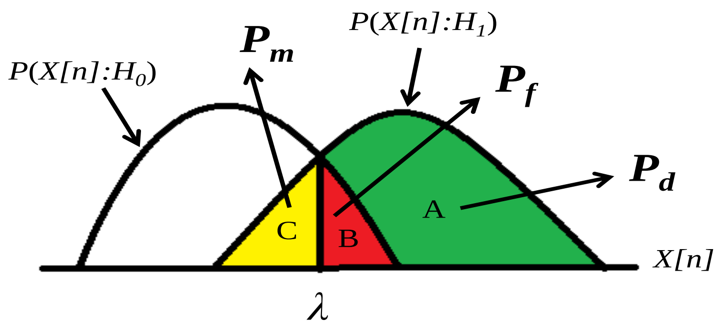


Figure 2.1: Effect of threshold on sensing performance.

Usually, EDSS employs fixed and dynamic threshold (FT and DT) selection schemes, which is also described in Section 1.3.1 of Chapter 1. In the fixed threshold (FT) method, constant false-alarm rate (CFAR) approach is commonly employed to find the fixed value of threshold while in DT method, constant detection rate (CDR) and/or minimizing error probability (MEP) approaches are employed for computing the variable threshold value with SNR variation.

Moreover, in CFAR approach, threshold (λ_{CFAR} or λ_f) is computed for the targeted value of false-alarm probability ($\overline{P_f}$) [187]–[189], while in CDR approach, the sensing threshold (λ_{CDR} or λ_m) is calculated for the desired or targeted value of detection probability ($\overline{P_d}$) [130], [190]–[192]. However, sensing error probability is minimized to find the value of sensing threshold in MEP approach (λ_{MEP} or λ_e) [185], [193], [194].

Different researchers have used above mentioned approaches to select the appropriate threshold for spectrum sensing to find the presence/absence of licensed user in the channel, which are detailed further in related work section of Chapter 2 and in Table 2.1.

2.2 Related Work

In this section, we have presented the related work on CFAR, CDR and MEP approaches which are as follows:

2.2.1 CFAR and CDR Approaches

As discussed above, in CFAR approach the threshold value is computed for targeted value of false alarm probability. In this perspective, Gandhi and Kassam [195] have employed the CFAR threshold selection approach to find out the status of licensed channel and show that CFAR performance is highly degraded in the presence of noise variation. Further, in the presence of noise uncertainty, Kortun et. al. [196] have employed EVD to enhance the sensing performance and maximized the throughput. Moreover, forward-detection methods is employed in [187] to control the P_f under multiple PUs environment. However to improve the P_d, Badrawi and Kirsh in [197] have employed the CFAR and empirical mode decomposition (EMD) techniques. Recently, simultaneously sensing and transmission at CU is employed by the researchers in [198] to improved the throughput. Moreover in [199], CDR approach is employed and found the throughput. Further, Gaurav and Sahu [200] improved the throughput of CU at low SNR by employing combination of CFAR and CDR approaches. Further, Zhang et al. [201] have also employed CDR approach and designed a framework for sensing time optimization and the power control. Moreover, in various literature [187], [195]–[197], [200], researchers have investigated on CFAR and CDR approaches.

2.2.2 MEP and other approaches

In MEP approach, the threshold is computed by minimizing the sensing error probability. In [185], [202], the researchers computed the dynamic value of threshold for Gaussian channel with MEP approach. Further, dynamic value of threshold is computed by Choi et.al. in [203] by considering the CU transmit power. Moreover, gradient descent algorithm is employed by Joshi et. al. [143][204] to obtain the dynamic value of sensing threshold without considering the CU's transmitted power. Further, researchers in [205] found the dynamic value of threshold by considering the distance between CU and base station as well as maximum allowable transmission power of CU. Further, Yu et. al. [206] have considered variable sensing duration, dynamic threshold to achieve the targeted value of false-alarm and detection probabilities and suggested that dynamic threshold is a more appropriate method to achieve the desired value of detection instead of increasing the sensing duration.

Moreover, the dynamic threshold is computed by Ling et. al. [120] whose dependence on signal-to-interference plus noise ratio (SINR) is shown and maximized the throughput of their system. However, researchers in [207] employed the information related to previous state of licensed channel to select the threshold and improved the sensing performance. Further for better utilization of spectrum, spectrum prediction techniques are employed by Ding et. al. in [208] which were based on channel utilization and resources of spectrum information. However, optimization of multiple parameters such as sensing time, sensing threshold and selection of CUs is employed by Kerdabadi et. al. in [134] and have maximized the throughput of CU. Further in [74], to minimize the sensing error probability, adaptive threshold is employed and sufficient protection is provided to licensed user. However, to enhance the probability of detection and minimize the sensing time, constant energy (CE) technique is employed by Benedetto and Giunta [209]. Afterwards, the weighted-covariance-based detection (WCD) is employed by Jit et al. in [45] and shown that low correlation CU's receiver antennas has reduced the detection probability in WCD. Therefore, Ljung-Box (LB) test is employed by Chen et.al. [210] to conquer problem of WCD and improve the detection probability. However, PU activity model is employed in adaptive spectrum sensing strategy (ASSS) by Xiong et. al. [211] to find the quick detection of free licensed channel. Further, Bayat and Aïssa [212] have considered the full duplex cognitive radio and use the sleep period between the neighboring sensing period to improve the energy efficiency without any considerable deterioration in throughput.

2.3 Problem Formulation and Contribution

As per above discussion, the threshold is mainly selected with CFAR, CDR or MEP in EDSS. In [130], Verma and Sahu selected the threshold with CFAR and CDR approaches individually which provides target value of false-alarm or detection probabilities individually but not achieved both the desired values simultaneously. Further, they exploited the combination of CFAR and CDR approaches to select the threshold at different SNR in order to improve the overall throughput [200]. In [200] the researchers achieved the improved throughput at low SNR however, both the desired values of sensing metric P_f and P_d have not been achieved at the same time, which is one of the challenging issues. Moreover, the optimality conditions for threshold selection have not considered by the researchers which is necessary to attain the desired P_f and P_d simultaneously. Therefore in this chapter, we have presented the approach to select the optimal threshold in EDSS for targeted P_f and P_d simultaneously at low and high SNR. Further, the throughput is computed for the proposed approach which has satisfied the optimality limits for the threshold selection. The prospective contributions of this chapter are summed up as follows.

- For a fixed samples (*N*) of received signal and primary SNR at CU (γ), threshold values are computed in CFAR, CDR and MEP approaches.
- Since most of the authors have worked on the selection of threshold either by fixing the value of P_f or P_d individually but not simultaneously which degraded the sensing results at low SNR. Therefore, to improve the spectrum sensing performance, we have selected the threshold by considering both P_f and P_d simultaneously.
- Thereafter, the condition for a single optimal threshold is analyzed to achieve the desired values of P_f and P_d simultaneously at all SNR. However, at low SNR region, we have observed that the threshold with CFAR approach is greater than that of the CDR approach ($\lambda_f > \lambda_m$), therefore the optimality condition for the selection of threshold has not been satisfied as discussed in detail in Section 2.5.1. Further, we have obtained the

optimal number of samples such that the same optimality condition is satisfied even at low SNR.

- The closed-form expressions of different spectrum sensing performance metrics such as the probability of detection, the probability of false-alarm, and the probability of error have been computed for the proposed approach and compared with the state-of-the-art work. Thereafter, throughput for the proposed approach has been computed and compared with reported literature.

Table 2.1 shows the major contributions and comparison with various reported literatures in the direction of threshold selection approaches.

Table 2.1: Summary and comparison of literature employing different threshold selection methods.

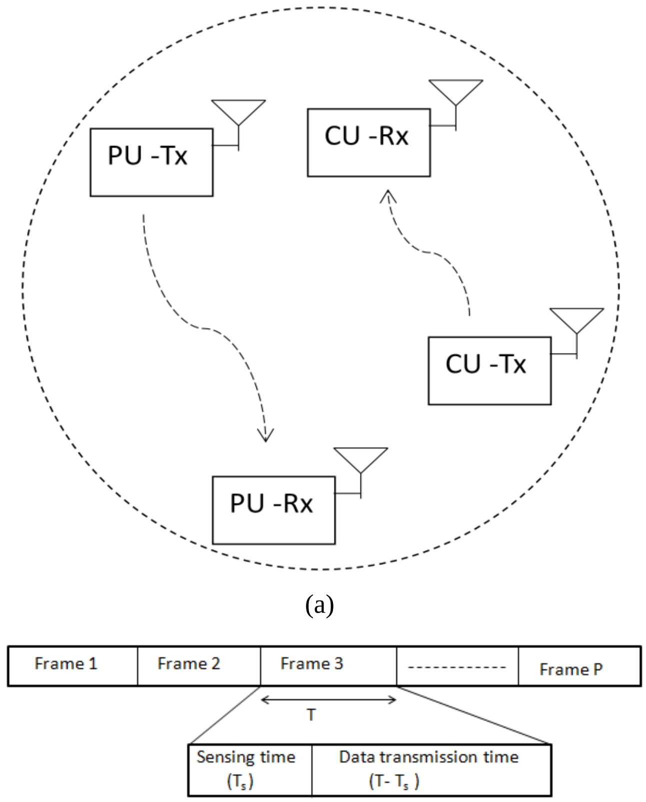
[Ref. No.]	Threshold selection	Major contribution	Pros and cons
[187], [195]	CFAR	• Maximized the detection probability	• Multiple primary user environments have been considered. • Threshold selection through the proposed approaches is not appropriate when there is abrupt variation in noise.
[143], [204]	MEP, Gradient descent	• Dynamic threshold approach has been employed to minimize the sensing error as compare to fixed threshold scheme.	• Sensing performance has improved, and threshold value has been adapted according to the noise power of the channel. • Employed for wideband spectrum sensing. • Tradeoff between the sensing time and power consumption.
[185]	MEP	• Closed form expression for miss-detection probability has been derived for Rayleigh and Nakagami-*m* fading channels.	• Sensing performance is measured at low SNR. • The desired value of sensing parameters has not been achieved at low SNR.
[120]	Variable threshold according to the SINR	• Improved the transmission rate of CU by employing the dynamic threshold with respect to fixed threshold.	• Transmission rate of CU is maximized • This approach is applied only for slotted spectrum sensing.
[213]	Threshold is randomly selected to minimize the sensing error.	• Interference effect of other cognitive users on the sensing node of respective CU has been computed and sensing results show significant degradation due to interference effect. • Further, the sensing errors have been improved by proper selection of threshold.	• Multiple CU environments have been considered. • However, the cooperative spectrum sensing has not been employed to improve the sensing performance.
[196]	CDR, Eigen-value based spectrum sensing.	• Eigen-value based spectrum sensing has provided the improved spectrum sensing performance in comparison to ED for noise uncertainty environment. • Further, the throughput of CU	• Energy with minimum eigen-value (EME) based detector has provided higher throughput as compare to energy detector and maximum eigen-value based detector under noise uncertainty scenario. • However, this proposed approach requires

		has been maximized at low SNR in the presence of noise uncertainty.	multiple antennas.
[214]	Gradient based detection	• Improved the detection probability at low SNR	• This approach is useful in WBSS and variable noise floor environment to improve the detection of PU at low SNR. • The simulated probability of detection curves deviates with the theoretical ones for higher signal bandwidths.
[197]	Cell averaging CFAR and empirical mode decomposition	• Use empirical mode decomposition (EMD) technique to improve the detection probability. • Identified multiple idle channels using multiple detectors in CU for the given frequency band.	• Threshold selection is not affected with variation in noise and/ interference, therefore this approach could be blindly used for sensing the channel without prior knowledge of PU signal. • Sampling rate has been adapted to achieve the sensing performance which increases the implementation cost. • Miss detection has increased for lower valued of the false alarm even after increasing the sampling rate.
[45]	CFAR, Weighted Covariance based spectrum sensing	• Achieved better sensing performance by employing the data aided weight to covariance matrix and employing multiple antennas at cognitive user.	• It is a blind spectrum sensing. • Detection performance is improved even when there is low correlation between PU signals.
[130], [200]	CFAR, CDR, CFAR and CDR	• In order to improve the throughput, the combination of both CFAR and CDR is employed to choose the threshold.	• Achieved higher throughput at low SNR. • However, the desired value of both sensing parameters ($P_f < 0.1$ and $P_d > 0.9$) at low SNR has not been achieved simultaneously. • Noise uncertainty and cooperative spectrum sensing is also not considered.
[74]	MEP, Covariance based spectrum sensing	• Threshold selection is performed to provide protection to PU from CU signal.	• Improved the sensing performance under noise uncertainty scenario. • At low SNR, the proposed approach is performing better than the ED however could not achieve the targeted detection probability.
[215]	Threshold is selected for efficient spectrum utilization.	• Improved the sensing performance by jointly optimizing the detection threshold and sensing time.	• Improved the spectrum utilization at low SNR. • Spectrum utilization is increased in single PU and CU scenario. However, single PU and CU is not a practical scenario.
[207]	Threshold is selected on the basis of prior channel state information.	• Detection probability has been improved by employing the channel statistical information.	• This approach is more effective when large number of samples is employed for sensing.
[209]	Variance of received signal energy over group of samples are defined and used for PU detection.	• Detection of PU is fast with higher detection probability as compare to conventional energy detection approach.	• Sensing is fast and is generally employed when there is noise uncertainty in the channel. • Approach work effectively only when signal energy over a group of samples remains constant.
[210]	Employ Ljung-Box test for detection of PU, Covariance based SS.	• Improved the sensing performance when there are low-correlated antennas present at the CU.	• It is a blind detection method. • The proposed method attains a significant detection performance improvement compared with the existing covariance-based methods in fading channel.

[134]	Threshold selection to maximize the throughput.	• Developed an approach to maximize the throughput by jointly optimizing the threshold value for sensing, sensing time, and selection of sensing and data transmission.	• Improved the throughput and energy efficiency of cognitive radio under cooperative spectrum scenario.
[198]	CFAR	• Applied the concept of simultaneous spectrum sensing and data transmission with single antenna to improve the throughput. • Successive interference cancellation (SIC) is employed to sense the channel state and decoding error effects on the sensing reliability is observed.	• Detection performance is better as compare to conventional energy detector. • Employ single antenna at CR terminal • Cooperation among CU transmitter and CU receiver is required to employ this approach.
[211]	Random spectrum sensing strategy	• By employing PU traffic pattern, an adaptive spectrum sensing strategy is proposed to determine the channel to be sensed which has high possibility of being idle.	• Hardware requirement problem of multiband spectrum sensing is overcome by employing adaptive spectrum sensing.
[212]	Embedded Markov chain with full-duplex	• Analyzed the effect of sensing frequency on energy efficiency, throughput and probability of collision.	• By considering proper sensing frequency, energy efficiency in full-duplex cognitive radio is improved without loss in throughput as compare to contiguous sensing. • For this approach, primary user's arrival rate and departure rate on a channel should be known to the CU.
Proposed approach	CFAR, CDR, MEP	• Optimal threshold is computed at low SNR which has jointly satisfied the sensing matrices i.e. detection probability $\geq$ 0.9 and false alarm probability $\leq$ 0.1. Further, the throughput is computed for the CR user.	• Even at low SNR, the desired value of both the sensing parameters has been achieved by employing the adaptive threshold and optimal number of samples (ONS). • Throughput improvement is achieved in the proposed threshold selection approach in comparison to CDR however, less than CFAR approach.

2.4 System Model

In CRN, the key challenge is the incorporation of lesser priority CUs on the licensed channel which is not detrimentally affecting the communication of PU. Therefore, to recognize the actual state of PU before allowing the CU to access the licensed channel is a critical aspect of CRN system model. We have presented the proposed system model in Fig. 2.2(a), where single pair of PU and CU transceiver is considered. Further, we have assumed the unchanged state (active or idle) of PU activity during sensing process of CU [216], [217] and CU is executing periodical spectrum sensing in which sensing process repeats after T units of time and frame structure of CU is shown in Fig. 2.2(b). The frame structure of CU consists of P frames and each frame comprises sensing phase (T_s) and transmission phase ($T - T_s$).



(b)

Figure 2.2: The proposed (a) system model and (b) frame structure of cognitive user [153].

The transmitted modulated signals and noise are assumed which are Gaussian random variables with independent and identically distribution (IID). The phase shift keying (PSK) based complex-valued signal and circularly symmetric complex Gaussian (CSCG) noise samples are assumed for the proposed system. Further, the received signal $X(n)$ at CU is represented in equation (1.1) of Chapter 1 and the test statistics ($T(x)$) for EDSS is given below [218]:

$$T(x) = \frac{1}{N}\sum_{n=0}^{N-1} |X(n)|^2 \tag{2.1}$$

where, N is the total number of samples of the received signal at CU used for determining the energy. Under the binary hypothesis, the probability density function (PDF) of test statistics T(x) follows a Chi-square distribution with N degree of freedom for real valued noise. When we consider N>250, the PDF of T(x) under binary hypothesis (H_0 and H_1) followed the Gaussian distribution [219]. In this context, H_0 and H_1 under the Gaussian approximation is represented as [153]:

$H_0: \mathcal{N}(N\sigma_n^2, N\sigma_n^4) \& H_1: \mathcal{N}(N\sigma_n^2(1+\gamma), N\sigma_n^4(1+\gamma)^2)$,

where σ_n^2 is the noise power or noise variance and γ is the SNR received at CU due to PU. Moreover, the false-alarm and detection probabilities (P_f and P_d) are presented as follows [185]:

$$P_f = \frac{1}{2}\,\mathrm{E}rfc\left(\frac{\lambda - N\sigma_n^2}{\sqrt{2N\sigma_n^4}}\right) \tag{2.2}$$

$$P_d = \frac{1}{2}\,\mathrm{E}rfc\left(\frac{\lambda - N\sigma_n^2(1+\gamma)}{\sqrt{2N\sigma_n^4(1+\gamma)^2}}\right) \tag{2.3}$$

$$P_m = 1 - P_d \tag{2.4}$$

$$P_e = P_f + P_m \tag{2.5}$$

where, Erfc(.) is the error function.

2.5 Performance Analysis

False-alarm, detection, and sensing error probabilities are the key performance parameters to determine the spectrum sensing results and these values can be computed with the help of equation (2.2), (2.3) and (2.5), respectively. Further, the desired values of the false-alarm, detection probability and number of samples affect the threshold value in EDSS as detailed in Section 2.5.2. Moreover, from Fig. 2.1 it is clear that, to achieve the preferred values of both the metrics i.e. P_f and P_d, is difficult because there exists a trade-off between these two with the selection of threshold. Therefore, optimal threshold selection is required which provide required value of P_f and P_d, concurrently. Consequently, optimal threshold condition is analyzed and satisfied the optimal threshold condition by employing optimal number of samples (N*) at low SNR. Further, optimal threshold condition and threshold selection approach, thresholds computations with CFAR, CDR and MEP approaches, critical SNR computation and throughput analysis have been illustrated in the next subsequent section of this chapter.

2.5.1 Optimal threshold condition

It is observed from Fig. 2.1, that there is a direct and an inverse relation in P_f and P_m with the threshold (λ). Since in CFAR and CDR approaches, the threshold λ_f and λ_m are computed for the desired values of false-alarm and miss detection probabilities, respectively. Further, from Fig. 2.1, it is obvious that λ_f needs to be as high as possible in order to minimize the P_f while λ_m needs to be as low as possible to minimize the P_m. Therefore, we have concluded that single optimal threshold exist to achieve both the desired P_f and P_m values simultaneously, only when $\lambda_f \leq \lambda_m$ (optimal threshold condition) [220].

2.5.2 Computation of different thresholds

In CFAR approach, the threshold (λ_f) is computed with the help of equation (2.2) for the targeted or desired value of false-alarm probability ($\overline{P_f}$ or P_{f_fixed}) and given as follows:

$$\lambda_f = \left\{\sqrt{\frac{2}{N}} Erfc^{-1}\left(2\overline{P_f}\right) + 1\right\} N\sigma_n^2 \tag{2.6}$$

In CDR approach, the threshold (λ_m) is computed with the help of equation (2.3) and equation (2.4) for the targeted or desired value of detection probability ($\overline{P_d}$) and given as follows

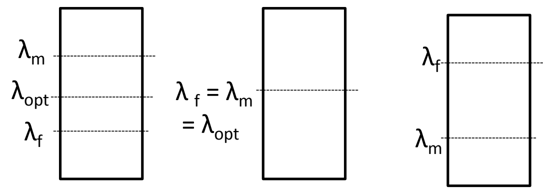
$$\lambda_m = \left\{\sqrt{\frac{2}{N}}(1+\gamma) Erfc^{-1}(2(1-\overline{P_m})) + (1+\gamma)\right\} N\sigma_n^2 \tag{2.7}$$

Further in MEP approach, the threshold (λ_e) is computed by minimizing the P_e with respect to the threshold and given as follows [220]:

$$\lambda_e = \frac{N\sigma_n^2}{2}\left\{1 + \sqrt{1 + \frac{2(2+\gamma)ln(1+\gamma)}{N\gamma}}\right\}\left(\frac{1+\gamma}{1+\frac{\gamma}{2}}\right) \tag{2.8}$$

2.5.3 Proposed optimal threshold selection approach

As mentioned in Section 2.5.1, the optimal threshold value is selected only when the optimality condition for the threshold is satisfied. Firstly, we have found the threshold values λ_f and λ_m with the help of equation (2.6) and equation (2.7) and all possible conditions of λ_f and λ_m are shown in Fig. 2.3. It is obvious from Fig. 2.3(a), $\lambda_f < \lambda_m$ (the threshold value with CDR approach is greater than the CFAR approach) and optimal threshold condition is fulfilled. Hence, any threshold value considered as optimal threshold which is in between λ_f and λ_m.



(a)$\lambda_f < \lambda_m$ (b)$\lambda_f = \lambda_m$ (c)$\lambda_f > \lambda_m$

Figure 2.3: The optimal threshold selection.

Moreover in Fig. 2.3(b), $\lambda_f = \lambda_m$ and here again, the optimal threshold condition is fulfilled, and either λ_f or λ_m can be considered as an optimal threshold. However, in Fig. 2.3(c), $\lambda_f > \lambda_m$, the optimal threshold condition is not satisfied. Therefore with the help of equation (2.9), we have found the optimal number of samples (N^*) to satisfy the optimal threshold condition and achieved the desired P_f and P_d simultaneously. $\lambda_f{}^*$, $\lambda_m{}^*$ and $\lambda_e{}^*$are the threshold values with CFAR, CDR and MEP approaches when N is replaced by N^* in equation (2.6), (2.7), and (2.8), respectively. Further, the value of optimal number of samples is given as:

$$N^* = \frac{1}{\gamma^2}\left\{Q^{-1}\left(\overline{P_f}\right) - Q^{-1}(\overline{P_d})\sqrt{2\gamma+1}\right\}^2 \tag{2.9}$$

where $Q^{-1}(.)$ is the inverse complementary distribution function of the standard Gaussian distribution. Further, in Fig. 2.4 we have presented the flow diagram of the proposed optimal threshold scheme.

2.5.4 The condition for critical SNR

The critical SNR (γ_c) is defined as the SNR at which $\lambda_f = \lambda_m$ and below which optimality threshold condition will not be fulfilled. We have computed the minimum SNR (γ) called critical SNR (γ_c), at which the optimality threshold condition is fulfilling and this value is computed by comparing equation (2.6) with equation (2.7):

$$\gamma_c = \frac{\sqrt{\frac{2}{N}}\{Erfc^{-1}(2\overline{P_f}) - Erfc^{-1}(2\overline{P_d})\}}{1+\sqrt{\frac{2}{N}}Erfc^{-1}(2\overline{P_d})} \tag{2.10}$$

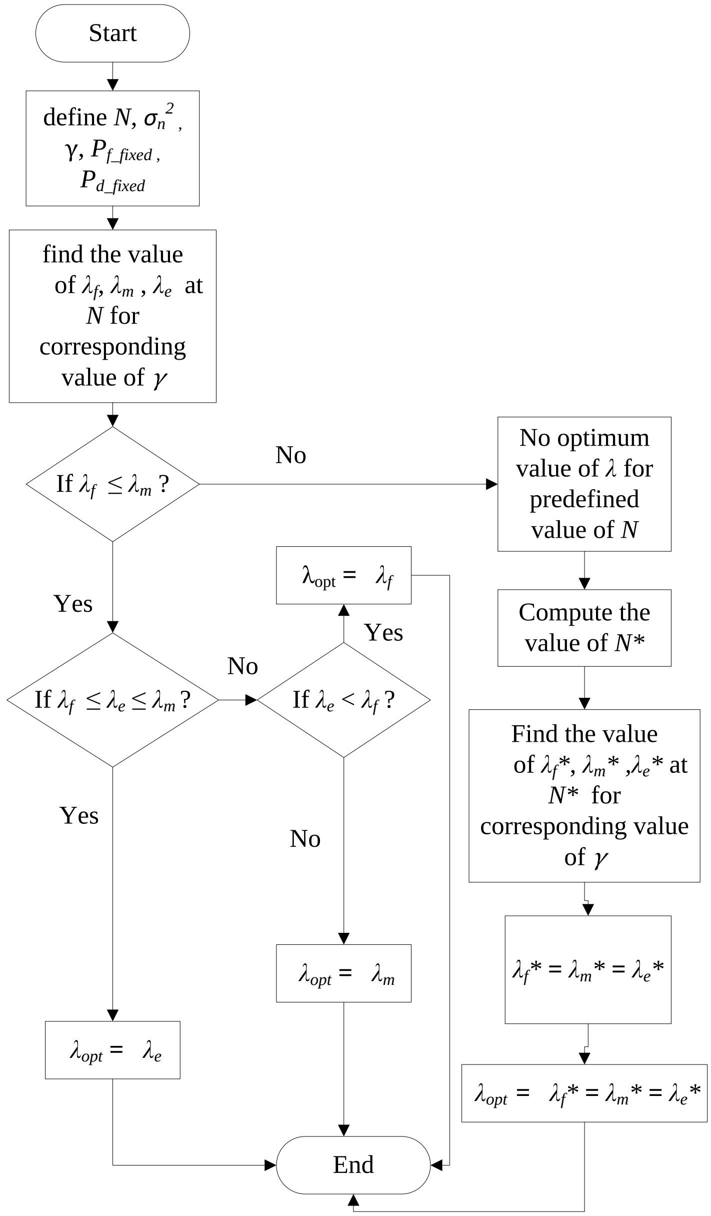


Figure 2.4: Flow chart for optimal threshold selection.

2.5.5 Throughput computation

We have considered following two cases for throughput computation of CU. In **Case-1**, the PU is missing on the licensed channel and no false-alarm is generated by the CU while in **Case-2**, the PU is there on the licensed channel and it is not perceived by the CU. Moreover, $R_0(T_s)$ and $R_1(T_s)$, are the throughput in first and second case, respectively. Further, $P(H_0)$ and $P(H_1)$ are considered probabilities of channel being idle and active respectively in a specified frequency band therefore, average throughput, $R(T_s)$ of CU has been computed as follows [153].

$$R_0(T_s) = \left(\frac{T-T_s}{T}\right)\left(1-P_f\right)log_2(1+\gamma_s) \quad (2.11)$$

$$R_1(T_s) = \left(\frac{T-T_s}{T}\right)(1-P_d)log_2\left(1+\frac{\gamma_s}{1+\gamma}\right) \quad (2.12)$$

$$\mathrm{R}(T_s) = P(H_0)R_0(T_s) + P(H_1)R_1(T_s) \quad (2.13)$$

where γ_s is the CU SNR.

2.6 Result and Discussion

This section presents the performance results of spectrum sensing performance parameters namely the false-alarm, detection and sensing error probability. In addition, the values of threshold and throughput through CFAR, CDR, and MEP approaches have been shown in numerically simulated results and are judged against the proposed optimal threshold selection approach. MATLAB 2010 has been used for the simulation and the simulation parameter's values are chosen as per IEEE 802.22 wireless regional area network (WRAN) standard. Theses simulation parameters along with their values are presented in Table 2.2. We have assumed 250 minimum number of samples based on which the computed upper limit of SNR will be -8dB [219]. Further, the frame duration (T) and the sensing time ($\mathrm{T_s}$) are assumed to be of 100 msec. and 2.5 msec. respectively. We have selected the parameters based on reference papers from which we have compared our results and these are standard value which is considered by researchers in their research articles.

Table 2.2: The simulation parameters for the proposed CRN.

Parameter	Value	Parameter	Value
N	15000	$P(H_0)$	0.8
γ_s	20dB	$P(H_1)$	0.2
T_s	2.5msec	$\overline{P_f}$	0.1
T	100msec	$\overline{P_d}$	0.9

The analytical results presented in Fig. 2.5 shows the threshold value variations in the CFAR (λ_f), CDR (λ_d), and MEP (λ_e) approaches with the received SNR of the primary user (γ). It is clear that with change in γ in CFAR approach, the threshold is constant however its value is augmented with increase in γ through CDR and MEP approaches. We have stated the term critical SNR (SNR_c or γ_c) as that PU SNR value (γ) below which λ_f>λ_m. Further, it is illustrated in Fig. 2.5 that at higher SNR values i.e. at SNR $\geq SNR_c$, the optimal threshold condition $(\lambda_f < \lambda_m)$ is already true, moreover the threshold value is in between λ_f and λ_m for MEP approach.

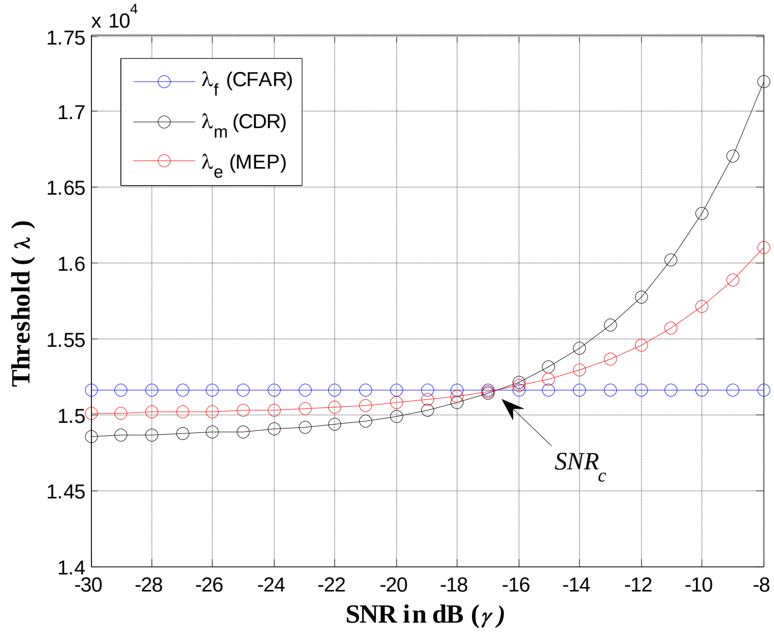


Figure 2.5: The variation of threshold value with SNR (γ) for CFAR, CDR and MEP approaches at N=15000.

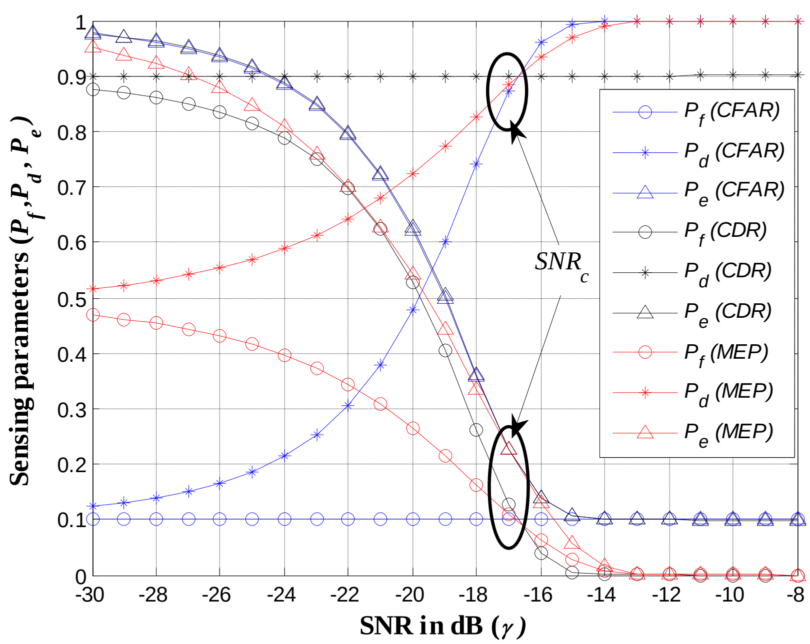


Figure 2.6: Sensing performance parameters (P_f ,P_d , P_e) variation with SNR (γ) for CFAR, CDR and MEP approaches at N =15000.

However, it is obvious from Fig. 2.5 that the optimal threshold condition is not satisfied in the low SNR values i.e. at SNR<SNR_c, since this region has following measurement: $\lambda_f > \lambda_m$. In addition, the transformation of sensing performance parameters (P_f,P_d,P_e) with SNR for CFAR, CDR and MEP approaches is presented in Fig. 2.6. For CFAR approach at each value of γ, the P_f is fixed (0.1), however the P_d value is less (<0.9) for $SNR \le SNR_c$ and shows an increased variation till the point where γ becomes equal to SNR_c. Further, CDR approach fixed the P_d value to 0.9 for all values of γ as is clear from Fig. 2.6 however the P_f value is significantly more (i.e >0.1) for $SNR \le SNR_c$. Also, it is illustrated from Fig. 2.6 that in CFAR and CDR approaches, the probability of error (P_e) is approximately same. Moreover, MEP approach has given a better error probability (P_e) in comparison to the CFAR and CDR approaches at all γ. However MEP approach, has again not achieved the desired of P_f and P_d values simultaneously in $SNR \le SNR_c$ region. Fig. 2.6 draws the conclusion that the probability of error (P_e) decreases with primary received SNR (γ) in all the threshold selection approaches and out of above three mentioned threshold selection approaches, MEP is providing least value of sensing error (P_e). Hence, any approach among CFAR, CDR and MEP does not fulfill the sensing parameter's requirements of CR i.e. P_f<0.1 and P_d>0.9, simultaneously at $SNR \le SNR_c$. Further, the throughput variation of CU with SNR, in CFAR, CDR and MEP approaches with preset number of samples (*N*=15000) is shown in Fig. 2.7.

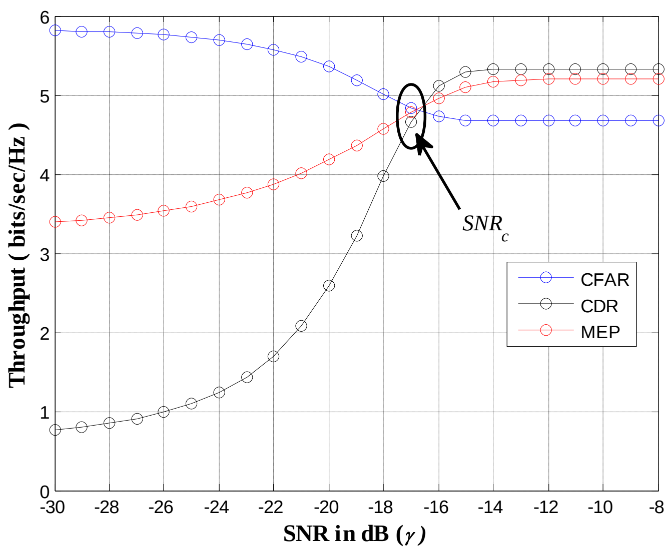


Figure 2.7: Throughput variation of CU with SNR (γ) for CFAR, CDR and MEP approaches at *N*=15000.

From Fig. 2.7, it is clear that the throughput value decreases in CFAR approach with SNR from 5.812 bps/Hz to 4.674bps/Hz and afterward becomes constant. However in CDR and MEP threshold selection approaches, its value increases from 0.7684bps/Hz and 3.414bps/Hz to 5.319bps/Hz and 5.194bps/Hz, respectively and remains constant thereafter. It is observed from the results that at $SNR \leq SNR_c$, the throughput is high with CFAR approach, however its value is more in CDR approach for $SNR > SNR_c$. Therefore in context of above results, we have proposed a method in Section 2.5.3 to attain the optimal threshold condition in $SNR < SNR_c$ region for which the optimal number of samples (N*) are computed to get the required P_f and P_d values, simultaneously. Further, the sensing parameters (P_f, P_m) performance for the proposed approach is compared with [200] and presented in Fig. 2.8.

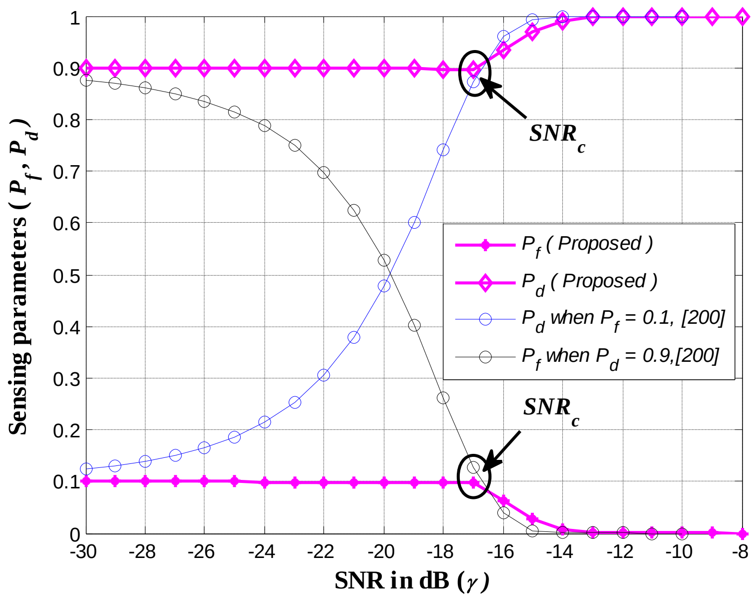


Figure 2.8: Sensing performance parameters (P_f , P_d) variation with SNR (γ).

From the results of the proposed approach, it is illustrated that both the desired P_f = 0.1 and P_d = 0.9 values are achieved, simultaneously in $SNR \leq SNR_c$ region however in [200], the authors have first fixed any one of the sensing performance parameter (either P_f or P_d) and then have tried to improve the other (P_d or P_f), as is clear from Fig. 2.8. Further, the authors in [200] have failed to achieve the required spectrum sensing performance improvement in $SNR \leq SNR_c$ region. Moreover, the comparative results of the achieved throughput are presented in Fig. 2.9 for different SNR with fixed and optimal number of samples (FNS & ONS) through CFAR, CDR and MEP approaches.

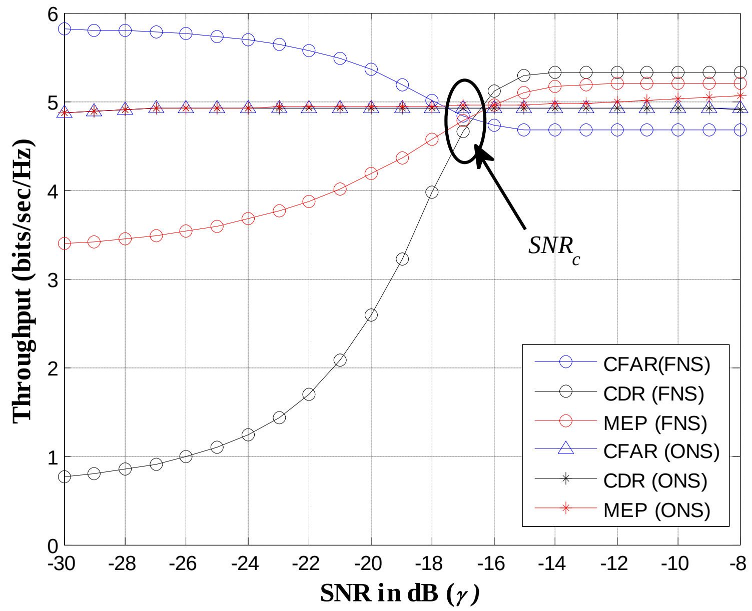


Figure 2.9: Variation of throughput with for the fixed and optimal number of samples (ONS) for CFAR, CDR and MEP approaches.

For further analysis, four possible cases are considered in the system as: **a**) **Case-1** $SNR<SNR_c$ with fixed numbers of samples (FNS): the throughput in this case is more with CFAR approach **b**) **Case-2** $SNR<SNR_c$ with optimal number of samples (ONS): the throughput is almost similar in all the three, CFAR, CDR, and MEP approaches, however less than the throughput achieved from Case 1 **c) Case-3** $SNR \geq SNR_c$ with fixed number of samples (FNS): highest throughput and it remained almost steady with CDR approach **d**) **Case-4** $SNR \geq SNR_c$ with optimal number of samples (ONS): highest throughput with MEP approach in comparison to CDR and CFAR, however it is less compare to the one achieved in Case-3. Therefore, the benefit of Case-2 (i.e. the use of ONS when $SNR<SNR_c$) is that we are able to achieve the desired false and detection probabilities however at the price of reduced throughput, while the advantage of Case-3 (use of FNS when $SNR \geq SNR_c$) is ability to achieve higher throughput. Hence it is clear that the proposed approach has combined the benefits of ONS when $SNR<SNR_c$ and FNS when $SNR \geq SNR_c$ and has subsequently improved the throughput as shown in Fig. 2.10. Further, the throughput of the proposed approach nearly remains steady with decrease in SNR (region $SNR \leq SNR_c$) as shown in Fig. 2.10. Moreover the proposed approach throughput, in which we

have adapted the samples as per SNR (ONS when $SNR<SNR_c$ and FNS when $SNR \geq SNR_c$), is shown in Fig. 2.10 and compared with [200].

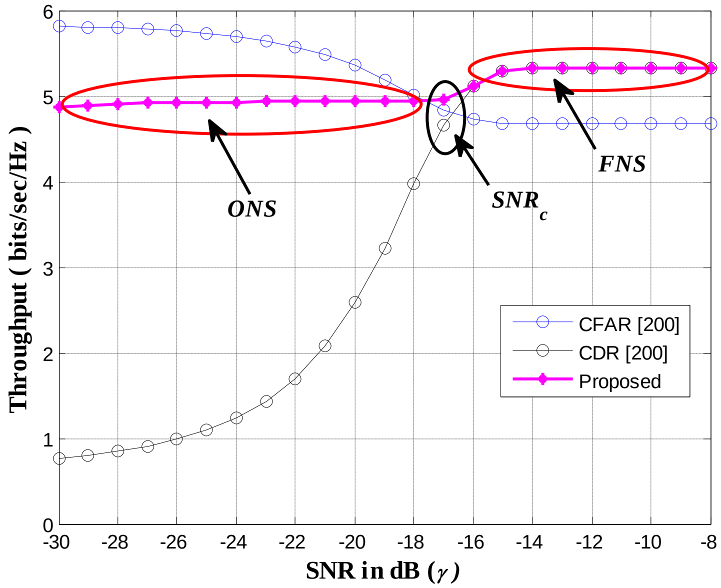


Figure 2.10: Throughput variation with SNR (γ) for the proposed approach.

It is observed from Fig. 2.10 that the significant performance improvement is achieved in the proposed approach in contrast to the CDR approach when $SNR<SNR_c$. It is seen that the proposed approach has approximately 24.63% improvement in the throughput, at SNR equals to -18 dB (near to SNR_c), in comparison to the CDR approach. The percentage improvement in the proposed approach throughput is significantly high compare to the CDR when SNR is decreased. This is because the throughput is reducing in the CDR approach with decrease in the SNR as is clear from Fig. 2.10. It is obvious from the results that the CFAR throughput is better than the proposed method but at the cost of lower protection of PU, due to its significantly less detection probability value shown in Fig. 2.8.

Table 2.3: The comparison table of the simulation results.

	CFAR			**CDR**			**MEP**			**Proposed**		
SNR (dB)	P_f	P_d	**Throughput (bits/sec/Hz)**	P_f	P_d	**Throughput (bits/sec/Hz)**	P_f	P_d	**Throughput (bits/sec/Hz)**	P_f	P_d	**Throughput (bits/sec/Hz)**
-17	0.1	0.872	4.776	0.127	0.9	4.659	0.109	0.516	4.776	0.1	0.9	4.947
-21	0.1	0.379	5.478	0.628	0.9	2.077	0.307	0.569	4.013	0.1	0.9	4.935
-25	0.1	0.186	5.730	0.815	0.9	1.088	0.415	0.679	3.592	0.1	0.9	4.925
-30	0.1	0.123	5.812	0.877	0.9	0.768	0.468	0.883	3.390	0.1	0.9	4.874

Further, the analysis and comparison of the different results of the threshold selection approaches is presented in Table 2.3.

2.7 Conclusion

In this chapter, CFAR, CDR and MEP approaches are explored for threshold computation and to achieve the desired values of P_f and P_d simultaneously, optimality condition for threshold selection is analyzed. Further, the computation of SNR as a critical SNR (SNR_c) below which the optimality condition is not satisfied, has been performed. Afterwards, we have proposed an approach for low SNR ($SNR<SNR_c$ or $\gamma < \gamma_c$) region in order to satisfy the optimal threshold condition and achieved the desired values of P_f and P_d . Further the throughput comparison with our proposed approach is done with reported literature and perceived that at low SNR, throughput for the proposed approach is greater than the MEP and CDR approaches however, lower than that of CFAR approach. Moreover, the throughputs achieved using MEP, CDR, and CFAR approaches are not fulfilling the desired P_f and P_d values when compared with the proposed approach. Hence with our proposed approach, we have attained the maximum throughput while accomplishing the desired P_f and P_d simultaneously at all considered SNR. Further at γ equals to -18 dB (near to SNR_c), there is approximately 24.63% improvement in throughput with our proposed approach when compared with CDR approach. However, the proposed method presented in this chapter considered only AWGN and non-cooperative scenario. Therefore, in Chapter 3 we have considered the cooperative spectrum sensing in fading channels.

CHAPTER 3

THRESHOLD SELECTION EFFECTS IN FADING CHANNEL UNDER COOPERATION

3.1 Introduction

The sensing results in non-cooperative spectrum sensing may be inaccurate under real wireless scenario i. e destructive channel conditions (multipath fading, shadowing and non-line-of-sight communication) between the target-under-detection and the cognitive radios. Therefore, to increases the reliability under real wireless scenario, individual sensing results of multiple CUs are shared among each other through CSS by exploiting spatial diversity among cognitive users [221]. CSS can be applied between homogeneous or heterogeneous network and across the OSI layers. In CSS, voting rule is commonly employed by researchers [221] in which the number of cognitive user that vote for the presence of the licensed channel are counted and compared against a given threshold. For hard based CSS, each CU sends the one bit sensing decision to FC, while in soft decision based CSS, a quantized version of local sensing decision is sent to the FC. Moreover, it is reported in the literature that the soft decision combination provides better gain over hard decision combining but at the cost of high reporting bandwidth. Therefore, in this chapter, we have employed centralized cooperative spectrum sensing (C-CSS) technique in which hard voting rules (AND, OR and Majority) are employed. Several researchers have considered different fading environments and selected the threshold by employing CFAR, CDR or MEP approaches in CSS and their key contributions are described in related work section of this chapter.

3.2 Related Work and Problem Formulation

The closed-form expressions of detection probability for the Rayleigh and Nakagami-*m* fading channels are presented and the effect of diversity schemes on sensing performance of CR while employing CFAR threshold approach is analyzed in [222]. Further, the selection of threshold by minimizing the error probability is computed by Atapattu et.al. [185], [220] for AWGN, Rayleigh and Nakagami-*m* fading channels and they have analyzed the sensing performance of the CR with diversity and cooperation [220]. However, the sensing performance of cooperative spectrum sensing for other fading channels such as Rician, Hoyt, Weibull and Lognormal fading is discussed by Nallagonda et. al. [111]. Several researchers employed CSS [111], [223]–[227] approach to improve the sensing performance of CR under different fading channels however, at the cost of increased overhead bits for cooperation [224]. In addition, Vien et.al. [225], [226] have proposed an approach to select the CU in cooperation to reduce the power consumption by employing reduced overhead bits and improved the throughput. Moreover, Sun et.al. [228] computed the approximation of detection probability over slow fading channel but the computation of detection probability has some truncation errors due to infinite numbers in the summation part. This problem is resolved by Patil et.al. [229] for different fading channels. The throughput analysis for noise plus generalized $K-\mu$ and $\eta-\mu$ fading channels is performed in [223] by using CFAR approach under cooperative spectrum sensing scenario. Most of the researchers have employed the threshold selection with CFAR approach [200], [222], where as Atapattu et.al. [185], [220] have used MEP approach. In conclusion, Table 3.1 presents the work of various researchers with considered channel models and threshold selection approaches in EDSS for cooperative and non-cooperative spectrum sensing techniques.

Several researchers have employed the threshold selection techniques in spectrum sensing using CFAR or MEP approach and analyzed the sensing performance of CU. Gaurav and Sahu [200] have considered the threshold with CFAR approach and computed the throughput for AWGN channel in a non-cooperative scenario. Further, Atapattu et.al. [220] have computed the threshold with MEP approach for AWGN, Rayleigh and Nakagami channels by considering cooperative scenario, however they have applied individual OR fusion rule. Further, the sensing performance of CRN under several fusion (AND, OR, Majority) rules for different fading environments is analyzed by Nallagonda et.al. [111] and have employed threshold with CFAR. To the best of the author’s knowledge, none of the literatures have presented the effect of threshold selections approaches on throughput for different fading channels under cooperative and non-cooperative scenarios. Therefore, in this chapter, we have presented throughput as well as total error (sensing error) probability analysis of CRN using CFAR and MEP approaches for cooperative and non-cooperative scenario under different fading channels. Further, the author’s potential contributions in this chapter are as follows.

- We have analyzed the effect of SNR and variations in number of samples of the received signal on ROC curve of CRN under different fading channels for non-cooperative and cooperative scenario while employing fixed threshold approach. In this context, we have investigated the dominant parameter affecting the ROC curve.
- Further, the sensing performance of CRN is analyzed under ROC curve with different cooperation rules and its consequences have been observed over spectrum sensing and throughput.
- Afterwards, we have analyzed the need of dynamic threshold in energy detector which is function of SNR and is providing more accuracy at low SNR than that of the fixed threshold approach in terms of less sensing error.
- In addition, we have compared the effect of selection of threshold using fixed (CFAR) and dynamic (MEP) threshold selection approaches on non-cooperative and cooperative (Majority rule) CRN under AWGN, Rayleigh and Nakagami-*m* fading channels. Since the earlier literature lacks the computation of throughput and total error probability with MEP approach in CSS under different fading channels, therefore this chapter has provided throughput and total error probability computation with MEP as well as with CFAR approaches under CSS (Majority rule) in fading environment.

Table 3.1: Summary of the related work of spectrum sensing employing energy detection techniques in multipath fading environments.

[Ref. No.]	Channels	Key approaches	Contribution
[222], [230]	Rayleigh and Nakagami-*m* fading channels	• CFAR • Various diversity techniques	• Computed closed form expressions for detection probability. • Sensing performance comparison with and without diversity techniques.
[111]	Rician, Hoyt, Weibull and Lognormal fading channels	• CFAR • CSS	• Shown the impact of different fading parameters and number of cooperative users on sensing performance of CR. • Sensing performance comparison between cooperative and non-cooperative scenario.
[224]	Rayleigh fading channel	• CSS • Optimal selection of sensing time and number of CUs.	• Throughput analysis is presented by considering the overhead of CSS. • Two-stage sensing performed to improve the sensing performance.
[225], [226]	AWGN, Rayleigh, and Nakagami-*m* fading channels	• Hybrid double threshold • CSS • Algorithm for selection of CUs in CSS.	• Improved the sensing performance of CUs. • Minimized the power consumption of CRN by reducing the cooperative overhead bits.

[231]	Nakagami fading channel	• CSS • Formulation of threshold in terms of SNR	• Shown the trade-off between sensing time and achievable throughput. • Global false alarm probability was found in terms of SNR limit in the threshold expression below which outage on detection probability occurs.
[232]	Nakagami-*m* channel	• Noise uncertainty • Double threshold	• Improved the sensing performance with double threshold. • Analyzed the effect of noise uncertainty at low SNR.
[233]	Rayleigh fading channels	• Hybrid spectrum sensing and spectrum monitoring	• Analyzed the problem of spectrum monitoring in fading channels while CUs apply different diversity combining methods, • Reduced the sensing time and improved the channel utilization of CUs
[234]	$K-\mu$ shadowed fading channel	• Derived the detection probability in terms of sum of Gauss hyper-geometric functions, • Dynamic spectrum sensing cycle (SSC) to reduce the system latency	• Shows the detector performance improvement with dynamic SSC as compare to fixed SSC.
[235]	$K-\mu$ fading channels under moderate and severe fading condition	• Derived the expression for average probability of detection, • Square-law selection (SLS) diversity • Collaborative detection scenarios.	• Sensing performance is improved with increase in number of CR or by increasing the diversity combining branches.
[227]	Nakagami-*m* and Nakagami-*q*,	• Improved energy detector • CSS • Mobility of CU	• Analyzed the sensing performance of CR by considering CU mobility.
[223]	$K-\mu$ and $\eta-\mu$ fading	• CFAR • CSS	• An expression of detection probability of a single CU is derived over noise, $K-\mu$ and $\eta-\mu$ fading channels.
[185], [220]	AWGN, Rayleigh and Nakagami-*m* fading channels	• MEP • Diversity • Cooperative spectrum sensing (CSS)	• Computed optimal threshold to minimize the error probability. • Improvement in sensing performance of CR with different diversity combining or cooperation techniques.
[200]	AWGN	• CFAR • CDR	• Analyzed the throughput of CR with CFAR and CDR threshold selection approaches.
Proposed	AWGN, Rayleigh and Nakagami-*m*	• CFAR • MEP • CSS	• The effect of SNR and variation of number of samples is analyzed on sensing performance of CR. • Investigated the sensing performance of CR with ROC curve under non-cooperative and cooperative scenario, • Examined the need of dynamic threshold which is the function of SNR for accurate detection of licensed users. • Throughput analysis of CR using CFAR and MEP approaches with cooperative and non-cooperative scenario.

3.3 System Model and Performance Analysis

In the proposed system model, we have considered a PU transmitter with *M* number of CR nodes and one fusion center (FC). The fading environment is considered between PU transmitter and

CR as shown in Fig. 3.1. Further, the cooperation among CUs is considered where CU transmits their local decision to FC then several cooperation rules (AND, OR & Majority) are applied at FC to take final decision about the PU's presence or absence on the channel [83], [236]. However, we have considered that each CR is employing the periodical spectrum sensing scheme in which the frame repeats itself after T units of time and each frame comprises sensing and reporting phase of T_s and transmission phase of duration $(T - T_s)$ as shown in Fig. 2.2(b) of Chapter 2.

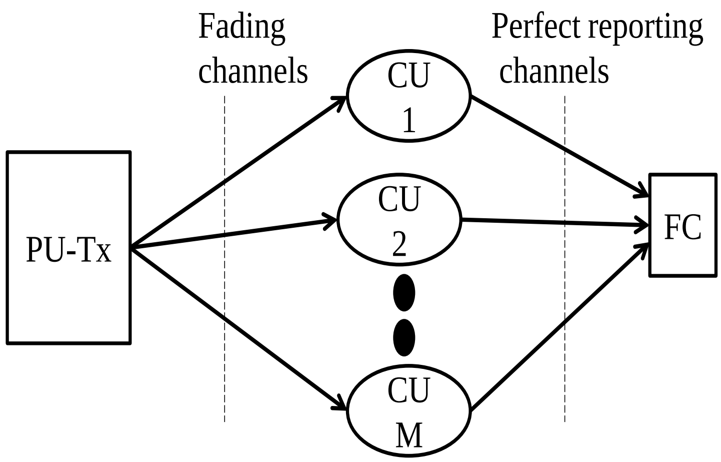


Figure 3.1: Schematic of the proposed cognitive radio network system model *[111]*.

Further, the performance of spectrum sensing in cognitive radio network is measured in terms of the false-alarm and detection probabilities. For the additive white Gaussian noise (AWGN) channel, these values are computed using equation (2.2) and (2.3), respectively. Further, the false-alarm probability is independent on the signal-to-noise (SNR) value, therefore its value remains same for all the fading channels [220]. However, the average detection probability ($\overline{P_d^f}$) over any fading channel is computed by averaging the detection probability over all SNR as shown in equation (3.1) [111].

$$\overline{P_d^f} = \int_0^\infty P_d(\gamma, \lambda)\, f(\gamma) d\gamma \tag{3.1}$$

where $f(\gamma)$, $P_d(\gamma, \lambda)$ and $\overline{P_d^f}$ are the SNR distribution of fading channel, detection probability and average value of detection probability in the considered CRN fading channels. The detection probability for different fading channels (Rayleigh and Nakagami-*m*) is presented as follows:

3.3.1 Detection probability

This section illustrates the expressions for the detection probability of CR over different fading channels as follows.

3.3.1.1 Rayleigh fading channel

The Rayleigh fading mainly occurs when there is no dominant path between PU and CU and the received signal amplitude at CU follows the Rayleigh distribution. Further, the SNR distribution for Rayleigh fading channel and its detection probability at CR is expressed by equation (3.2) and (3.3), respectively [185] .

$$f_{ray}(\gamma) = \frac{1}{\bar{\gamma}} e^{-\left(\frac{\gamma}{\bar{\gamma}}\right)} \tag{3.2}$$

$$\overline{P_d^{ray}} = 1 - \overline{P_m^{ray}} = 1 - \frac{1}{2}\left[Erfc\left(\frac{N\sigma_n^2-\lambda}{\sqrt{2N}\sigma_n^2}\right) - \left(e^{\left(\frac{\frac{1}{\bar{\gamma}^2}+\frac{4}{\bar{\gamma}}\left(\frac{N\sigma_n^2-\lambda}{\sqrt{2N}\sigma_n^2}\right)\sqrt{\frac{N}{2}}}{2N}\right)} Erfc\left(\frac{N\sigma_n^2-\lambda}{\sqrt{2N}\sigma_n^2} + \frac{1}{\bar{\gamma}\sqrt{2N}}\right)\right)\right] \tag{3.3}$$

3.3.1.2 Nakagami-m fading channel

The Nakagami-*m* fading is the general multipath fading scenario which mainly depends on the value of *m* (shape parameter) [237]. It is considered as Rayleigh fading when *m* = 1 and AWGN for *m* =∞. The SNR distribution and detection probability for Nakagami-*m* fading channel is given by equation (3.4) and (3.5), respectively [185], [229]:

$$f_{Naka}(x) = \frac{\left(\frac{m}{\bar{\gamma}}\right)^m}{\Gamma(m)} \left(x^{m-1}\right) e^{-\frac{m}{\bar{\gamma}}x} \qquad m \geq 0.5 \tag{3.4}$$

$$\overline{P_d^{Naka}} = 1 - \overline{P_d^{Naka}} = 1 - \frac{\left(\frac{m}{\bar{\gamma}}\right)^m}{2\Gamma(m)} \int_0^\infty \left(x^{m-1}\right)\left(e^{-\frac{mx}{\bar{\gamma}}}\right) Erfc\left(\sqrt{\frac{N}{2}}x + \frac{N\sigma_n^2-\lambda}{\sqrt{2N}\sigma_n^2}\right) \tag{3.5}$$

where, Γ (.) is the complete gamma function.

3.3.2 Selection of threshold

The sensing performance of CRN is affected with the selection of threshold as already shown in Fig. 2.1. As is clear from Fig. 2.1 that the increase in the threshold (λ), the P_f decreases while P_m increases, therefore the sensing performance is optimal when threshold is selected at the intersection of probability density function (PDF) of binary hypothesis H_0 and H_1 [238]. Though employing CFAR approach, the threshold value (λ_f) remains same for all channels and it is expressed by equation (3.6), however the selection of threshold with MEP approach (λ_e) for the Rayleigh and Nakagami-*m* fading channel is given by equation (3.7) and (3.8) [220].

$$\lambda_f(AWGN\ or\ Ray\ or\ Naka) = \left\{\sqrt{\frac{2}{N}}Erfc^{-1}\left(2P_{f\_fixed}\right) + 1\right\}N\sigma_n^2 \tag{3.6}$$

$$\lambda_e(Ray) = \left(1 + \frac{1}{N\bar{\gamma}} - \sqrt{\frac{2}{N\pi}} + \sqrt{\frac{2}{N}\left(\frac{1}{\pi} + \sqrt{\frac{2N}{\pi}}\bar{\gamma} - 1\right)}\right)N\sigma_n^2 \tag{3.7}$$

$$\lambda_e(Naka) = \left(1 + \frac{2}{N\bar{\gamma}} - \frac{1}{2\sqrt{2N}}\left(\sqrt{\pi} - \sqrt{\pi - 8 + 2N\bar{\gamma}^2}\right)\right)N\sigma_n^2 \tag{3.8}$$

In the result section of this chapter, we have illustrated the effect of selection of threshold along with cooperation of cognitive users spectrum sensing in the fading environment over sensing performance of ED.

3.3.3 Cooperative spectrum sensing

In CRN, the multipath fading is prominent phenomenon due to which the received signal at CR deteriorates. In the deep-fade scenario, the signal at CR user is deteriorated by the surrounding environment, which results the degradation of sensing performance. For this environment, the cooperation among CUs is useful to enhance the sensing performance of deep-faded CRN [83], [220]. Several researchers have worked on cooperative spectrum sensing (CSS) scenarios in which the FC receives the local decision of CUs and combine all the sensing results to yield the final decision about the status of the PU on the channel. In general, three cooperative rules (AND, OR and Majority rule) are employed to take the decision, and the overall false-alarm (Q_f) and detection probability (Q_d) at the FC is given as [83]:

$$Q_f = \sum_{l=k}^{M} \binom{M}{l} \left(P_f\right)^l \left(1 - P_f\right)^{M-l} \tag{3.9}$$

$$Q_d = \sum_{l=k}^{M} \binom{M}{l} (P_d)^l (1 - P_d)^{M-l} \quad (3.10)$$

$$Q_e = Q_f + (1 - Q_d) \quad (3.11)$$

where, Q_d, P_d, M and k are the total detection probability at FC, detection probability of each CUs, number of CUs and the number of CR terminals employed for cooperation, respectively. In the expressions (3.9) or (3.10) at k=1, M/2 and M, FC follows OR, Majority & AND cooperative rules, respectively.

3.3.4 Throughput computation

The perspective performance evaluation parameter that is the throughput of CRN is defined as the number of bits received through the channel in a given time period per unit band width. We have considered following two cases for throughput computation of CU. In the **First case**, no false-alarm is generated and the PU is missing on the channel (represented as R_0). However, the throughput for the **Second case** is computed for the assumption that PU is present on the channel but not detected by the CU (represented as R_1). Therefore, the average total throughput for CU in both cases is denoted by *R* which is described as follows [153].

$$R_0 = \left(\frac{T - T_s}{T}\right)\left(1 - P_f\right) log_2(1 + \gamma_s) \quad (3.12)$$

$$R_1 = \left(\frac{T - T_s}{T}\right)(1 - P_d) log_2\left(1 + \frac{\gamma_s}{1+\gamma}\right) \quad (3.13)$$

$$R = P(H_0)R_0 \;\; + \;\; P(H_1)R_1 \quad (3.14)$$

where, T is the total duration of frame, T_s is the sensing and reporting time of CR, γ_s is the *SNR* for secondary link. However, the throughput in case of CSS is computed by replacing P_f with Q_f and P_d with Q_d in equation (3.12) and (3.13), respectively. Further, the algorithm for computation of throughput and error probability with CFAR and MEP approach are presented as follows.

Algorithm-1: Throughput & total error probability with CFAR Approach

---

1 **Input:** N, σ_n^2, $\overline{P}_f$, γ_s, γ, M, T, T_s, $P(H_0)$, $P(H_1)$,
2 **Output:** R, Q_e
BEGIN {
3 **Compute** λ_f, for AWGN, Rayleigh and Nakagami-*m* channel using equation (3.6)
4 **Find** P_f from equation (2.2) and P_{d} using equation (2.3), (3.3) and (3.5) for AWGN, Rayleigh and Nakagami channels, respectively
5 **Select** the Majority rule {round (M/2)} for cooperation
6 **Compute** Q_f and Q_d from equation (3.9) and (3.10), respectively
7 **Find** R_0 and R_1 from equation (3.12) and (3.13), respectively.
8 **Compute** Q_e and R from equation (3.11) and (3.14), respectively.
} END

Algorithm-2: Throughput & total error probability with MEP Approach

---

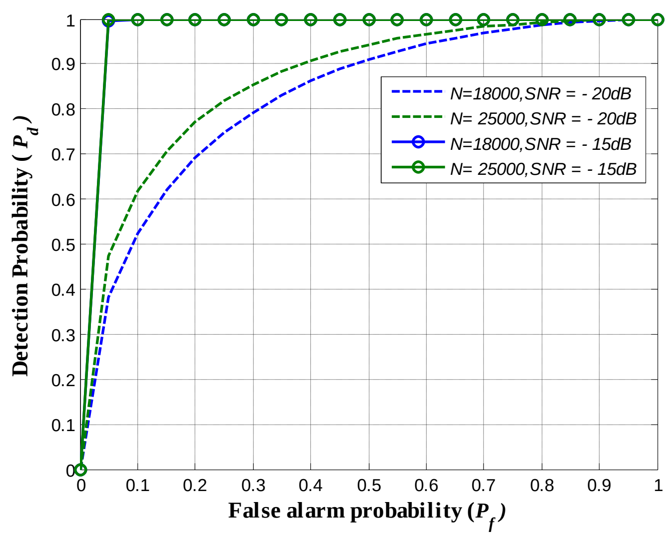
1 **Input:** N, σ_n^2, $\overline{P}_f$, γ_s, γ, M,T, T_s, $P(H_0)$, $P(H_1)$,
2 **Output:** R, Q_e
BEGIN{
3 **Compute** λ_e, for AWGN, Rayleigh and Nakagami-*m* channel using equation (2.8), (3.7) and (3.8), respectively
4 **if** $\lambda_e > 0$
5 **Find** P_f from equation (2.2) and P_{d} using equation (2.3), (3.3) and (3.5) for AWGN, Rayleigh and Nakagami channel, respectively.
6 **Select** the Majority rule {round (M/2)} for cooperation
7 **Compute** Q_f and Q_d from equation (3.9) and (3.10), respectively
8 **Find** R_0 and R_1 from equation (3.12) and (3.13), respectively.
9 **Compute** Q_e and R from equation (3.11) and (3.14), respectively.
10 **else**
11 $N^* \longleftarrow N$
12 go to (step-3)
13 **end**
}END

---

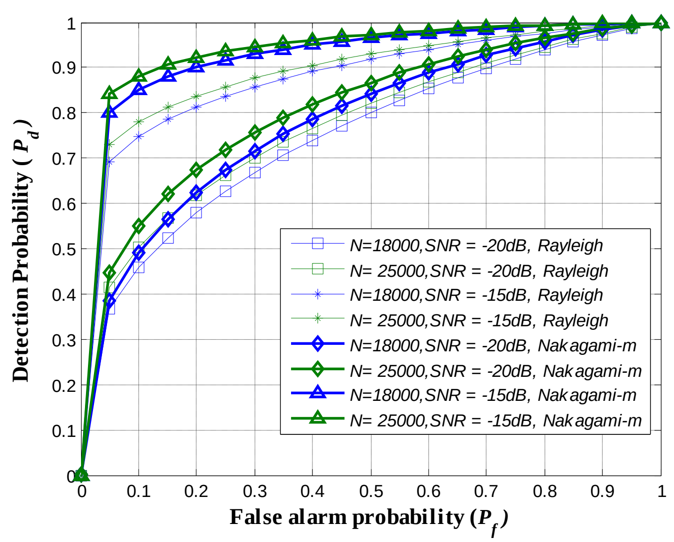
where, N^* is the value of N at which $\lambda_e > 0$.

3.4 Result and Discussion

In this section, we have illustrated the numerically simulated results of the proposed CRN system model. The parameters employed for simulation are the same as presented in Table 2.2 of Chapter 2 except N=25000. The selection of N is performed in such a way that λ_f and λ_e are positive for all the considered channels [220].We have illustrated the effect of variations in SNR and number of samples on ROC curve (plot between P_d and P_f) for AWGN channel in Fig. 3.2(a), and Rayleigh as well as Nakagami-*m* fading channels in Fig. 3.2(b).



(a)



(b)

Figure 3.2: ROC curve without cooperation for (a) AWGN channel and (b) Rayleigh and Nakagami-*m* (*m* =2) fading channel.

As shown in Fig. 3.2(a) and Fig. 3.2(b), for a particular value of false-alarm probability, detection probability increases with increase in the number of samples and also with increase in SNR.

Table 3.2: The effects of SNR over P_d at $P_f = 0.1$ with CFAR approach for AWGN, Rayleigh and Nakagami-m channels.

SNR(dB)	N	P_d		
		AWGN	Rayleigh	Nakagami-m
-20 dB	18000	0.52	0.45	0.49
	25000	0.61	0.50	0.54
-15 dB	18000	0.99	0.74	0.97
	25000	1.0	0.77	0.98

Further, at the fixed value of false-alarm probability (P_f=0.1) and N=25000, the percentage enhancement in detection probability are 63.93%, 54% and 81.48%, respectively for AWGN, Rayleigh and Nakagami-m fading channels at SNR=-20dB. The enhancement in P_d is because it depends on Erfc function and Erfc(.) value decreases with increase in (.) and vice-versa. Further, as shown in Equation (2.3), (3.3) and (3.5), Erfc(.) is showing dependency on N or SNR or on both, therefore with increase in N and SNR, P_d increases. Moreover, the variation in detection probability (P_d) with SNR for AWGN, Rayleigh and Nakagami-m (m = 2) fading channel is shown in Fig. 3.3.

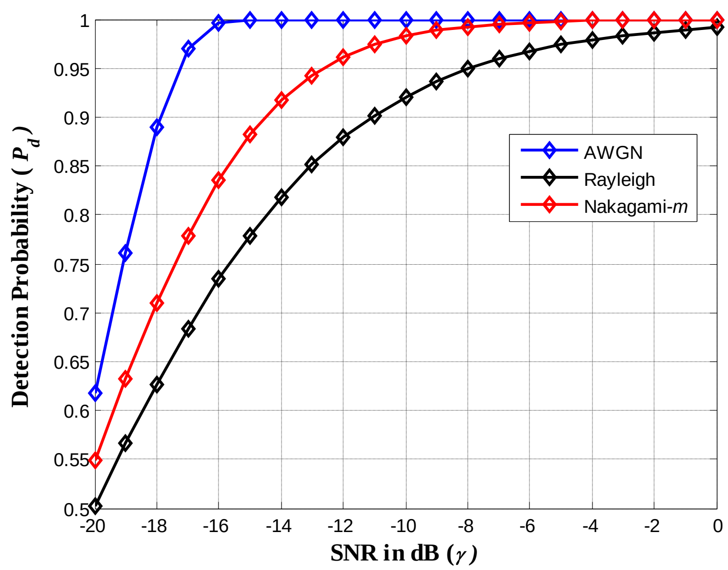
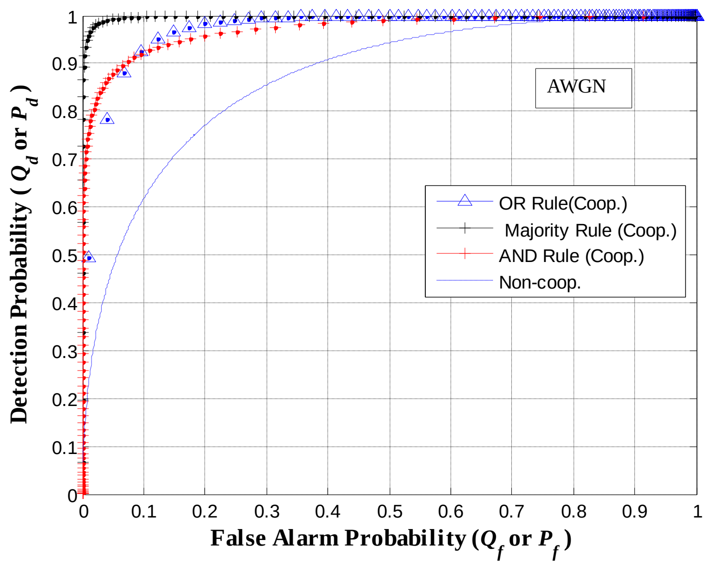
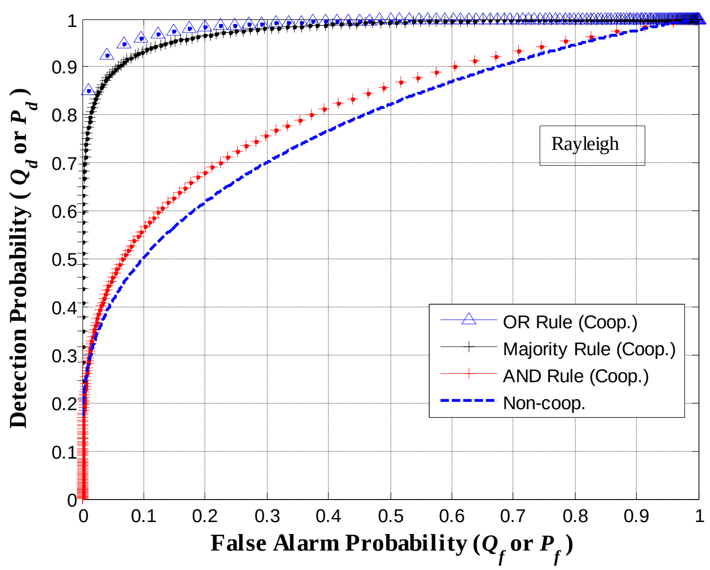


Figure 3.3: Detection probability variation with SNR for fading channels at N=25000 without cooperation.

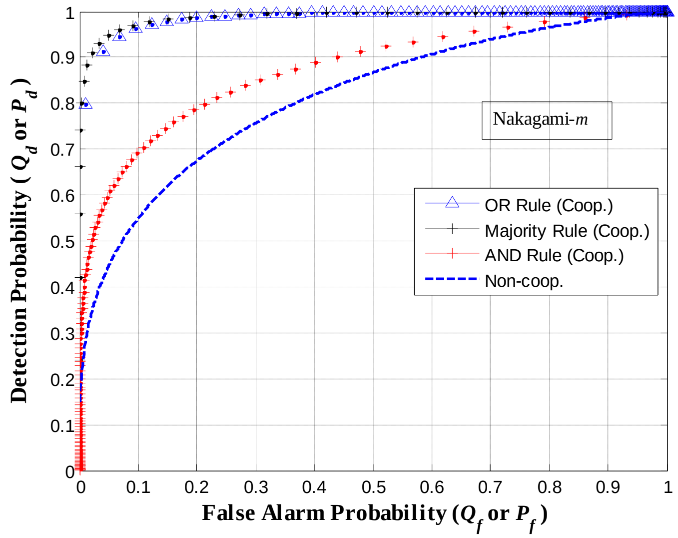
It is illustrated in Fig. 3.3 that the detection probability (P_d) has increased with increase in SNR for all fading channels. The P_d is highest for AWGN and lowest for Rayleigh fading channels. However, the ROC curve (Q_d verses Q_f or P_d verses P_f) for CR under the non-cooperative as well as different cooperative rules in AWGN, Rayleigh and Nakagami-m fading environments is shown in Fig. 3.4(a), Fig. 3.4(b) and Fig. 3.4(c), respectively.



(a)



(b)



(c)

Figure 3.4: ROC curve with cooperation for (a) AWGN channel, (b) Rayleigh channel and (c) Nakagami-*m* channel at SNR= -20 dB and N = 25000 with cooperation.

From Fig. 3.4(a)- Fig. 3.4(c), it is clear that after the cognitive user cooperation, the ROC curve has improved due to increase in the total detection probability and hence sensing performance of CRN has enhanced. From Fig 3.4(a), it is clear that in AWGN channel, the Majority rule outperforms the other cooperative AND as well as OR rule. However, from Fig. 3.4(b) and Fig. 3.4(c) it is shown that in the Rayleigh and Nakagami-*m* fading channel, the Majority rule and OR rules provide nearly same performance. It is clear from Table 3.3 that at total false-alarm probability (P_f or Q_f) of 0.1 and *SNR*= -20 dB, we have achieved 62.29%, 86%, and 76.36% enhancement in total detection probability while applying majority cooperative rule over non-cooperative scenario for AWGN, Rayleigh and Nakagami channels, respectively.

Table 3.3: Comparative analysis of false-alarm probability versus detection probability at N= 25000, SNR= -20 dB, CFAR approach for AWGN, Rayleigh and Nakagami-m channels.

P_f or Q_f	P_d or Q_d											
	AWGN				Rayleigh				Nakagami-*m*			
	Non-coop	Cooperative			Non-coop	Cooperative			Non-coop	Cooperative		
		OR	Majority	AND		OR	Majority	AND		OR	Majority	AND
0.1	0.61	0.93	0.99	0.92	0.50	0.96	0.93	0.57	0.55	0.96	0.97	0.69
0.3	0.85	0.99	0.99	0.97	0.70	0.99	0.98	0.76	0.75	0.99	0.99	0.84

Further, the need of dynamic threshold for AWGN channel is shown in Fig. 3.5 with the help of PDF curve of hypothesis H_0 and H_1. The PDF curve of hypothesis H_1 depends on the value of SNR, however it is independent of SNR for H_0. It is clear from Fig. 3.5, that PDF curve of H_1 shifted to rightside with the increase in SNR value from -20dB to -10dB.

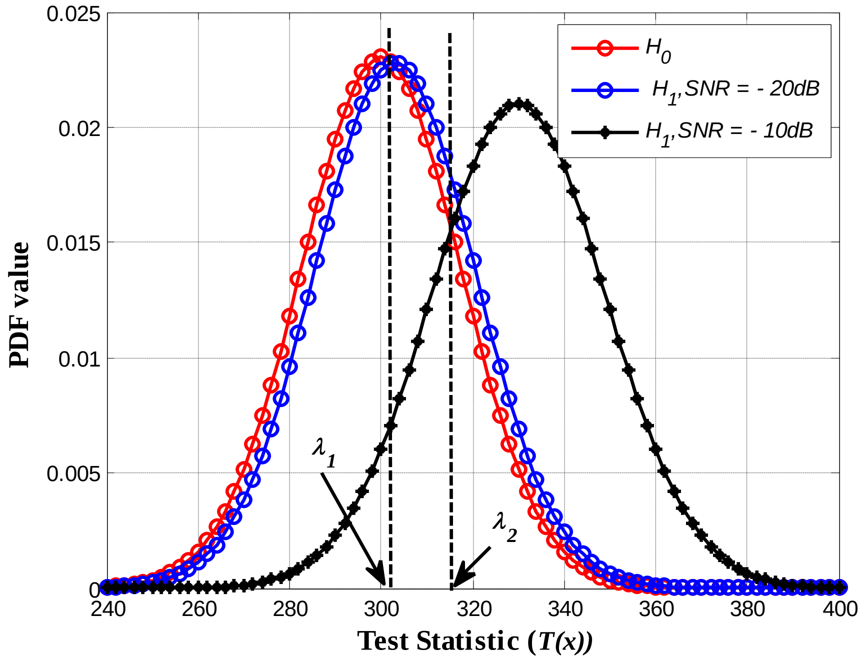
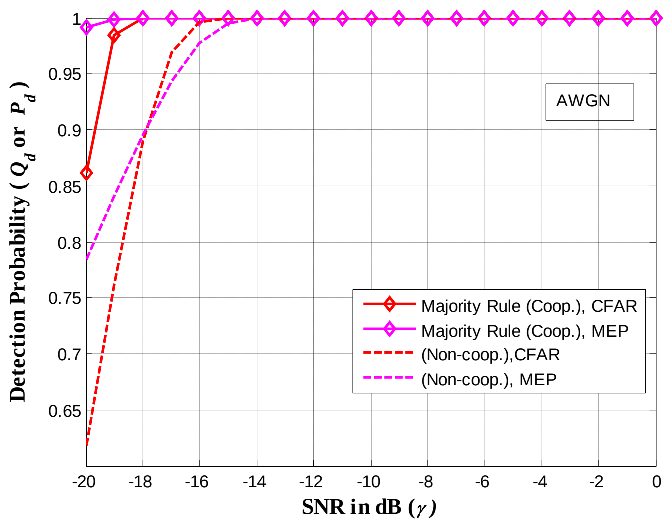


Figure 3.5: PDF of H_0 and H_1 under AWGN channel.

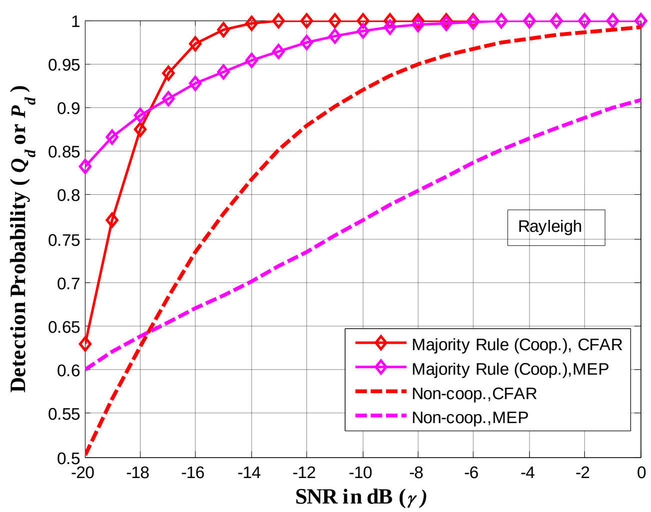
As we have already discussed in Section 3.3.2, the threshold is selected at the intersection of PDF of H_0 and H_1 for optimal miss-detection and false-alarm probabilities. Therefore, with the variation in SNR, the intersection of aforementioned PDF curves of hypothesis is different as is clear from Fig. 3.5 ($\lambda_1$at SNR= -20dB and λ_2 at SNR= -10dB). Hence, it is required that the selection of threshold must depend on the SNR values and in MEP approach, this requirement is fulfilled. Thus, based on the above discussion and simulation results, we have further analyzed the sensing performance of CR under majority cooperative rules by employing MEP threshold selection in AWGN, Rayleigh and Nakagami-*m* fading channels.

It is clear from Fig 3.6(a) to Fig. 3.6(c) that by employing either CFAR or MEP, the detection probability is improved after cooperation with respect to the non-cooperative scenario in above mentioned channels. However, at low SNR, in the cooperative scenario the detection probability is more with MEP approach, while at high SNR its value is more with CFAR approach except for

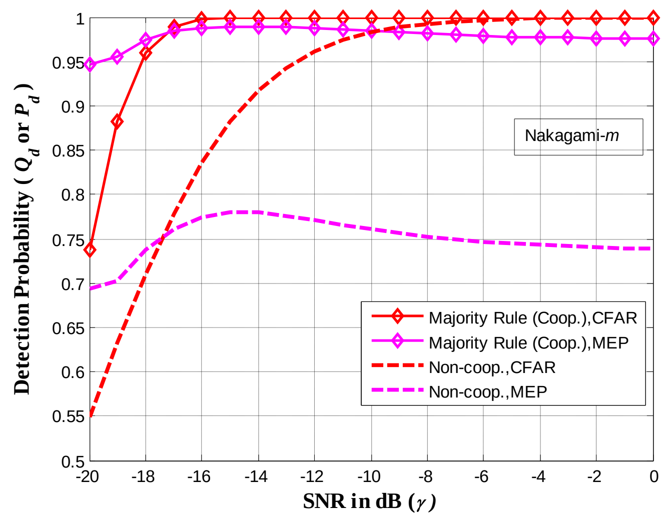
AWGN channel. It is because with CFAR approach threshold is fixed even with the variation in SNR, while in MEP approach its value increases with increase in SNR. Therefore, at high SNR, the threshold increases in MEP approach and its P_d decreases however it remains same throughout all SNR for CFAR approach. Further, high SNR region in different channels are considered when SNR>$SNR_c$where, SNRc is defined as the value of SNR at which threshold with CFAR and MEP approaches are equal. Moreover, at SNR= -20 dB with N=25000, there is 15.11%, 31.74%, and 28.76% enhancement in detection probability as illustrated in Fig. 3.6 and Table 3.4 and 3.6 while employing MEP over CFAR in CSS(majority)for AWGN, Rayleigh and Nakagami channel, respectively.



(a)



(b)



(c)

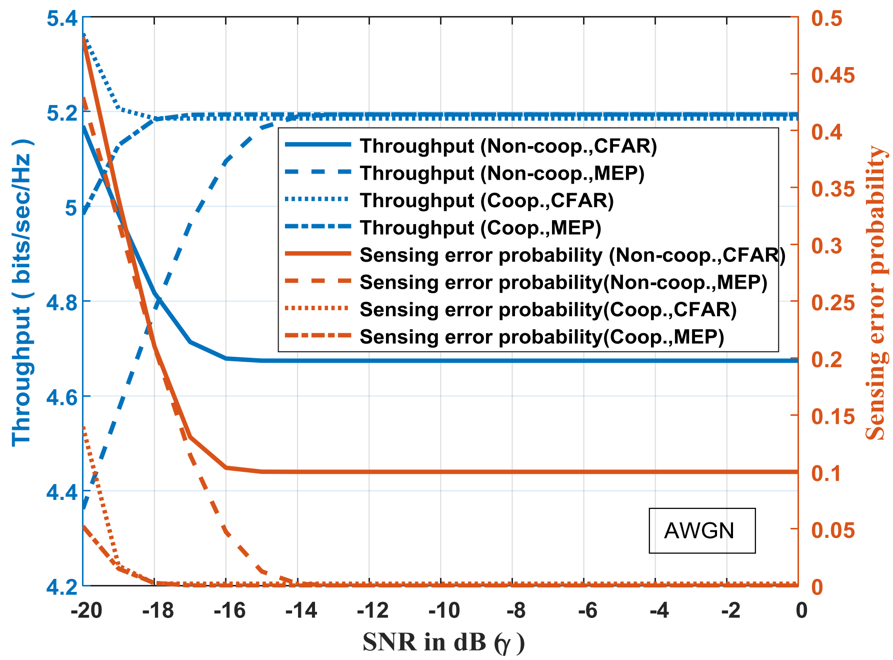
Figure 3.6: Variation of SNR with detection probability in cooperative (Majority rule) and non-cooperative (a)AWGN channel (b) Rayleigh fading channel and (c) Nakagami-*m* fading channel for CFAR and MEP (dynamic) threshold selection approach at, *M*=10, *N*= 25000.

Table 3.4: Comparative analysis of detection probability with non-cooperative and cooperative scenario at *N*= 25000, SNR= -20 dB for AWGN, Rayleigh and Nakagami-*m* channels.

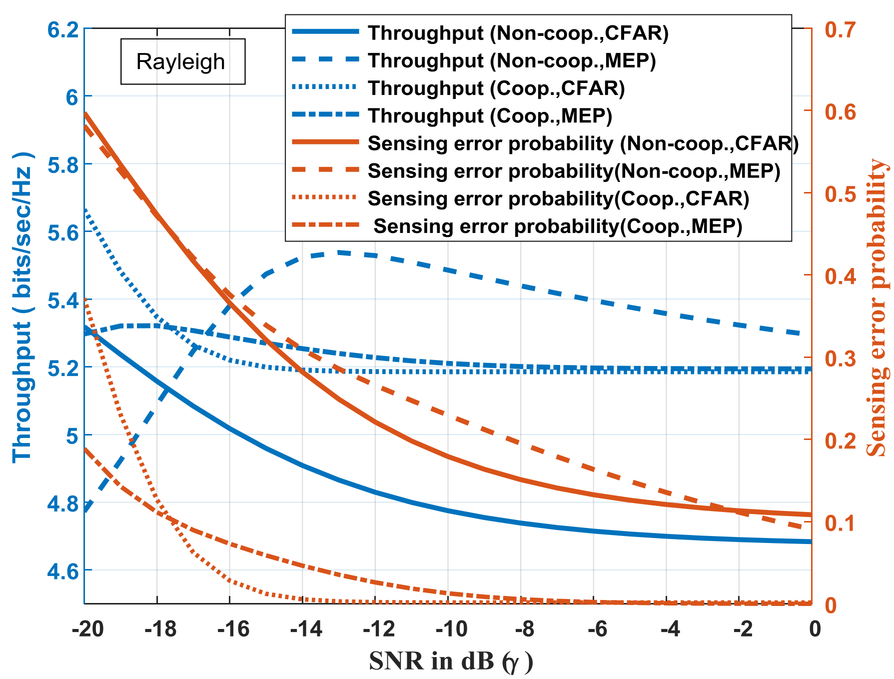
SNR (dB)	**P_d or Q_d**											
	AWGN				**Rayleigh**				**Nakagami-m**			
	CFAR		**MEP**		**CFAR**		**MEP**		**CFAR**		**MEP**	
	Non-Coop	Coop (Majority)	Non-Coop	Coop (Majority)	Non-Coop	Coop (Majority)	Non-Coop	Coop (Majority)	Non-Coop	Coop (Majority)	Non-Coop	Coop (Majority)
-20	0.61	0.86	0.78	0.99	0.50	0.63	0.59	0.83	0.54	0.73	0.69	0.94
-15	0.99	1.0	0.99	1.0	0.77	0.98	0.68	0.94	0.88	1.0	0.77	0.98
-10	1.0	1.0	1.0	1.0	0.92	1.0	0.77	0.98	0.98	1.0	0.76	0.98
-5	1.0	1.0	1.0	1.0	0.97	1.0	0.85	0.99	0.99	1.0	0.74	0.97

Further, the variation in throughput and total error probability of CU with SNR, for CFAR and MEP approaches under the non-cooperative and cooperative scenario in different fading environment is presented in Fig 3.7(a) to Fig. 3.7(c). It is clear from Fig. 3.7(a) to Fig. 3.7(c) that the throughput in CFAR approach reduces with increase in SNR however in MEP approach it increases. It is well illustrated by equation (3.14) that the total throughput R depend on R_0 and R_1, and in CFAR approach R_0 remains fixed due to fixed P_f or Q_f at all SNR and P_d or Q_d increases with increase in SNR which reduces the value of R_1 as per equation (3.13). Hence, the overall effect is the reduction in throughput of CFAR approach with increase in SNR. However, in MEP approach, both P_f or Q_f and P_d or Q_d improve with increase in SNR, and the enhancement in R_0

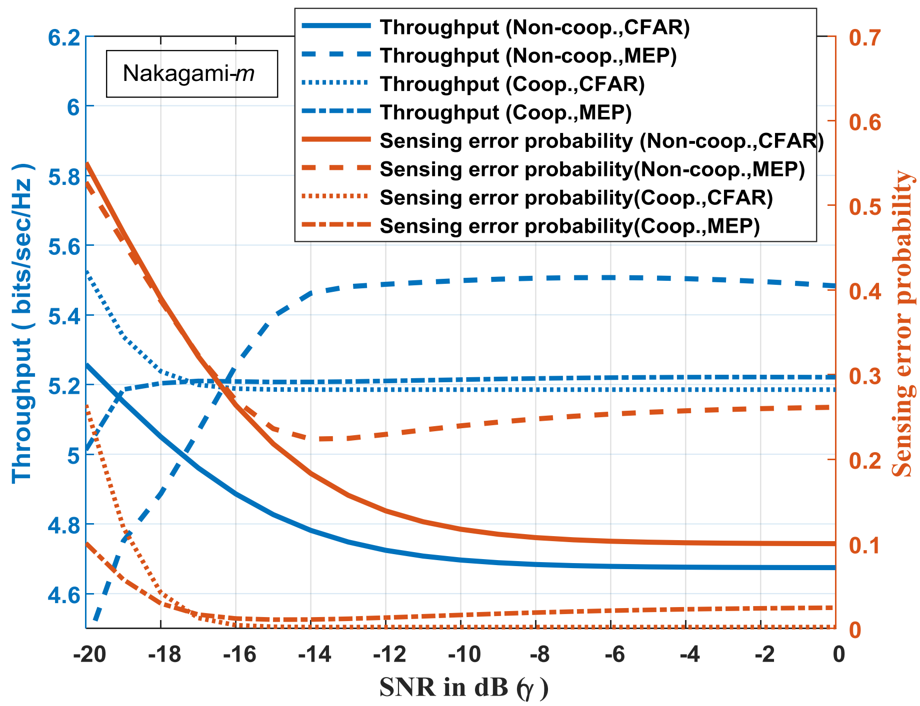
is more dominant than that of R_1 which results an increase in throughput with increased SNR. Moreover, for CFAR approach, the throughput increases after cooperation in all considered channels.



(a)



(b)



(c)

Figure 3.7: Variation of SNR with throughput and total error probability in the cooperative (Majority rule) and non-cooperative for (a) AWGN channel (b) Rayleigh fading channel and (c) Nakagami-*m* fading channel, for CFAR and MEP (dynamic) threshold selection approach at, *M*=10, *N*=25000.

This is because for CFAR approach, with cooperation both total detection and total false-alarm probability has improved in comparison to that of the non-cooperative scenario and resulting enhancement in R_0 is more compared to reduction in R_1 which leads to the increased throughput. However, in MEP approach, only at low SNR its value increases with cooperation. At high SNR, in MEP non-cooperative approach, the throughput is more due to high total error probability (sensing error probability) with respect to cooperative scenario.

Table 3.5: Comparative analysis of throughput and sensing error probability with non-cooperative v/s cooperative scenario and CFAR v/s MEP approach at *N*= 25000, for AWGN, Rayleigh and Nakagami-*m* channels.

SNR (dB)	AWGN								Rayleigh								Nakagami-*m*							
	Throughput				**Sensing error probability**				**Throughput**				**Sensing error probability**				**Throughput**				**Sensing error probability**			
	CFAR		MEP		CFAR		MEP		CFAR		MEP		CFAR		MEP		CFAR		MEP		CFAR		MEP	
	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.	Non-coop.	Coop.
-20	5.17	5.36	4.36	4.98	0.48	0.13	0.42	0.05	5.31	5.66	4.77	5.29	0.59	0.37	0.58	0.18	5.25	5.52	4.44	5.01	0.55	0.26	0.52	0.10
-15	4.67	5.19	5.16	5.19	0.10	0.00	0.01	0.00	4.95	5.19	5.47	5.27	0.32	0.01	0.33	0.05	4.82	5.18	5.39	5.20	0.21	0.00	0.23	0.01
-10	4.67	5.19	5.19	5.19	0.10	0.00	0.00	0.00	4.77	5.18	5.48	5.21	0.17	0.0	0.22	0.01	4.69	5.18	5.49	5.21	0.11	0.00	0.23	0.01
-5	4.67	5.19	5.19	5.19	0.10	0.00	0.00	0.00	4.70	5.18	5.37	5.19	0.12	0.0	0.14	0.00	4.67	5.18	5.50	5.22	0.10	0.00	0.25	0.02

Moreover, it is clear from Fig. 3.7(a) to Fig. 3.7(c) that generally the sensing error probability is least in the cooperative scenario in comparison to that of the non-cooperative spectrum sensing. Further, the percentage improvement in throughput and total error probability in different scenario is presented in Table 3.6.

Table 3.6: Comparative table of percentage improvement in detection probability, throughput and sensing error probability with different scenario for AWGN, Rayleigh and Nakagami-*m* channels at N= 25000, SNR= -20 dB.

Parameters	**Channel**	**% Improvement with Coop. over Non-coop. Scenario**		**% Improvement with MEP over CFAR approach**	
		CFAR	**MEP**	**Non-coop.**	**Coop.**
P_d	AWGN	40.98	26.92	27.86	15.11
	Rayleigh	26	40.67	18	31.74
	Nakagami-*m*	35.18	36.23	27.77	28.76
Throughput	AWGN	3.67	14.22	-15.66	-7.08
	Rayleigh	6.59	10.90	-10.16	-6.53
	Nakagami-*m*	5.14	12.83	-15.42	-9.23
Sensing Error Probability	AWGN	72.91	88.09	12.5	61.53
	Rayleigh	37.28	68.96	1.69	51.35
	Nakagami-*m*	52.72	80.76	5.45	61.53

3.5 Conclusion

In this chapter, we have illustrated the effect of variation in number of samples and SNR on sensing performance of CRN under AWGN, Rayleigh, and Nakagami-*m* fading environment in the non-cooperative scenario. The numerical analysis and simulation results reveal that the effect of variation in SNR is more dominant on sensing performance of CRN in comparison to that of the variation in number of samples. Further, we have also illustrated the need of dynamic threshold to enhance the sensing performance at low SNR. The ROC curve has provided best performance with Majority rule in the cooperative spectrum sensing environment therefore, we have shown the comparison between fixed CFAR and dynamic threshold MEP selection approach with Majority rule in different environment (AWGN, Rayleigh, and Nakagami-*m*). In addition, it has been observed that at low SNR, MEP approach provides better detection probability in comparison to that of CFAR approach. Further, the throughput computation has been performed for proposed environment employing CFAR and MEP approach under the cooperative and non-cooperative scenarios. Finally, we have concluded that at low SNR, the throughput is maximized by CFAR with cooperative rule while at high SNR its value is maximized with MEP in the non-cooperative scenario for the all mentioned fading channels. In addition, for the least sensing error (total error) probability, the cooperative rule outperformed the non-cooperative rule and in AWGN channel, the sensing error is minimum while employing MEP. However, in the Rayleigh and Nakagami-m fading environment, MEP approach provides least sensing error at low SNR while at high SNR, CFAR approach is outperforming. Moreover, in the cooperative spectrum sensing scenario with MEP approach, the improvement in detection probability, throughput, and total error probability in AWGN channel are: 15.11%, -7.08%, and 61.53%, respectively; in Rayleigh channel are 31.74%, -6.53%, and 51.35 %, respectively; and in Nakagami-m channel are 28.76%, -9.23 %, and 61.53%, respectively at SNR=-20dB. However the main challenging issue is the selection of threshold computation approach at different SNR since from the analysis it is observed that the single threshold selection approach with cooperative and non-cooperative spectrum sensing scenario is unable to provide maximum throughput and minimizing sensing error probability. These challenging issues are explored in the Chapter 4 of the thesis.

CHAPTER 4

IMPROVEMENT IN SENSING ERROR PROBABILITY AND THROUGHPUT

4.1 Introduction

It is reported in the literature that the threshold selection with CFAR approach is suitable from CU point of view only and has improved the throughput of CU however, it is unable to provide enough protection to the primary user (PU) [200]. In order to protect the PU from the CU's transmission, CDR approach is more appropriate but at the cost of throughput [130]. Liang et. al. [153] have employed CDR approach and formulated the spectrum sensing and throughput trade-off problem. However, the spectrum sensing performance in a non-cooperative scenario results false (incorrect) sensing decisions due to multipath fading and shadowing effects faced by CUs. Therefore, the cooperation between CUs is used to improve the credibility of sensing results. Jafarian and Hamdi [131]have employed double threshold selection approach to improve the detection probability of EDSS in the cooperative spectrum sensing environment. In the double thresholding approach, each CU employ two thresholds λ_1 and λ_2 (λ_2>λ_1) and when the energy of test statistics of received signal (T(x)) at each CU is $\geq \lambda_2(/\leq \lambda_1)$, the decision is in favour of PU presence (/absence) on the channel. Nevertheless, when the test statistics lies between two thresholds λ_2 and λ_1, CU is not able to take any sensing decision [131] and send the sensing information (observed energy value) to the FC for decision. Further, the closed-form expressions for threshold selection with CFAR, CDR and MEP approaches in the fading environment have been presented by Attapattu et. al. [220] and the optimal threshold selection criterion has been provided in the non-cooperative and cooperative (OR rule) spectrum sensing scenario to reduce the error probability without considering its effect on throughput of CU. Further, the effect of threshold selection on throughput while satisfying the optimal threshold condition under AWGN channel for the non-cooperative scenario is analyzed in [239]. Since, the effect of threshold selection with CFAR and MEP approaches in cooperative spectrum sensing scenario under the Majority rule for fading channel is presented in Chapter 3. However, from the previous results which are presented in Chapter 3, we have analyzed that under the fading channels, the single threshold selection approach with cooperative and non-cooperative spectrum sensing scenario is unable to provide maximum throughput and minimizing sensing error at all SNR. Therefore, in this chapter, we have framed the objectives as follows by taking into consideration aforementioned points.

- We have illustrated that when the number of cooperative cognitive users are high ($M \geq 10$), the Majority cooperative rule outperform the OR cooperative rule at FC.
- We have computed the value of critical SNR (γ_c) which provided the efficient threshold selection approach at different SNR to optimize the throughput and sensing error. Further, we have proposed algorithms to maximize the throughput and reduce the sensing error probability at all (low and high) SNR for Rayleigh and Nakagami-*m* fading channels.

4.2 System Model and Proposed Performance Analysis

We have considered same system model which is employed in Chapter 3 with the assumption of perfect reporting channels. Further, we have considered that there is no uncertainty in the noise and the activity of PU remains constant during the sensing period. The activity of PU remains constant means that if at the starting of spectrum sensing frame of CU, PU is present on the channel then it will not change its state and remains on the channel for the whole sensing duration or if the channel is unoccupied by the PU at the starting of frame then it will remain idle for the whole sensing duration.

4.2.1 Computation of critical SNR

Further, with the help of computed value of threshold with CFAR (λ_f) and MEP (λ_e) approaches, we have determined the critical SNR (γ_c) and its numerical value is computed by finding the SNR value at which the threshold with CFAR approach is same as that of MEP approach ($\lambda_f = \lambda_e$) for respective channels which is shown in Fig. 4.1 (Note: In Chapter 2, the critical SNR (γ_c) is computed with CFAR and CDR approaches). Subsequently on the basis of γ_c, we have divided the received SNR range in the low SNR and high SNR region. The low SNR region is considered when $\gamma \leq \gamma_c$ while, the high SNR region is considered when $\gamma > \gamma_c$ and γ_c will be different for AWGN, Rayleigh and Nakagami-*m* channels as shown in Fig. 4.1.

4.2.2 Cooperative spectrum sensing and throughput computation with majority rule

When FC follow Majority rule, the overall false-alarm (Q_f^M), miss-detection (Q_m^M) and total spectrum sensing error probability (Q_e^M) is given as [83]:

$$Q_f^M \;=\; \sum_{l=M/2}^{M} \binom{M}{l} \left(P_f\right)^l \left(1-P_f\right)^{M-l} \tag{4.1}$$

$$Q_m^M \;=\; \sum_{l=M/2}^{M} \binom{M}{l} (P_m)^l (1-P_m)^{M-l} \tag{4.2}$$

$$Q_e^M \;=(Q_f^M)\;+(Q_m^M) \tag{4.3}$$

Further, the throughput under cooperative spectrum sensing scenario (R_c) is computed by simply replacing the P_f with Q_f^M and P_d with Q_d^M in equation (3.14) and given as:

$$R_c = P(H_0)\left(\frac{T-T_s}{T}\right)\left(1-Q_f^M\right)log_2(1+\gamma_s) \;+P(H_1)\left(\frac{T-T_s}{T}\right)(1-Q_d^M)log_2\left(1+\frac{\gamma_s}{1+\gamma}\right) \tag{4.4}$$

With this context, the Algorithm-1 and Algorithm-2 are proposed for maximizing the throughput and minimizing the total error probability of CU, respectively under the Rayleigh and Nakagami-*m* fading environments at all SNR.

Algorithm-1: Throughput Computation

1. **Input:** N, σ_n^2, P_{f_fixed}, γ_s, γ, M, T, T_s, $P(H_0)$, $P(H_1)$,
2. **Output:** R or R_c

   BEGIN {
3. **Compute** λ_f from (3.6) and λ_e from (3.7) and (3.8) for Rayleigh and Nakagami-*m* fading channel, respectively.
4. Find the value of γ_c for respective fading channels
5. **If** $\gamma \leq \gamma_c$
6. $\lambda \leftarrow \lambda_f$
7. **Find** P_f from (2.2) and P_m using (3.3) and (3.5), for Rayleigh and Nakagami-*m* channels, respectively.
8. Find Q_f^M and Q_m^M from (4.1) and (4.2), respectively.
9. **Compute** R_c from (4.4) (Throughput after cooperation)
10. **else**
11. $\lambda \leftarrow \lambda_e$
12. **Find** P_f from equation (2.2) and P_m using (3.3) and (3.5), for Rayleigh and Nakagami-*m* channel, respectively
13. **Compute** R from (3.14)

    } END

Algorithm-2: Total Error Probability Computation

1. **Input:** N, σ_n^2, P_{f_fixed}, γ_s, γ, M, N
2. **Output:** Q_e

   BEGIN {
3. **Compute** λ_f from equation (3.6) and λ_e from equation (3.7) and (3.8) for Rayleigh and Nakagami-*m* fading channels, respectively.
4. Find the value of γ_c for respective fading channels
5. **If** $\gamma \leq \gamma_c$
6. $\lambda \leftarrow \lambda_e$

else

$\lambda \leftarrow \lambda_f$

Find P_f from (2.2) and P_m using (3.3) and (3.5), for Rayleigh and Nakagami-*m* channel, respectively.

Find Q_f^M and Q_m^M from (4.1) and (4.2), respectively.

Compute Q_e^M from (4.3)

} END

4.3 Result and Discussion

In this section, we have illustrated the numerically simulated results of the proposed system model. The parameters employed for simulation are as follows: N=25000, γ_s=20 dB, T_s =2.5ms, T=100ms, $P(H_0) = 0.8$, $P(H_1) = 0.2$, $P_{f\_fixed} = 0.1$, M=10, ${\sigma_n}^2$=1, and m = 2. In Fig. 4.1, we have illustrated the variation of normalized threshold $\left(\lambda^* = {}^{\lambda}/_{N}\right)$[220]with SNR for different channels while employing CFAR and MEP approaches. It is clear from Fig. 4.1 that the normalized threshold (λ^*) with CFAR approach remains constant for AWGN as well as for the considered fading channels while it increases with increase in SNR for MEP approach in all considered channels. The constant nature and same value of λ^* with CFAR approach for all the channels is due to the fact that false-alarm probability remains unchanged with SNR as already described in Chapter 3. Moreover, since the intersection point of threshold for CFAR and MEP approaches are different for the considered channels therefore, γ_c is different for these channels.

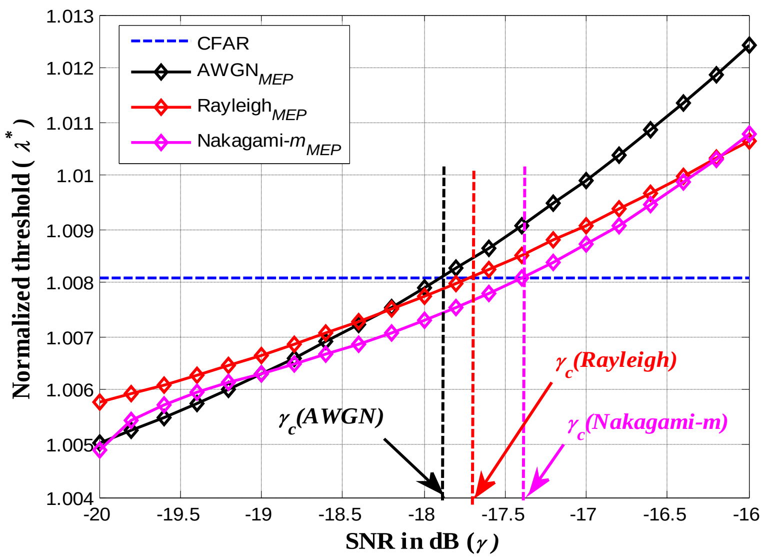
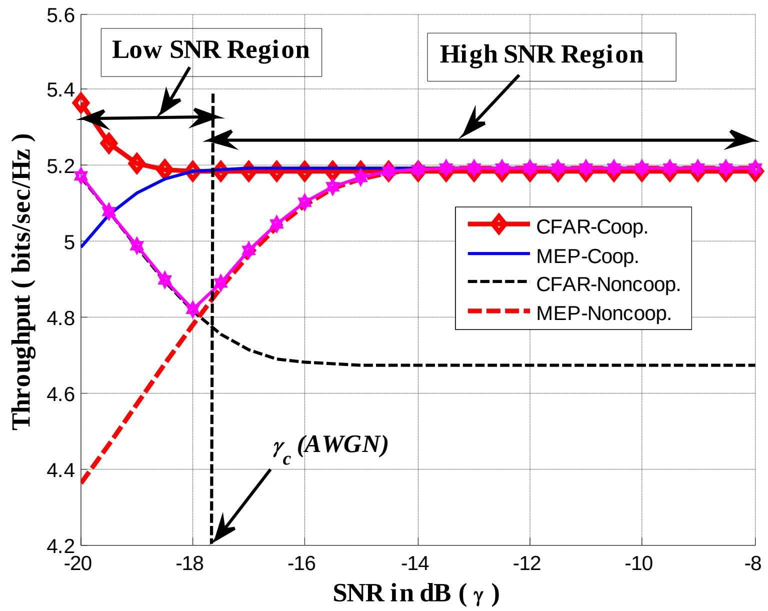
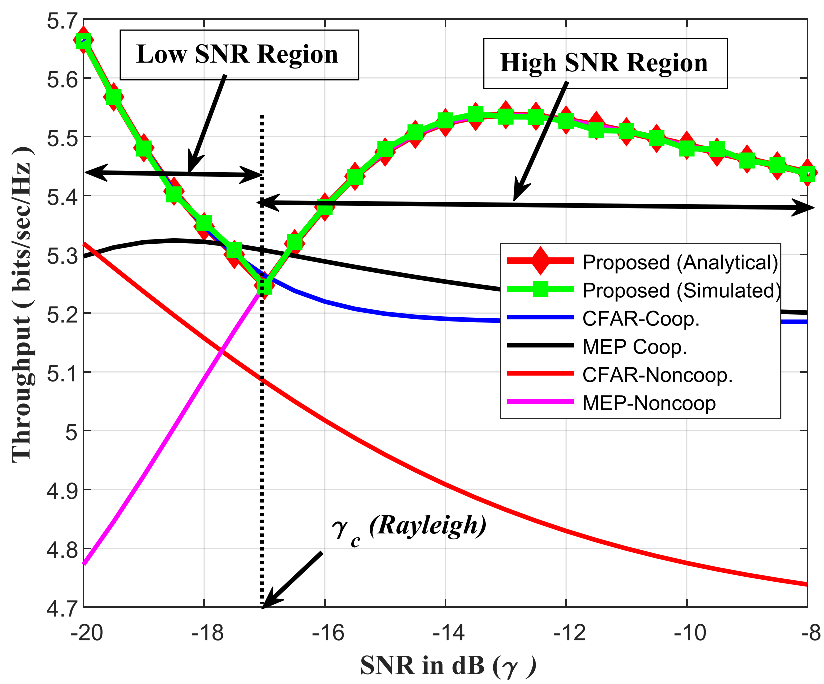


Figure 4.1: Variation of normalized threshold curve with SNR for AWGN, Rayleigh and Nakagami-*m* fading channels.

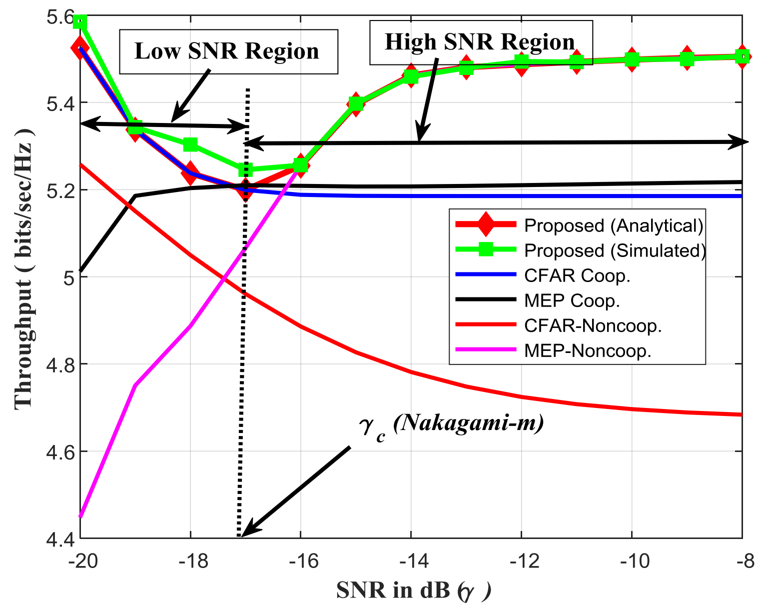
Moreover, in Fig. 4.2(a) to Fig. 4.2(c), we have depicted the variation of CU throughput with SNR, while employing CFAR and MEP approaches under the cooperative and non-cooperative spectrum sensing scenario in AWGN, Rayleigh and Nakagami-*m* fading environment, respectively.



(a)



(b)



(c)

Figure 4.2: Throughput versus SNR curve for (a) AWGN (b) Rayleigh and (c) Nakagami-m fading channels.

The throughput under AWGN channel is maximized with CFAR threshold selection in the cooperative spectrum sensing scenario as compare to that of the other approaches. Moreover, the analytical and simulated results of the proposed approach for the throughput with Algorithm-1 are shown in Fig. 4.2(b) and Fig. 4.2(c). The simulation results have been obtained from Monte Carlo simulation for 10000 iterations by adding the ambiguity of 5% around the considered analytical $P(H_0)$ value of 0.8 which also support the proposed analytical results. We have observed from Fig. 4.2(b) and Fig. 4.2(c) that with CFAR approach, the throughput is higher at low SNR region with the cooperation of CUs however at high SNR region, its value is higher with MEP approach in the non-cooperative environment. Also, it is illustrated that the single threshold selection approach (CFAR or MEP) at all (low and high) SNR region is not suitable to maximize the throughput in the Rayleigh and Nakagami-*m* fading environment.

Further, the response of SNR over the throughput for all the considered channels (AWGN, Rayleigh, and Nakagami-*m*) has been discussed as follows. With the increase of SNR, the value of Q_d^M (or P_d) is increasing initially and then becoming constant for CFAR approach as shown in Fig. 4.2. Since from equation (4.4), it is obvious that the throughput is high for low values of Q_f^M(or P_f) and Q_d^M(or P_d), therefore the throughput is initially reducing with increase in SNR and then remains constant in Fig. 4.2. However, with the MEP approach, Q_f^M (or P_f) is decreasing and

Q_d^M(or P_d) is increasing with increase in SNR and then remains constant, however the effect of reduction in Q_f^M(or P_f) is significantly more at most of the SNR values in comparison to enhancement in Q_d^M (or P_d), therefore overall effect is increase in throughput with increase in SNR initially and then it is remains constant.

Further, we have described the nature of the throughput characteristics of each channel for various threshold selection approaches. In the AWGN channel, as observed from the mathematical analysis of equation (4.1) to equation (4.4) as well as Fig. 4.2(a), the maximum throughput is achieved with only single threshold selection approach (CFAR) at all SNR ($\gamma \leq \gamma_c$ or $\gamma > \gamma_c$). As shown in Fig. 4.2(a), the cooperation in CFAR approach has enhanced the throughput as compare to that of the MEP approach at low SNR ($\gamma \leq \gamma_c$) because in this region, the value of Q_f^M and $Q_d^M$of CFAR is less in comparison to that of MEP, however for $\gamma > \gamma_c$, its values are remaining constant for both the approaches. Since from equation (4.4), it is obvious that the throughput is high for low values of Q_f^M(or P_f) and Q_d^M (or P_d), hence for $\gamma \leq \gamma_c$, the CFAR approach provides better throughput in comparison to that of the MEP approach and its value is almost constant for $\gamma > \gamma_c$ when considering AWGN channel. Further, similar behavior for the Rayleigh and Nakagami-*m* fading channels are achieved for low values of SNR, however for $\gamma > \gamma_c$ the Q_d of both CFAR and MEP is not constant due to fading channels. Q_d value of the CFAR and MEP are increasing with γ for $\gamma > \gamma_c$ which result degradation of throughput with γ in both CFAR and MEP because through the results we have obtained that the value of Q_f for $\gamma > \gamma_c$ is also remaining constant.

Further, Fig. 4.3 have enlightened the effect of *N* on the total error probability under OR and Majority cooperative rules for CFAR and MEP threshold selection approaches for the Rayleigh fading environment. We have observed that at SNR= -20 dB with OR cooperative rule, the error probability increases when the number of cooperative users increases from *M* = 2 to *M* =10 [220] and hence instead of that, Majority cooperative rule can be employed. Therefore, we have analyzed CFAR and MEP threshold selection approaches under the Majority cooperative rule and observed that the proposed approach is suitable to reduce the sensing error probability which is presented in Fig. 4.5 where results of the proposed approach with Algorithm-2 is shown.

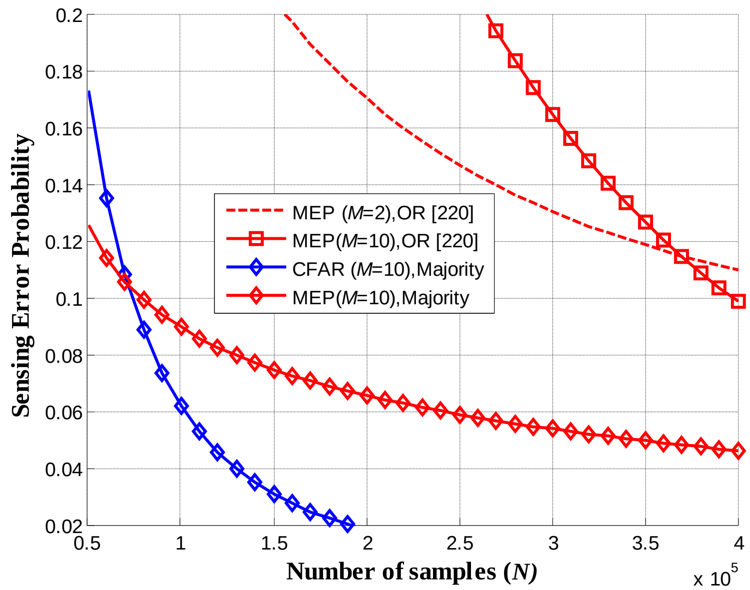


Figure 4.3: Variation in sensing error probability with number of samples (N) for Rayleigh channel at SNR= -20 dB.

Moreover, we have presented the variation in sensing error probability with SNR while employing CFAR and MEP approaches under CSS scenario for AWGN, Rayleigh and Nakagami-m fading environment and compared its performance with proposed approach in Fig. 4.4. Since the sensing error probability reduces after cooperation when compared with non-cooperative spectrum sensing scenario therefore, we have considered the CSS scenario.

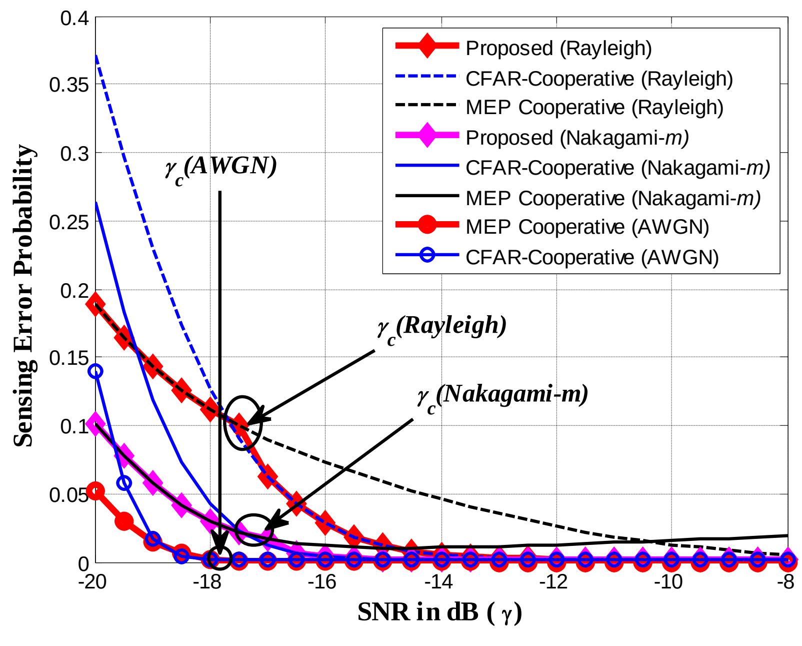


Figure 4.4: Variation in sensing error probability with SNR for AWGN, Rayleigh and Nakagami-m fading channels.

It is clear that MEP cooperative approach provides least sensing error probability as compare to that of the other approaches in AWGN environment. Moreover, at low SNR region, the sensing error probability is low with MEP approach while at high SNR region its value is low with CFAR approach for Rayleigh and Nakagami-*m* fading channel. However, in the proposed approach, we have selected the threshold with CFAR and MEP approaches at different SNR therefore we have achieved least spectrum sensing error probability at all SNR as illustrated in Fig. 4.4. At higher SNR values, the spectrum sensing error probability is nearly same in all channels while at low SNR its value is least with AWGN and highest for Rayleigh fading in the proposed approach. Further, as it is clear from above discussion that the major objective is to select the appropriate threshold selection technique among various approaches for better performance (throughput and sensing error probability). However, for AWGN channel, Fig. 4.2(a) and Fig. 4.4 shows the mathematical analysis of equation (4.1) to equation (4.4), and it is observed that the highest throughput (/and minimum sensing error probability) is achieved with only single threshold selection approach i.e. CFAR (/and MEP) at all SNR ($\gamma \leq \gamma_c$ or $\gamma > \gamma_c$). In addition, Fig. 4.2(b) and Fig. 4.2(c) shows that the single threshold selection approach (either CFAR or MEP) at all SNR is not suitable for maximizing the throughput or minimizing the sensing error probability in Rayleigh and Nakagami-*m* fading channels.

Further, Fig. 4.5 shows the trade-off between throughput and spectrum sensing error probability which we have obtained from the proposed Algorithm-1 and Algorithm-2. It is clear from Fig. 4.5 that the Algorithm-1 provides higher throughput at the cost of high sensing error probability and Algorithm-2 offers less sensing error at the cost of degraded throughput. As per the IEEE 802.22 standard, the false-alarm and miss-detection probability requirement in CRN is ≤ 0.1 or sensing error should be$\leq$0.2. The results presented for Rayleigh fading channel in Fig. 4.5 shows that the above quality-of-service (QoS) requirement of CRN is only achieved by Algorithm-2 for the given SNR values and similar behavior can be achieved for Nakagami-*m* fading channel.

The trade-off between sensing error and throughput occurs because in the proposed system model, the total throughput computation is performed with the help of following two cases which have been also presented earlier in Section 3.3.4 of Chapter 3. In the first case, the communication channel is assumed to be free and no false-alarm is generated while in the second case, the channel is considered to be occupied by the PU, and CU has missed the detection of PU. Moreover, when the sensing error is less due to less miss-detection probability then the chances of CU to transmit the data in second case is also reduced, therefore the total throughput decreases with decrease in sensing error. In Fig. 4.5, we have illustrated the effect of SNR on both the throughputs and sensing error probabilities of Algorithm-1 and Algorithm-2. It is clear from Fig. 4.5 that when the Algorithm-2 is employed, we have achieved least sensing error along with decent value of throughput at all considered SNR. However, if higher sensing error probability is tolerable by the user, then the high value of throughput could be achieved by Algorithm-1 in comparison to that of the Algorithm-2.

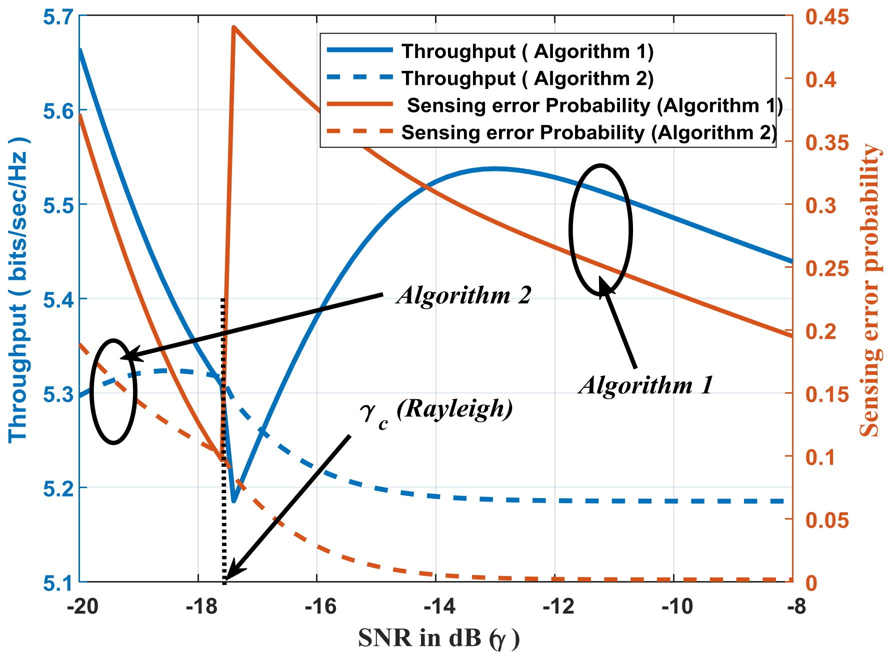


Figure 4.5: The trade-off between throughput and total error probability in Algorithm-1 and Algorithm-2 for the Rayleigh fading channel.

4.4 Conclusion

In this chapter, we have considered the AWGN, Rayleigh and Nakagami-*m* fading channels environment and computed the critical SNR (γ_c).We have attained low and high SNR regions on the basis of critical SNR however its value is different for aforementioned fading environments. Further, it is shown that the individual selection of CFAR or MEP approach under the cooperative and non-cooperative spectrum sensing scenario provides high throughput or least sensing error probability either at low SNR region or at high SNR region. However, in the proposed approach, we have achieved high throughput and least sensing error probability at both the low and high SNR region. Since in this chapter, we have analyzed the performance of CRN perfect reporting channels, however the imperfect reporting channel is a practical scenario, which is presented in Chapter 5.

CHAPTER 5

CENSORING WITH IMPERFECT REPORTING IN CRN

5.1 Introduction

In CSS technique, the sensing decision of each CU is sent to the fusion center (FC) via reporting channels where FC apply different cooperative rules [111] to take global decision about the status of primary user channel. In practice, the reporting channels are imperfect which leads to inaccurate sensing decisions by the FC [97]. However, in CSS technique, the energy consumption increases due to cooperation overhead bits [224], therefore to reduce the energy consumption and to save the bandwidth of reporting channels, the censoring approach [240], [241] is commonly employed by several researchers in which sensing results of only limited number of CUs are sent to the FC. Numerous researchers have worked in this context which is briefed below along with the limitations of their proposed work, which are presented in the related work section of this chapter.

- In [214], the authors suggested that to improve the throughput of CU, CFAR threshold selection approach is better, however to provide sufficient protection to PU from CU, the threshold selection with CDR approach is better.
- As the threshold selection effect on both the throughput and error probability of CU is analyzed in Chapter 2 already, however only for non-cooperative AWGN environment. Further, in previous Chapters 3 and 4, we have considered the fading environment and analyzed the effect of threshold selection on both the throughput and error probability of CU under Majority cooperative rule at FC. However, the proposed analysis was limited to only perfect reporting channels.
- Recently, Li et al. [241] have assumed the predefined value of threshold in EDSS and observed the individual effect on both the false alarm and detection probabilities (P_f and P_d) of CU at high SNR under CSS technique (OR rule) in the Rayleigh fading environment. The censoring approach with imperfect reporting channel is considered, and the effect of number of CUs and antennas on the false-alarm probability and throughput of Rayleigh fading channel is

analyzed. However, Li et al. [241] lacks the method for computation of threshold in different fading channels and its effect on the total sensing error and throughput for different channels at low SNR.

Therefore, based on the limitations of above mentioned work, we have attempted to overcome these issues. In this context, the author's contributions are stated as follows.

- In this chapter, we have considered more realistic low SNR scenario for sensing in AWGN, Rayleigh and Nakagami-*m* channels.
- The imperfect reporting channel is employed which has affected the sensing decision at FC and two scenarios are considered in such a manner where the sensing decision of CUs are sent to the FC with and without the censoring approach. The comparison among censoring and non-censoring approach is further described.
- Further, we have derived the expressions of total sensing error probability and throughput for the fading channels while employing perfect/imperfect reporting channel in the censoring and non-censoring approaches.
- In addition to this, we have also analyzed the effect of threshold selection approaches on the throughput and total sensing error probability in above mentioned scenario.

5.2 Related Work

In CSS technique, the advantages of spatial diversity are employed in CRN to enhance the sensing performance of CUs when the sensing channels suffer from fading. Moreover, in CSS technique two phases, namely, the spectrum sensing and reporting are considered. Various researchers have considered perfect reporting (PR) or/and imperfect reporting (IR) channels and have employed censoring/non-censoring approaches to analyze the performance of CRN which is described below.

5.2.1 Perfect reporting channels

In the perfect reporting channels, Zhang et al. [186] have minimized the total sensing error probability by employing Majority rule at FC when P_f (probability of false-alarm) and P_m (probability miss-detection) are nearly same. Moreover, the authors in [220] illustrates the effect of number of samples (*N)* on the total spectrum sensing error probability for perfect reporting channel under OR and Majority fusion rules for MEP threshold selection approach in fading environment. It has already been observed in Fig. 4.3 of Chapter 4 that at SNR= -20 dB, the Majority cooperative rule provides less total sensing error probability as compare to that of OR cooperative rule for same number of CUs (M=10). Moreover, the optimal spectrum sensing time and number of cooperative CUs are reported by Peh et al. [154] as well as Liu and Tan [136] to improve the throughput of CU. Further, the throughput enhancement is performed by Lu et al. [242] while considering adaptive spectrum sensing window for CR. Furthermore, the multi-objective optimization models are employed by Li and Liu [243] to maximize the throughput of CU by addressing joint CSS and power allocation technique in CRN. However, to maximize the throughput in multi-channel CSS, Fan and Jiang [244] have computed the total sensing duration in the CU's frame structure and have proposed the approach to allocate this optimal total sensing duration among different channels. Moreover, Tang et al. [245] have considered both the perfect and imperfect spectrum sensing channels and achieved the closed-form expression for normalized throughput in multi-PU cognitive radio network. In addition, they analyzed the effect of frame duration of CU and traffic pattern of PU on the normalized throughput. Moreover, Yadav et al. in [246] and Sharifi et al. in [247] have considered the multi-level hypothesis in CSS technique to improve the sensing accuracy of CU under the primary user emulation attack (PUEA). Since the energy consumption increases with the number of cooperative users therefore, Althunibat et al. [179], [248] have enhanced the energy efficiency (EE) by obtaining the optimal detection threshold at FC. Further, as EE is enhanced, there is degradation in the spectral efficiency (SE) and this trade-off between SE and EE is shown by Hu et al. in [249].

5.2.2 Imperfect reporting channels

In CRN, the CSS is promising technique to mitigate the effect of fading, shadowing and hidden node problems on sensing performance of CR however, it leads to degradation in EE of the CRN. In the context of energy efficiency, Bhowmick et al. [250] have presented the trade-off between the spectrum sensing time and throughput of CU while considering the imperfect sensing along with imperfect reporting channels under the Rayleigh fading environment. Further, in CSS, Najimi [251]has proposed a scheme to improve the energy efficiency of multichannel, multi-antenna CRN by optimizing the sensing time and node selection strategy in the imperfect reporting channel. Moreover, Zhao et al. [252] have considered multichannel CSS with imperfect reporting and has maximized the throughput of CU under the constraints on PU interference and sensing overhead without considering the mobility of CUs. In this context, Gahane et. al. [253] have shown the effect of CU mobility on the sensing performance in multi-antenna environment at CU in improved energy detector spectrum sensing (IEDSS). Moreover, the consideration of reporting time is of great importance as it affects the throughput of CRN therefore, Firouzabadi and Rabiei [254] have considered the multi-channel spectrum sensing and maximized the throughput of CRN by optimizing the sensing time, reporting time, sensing threshold and overall sensing plus reporting time in each sub-band.

5.2.3 Censoring approach

One of the main advantages of CSS technique is to increase the sensing performance of CU however, the energy consumption also increases with number of cooperative users. Therefore, this issue is more critical for battery powered users. In order to reduce the energy consumption in CSS technique, several researchers [240], [241] have employed censoring approach where the sensing decision of some limited CUs are transmitted over the reporting channels for energy saving point of view. However, Nallagonda et. al. [240] have suggested that when the reporting channels are deeply faded, the decision received at FC due to these channels will be erroneous, therefore the authors have employed censoring approach by preventing the reporting of sensing results through these erroneous reporting channels. However, Li et al. [241] have used censoring approach by transmitting decisions of only those CUs which has sensed active PUs on the channel. Subsequently, the authors in [255] have improved the throughput of network by reducing the signaling cost with censoring based CSS. Further, Sun et al. [97], Jiang et al [256], have employed censoring approach under the perfect/imperfect reporting channels and analyzed the detection performance of CU. However, in [241], Li et. al. have considered that each CU perform spectrum sensing through multiple antennas and send sensing results to FC through single antenna in imperfect sensing and reporting channel environment. Further, they have derived the expressions for false-alarm probability, detection probability and normalized throughput in the Rayleigh fading channels. In addition, Li et al. [241] have presented the variation in detection probability of CU with predefined threshold for different number of cooperative CUs and number of antennas (L) while employing censoring and non-censoring approaches. Further, they concluded that for the same number of CUs and number of antennas, the non-censoring approach outperformed censoring approach in terms of detection probability. However, in the non-censoring approach, degradation in detection probability (sensing tail problem) occurs due to high error probability in the reporting channel. Therefore, based on the above literature survey on censoring and perfect/imperfect reporting channel, in the the proposed work, we have derived the expressions for the total sensing error and throughput in the fading environment while employing perfect/imperfect reporting with the censoring and non-censoring approaches. In addition to this, we have analyzed the effect of CFAR and MEP threshold selection approaches.

In summary, the comparative analysis of various researchers' reported works with the proposed CRN system model in terms of CUs performance parameters has been presented in Table 5.1.

Table 5.1: Comparative study between different threshold selection approaches under different scenario.

Ref.e No.	Channel	Threshold Selection Approach	CSS	Reporting Channels	Censoring Approach	Throughput	Sensing Error Probability
[246]	Rayleigh	CDR	✓	✗	✗	✓	✗
[247]	Rayleigh	Predefined	✓	✗	✗	✗	✓
[257]	---	CDR	✓ (*K* out of *M*)	✗	✗	✓	✗
[258]	---	CFAR+CDR	✓ (OR)	✗	✗	✓	✗
[244]	---	CFAR+ CDR	✓ (AND)	✗	✗	✓	✗
[231]	Nakagami-*m*	CDR	✓ (Soft decision)	✗	✗	✓	✗
[179]	---	MEP	✓ (*K* out of *M*)	Imperfect	✗	✗	✓
[160]	---	Selected threshold maximized the throughput	✓	✗	✗	✓	✗
[259]	AWGN,	Double threshold	✓(OR)	Imperfect	✗	✓	✗
[260]	Rayleigh	Double threshold	✓(OR)	Imperfect	✗	✓	✓
[254]	---	-----	✓(OR)	Imperfect	✗	✓	✗
[250]	Rayleigh	Predefined	✓(OR, AND, Majority)	Imperfect	✗	✓	✗
[241]	Rayleigh	Predefined	✓ (OR rule)	Perfect, Imperfect	✓	✓	✗
Proposed	AWGN, Rayleigh, Nakagami-*m*	CFAR, MEP	✓(Majority)	Perfect, Imperfect	✓	✓	✓

5.3 Proposed System Model and Performance Analysis

In the proposed interweave based CRN system model, we have considered one PU transmitter, *M* cognitive users nodes and one fusion center (FC) as shown in Fig. 5.1(a). Each CU employs EDSS and sends the sensing results to FC via the reporting channels where the sensing results of CUs are affected due to different types of sensing channels (AWGN, Rayleigh or Nakagami-*m* fading). Further, the reporting channels are considered imperfect with different reporting error probabilities (P_e^r) and at FC, Majority cooperative rule is applied to take the global final decision about the presence/absence of PU on the channel. Moreover, the periodic frame structure of CU is assumed as shown in Fig. 5.1(b) where each CU senses the channel after T frame duration in which sensing plus reporting time (T_{sr}) is fixed.

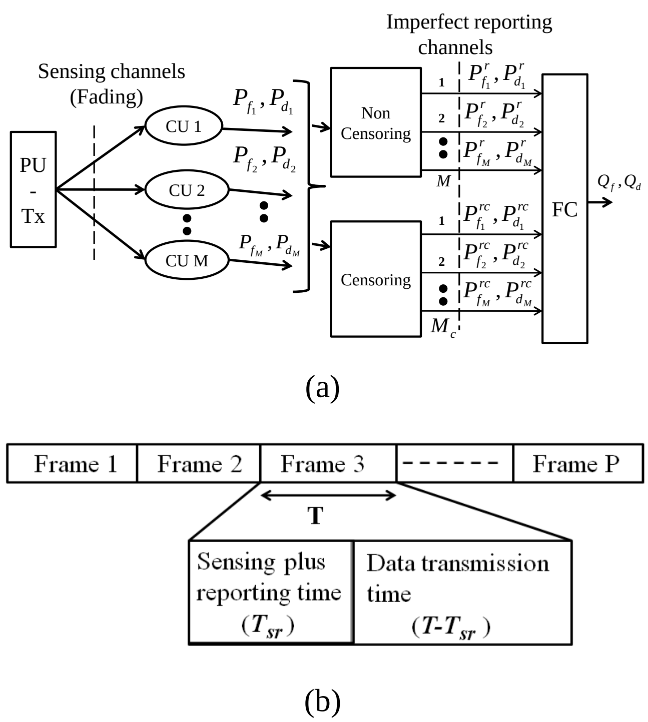


Figure 5.1: Schematic of the proposed cognitive radio network (a) system model and (b) frame structure.

The false-alarm and detection probabilities of i[th] CU is assumed to be P_{f_i} and P_{d_i}, where i=1,2…*M*. In addition, the sensing decision of each CU is sent to the FC via imperfect reporting channels. The censoring effect has been considered in the system model and comparison with the non-censoring based system has been made in the further sections of this chapter. In the non-censoring approach, the sensing results of all *M* cognitive users are sent to the FC for which the received false-alarm and detection probabilities of i[th] CU at FC due to the imperfect reporting is presented as: $P_{f_i}^{r}$ and $P_{d_i}^{r}$, respectively. However, for the censoring approach (where limited number of CUs send their sensing results to FC), FC receives sensing decision of only M_c (where, $M_c \leq$M) CUs for which the received false-alarm and detection probability of CU at FC with imperfect reporting is presented as: $P_{f_i}^{rc}$ and $P_{d_i}^{rc}$, respectively. In the proposed analysis presented further, we have assumed that each CU has same false-alarm and detection probability due to particular considered threshold detection approach and sensing decision of each CU is affected equally at FC in the reporting channel. Therefore, for simplicity, we have removed the subscript i e.g. P_{f_i} and P_{d_i} are represented simply as: P_f and P_d in further analysis and same for the other symbolic representations. The detailed discussion about the censoring approach and method for the computation of M_c is presented in Section 5.3.1.3.

5.3.1 Effect of reporting error and censoring on the sensing and throughput performance

5.3.1.1 Imperfect reporting channels

When the imperfect reporting channel is considered between CUs and FC, then spectrum sensing results of CUs received at FC is affected with the amount of error probability in the reporting channel (P_e^r). Each CU sends the sensing decision to FC in favor of either PU is active or idle on the channel. Moreover, following four possible scenarios are considered in Table 5.2 for which FC receives active status of PU either due to perfect/imperfect sensing at CU or due to perfect/imperfect reporting at FC.

Table 5.2: Detection and false alarm probabilities received at FC by CU for censoring and non-censoring approach.

Actual Status of PU	**Status of PU detected by CU**	**PU status received at FC (due to perfect /imperfect reporting)**	**Test statistics**	**Detection / false alarm probability of CU at FC (non-censoring)**	**Detection /false alarm probability of CU at FC (censoring)**
Active	Active	Active	P_d=(T>λ/H_1)	$P_d(1-P_e^r)$	$P_d(1-P_e^r)$
Active	Idle	Active		$(1-P_d)P_e^r$	0
Idle	Active	Active	P_f=(T>λ/H_0)	$P_f(1-P_e^r)$	$P_f(1-P_e^r)$
Idle	Idle	Active		$(1-P_f)P_e^r$	0

From Table 5.2, the false-alarm and detection probabilities received at FC by each CU under imperfect reporting channel, are given as:

$$P_f^r = (1 - P_f)P_e^r + P_f(1 - P_e^r) \tag{5.1}$$

$$P_d^r = (1 - P_d)P_e^r + P_d(1 - P_e^r) \tag{5.2}$$

where, P_f^r and P_d^r are received false-alarm and detection probability at FC by each CU under the imperfect reporting channels as already described in system model of the proposed scheme. Afterwards FC applies cooperative rules to take the global single decision about the status of licensed channel sensed by multiple CUs. Since the individual CU has particular false-alarm (P_f) and detection probability (P_d), and the FC measures the collective (total) false-alarm (Q_f^r) and detection probability (Q_d^r) by taking into account P_f^r and P_d^r of each CUs, which is represented as follows:

$$Q_f^r = \sum_{l=k}^{M} \binom{M}{l} \left(P_f^r\right)^l \left(1 - P_f^r\right)^{M-l} \tag{5.3}$$

$$Q_d^r = \sum_{l=k}^{M} \binom{M}{l} (P_d^r)^l (1 - P_d^r)^{M-l} \tag{5.4}$$

$$Q_e^r = Q_f^r + (1 - Q_d^r) \tag{5.5}$$

where, M and k are the total number of CUs and the number of CU terminals employed for cooperation, respectively. In the expressions (5.3) or (5.4), FC follows Majority cooperative rule at $k = M/2$. In addition, the total spectrum sensing error probability (Q_e^r) provides the measure for sensing performance of CU. Moreover, the throughput of CU under the imperfect reporting channels (R_I) after cooperation is given as:

$$R_I = P(H_0)\left(\frac{T - T_{sr}}{T}\right)\left(1 - Q_f^r\right)log_2(1 + \gamma_s) + P(H_1)\left(\frac{T - T_{sr}}{T}\right)(1 - Q_d^r)log_2\left(1 + \frac{\gamma_s}{1+\gamma}\right) \tag{5.6}$$

where the 1st and 2nd terms are the throughput of the CU in Case 1 and Case 2, respectively (as discussed in Chapter 3) for the imperfect reporting scenario.

5.3.1.2 Perfect reporting channel

In the perfect reporting channels, it is assumed that whatever the decision is sent by CUs over the reporting channel, is received same at FC. Therefore, it is a special case of imperfect reporting channel where P_e^r=0. Further, the total error probability and throughput of perfect reporting channel can be computed with the help of equation (5.5) and (5.6), respectively by placing P_e^r=0 in equation (5.1) and (5.2).

5.3.1.3 Censoring with imperfect reporting

In the censoring approach, the sensing results of only those CUs are sent to the FC through reporting channel who has detected the presence of PU on the channel (i.e. PU is active on the channel). Therefore, the number of cooperative users (M_c) who has sent the sensing results to FC with censoring approach are computed with the help of Table 5.2.

$$M_c = \lceil \left(M\left\{P(H_0)P_f + P(H_1)P_d\right\}\right) \rceil \tag{5.7}$$

where, $\lceil . \rceil$ indicate the ceiling function. Further in the censoring approach, the received false-alarm and detection probability at FC while considering imperfect reporting channels is computed from Table 5.2 and is given as:

$$P_f^{rc} = P_f(1 - P_e^r) \tag{5.8}$$

$$P_d^{rc} = P_d(1 - P_e^r) \tag{5.9}$$

Moreover, the total false-alarm (Q_f^{rc}), detection (Q_d^{rc}) and error (Q_e^{rc}) probabilities with censoring under the imperfect reporting channel is given as:

$$Q_f^{rc} = \sum_{l=k}^{M_c} \binom{M_c}{l} \left(P_f^{rc}\right)^l \left(1 - P_f^{rc}\right)^{M_c - l} \tag{5.10}$$

$$Q_d^{rc} = \sum_{l=k}^{M_c} \binom{M_c}{l} (P_d^{rc})^l (1 - P_d^{rc})^{M_c - l} \tag{5.11}$$

$$Q_e^{rc} = Q_f^{rc} + (1 - Q_d^{rc}) \tag{5.12}$$

In this context, the throughput of CU after cooperation with censoring is computed with the help of equation (5.6) by replacing Q_f^r with Q_f^{rc} and Q_d^r with Q_d^{rc} and expressed as follows:

$$R_{IC} = P(H_0)\left(\frac{T-T_{sr}}{T}\right)\left(1-Q_f^{rc}\right)log_2(1+\gamma_s) \; + P(H_1)\left(\frac{T-T_{sr}}{T}\right)\left(1-Q_d^{rc}\right)log_2\left(1+\frac{\gamma_s}{1+\gamma}\right) \quad (5.13)$$

where the 1st and 2nd terms are the throughput of the CU in Case 1 and Case 2, respectively (as discussed in Chapter 3) for imperfect reporting with censoring scenarios.

5.3.1.4 Censoring with perfect reporting

It is a special case of censoring with imperfect reporting where P_e^r=0. Further, in this scenario, the total sensing error probability and throughput of CU is computed with the help of equation (5.12) and equation (5.13), respectively, by placing P_e^r=0 in equation (5.8) and (5.9). Further, we have presented an Algorithm-1 to compute the throughput and total sensing error probability in the above considered scenario.

Algorithm-1: Total sensing error probability & throughput computation

Input: Reporting channel (RC) ={Perfect, Imperfect}, Threshold selection approach (TSA) = {CFAR, MEP}, Sensing channel (SC) ={AWGN, Rayleigh, Nakagami-m},Event sequence (ES) = {Censoring, Non-censoring}, γ

Output: R and Q_e

Initialization: N, σ_n^2,P_{f_fixed} , γ_s, M , T, T_{sr} , $P(H_0)$,γ_{set} = [- 20,-8], $p \epsilon (0,1]$
if $\gamma \epsilon \gamma_{set}$
  if RC = = Imperfect
    $P_e^r \leftarrow p$
  else
    $P_e^r \leftarrow 0$
  end if
  if TSA = = CFAR
    find the value of λ_f using (3.6)
    $\lambda \leftarrow \lambda_f$
    Compute P_f using (2.2)
    if SC = =AWGN
      compute P_d using (2.3)
    else if SC = = Rayleigh
      compute $\overline{P_d^{ray}}$ using (3.3)
    else
      compute $\overline{P_d^{Naka}}$ using (3.5)
    end if
  else
  if SC = = AWGN
    find out $\lambda_e(AWGN)$ using (2.8)
      $\lambda \leftarrow \lambda_e$
    compute P_f and P_d using (2.2) and (2.3) respectively
  else if SC = = Rayleigh
    find out $\lambda_e(Ray)$ using (3.7)
      $\lambda \leftarrow \lambda_e(Ray)$
    compute P_f and $\overline{P_d^{ray}}$ using (2.2) and (3.3) respectively

else

find out $\lambda_e(Naka)$ using (3.8)

$\lambda \leftarrow \lambda_e(Naka)$

compute P_f and $\overline{P_d^{Naka}}$ using (2.2) and (3.5) respectively

end if

end if

if ES = = Censoring

compute M_c using (5.7)

find P_f^{rc} from (5.8) and P_d^{rc} using (5.9)

find Q_e^{rc} from (5.12) and R_{IC} using (5.13)

else

find P_f^{r} from (5.1) and P_d^{r} using (5.2)

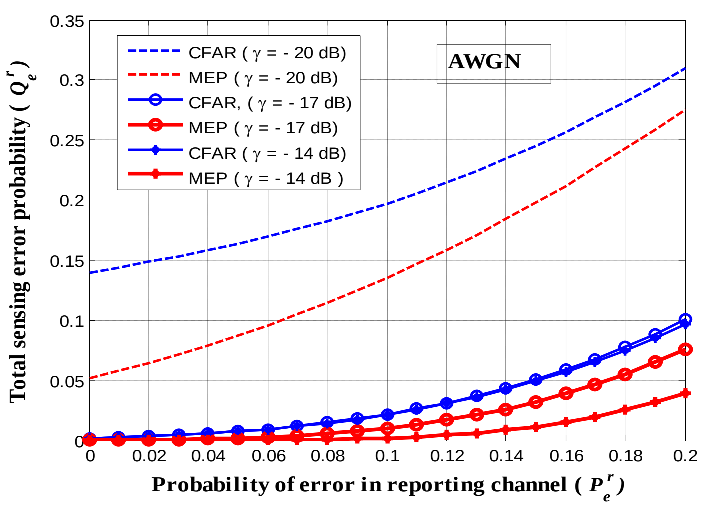
find Q_e^{r} from (5.5) and R_I using (5.6)

end if

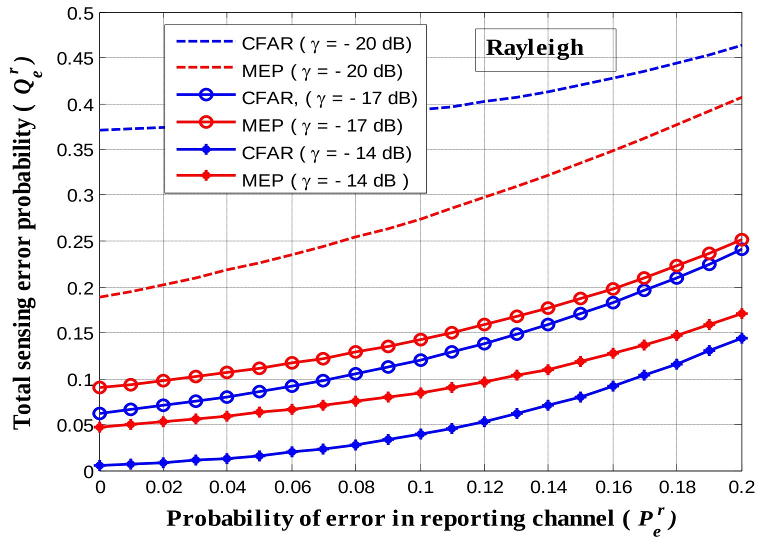
end if

5.4 Result and Discussion

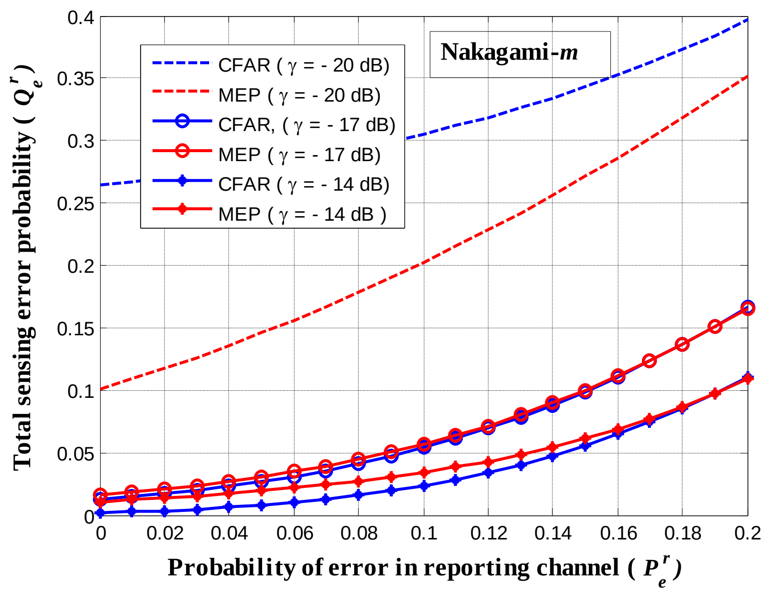
In this section, we have illustrated numerically simulated results of the proposed CRN system model. In the proposed system model, we have considered CSS technique in which FC employed Majority cooperative rule. Further, the parameters employed for simulation of the results are considered same as that in Chapter 4. Moreover, the variation in total sensing error probability (Q_e^r) of CU with different probability of error in reporting channel (P_e^r) while employing CFAR and MEP threshold selection approaches at different SNR is illustrated in Fig. 5.2(a), Fig. 5.2(b) and Fig. 5.2(c) for AWGN, Rayleigh and Nakagami-*m* channels, respectively.



(a)



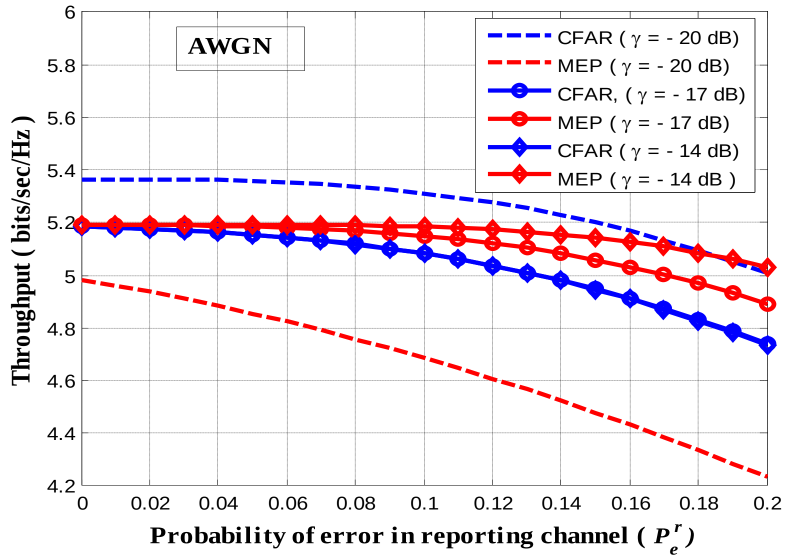
(b)



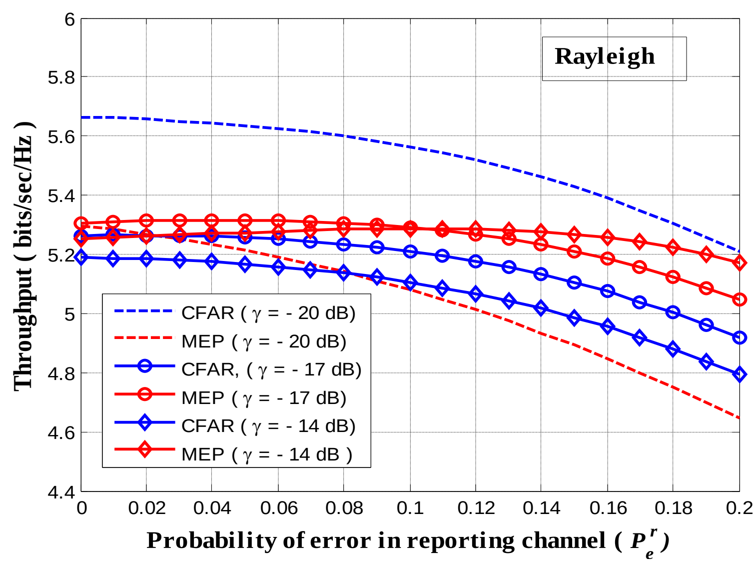
(c)

Figure 5.2: Variation in total sensing error probability with probability of error in reporting channel for different threshold selection approaches under (a) AWGN (b) Rayleigh, and (c) Nakagami-*m* fading channel.

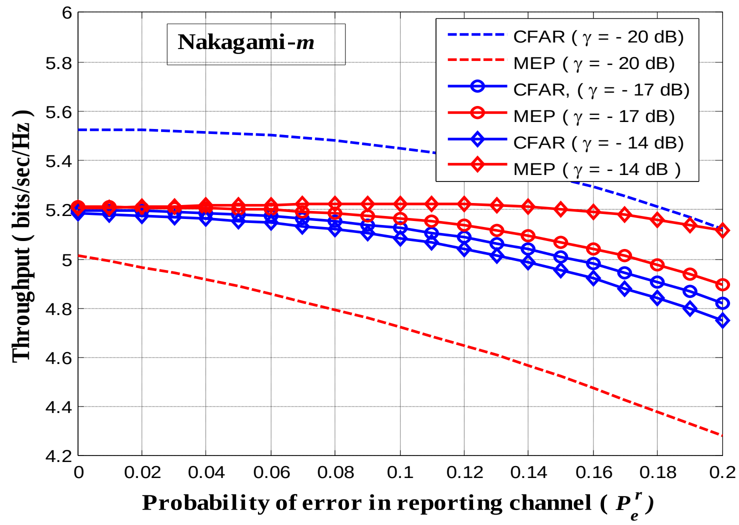
Further, the variation in throughput of CU with probability of error in reporting channel while employing both CFAR and MEP threshold selection approaches at different SNR for AWGN, Rayleigh and Nakagami-*m* channels are presented in Fig. 5.3(a), Fig. 5.3(b) and Fig. 5.3(c), respectively. From Fig. 5.3, it is clear that under all channels for fixed SNR, the throughput of CU decreases with increases in P_e^r for both CFAR and MEP approaches. As already described in the proposed system model (presented in section 5.3.1), the total throughput is computed with the combination of throughputs of two terms. With the increase in reporting error P_e^r, the throughput of Case-1 decreases and it increases for Case-2. However, the effect of decrease in throughput of 1st term of equation (5.6) is more dominating than that increase of throughput of 2nd term, resulting in overall throughput reduction with increase in P_e^r. Further, under all the considered channels with increase in SNR, the throughput of CU decreases for CFAR and increases for MEP at a particular value of P_e^r.



(a)



(b)

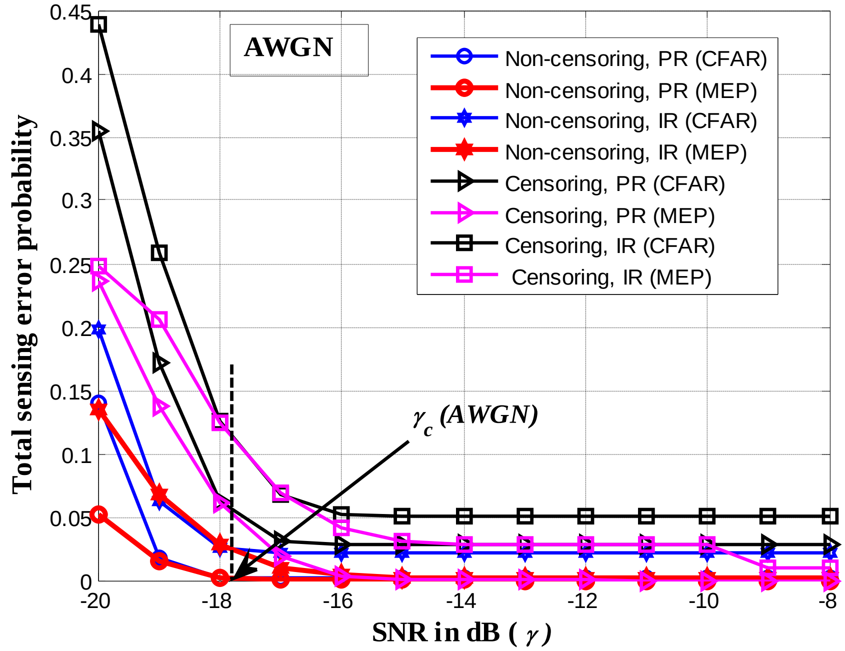


(c)

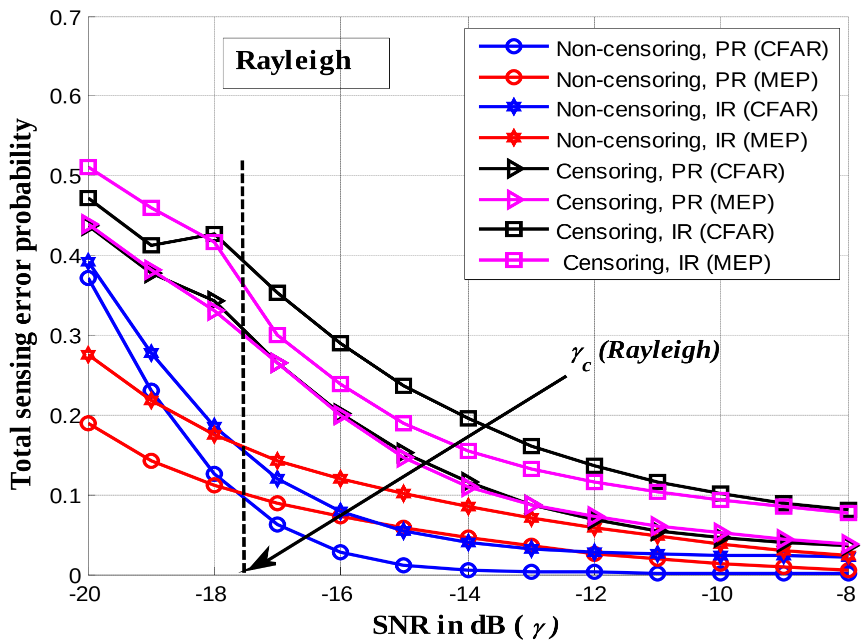
Figure 5.3: Variation in throughput with probability of error in reporting channel for different threshold selection approaches in CSS technique under (a) AWGN, (b) Rayleigh, and (c) Nakagami-*m* fading channel.

It is further depicted that the increased SNR provide better total detection probability (Q_d^r) and from equation (5.6) it is clear that the increase in Q_d^r results reduction of throughput. In addition, it is illustrated from Fig. 5.3(a) to Fig. 5.3(c), under all the considered channels, the throughput is enhanced with CFAR approach for $\gamma \leq \gamma_c$ (γ= -20dB) while for $\gamma > \gamma_c$ (γ = -17dB or -14dB) it is maximized with MEP approach at a fixed P_e^r. The significantly high throughput with CFAR in comparison to MEP at $\gamma \leq \gamma_c$ is resulting due to increased value of R_1 and R_2, whereas increased R_1 with MEP results higher throughput at $\gamma > \gamma_c$ as compare to that of CFAR.

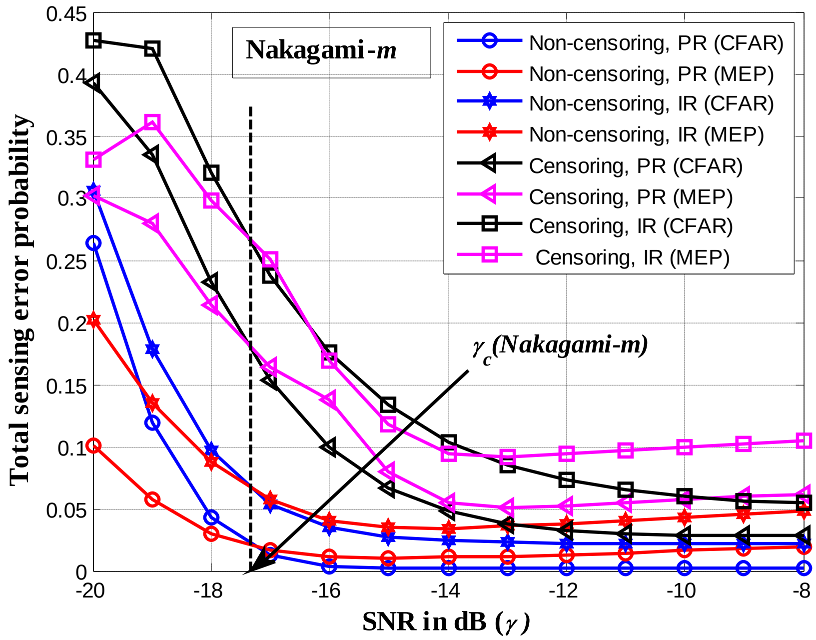
Further, in Fig. 5.4(a) to Fig. 5.4(c),we have illustrated the variation in total sensing error probability with γ for AWGN, Rayleigh and Nakagami-*m* channels while employing CFAR/MEP threshold selection approaches in the non-censoring/censoring scenarios under perfect/imperfect reporting (PR/IR). For the non-censoring scenario, the effect of γ and reporting error on total spectrum sensing error probability is already presented in Fig. 5.2. Moreover, for the fixed value of γ while employing either CFAR or MEP approach, the total sensing error probability is high in censoring approach as compare to that of the non-censoring approach. This is because at FC, the false-alarm and miss-detection probability is high in censoring approach as compared to that of the non-censoring approach. Moreover, from Fig. 5.4 it is clear that there is switching between CFAR and MEP threshold approach to achieve less total sensing error probability with variation in γ in censoring scenario under either PR or IR. This is because from equation (5.7)-(5.12), the total sensing error probability changes with number of cooperative CUs in censoring (M_c) and Q_f and Q_m, where M_c, P_f and P_m varies with γ and threshold selection approaches.



(a)



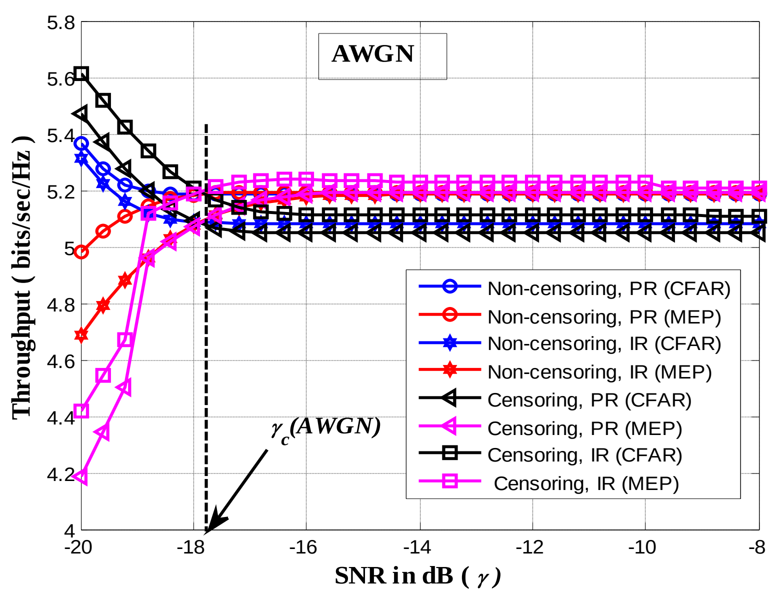
(b)



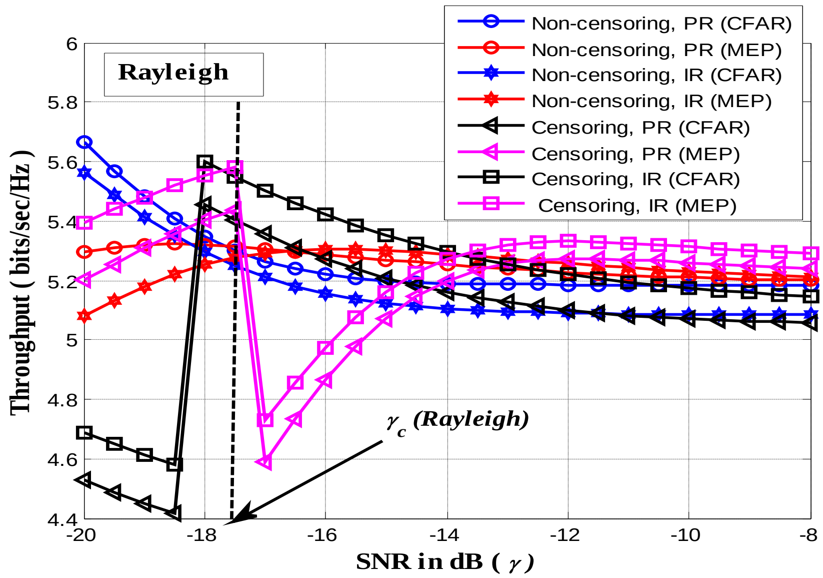
(c)

Figure 5.4: Variation in total sensing error probability with SNR for different threshold selection approaches at imperfect reporting error (P_e^r) of 0.1 for (a) AWGN, (b) Rayleigh and (c) Nakagami-*m* fading channel.

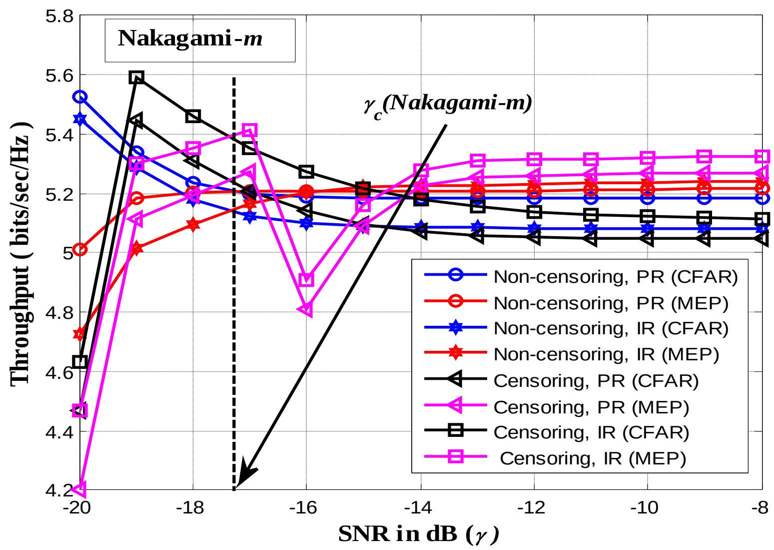
Moreover, Fig. 5.5(a), Fig. 5.5(b) and Fig. 5.5(c) demonstrate the variation in throughput with SNR for AWGN, Rayleigh and Nakagami-*m* channels, respectively while employing CFAR/MEP threshold selection approaches under the non-censoring/censoring and perfect/imperfect reporting (PR/IR).



(a)



(b)



(c)

Figure 5.5: Variation in throughput with SNR for different threshold selection approaches under perfect and imperfect reporting ($P_e^r = 0.1$)channel for (a) AWGN, (b) Rayleigh and (c) Nakagami-m fading.

It is clear from Fig. 5.5 that in the non-censoring scenario, initially the throughput decreases with increase in SNR for CFAR approach however it increases in MEP approach and then becomes nearly constant. From equation (5.6), it is clear that the throughput is high for low values of Q_f^r and Q_d^r.Therefore, with increase in γ, initially the throughput reduction with CFAR is due to Q_d^r increase and afterwards Q_d^r remains constant causing constant throughput with increase of γ.

Whereas in MEP approach, initially with increase in γ, there is reduction in Q_f^r and increase in Q_d^r causing throughput increase due to more prominent effect of decreased Q_f^r and afterwards throughput is nearly constant due to minor change in Q_f^r and Q_d^r with change in γ. When further comparison is made between CFAR and MEP approaches at $\gamma \leq \gamma_c$, the throughput is higher with CFAR as compare to that of MEP approach since the false-alarm and miss-detection probabilities are less in CFAR. In addition, at $\gamma \leq \gamma_c$ in the non-censoring scenario, the throughput is higher with perfect reporting (PR) channel as compare to that of the imperfect reporting (IR) while employing MEP threshold selection approach. The higher throughput with perfect reporting in MEP approach is achieved because the throughput of Case-1 of equation (5.13) is more and of Case-2 is less in perfect reporting as compare to that of the imperfect reporting. However, the total throughput is affected more by Case-1 throughput, resulting in increased throughput with perfect reporting. Further, in the censoring scenario, the throughput of imperfect reporting is higher than that of the perfect reporting channel while employing any threshold selection approaches. It is because throughput of both cases are high in imperfect reporting as compare to that of the perfect reporting for censoring scenario.

Moreover, from Fig. 5.5, it is clear that in the censoring scenario in order to yield high throughput for all γ, there is need of switching between CFAR and MEP threshold selection approaches for both the perfect and imperfect reporting channels. This is because with variation in γ under the censoring scenario, CFAR and MEP threshold selection approaches varies with the number of CUs (M_c) and hence accordingly Q_f and Q_d values are updated at FC. This requirement of γ and threshold selection approach on M_c, Q_f, Q_d is also obvious from equation (5.7) - (5.12).

5.5 Conclusion

In this chapter, we have illustrated the effect of CFAR and MEP threshold selection approaches on the total sensing error probability and throughput of CU under the perfect/imperfect reporting and censoring/non-censoring based CRN. From the results of non-censoring and imperfect reporting channel scenario, we have concluded that in the Rayleigh and Nakagami-*m* fading channels when $\gamma \leq \gamma_c$, the MEP approach has provided better total sensing error probability performance. However, for $\gamma > \gamma_c$, the CFAR approach is better. Further, for the throughput enhancement, reverse is true i.e. for $\gamma \leq \gamma_c$, the throughput is significantly higher with CFAR approach however for $\gamma > \gamma_c$, its value is higher with MEP approach. Hence, there exist a trade-off between sensing error probability and throughput with threshold selection approaches. The censoring scenario has although reduced the sensing overhead information but at the cost of increased total sensing error probability as compare to that of the non-censoring scenario due to a smaller number of users' reporting to FC. In the censoring scenario, we have to change the CFAR and MEP threshold selection approaches according to γ to enhance the throughput and decrease the sensing error probability as illustrated in the results. Further, in this chapter, we have only employed single cooperative rule at all SNR, however to minimize the sensing error, it is required to vary the cooperative rule according to SNR, which is explored in Chapter 6.

CHAPTER 6

OPTIMIZING COOPERATIVE RULES WITH THRESHOLD IN CRN

6.1 Introduction and Related Work

Various researchers have tried to improve the spectrum sensing performance of CU in terms of throughput, sensing error and energy efficiency by employing different approaches. Firouzabadi and Rabiei [254] have optimized the spectrum sensing threshold (λ) along with sensing and reporting time in order to maximize the throughput. However, Zhang et. al. [186] have minimized the sensing error by adapting the cooperative rule at FC (i.e. finding the optimal value of *K* in *K*-out of *M* rule) according to selected spectrum sensing threshold value. Further, their analysis is only limited to perfect reporting channel with single antenna without considering the licensed channel's idle and active probability. Recently, Li et. al. [241] have analyzed the effect of multiple antennas, reporting error probability and number of CUs on probability of false-alarm (P_f) and probability of detection (P_d) individually at significantly higher SNR with OR cooperative rule for predefined value of threshold (λ). However, the proposed analysis was lacking in context of total sensing error [241].

Moreover, in CSS, with increase in the number of CUs the sensing error is reduced but at the cost of increased energy consumption [224]. To increase the life time of battery powered CU in CRN, the energy consumption should be minimized. In this context, Maleki et.al. [164] have employed censoring and sleeping schemes simultaneously, Najimi et. al. in [172] initiated best sensing CU nodes, and Eryigit et.al. in [261]have minimized the energy consumed in sensing. Further, in the multi-antenna and imperfect reporting environment, the energy efficiency (EE) is maximized in [251] by properly selecting the duration of spectrum sensing time and afterwards selecting the best CUs to report to FC about sensing decision. Moreover, motivated by the above discussed related work performed by various researchers in the direction to minimizing the sensing error and maximizing the energy efficiency, the authors contributions in this chapter are as follows.

- We came across the expressions for spectrum sensing error in CSS by considering the effect of multiple antennas, reporting error and idle/active channel's probability while employing different threshold selection approaches. Further, we have derived the expressions for optimal value of K in K-out-of-M fusion rule at FC to minimize the sensing error.

- It is shown that by employing the optimal rule at FC, the sensing error is minimized with respect to Majority fusion rule.
- Further, the censoring approach is employed to improve the energy efficiency, and the closed-form expressions are derived for the optimal number of CUs at FC.
- Moreover, the energy efficiency comparison is also illustrated under the non-censoring and censoring scenario for CFAR and MEP threshold selection approaches when the respective optimal value of K is employed at FC in order to reduce the sensing error. Further, from the results, it is depicted that the energy efficiency is significantly higher in the censoring scenario as compare to that of the non-censoring scenario.

6.2 Proposed System Model

In the proposed CRN system model, we have considered single PU transmitter (PU-Tx), M CU nodes and one fusion center (FC) as shown in Fig. 6.1. Each CU consists of L_a number of antennas and has employed EDSS for spectrum sensing. Further, the spectrum sensing decision of each CU is sent to the FC via the censoring and non-censoring approaches. In the censoring approach, it is considered that only M_c ($\leq M$) CUs send their sensing results to FC via the imperfect reporting channels where the imperfect reporting error probability is given by P_e^r.

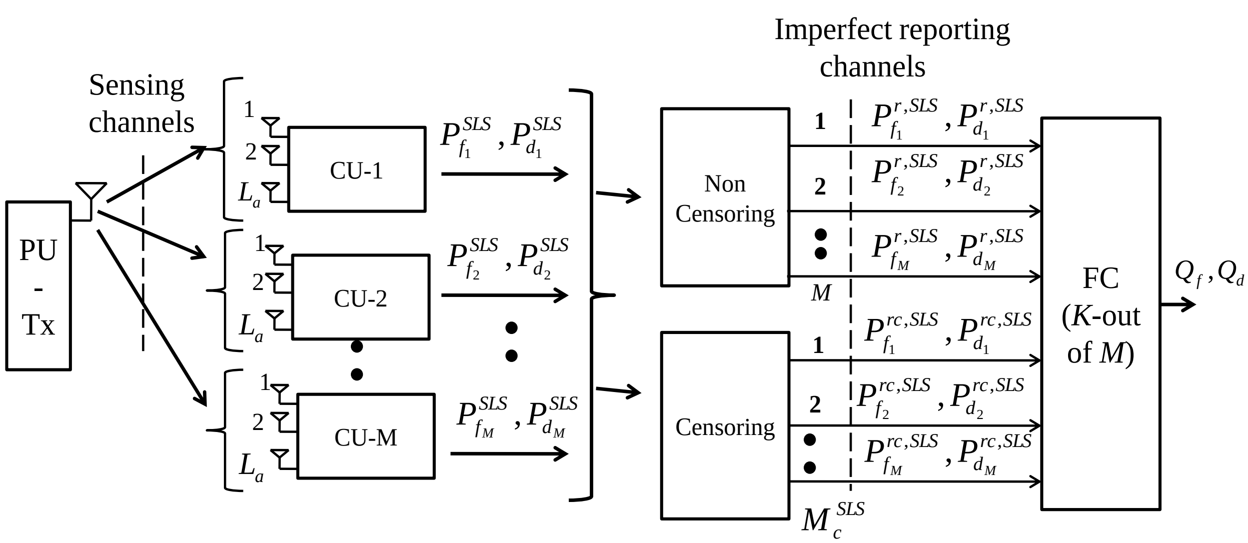


Figure 6.1: Schematic of the proposed cognitive radio network system model

Further, the description of censoring and the method for computation of M_c is presented. Moreover, in the non-censoring scenario, all M CUs report their sensing decision to the FC via the imperfect reporting channels. Further, at FC, the optimal value of *K* is computed in *K*-out-of-*M* rule to take the global final decision about the status of licensed/PU channels after reporting by CUs through the censoring or non-censoring approaches. In addition, we have assumed that each CU has same value of $P_{f_i}^{SLS}$ and $P_{d_i}^{SLS}$ and the spectrum sensing decision of each CU is affected equally in reporting channel via censoring or non-censoring approaches. Therefore, we have removed the subscript i e.g. $P_{f_i}^{SLS}$ and $P_{d_i}^{SLS}$ are demonstrated simply as: P_f^{SLS} and P_d^{SLS} in further analysis and same for the other symbolic representations.

6.3 Performance Analysis of Proposed System Model

In this section, we have derived the expressions for spectrum sensing error and energy efficiency in CSS technique under the non-censoring and censoring approaches in AWGN channel. The analysis has been performed while taking into consideration following parameters: the number of antennas of CUs, sensing threshold approach, reporting error, and idle/active state probability of the licensed channel. The spectrum sensing threshold approaches which are employed in this section for computation of λ (λ_f or λ_e) are considered to be CFAR and MEP.

6.3.1 Multiple antennas

It is reported in the available literature [220], [241], [262] that the multiple antennas are employed at CU for receiver diversity in order to yield the detection performance improvement. Atapattu et. al. in [220] have employed the square law combining (SLC) and square law selection (SLS) receiver diversity techniques for SS in CRN. In the proposed analysis, we have assumed SLS based combining schemes due to its least complexity. In SLS, the maximum SNR branch (γ_j) of multiple antennas is selected by each CU such as:

$$\gamma^{SLS} = \max_{j=1,2,\ldots L_a} \gamma_j \tag{6.1}$$

where, L_a denotes the number of antennas at each CU. Therefore, the false-alarm probability and detection probability at each CU under SLS can be computed with the help of equation (6.1) and is given as [241]:

$$P_f^{SLS} = 1 - Prob.(\gamma^{SLS} < \lambda | H_0) \quad (6.2)$$

$$P_d^{SLS} = Prob.(\gamma^{SLS} \geq \lambda | H_1) \quad (6.3)$$

Further, the equations (6.2) and (6.3) can also be written as:

$$P_f^{SLS} = 1 - \left(1 - P_f\right)^{L_a} \quad (6.4)$$

$$P_d^{SLS} = 1 - (1 - P_d)^{L_a} \quad (6.5)$$

where P_f and P_d are the false-alarm and detection probabilities, respectively of CU when CU employed single antenna.

6.3.2 Non-censoring approach with imperfect reporting

The spectrum sensing results of each CU which is transmitted through imperfect reporting channels can be received at FC with sensing error. Moreover, there are four probable scenarios considered as presented in Table 6.1 where FC receives the sensing results from CUs in favour of active state of PU channel.

Table 6.1: The false-alarm and detection probabilities of CU received at FC under the non-censoring and censoring approaches.

True state of PU channel	**State of PU channel detected by CU**	**PU channel state received at FC**	**Detection / false-alarm probability of CU at FC under imperfect reporting with non-censoring**	**Detection / false-alarm probability of CU at FC under imperfect reporting with censoring**
Busy	Busy	Busy	$P_d^{SLS}(1 - P_e^r)$	$P_d^{SLS}(1 - P_e^r)$
Busy	Free	Busy	$(1\text{-}P_d^{SLS})P_e^r$	0
Free	Busy	Busy	$P_f^{SLS}(1 - P_e^r)$	$P_f^{SLS}(1 - P_e^r)$
Free	Free	Busy	$(1 - P_f^{SLS})P_e^r$	0

These scenarios are either due to the perfect or imperfect spectrum sensing and reporting. The false-alarm ($P_f^{r,SLS}$) and detection probabilities ($P_d^{r,SLS}$) received at FC due to each CU under the imperfect reporting channel can be computed with the help of Table 6.1 and are expressed as:

$$P_f^{r,SLS} = (1 - P_f^{SLS})P_e^r + P_f^{SLS}(1 - P_e^r) \quad (6.6)$$

$$P_d^{r,SLS} = (1 - P_d^{SLS})P_e^r + P_d^{SLS}(1 - P_e^r) \quad (6.7)$$

$$P_m^{r,SLS} = 1 - P_d^{r,SLS} \quad (6.8)$$

where, P_e^r is the reporting error probability, $P_f^{r,SLS}$,$P_d^{r,SLS}$and $P_m^{r,SLS}$are the false-alarm, detection and miss-detection probabilities received at FC due to the imperfect reporting channels when each CU employed multiple antennas. Afterwards, FC applies *K*-out-of-*M* cooperative rules to take the global decision about the status of PU channel. Since in the non-censoring approach, all M CUs report to the FC therefore, the total false-alarm ($Q_f^{r,SLS}$) and detection probabilities ($Q_d^{r,SLS}$) at FC is represented as follows:

$$Q_f^{r,SLS} = \sum_{l=k}^{M} \binom{M}{l} \left(P_f^{r,SLS}\right)^l \left(1 - P_f^{r,SLS}\right)^{M-l} \tag{6.9}$$

$$Q_d^{r,SLS} = \sum_{l=k}^{M} \binom{M}{l} \left(P_d^{r,SLS}\right)^l \left(1 - P_d^{r,SLS}\right)^{M-l} \tag{6.10}$$

$$Q_e^{r,SLS} = P(H_0)Q_f^{r,SLS} + P(H_1)(1 - Q_d^{r,SLS}) \tag{6.11}$$

where, M is the total number of CUs, *k is* the number of CU terminals employed for cooperation, and $Q_e^{r,SLS}$ is the sensing error after cooperation in CSS.

6.3.3 Censoring approach with imperfect reporting

In the censoring scenario, the spectrum sensing results of only reliable CUs are sent to the FC [240]. In the proposed analysis, we have assumed that the CUs detecting the active state of PU channel send their sensing results to FC. Therefore, firstly we compute the number of cooperative CUs (M_c^{SLS}) sending the spectrum sensing results to FC with the help of Table 6.1 as given below [241]:

$$M_c^{SLS} = \lceil \left(M\left\{P(H_0)P_f^{SLS} + P(H_1)P_d^{SLS}\right\}\right) \rceil \tag{6.12}$$

where, $\lceil . \rceil$ indicate the ceiling function and $M_c^{SLS} \leq M$. In addition, the received false-alarm and detection probabilities at FC while considering the imperfect reporting channels can be determined from Table 6.1 and are given as:

$$P_f^{rc,SLS} = P_f^{SLS}(1 - P_e^r) \tag{6.13}$$

$$P_d^{rc,SLS} = P_d^{SLS}(1 - P_e^r) \tag{6.14}$$

$$P_m^{rc,SLS} = 1 - P_d^{rc,SLS} \tag{6.15}$$

Moreover, the false-alarm ($Q_f^{rc,SLS}$), detection ($Q_d^{rc,SLS}$) and error probability ($Q_e^{rc,SLS}$) at FC with censoring approach under the imperfect reporting channels are computed as:

$$Q_f^{rc,SLS} = \sum_{l=k}^{M_c^{SLS}} \binom{M_c^{SLS}}{l} \left(P_f^{rc,SLS}\right)^l \left(1 - P_f^{rc,SLS}\right)^{M_c - l} \tag{6.16}$$

$$Q_d^{rc,SLS} = \sum_{l=k}^{M_c^{SLS}} \binom{M_c^{SLS}}{l} \left(P_d^{rc,SLS}\right)^l \left(1 - P_d^{rc,SLS}\right)^{M_c - l} \tag{6.17}$$

$$Q_e^{rc,SLS} = P(H_0)Q_f^{rc,SLS} + P(H_1)(1 - Q_d^{rc,SLS}) \tag{6.18}$$

Further, for the perfect reporting channels, the spectrum sensing error under non-censoring/censoring approaches at FC can be computed from equations (6.11) and (6.18), respectively by placing P_e^r=0 in equations (6.6)-(6.7) and (6.13)-(6.14).

6.3.4 Energy efficiency

For the computation of energy efficiency (EE), we have presented the frame structure of CRN for CSS in Fig. 6.2. In a chosen band of spectrum, all CUs (*M*) sense the channel simultaneously for T_s sensing duration. Subsequently, the sensing decision of each CU is reported to the FC during T_R with time division multiple access scheme.

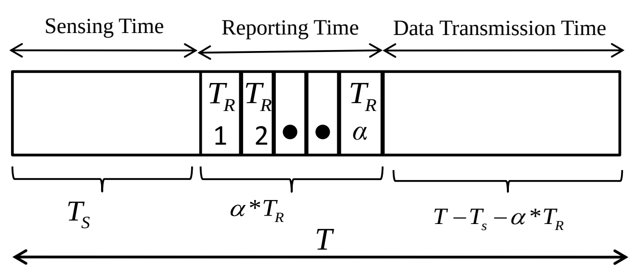


Figure 6.2: Frame structure of CSS CRN.

Therefore, the total reporting time equals to αT_R, where α is the number of CUs reporting the spectrum sensing decision to FC. In the non-censoring scenario, α will equate to *M* however, it is M_c for the censoring scenario. Consequently, the data transmission time will be: $T - T_s - \alpha T_R$. Further, EE is computed as the ratio of average number of bits transmitted successfully (C) to the average energy consumed (E_{Total}) [263].

With the help of Fig. 6.2, we observed that CRN frame structure has following three phases: the spectrum sensing, reporting, and transmitting phases. There will be power consumption by the circuit components and by the terminal in the idle phase also, which we have neglected in proposed analysis. Therefore, the energy is consumed only in the spectrum sensing, reporting and transmission which are expressed as: E_S, E_R, and E_T, respectively. Moreover, these values can be computed as: $E_s = P_S T_S$, $E_R = P_R T_R$, $E_T = P_T(T - T_S - T_R)$, where, P_S, P_R and P_T are the power consumed in the spectrum sensing, reporting and data transmission phases of the single frame structure of CRN. Further, in Table 6.2 we have considered four cases on the basis of actual and predicted states by CU of licensed channels.

Table 6.2: Energy efficiency metric

Case	**Actual state of licensed channel**	**Predicted state of licensed channel by CU**	**Probability of respective case being true (*p*)**	**Data transmission**	**Successful transmitted data (Bits)**	**Energy consumed in Joule (with/without censoring)**
1	Idle	Idle	$p_1 = P(H_0)(1 - P_f)$	Yes	$C = p_1(T - T_s - \alpha * T_R)R$	$E_1 = M * E_s + \alpha * E_R + E_T$
2	Idle	Busy	$p_2 = P(H_0)(P_f)$	No	0	$E_2 = M * E_s + \alpha * E_R$
3	Busy	Idle	$p_3 = P(H_1)(1 - P_d)$	Yes	0	$E_3 = M * E_s + \alpha * E_R + E_T$
4	Busy	Busy	$p_4 = P(H_1)(P_d)$	No	0	$E_4 = M * E_s + \alpha * E_R$

From Table 6.2, it is clear that the successful data transmission occurs only in Case-1, however CU consumed energy in all four cases. Therefore, from the frame structure of Fig. 6.2, it is clear that all M CUs sense the channels for T_S duration therefore the total energy consumed in spectrum sensing is: $M * E_s$, and the total energy consumed in reporting phase is: $\alpha * E_R$ where α CUs report to the FC. Further, in Case-2 and Case-4 of the predicted state by CU of the licensed channel is active therefore, CU will not transmit the data and hence no energy is consumed in transmission for Case-2 and Case-4. Therefore, E_{Total} can be computed as:

$$E_{Total} = p_1 E_1 + p_2 E_2 + p_3 E_3 + p_4 E_4 \tag{6.19}$$

and average number of successfully transmitted bits are:

$$C = P(H_0)(1 - P_f)(T - T_s - \alpha * T_R)R \tag{6.20}$$

where, R is the throughput of secondary link and can be computed as: $R = log_2(1+\gamma_s)$, where γ_s is the SNR of the link between CU transmitter and CU receiver. Further, EE can be computed as:

$$EE = \frac{P(H_0)(1-P_f)(T-T_s-\alpha * T_R)R}{p_1E_1+p_2E_2+p_3E_3+p_4E_4} \tag{6.21}$$

6.3.5 Optimization of voting rule in CSS

In this section, we have presented the optimal value of *K* to minimize the sensing error when *K*-out-of-*M* rule is employed at FC under the non-censoring and censoring approaches. Zhang et. al. [186] have also presented the optimal value of *K* for predefined value of threshold, however without considering the effect of licensed channel's idle/active probability, multi-antenna effect, and reporting error probability. However, we have computed threshold values at different SNR with CFAR and MEP threshold selection approaches and achieved the optimal *K* at different SNR by considering all above parameters with censoring, which is significant contribution with respect to Zhang et. al. [186].

6.3.5.1 Non-censoring scenario with multiple antennas under imperfect reporting

In this scenario, the spectrum sensing error with CSS technique is given as:$Q_e^{r,SLS}$ from (6.11). The main objective is the computation of optimal *K*: $\mathrm{K_{opt}} = \arg^{\min}_{\mathrm{K}} \mathrm{Q_e^{r,SLS}}(K)$ which is achieved when $\frac{\partial \mathrm{Q_e^{r,SLS}}(\mathrm{K})}{\partial \mathrm{K}} = 0$. Therefore,

$$\frac{\partial \mathrm{Q_e^{r,SLS}}(\mathrm{K})}{\partial \mathrm{K}} = \mathrm{Q_e^{r,SLS}}(\mathrm{K}+1) - \mathrm{Q_e^{r,SLS}}(\mathrm{K}) \tag{6.22}$$

After finding the value of $\mathrm{Q_e^{r,SLS}}(\mathrm{K}+1)$ and $\mathrm{Q_e^{r,SLS}}(\mathrm{K})$ from (6.11), we get:

$$\mathrm{Q_e^{r,SLS}}(\mathrm{K}+1) = \mathrm{P(H_0)} \sum_{\mathrm{l=k+1}}^{\mathrm{M}} \binom{\mathrm{M}}{\mathrm{l}} \left(\mathrm{P_f^{r,SLS}}\right)^{\mathrm{l}} \left(1-\mathrm{P_f^{r,SLS}}\right)^{\mathrm{M-l}} + \mathrm{P(H_1)} \left\{1 - \sum_{\mathrm{l=k+1}}^{\mathrm{M}} \binom{\mathrm{M}}{\mathrm{l}} \left(\mathrm{P_d^{r,SLS}}\right)^{\mathrm{l}} \left(1-\mathrm{P_d^{r,SLS}}\right)^{\mathrm{M-l}}\right\} \tag{6.23}$$

$$\mathrm{Q_e^{r,SLS}}(\mathrm{K}) = \mathrm{P(H_0)} \sum_{\mathrm{l=k}}^{\mathrm{M}} \binom{\mathrm{M}}{\mathrm{l}} \left(\mathrm{P_f^{r,SLS}}\right)^{\mathrm{l}} \left(1-\mathrm{P_f^{r,SLS}}\right)^{\mathrm{M-l}} + \mathrm{P(H_1)} \left\{1 - \sum_{\mathrm{l=k}}^{\mathrm{M}} \binom{\mathrm{M}}{\mathrm{l}} \left(\mathrm{P_d^{r,SLS}}\right)^{\mathrm{l}} \left(1-\mathrm{P_d^{r,SLS}}\right)^{\mathrm{M-l}}\right\} \tag{6.24}$$

Compute (6.22) by using (6.23) and (6.24), we get:

$$\frac{\partial Q_e^{r,SLS}(K)}{\partial K} = \binom{M}{K}\left\{P(H_1)\left(1-P_m^{r,SLS}\right)^K\left(P_m^{r,SLS}\right)^{M-K} - P(H_0)\left(P_f^{r,SLS}\right)^K\left(1-P_f^{r,SLS}\right)^{M-K}\right\} \tag{6.25}$$

For finding the value of K at which sensing error is minimize, put $\frac{\partial Q_e^{r,SLS}(K)}{\partial K} = 0$, i.e.

$$\binom{M}{K}\left\{P(H_1)\left(1-P_m^{r,SLS}\right)^K\left(P_m^{r,SLS}\right)^{M-K} - P(H_0)\left(P_f^{r,SLS}\right)^K\left(1-P_f^{r,SLS}\right)^{M-K}\right\} = 0 \tag{6.26}$$

After solving (6.26) we get the solution for *K*, which is given as:

$$K = \frac{M * log\left(\frac{P_m^{r,SLS}}{1-P_f^{r,SLS}}\right) + log\left(\frac{P(H_1)}{P(H_0)}\right)}{log\frac{\left(P_f^{r,SLS}\right)\left(P_m^{r,SLS}\right)}{\left(1-P_f^{r,SLS}\right)\left(1-P_m^{r,SLS}\right)}} \tag{6.27}$$

$$K_{opt} = \lceil K \rceil \tag{6.28}$$

where, K_{opt} is the optimal *K* value for non-censoring approach.

6.3.5.2 Censoring approach with multiple antennas under imperfect reporting

In this scenario, the spectrum sensing error with CSS is given as: $Q_e^{rc,SLS}$ from (6.18) and appropriate value of *K* is computed by putting $\frac{\partial Q_e^{rc,SLS}(K)}{\partial K} = 0$ which is presented below and is computed on the same manner as that for the non-censoring scenario:

$$K = \frac{M_c^{SLS} * log\left(\frac{P_m^{rc,SLS}}{1-P_f^{rc,SLS}}\right) + log\left(\frac{P(H_1)}{P(H_0)}\right)}{log\frac{\left(P_f^{rc,SLS}\right)\left(P_m^{rc,SLS}\right)}{\left(1-P_f^{rc,SLS}\right)\left(1-P_m^{rc,SLS}\right)}} \tag{6.29}$$

$$K_{opt} = \lceil K \rceil \tag{6.30}$$

where, K_{opt} is the optimal *K* value in censoring scenario.

Further, the computation of K_{opt} in perfect/imperfect reporting with CFAR/MEP threshold selection under the censoring and non-censoring approaches is presented with algorithm.

Algorithm: Computation of optimal *K* at FC

Input: Threshold selection approach (TSA) = {CFAR, MEP}, Reporting channel (RC) ={ Imperfect, Perfect}, Event sequence (ES) = {Censoring, Non-censoring},γ

Output: K_{opt}

Initialization: N, σ_n^2, M ,$P(H_0)$, $p \epsilon$ (0,1], γ_{set} = [-20,-8], L_a
if $\gamma \epsilon \gamma_{set}$
  if TSA = = CFAR
    $\lambda \leftarrow \lambda_f$
  else
    $\lambda \leftarrow \lambda_e$
  end if
  compute P_f and P_d using (2.2) and (2.3) respectively
  compute P_f^{SLS} and P_d^{SLS} using (6.4) and (6.5) respectively
  if RC = = Imperfect
    $P_e^r \leftarrow p$
  else
    $P_e^r \leftarrow 0$
  end if
  if ES = = Censoring
    compute M_c^{SLS} using (6.12)
    find $P_f^{rc,SLS}$ from (6.13) and $P_d^{rc,SLS}$ using (6.14)
    find $Q_e^{rc,SLS}$ from (6.18)
    compute K_{opt} from (6.30)
  else
    find $P_f^{r,SLS}$ from (6.6) and $P_d^{r,SLS}$ using (6.7)
    find $Q_e^{rc,SLS}$ from (6.18)
    compute K_{opt} from (6.28)
  end if
end if

6.4 Simulation Results

In this section, we have demonstrated the MATLAB simulated results of the proposed CRN system. The parameters employed for simulation of the results are presented in Table 6.3.

Table 6.3: The parameters for simulation.

Parameter	Value	Parameter	Value
N	25000	T_R	0.001Sec.
$\overline{P_f}$	0.1	P_S	0.02 Watt
M	10	P_R	0.1 Watt
T	0.1Sec.	P_T	0.1 Watt
T_S	.0025Sec	γ_s	20 dB

The variations in spectrum sensing error with threshold (λ) for different values of K in K-out-of-M rule which has been presented by Li et.al. in [241] and Zhang et.al. in [186] is shown in Fig. 6.3. It is clear from Fig. 6.3 that for any value of K, the sensing error is a convex function of λ which provides a minimum value of sensing error. Therefore, at different selected threshold, the value of K is different to minimize the sensing error.

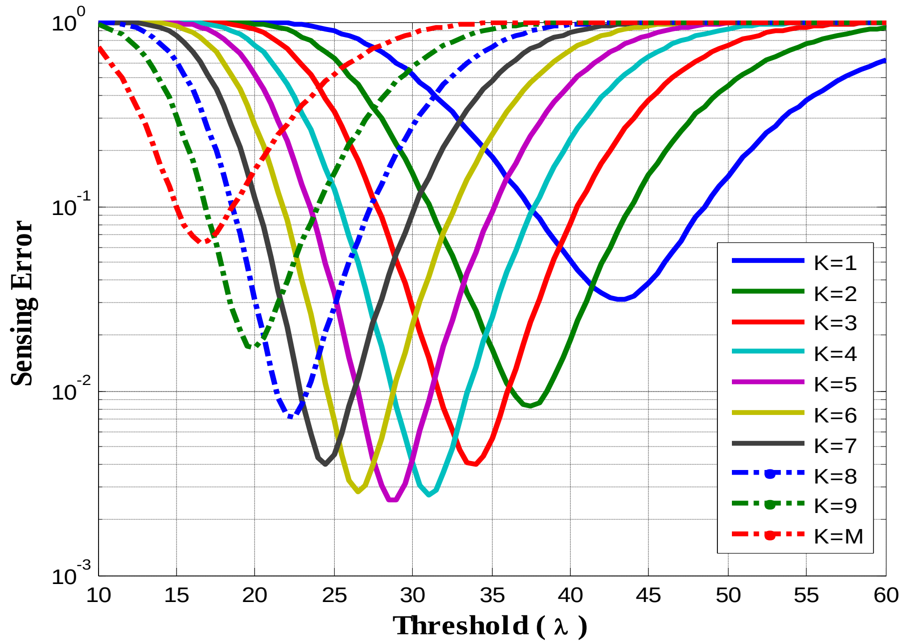
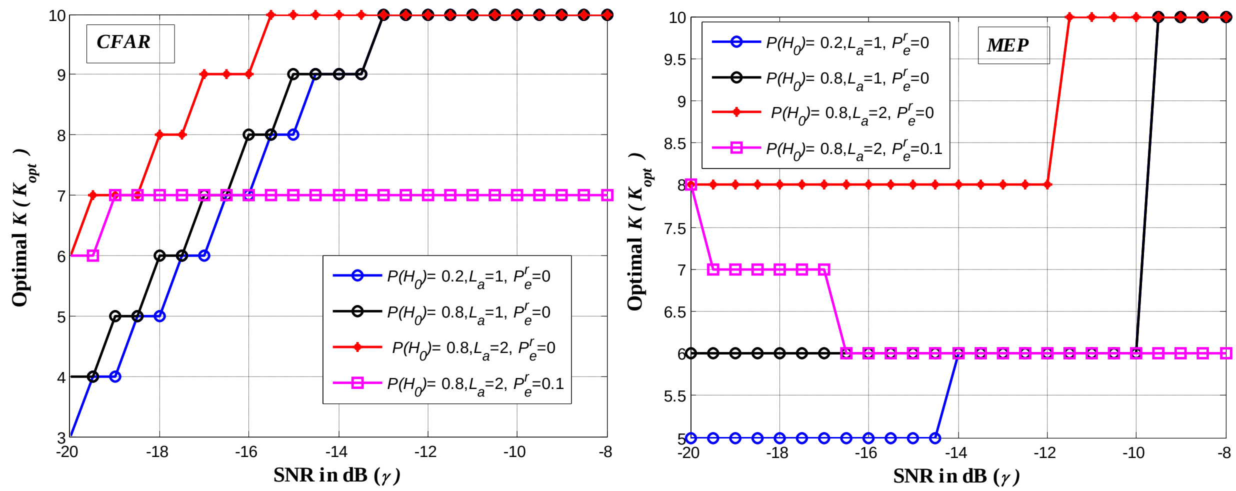


Figure 6.3: Variation in sensing error with threshold for different values of K, L_a=1, P_e^r=0 [186], [241]

Further, we have illustrated the optimal value of K at different SNR to minimize the sensing error while considering the combined effect of multiple antennas (L_a) employed by CU, reporting error probability (P_e^r) and licensed channel's idle/active probability ($P(H_0)$/ $P(H_1)$). Therefore, in Fig. 6.4(a) and Fig. 6.4(b), we have employed CFAR and MEP threshold selection approaches and achieved the optimal K at different SNR to minimize the sensing error in the non-censoring approach, respectively. Further, Fig. 6.4(a) and Fig. 6.4(b) demonstrated that at fixed SNR under perfect reporting channel (P_e^r=0), as $P(H_0)$ or L_a increases, the optimal K also increases due to increment in P_f and decrement in P_m. However, for same value of $P(H_0)$ and L_a, the optimal K decreases when P_e^r increases due to increment in both P_f and P_m.



(a) (b)

Figure 6.4: Variation in optimal number of CU at FC (K_{opt}) with SNR at different values of $P(H_0)$, L_a and P_e^r under non-censoring scenario with (a) CFAR, and (b) MEP threshold selection approaches.

Moreover, in Fig. 6.5, we have presented the variation in spectrum sensing error with γ while employing Majority rule and optimal K at FC using CFAR and MEP threshold selection approaches. From Fig. 6.5, it is clear that the proposed approach with optimal K provides less spectrum sensing error as compare to that of the Majority rule applied in [264] when CFAR approach is employed. However, the MEP approach provides nearly same sensing error with both the schemes.

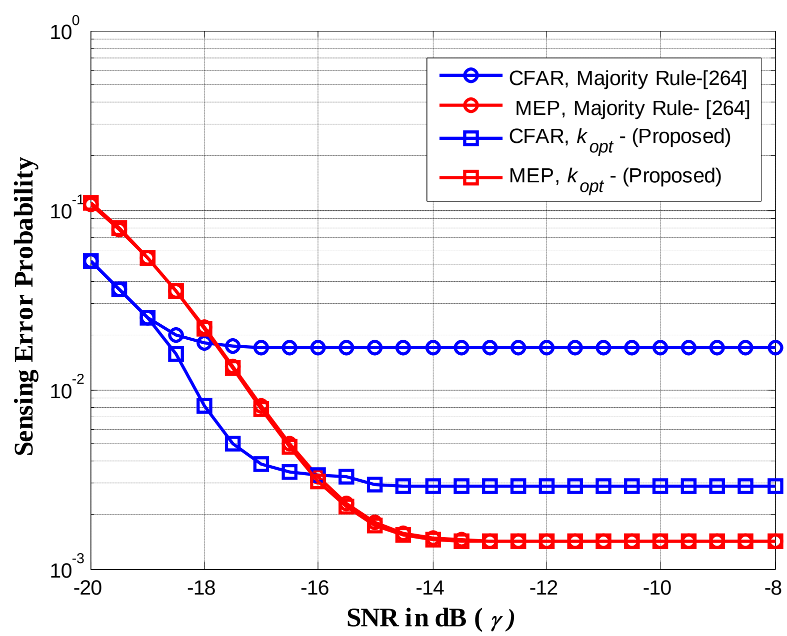


Figure 6.5: Variation in sensing error with SNR at $P(H_0)$=0.8, L_a=1, and P_e^r=0.1.

In addition, the effect of variation in reporting error probability and number of antennas employed at each CU on the sensing error at different SNR is presented in Fig. 6.6, while employing optimal value of K under the CFAR and MEP threshold selection approaches.

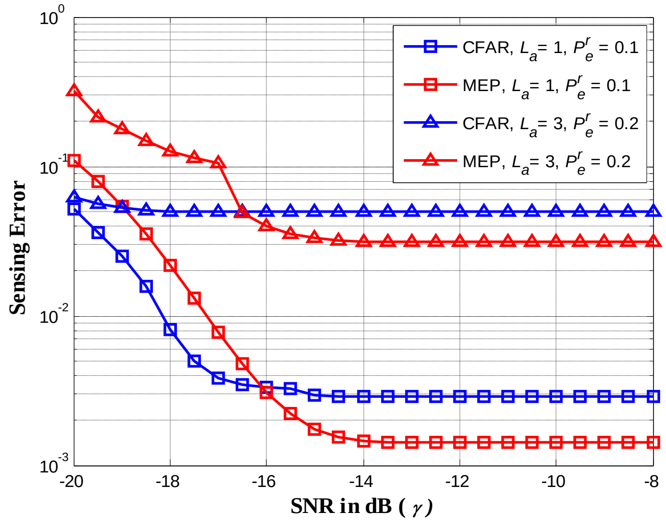
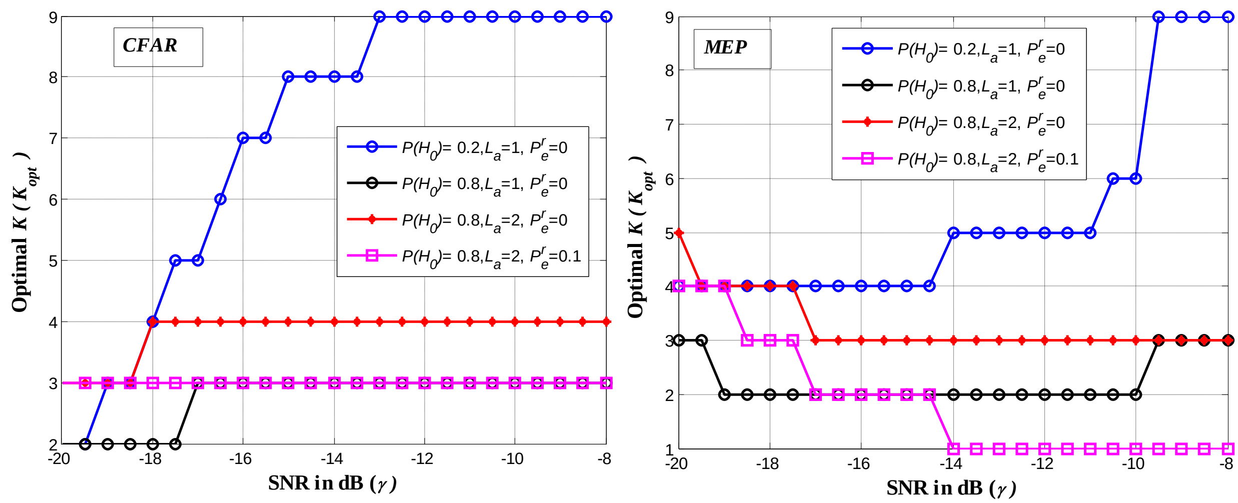


Figure 6.6: Variation in sensing error with SNR for different values of L_a and P_e^r at $P(H_0)$ = 0.8.

From Fig. 6.6, it is illustrated that for the imperfect reporting channel (P_e^r=0.1 or 0.2), at fixed value of SNR, the spectrum sensing error increases with increase in L_a due to enlarged false-alarm and detection probability values in both CFAR and MEP approaches. However, at high SNR, increase in the false-alarm probability with MEP approach is less as compare to that of the CFAR approach. Therefore, at high SNR, the MEP approach provides less spectrum sensing error when CU has employed multiple antennas. Further, Fig. 6.7(a) and Fig. 6.7(b) show the variation in optimal value of K for censoring scenario with SNR in CFAR and MEP threshold selection approaches. It is obvious from comparison of Fig. 6.4 and Fig. 6.7 that the optimal K value required in censoring approach is less in comparison to that of the non-censoring scenario for both CFAR and MEP threshold selection.

Moreover, Fig. 6.8 has presented the variation in sensing error with SNR while employing optimal K in CFAR and MEP threshold selection approaches for different values of L_a and P_e^r under the censoring approach. From Fig. 6.8, it is clear that with the censoring approach, for fixed value of L_a and P_e^r, the spectrum sensing error is nearly constant with variation in SNR due to constant value of optimal K in CFAR. Moreover, for the fixed value of L_a and P_e^r, the spectrum sensing error is less in MEP approach as compare to that of the CFAR approach due to minimum value of false-alarm and miss-detection probabilities achieved.



(a) (b)

Figure 6.7: Variation in optimal number of CU at FC (K) with SNR at different value of $P(H_0)$, L_a, and P_e^r under censoring scenario with (a) CFAR and (b) MEP.

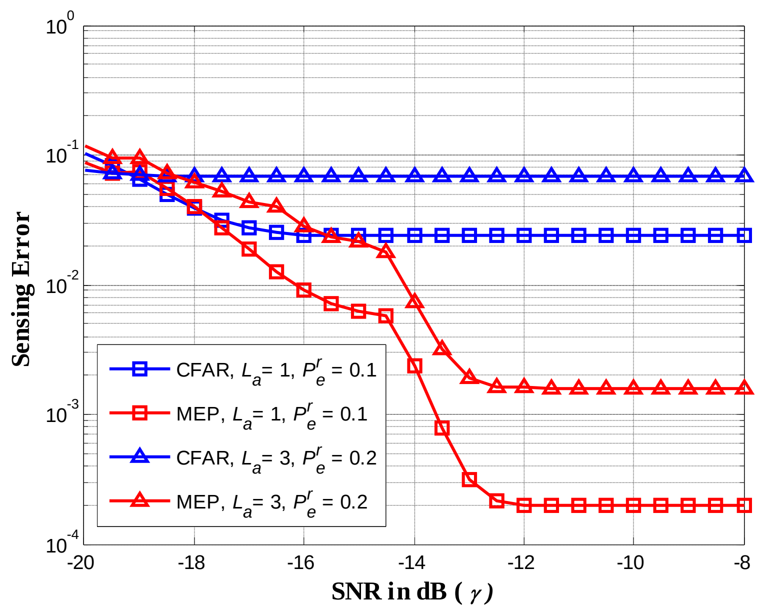


Figure 6.8: Variation in sensing error with SNR for different value of L_a and P_e^r at $P(H_0)$*=0.8,* in the censoring scenario.

Further, the variation in energy efficiency with SNR with the censoring and non-censoring approaches with CFAR and MEP threshold selection techniques are presented in Fig. 6.9.

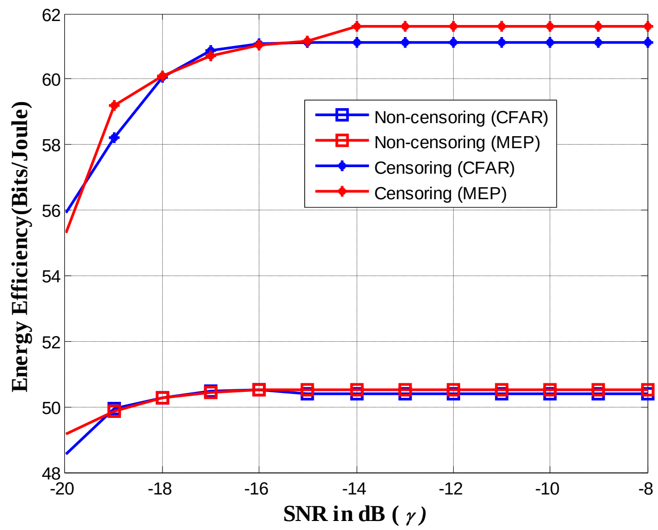


Figure 6.9: Variation in energy efficiency with SNR for CFAR and MEP threshold selection in censoring and non-censoring approaches at $P(H_0) = 0.8$, L_a=1 and $P_e^r = 0.1$.

We have employed optimal K for all SNR to yield the energy efficiency with both the censoring and non-censoring approaches. In Fig. 6.9, it is illustrated that in the non-censoring approach, the performance of CFAR and MEP techniques are nearly same however with the censoring approach, MEP threshold selection approach slightly outperformed CFAR. Further, the energy efficiency achieved in censoring approach is significantly higher as compare to that of the non-censoring for both the threshold selection approaches (CFAR or MEP). This is due to the smaller number of CUs reporting to FC in censoring, resulting energy consumption reduction in the reporting phase. From the results illustrated in Fig. 6.9, it is computed that the percentage enhancement in energy efficiency during censoring is 19.53 % and 19.9% with CFAR and MEP approaches, respectively in comparison to that of the non-censoring. Since MEP threshold selection technique in censoring approach has provided higher energy efficiency as compare to CFAR, therefore Fig. 6.10 depicts the variation in energy efficiency with SNR and number of antennas for MEP threshold selection under the censoring. It is illustrated from Fig. 6.10 that at high SNR, the effect of variation in number of antennas on energy efficiency is nearly constant. However, the energy efficiency decreases with increase in the number of antennas at low SNR due to increase in the value of K_{opt} .

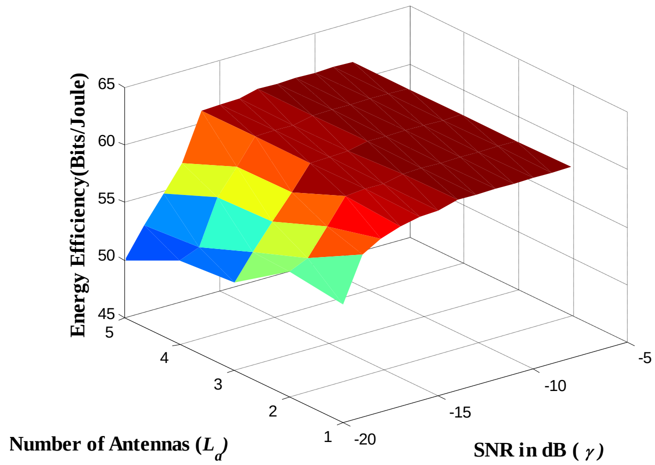


Figure 6.10: Variation in energy efficiency with SNR and L_a with MEP threshold selection under censoring approach at $P_e^r = 0.1$, $P(H_0) = 0.8$.

6.5 Conclusion

In this chapter, we have computed the optimal value of K at FC to reduce the spectrum sensing error with the censoring and non-censoring based cooperative spectrum sensing approach. We have employed CFAR and MEP threshold selection methods to yield the optimal K while considering the effect of variation of number of antennas and reporting error probability. It has been illustrated that the optimal K selection at different SNR has provided minimum sensing error in comparison to that of the single selection rule (e.g. Majority) at FC. Further, we have achieved the significant improvement in EE in censoring approach with both CFAR and MEP based threshold selection approaches as compare to that of the non-censoring.

CHAPTER 7

CONCLUSION AND FUTURE PERSPECTIVES

This chapter concludes the thesis as follows. The proposed research work is focused on optimal threshold selection for the energy detection based spectrum sensing technique to improve the performance of CRN. We have broadly considered three parameters for measuring the performance of CRN which are the sensing error, throughput and energy efficiency. In this thesis, first, we have exploited the energy detection based spectrum sensing in the non-cooperative scenario of CRN with AWGN to propose the optimality condition for threshold selection to achieve the desired values of P_f and P_d. Further, the computation of SNR (γ) as a critical SNR (γ_c) below which the optimality condition is not satisfied, has been performed. Moreover, we have proposed an approach in order to satisfy the optimality condition at all SNR and have computed the throughput for the proposed approach. It has been perceived that at low SNR, the throughput for proposed approach is higher than CDR and MEP approaches however, less than that of CFAR approach. Moreover, it has been observed that the throughputs computed using CDR, CFAR and MEP approaches are not satisfying the desired P_f and P_d values when compared with the proposed approach. Hence, in the proposed approach, we have achieved the maximum throughput while achieving the desired P_f and P_d simultaneously at all SNR (γ). The proposed approach has shown approximately 24.63% improved throughput when compared with CDR at γ equals to -18 dB (near to γ_c).

Further, we have also presented the effect of variation in number of samples and SNR on the spectrum sensing performance of CRN when the threshold is selected using CFAR approach in the non-cooperative scenario for the AWGN and fading channels. For the fading channels (Rayleigh, and Nakagami-m), we have analyzed the effects of threshold selection as well as different cooperative rules on spectrum sensing performance. The numerical analysis and simulation results reveal that the effect of variation in SNR is more dominant on the spectrum sensing performance of CRN in comparison to that of the variation in number of samples. In addition, we have also illustrated the need of dynamic threshold selection to enhance the sensing performance at low SNR. Subsequently, we have shown the improvement of sensing results after the cognitive user cooperation and performance of different cooperative rules (AND, OR, Majority) is analyzed in terms of ROC curve. It is observed that the performance with Majority rule is better than that of other cooperative rules in AWGN and Nakagami-*m* however in Rayleigh fading channel the performance with OR and Majority rule is nearly same. Therefore, we have selected the Majority rule for cognitive user cooperation for further analysis in the thesis. The throughput computation has been performed for the proposed environment by employing CFAR and MEP approaches for the cooperative and non-cooperative spectrum sensing scenarios. The results concludes that the throughput is maximized by CFAR with cooperative rule at low SNR while at high SNR its value is maximum with MEP in non-cooperative scenario. In addition, for the least spectrum sensing error (total error probability), the cooperative rule outperforms the non-cooperative rule and in AWGN channel sensing error is minimum while employing MEP. However, in the Rayleigh and Nakagami-*m* fading environment, the MEP approach provides least spectrum sensing error at low SNR while at high SNR, the CFAR approach is outperforming. Moreover, in the cooperative spectrum sensing with MEP approach, the improvement in detection probability, throughput, and total error probability in AWGN channel are: 15.11%, -7.08%, and 61.53%, respectively; in the Rayleigh fading channel are: 31.74%, -6.53%, and 51.35 %, respectively; in the Nakagami-*m* channel: 28.76%, -9.23 %, and 61.53%, respectively at SNR=-20dB. Further, it is illustrated that the individual selection of CFAR or MEP approach for the cooperative and non-cooperative spectrum sensing scenario provides significantly higher throughput or least total spectrum sensing error probability either at low SNR or high SNR region. Therefore, we have employed the concept of critical SNR to select the threshold intelligently and proposed the algorithms to maximize the throughput and to minimize the spectrum sensing error. Afterwards, we have achieved high throughput and least total sensing error probability at both the low and high-SNR region.

Moreover, the perfect reporting channels are considered to yield the spectrum sensing results, however the sensing results degrade with imperfect reporting channel and cooperation may increase the energy consumption. Therefore, the censoring concept is employed to reduce the energy consumption. Further, we have illustrated the effect of CFAR and MEP threshold selection approaches on the total spectrum sensing error probability and throughput of CU under the perfect/imperfect reporting channels and censoring/non-censoring based CRN environment.

From the results of non-censoring and imperfect reporting channel scenario, we have concluded that in the Rayleigh and Nakagami-*m* fading channels when $\gamma \leq \gamma_c$, the MEP approach has provided better total spectrum sensing error probability performance however for $\gamma > \gamma_c$, CFAR approach is better. Further, for the throughput enhancement, reverse is true *i.e*. for $\gamma \leq \gamma_c$, the throughput is significantly higher with CFAR approach however for $\gamma > \gamma_c$, its value is higher with MEP approach. Hence there exist a trade-off between sensing error probability and throughput with threshold selection approaches. The censoring scenario has although reduced the sensing overhead information but at the cost of increased total spectrum sensing error probability as compare to that of the non-censoring scenario due to smaller number of users' reporting to FC. In the censoring scenario, we have to switch among the CFAR and MEP threshold selection approaches according to γ to enhance the throughput and decrease the spectrum sensing error probability as illustrated in the results.

In the considered cooperative spectrum sensing scenario, we have employed only single cooperative rule at all SNR, however to minimize the spectrum sensing error, it is required to vary the cooperative rule according to SNR. Therefore, we have computed the optimal value of *K* at FC to reduce the spectrum sensing error under the censoring and non-censoring based cooperative spectrum sensing scenarios. We have employed CFAR and MEP threshold selection methods to compute optimal *K* while considering the effect of variation of number of antennas and the reporting error probability. It has been illustrated that the optimal *K* selection at different SNR has provided minimum spectrum sensing error in comparison to that of the single rule selection (e.g. Majority) at FC. Further, we have achieved the significant improvement in EE in the censoring approach with both CFAR and MEP based threshold selection technique as compared to that of the non-censoring.

Finally, we can summarize the work of our thesis in following points:

- Proposed an optimal threshold condition and selected the optimal threshold which satisfied the sensing requirement under AWGN channel in non-cooperative scenario.
- The cooperative rule has outperformed the non-cooperative rule to achieve least sensing error probability in both AWGN and fading channels.

- We have proposed the algorithms for threshold selection in fading channels in order to minimize the sensing error probability and maximize the throughput separately.
- Threshold selection with optimal K at FC has provided least sensing error probability at different SNR under AWGN channel.
- Significant improvement in EE is achieved in the censoring as compared to that of the non-censoring approach with both CFAR and MEP based threshold selection technique.

In this thesis, we have illustrated the sensing-throughput tradeoff problem, in which the single proposed method is not providing high throughput and less sensing error at the same time. Therefore, it is to required to devise some method to avoid this problem which is the future scope of our work. In addition, the optimal K analysis in censoring/non-censoring scenario is provided for only AWGN environment in this thesis, which can be further done for the fading channels. Moreover, the effect of primary user activity during the spectrum sensing as well as noise uncertainty on the sensing performance can also be seen. Further, as we are moving towards Industry 4.0, in which we are employing Internet of Things (IoT), Industrial Internet of Things (IIoT), Internet of Vehicle (IoV), Cloud Computing etc. to provide better interconnection of the devices digitally, resulting into performance improvement of systems without human intervention. Therefore, another new direction of our work could be the integration of CR system with Industry 4.0 to take sensing decision on the spectrum automatically.

REFERENCES

[1] "GSMAi research & analysis." [Online]. Available: https://data.gsmaintelligence.com.

[2] M. Amjad, M. H. Rehmani, and S. Mao, "Wireless multimedia cognitive radio networks: A comprehensive survey," *IEEE Communications Surveys Tutorials*, vol. 20, no. 2, pp. 1056–1103, Secondquarter 2018, doi: 10.1109/COMST.2018.2794358.

[3] H. Sun, A. Nallanathan, C. Wang, and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: a survey," *IEEE Wireless Communications*, vol. 20, no. 2, pp. 74–81, Apr. 2013, doi: 10.1109/MWC.2013.6507397.

[4] A. A. Khan, M. H. Rehmani, and A. Rachedi, "Cognitive-radio-based internet of things: Applications, architectures, spectrum related functionalities, and future research directions," *IEEE Wireless Communications*, vol. 24, no. 3, pp. 17–25, Jun. 2017, doi: 10.1109/MWC.2017.1600404.

[5] H. Bezabih, B. Ellingsaeter, J. Noll, and T. T. Maseng, "Digital broadcasting: Increasing the available white space spectrum using tv receiver information," *IEEE Vehicular Technology Magazine*, vol. 7, no. 1, pp. 24–30, Mar. 2012, doi: 10.1109/MVT.2011.2179344.

[6] S. Parvin, F. K. Hussain, O. K. Hussain, S. Han, B. Tian, and E. Chang, "Cognitive radio network security: A survey," *Journal of Network and Computer Applications*, vol. 35, no. 6, pp. 1691–1708, Nov. 2012, doi: 10.1016/j.jnca.2012.06.006.

[7] D. Das and S. Das, "A survey on spectrum occupancy measurement for cognitive radio," *Wireless Pers Commun*, vol. 85, no. 4, pp. 2581–2598, Dec. 2015, doi: 10.1007/s11277-015-2921-1.

[8] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, Sep. 2006, doi: 10.1016/j.comnet.2006.05.001.

[9] Q. Zhao and A. Swami, “A survey of dynamic spectrum access: signal processing and networking perspectives,” *Proceedings of 2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP ’07*, 2007, vol. 4, pp. IV-1349-IV–1352, doi: 10.1109/ICASSP.2007.367328.

[10] S. Agarwal and S. De, “eDSA: Energy-efficient dynamic spectrum access protocols for cognitive radio networks,” *IEEE Transactions on Mobile Computing*, vol. 15, no. 12, pp. 3057–3071, Dec. 2016, doi: 10.1109/TMC.2016.2535405.

[11] S. Geirhofer, L. Tong, and B. M. Sadler, “Cognitive radios for dynamic spectrum access - dynamic spectrum access in the time domain: Modeling and exploiting white space,” *IEEE Communications Magazine*, vol. 45, no. 5, pp. 66–72, May 2007, doi: 10.1109/MCOM.2007.358851.

[12] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y. Yao, “Opportunistic spectrum access in unknown dynamic environment: a game-theoretic stochastic learning solution,” *IEEE Transactions on Wireless Communications*, vol. 11, no. 4, pp. 1380–1391, Apr. 2012, doi: 10.1109/TWC.2012.020812.110025.

[13] M. Song, C. Xin, Y. Zhao, and X. Cheng, “Dynamic spectrum access: from cognitive radio to network radio,” *IEEE Wireless Communications*, vol. 19, no. 1, pp. 23–29, Feb. 2012, doi: 10.1109/MWC.2012.6155873.

[14] X. Li, D. Li, J. Wan, A. V. Vasilakos, C.-F. Lai, and S. Wang, “A review of industrial wireless networks in the context of Industry 4.0,” *Wireless Netw*, vol. 23, no. 1, pp. 23–41, Jan. 2017, doi: 10.1007/s11276-015-1133-7.

[15] M. Chen, “Towards smart city: M2M communications with software agent intelligence,” *Multimed Tools Appl*, vol. 67, no. 1, pp. 167–178, Nov. 2013, doi: 10.1007/s11042-012-1013-4.

[16] S. Wang, J. Wan, D. Zhang, D. Li, and C. Zhang, “Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination,” *Computer Networks*, vol. 101, pp. 158–168, Jun. 2016, doi: 10.1016/j.comnet.2015.12.017.

[17] Z. Shu, J. Wan, D. Zhang, and D. Li, “Cloud-integrated cyber-physical systems for complex industrial applications,” *Mobile Netw Appl*, vol. 21, no. 5, pp. 865–878, Oct. 2016, doi: 10.1007/s11036-015-0664-6.

[18] M. Gerla, E.-K. Lee, G. Pau, and U. Lee, “Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds,” *Proceedings of 2014 IEEE World Forum on Internet of Things (WF-IoT)*, 2014, pp. 241–246, doi: 10.1109/WF-IoT.2014.6803166.

[19] A. Gatouillat, Y. Badr, B. Massot, and E. Sejdić, “Internet of medical things: A review of recent contributions dealing with cyber-physical systems in medicine,” *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3810–3822, Oct. 2018, doi: 10.1109/JIOT.2018.2849014.

[20] H. Magsi, A. H. Sodhro, F. A. Chachar, S. A. K. Abro, G. H. Sodhro, and S. Pirbhulal, “Evolution of 5G in internet of medical things,” *Proceedings of 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, 2018, pp. 1–7, doi: 10.1109/ICOMET.2018.8346428.

[21] S. Wang, J. Wan, D. Li, and C. Zhang, “Implementing smart factory of industrie 4.0: An outlook,” *International Journal of Distributed Sensor Networks*, vol. 12, no. 1, p. 3159805, Jan. 2016, doi: 10.1155/2016/3159805.

[22] J. Wan *et al.*, “Software-defined industrial internet of things in the context of industry 4.0,” *IEEE Sensors Journal*, vol. 16, no. 20, pp. 7373–7380, Oct. 2016, doi: 10.1109/JSEN.2016.2565621.

[23] J. Zhu, Y. Song, D. Jiang, and H. Song, “Multi-armed bandit channel access scheme with cognitive radio technology in wireless sensor networks for the internet of things,” *IEEE Access*, vol. 4, pp. 4609–4617, 2016, doi: 10.1109/ACCESS.2016.2600633.

[24] M. M. Abdel-Sayed, A. Khattab, and M. F. Abu-Elyazeed, “Fast matching pursuit for wideband spectrum sensing in cognitive radio networks,” *Wireless Netw*, vol. 25, no. 1, pp. 131–143, Jan. 2019, doi: 10.1007/s11276-017-1545-7.

[25] Z. Li, B. Chang, S. Wang, A. Liu, F. Zeng, and G. Luo, “Dynamic compressive wide-band spectrum sensing based on channel energy reconstruction in cognitive internet of things,”

IEEE Transactions on Industrial Informatics, vol. 14, no. 6, pp. 2598–2607, Jun. 2018, doi: 10.1109/TII.2018.2797096.

[26] X. Liu, M. Jia, X. Zhang, and W. Lu, "A novel multichannel internet of things based on dynamic spectrum sharing in 5G communication," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 5962–5970, Aug. 2019, doi: 10.1109/JIOT.2018.2847731.

[27] L. Wan, G. Han, L. Shu, N. Feng, C. Zhu, and J. Lloret, "Distributed parameter estimation for mobile wireless sensor network based on cloud computing in battlefield surveillance system," *IEEE Access*, vol. 3, pp. 1729–1739, 2015, doi: 10.1109/ACCESS.2015.2482981.

[28] K. A. Meerja, A. Shami, and A. Refaey, "Hailing cloud empowered radio access networks," *IEEE Wireless Communications*, vol. 22, no. 1, pp. 122–129, Feb. 2015, doi: 10.1109/MWC.2015.7054727.

[29] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys Tutorials*, vol. 11, no. 1, pp. 116–130, First 2009, doi: 10.1109/SURV.2009.090109.

[30] A. Paul, A. Daniel, A. Ahmad, and S. Rho, "Cooperative cognitive intelligence for internet of vehicles," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1249–1258, Sep. 2017, doi: 10.1109/JSYST.2015.2411856.

[31] R. Umar and A. U. H. Sheikh, "A comparative study of spectrum awareness techniques for cognitive radio oriented wireless networks," *Physical Communication*, vol. 9, pp. 148–170, Dec. 2013, doi: 10.1016/j.phycom.2012.07.005.

[32] P. Y. Dibal, E. N. Onwuka, J. Agajo, and C. O. Alenoghena, "Application of wavelet transform in spectrum sensing for cognitive radio: A survey," *Physical Communication*, vol. 28, pp. 45–57, Jun. 2018, doi: 10.1016/j.phycom.2018.03.004.

[33] I. F. Akyildiz, W. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40–48, Apr. 2008, doi: 10.1109/MCOM.2008.4481339.

[34] A. Fakhrudeen and O. Y. Alani, “Comprehensive survey on quality of service provisioning approaches in cognitive radio networks: Part one,” *Int J Wireless Inf Networks*, vol. 24, no. 4, pp. 356–388, Dec. 2017, doi: 10.1007/s10776-017-0352-5.

[35] S. K. Sharma, T. E. Bogale, S. Chatzinotas, B. Ottersten, L. B. Le, and X. Wang, “Cognitive radio techniques under practical imperfections: A survey,” *IEEE Communications Surveys Tutorials*, vol. 17, no. 4, pp. 1858–1884, Fourthquarter 2015, doi: 10.1109/COMST.2015.2452414.

[36] S. Atapattu, C. Tellambura, and H. Jiang, “Energy detection based cooperative spectrum sensing in cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 10, no. 4, pp. 1232–1241, Apr. 2011, doi: 10.1109/TWC.2011.012411.100611.

[37] R. Umar, A. U. H. Sheikh, and M. Deriche, “Unveiling the hidden assumptions of energy detector based spectrum sensing for cognitive radios,” *IEEE Communications Surveys Tutorials*, vol. 16, no. 2, pp. 713–728, Second 2014, doi: 10.1109/SURV.2013.081313.00054.

[38] J. Ma, G. Y. Li, and B. H. Juang, “Signal processing in cognitive radio,” *Proceedings of the IEEE*, vol. 97, no. 5, May 2009, pp. 805–823, doi: 10.1109/JPROC.2009.2015707.

[39] B. Ramkumar, “Automatic modulation classification for cognitive radios using cyclic feature detection,” *IEEE Circuits and Systems Magazine*, vol. 9, no. 2, pp. 27–45, Second 2009, doi: 10.1109/MCAS.2008.931739.

[40] K.- Du and W. H. Mow, “Affordable cyclostationarity-based spectrum sensing for cognitive radio with smart antennas,” *IEEE Transactions on Vehicular Technology*, vol. 59, no. 4, pp. 1877–1886, May 2010, doi: 10.1109/TVT.2010.2043860.

[41] S. Kapoor, S. Rao, and G. Singh, “Opportunistic spectrum sensing by employing matched filter in cognitive radio network,” *Proceedings of 2011 International Conference on Communication Systems and Network Technologies*, 2011, pp. 580–583, doi: 10.1109/CSNT.2011.124.

[42] D. Bhargavi and C. R. Murthy, “Performance comparison of energy, matched-filter and cyclostationarity-based spectrum sensing,” *Proceedings of 2010 IEEE 11th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2010, pp. 1–5, doi: 10.1109/SPAWC.2010.5670882.

[43] Y. Zeng and Y. Liang, “Covariance based signal detections for cognitive radio,” *Proceedings of 2007, 2nd IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, 2007, pp. 202–207, doi: 10.1109/DYSPAN.2007.33.

[44] M. Jin, Y. Li, and H. Ryu, “On the performance of covariance based spectrum sensing for cognitive radio,” *IEEE Transactions on Signal Processing*, vol. 60, no. 7, pp. 3670–3682, Jul. 2012, doi: 10.1109/TSP.2012.2194708.

[45] M. Jin, Q. Guo, J. Xi, Y. Li, Y. Yu, and D. Huang, “Spectrum sensing using weighted covariance matrix in rayleigh fading channels,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 11, pp. 5137–5148, Nov. 2015, doi: 10.1109/TVT.2014.2379924.

[46] M. Naraghi-Pour and T. Ikuma, “Autocorrelation-based spectrum sensing for cognitive radios,” *IEEE Transactions on Vehicular Technology*, vol. 59, no. 2, pp. 718–733, Feb. 2010, doi: 10.1109/TVT.2009.2035628.

[47] Y. Huang and X. Huang, “Detection of temporally correlated signals over multipath fading channels,” *IEEE Transactions on Wireless Communications*, vol. 12, no. 3, pp. 1290–1299, Mar. 2013, doi: 10.1109/TWC.2013.011713.120748.

[48] F. Penna, R. Garello, D. Figlioli, and M. A. Spirito, “Exact non-asymptotic threshold for eigenvalue-based spectrum sensing,” *Proceedings of 2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, 2009, pp. 1–5, doi: 10.1109/CROWNCOM.2009.5189008.

[49] Y. Zeng and Y.- Liang, “Eigenvalue-based spectrum sensing algorithms for cognitive radio,” *IEEE Transactions on Communications*, vol. 57, no. 6, pp. 1784–1793, Jun. 2009, doi: 10.1109/TCOMM.2009.06.070402.

[50] L. Huang, J. Fang, K. Liu, H. C. So, and H. Li, "An eigenvalue-moment-ratio approach to blind spectrum sensing for cognitive radio under sample-starving environment," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 8, pp. 3465–3480, Aug. 2015, doi: 10.1109/TVT.2014.2359217.

[51] S. Nandakumar *et al.*, "Efficient spectrum management techniques for cognitive radio networks for proximity service," *IEEE Access*, vol. 7, pp. 43795–43805, 2019, doi: 10.1109/ACCESS.2019.2906469.

[52] N. Pillay and H. J. Xu, "Blind eigenvalue-based spectrum sensing for cognitive radio networks," *IET Communications*, vol. 6, no. 11, pp. 1388–1396, Jul. 2012, doi: 10.1049/iet-com.2011.0506.

[53] A. Gokceoglu, S. Dikmese, M. Valkama, and M. Renfors, "Energy detection under iq imbalance with single- and multi-channel direct-conversion receiver: Analysis and mitigation," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 3, pp. 411–424, Mar. 2014, doi: 10.1109/JSAC.2014.1403001.

[54] O. Semiari, B. Maham, and C. Yuen, "On the effect of i/q imbalance on energy detection and a novel four-level hypothesis spectrum sensing," *IEEE Transactions on Vehicular Technology,* vol. 63, no. 8, pp. 4136–4141, Oct. 2014, doi: 10.1109/TVT.2014.2306684.

[55] A. Abu Alkheir and H. T. Mouftah, "An improved energy detector using outdated channel state information," *IEEE Communications Letters*, vol. 19, no. 7, pp. 1237–1240, Jul. 2015, doi: 10.1109/LCOMM.2015.2430330.

[56] A. Nafkha and B. Aziz, "Closed-form approximation for the performance of finite sample-based energy detection using correlated receiving antennas," *IEEE Wireless Communications Letters*, vol. 3, no. 6, pp. 577–580, Dec. 2014, doi: 10.1109/LWC.2014.2348998.

[57] I. Sobron, P. S. R. Diniz, W. A. Martins, and M. Velez, "Energy detection technique for adaptive spectrum sensing," *IEEE Transactions on Communications*, vol. 63, no. 3, pp. 617–627, Mar. 2015, doi: 10.1109/TCOMM.2015.2394436.

[58] A. Ali and W. Hamouda, “Advances on spectrum sensing for cognitive radio networks: theory and applications,” *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 1277–1304, Secondquarter 2017, doi: 10.1109/COMST.2016.2631080.

[59] P. V. Yadav, A. Alimohammad, and F. Harris, “Efficient design and implementation of energy detection-based spectrum sensing,” *Circuits Syst Signal Process*, vol. 38, no. 11, pp. 5187–5211, Nov. 2019, doi: 10.1007/s00034-019-01115-z.

[60] S. Chaudhari, V. Koivunen, and H. V. Poor, “Autocorrelation-based decentralized sequential detection of ofdm signals in cognitive radios,” *IEEE Transactions on Signal Processing*, vol. 57, no. 7, pp. 2690–2700, Jul. 2009, doi: 10.1109/TSP.2009.2019176.

[61] P. D. Sutton, K. E. Nolan, and L. E. Doyle, “Cyclostationary signatures in practical cognitive radio applications,” *IEEE Journal on Selected Areas in Communications*, vol. 26, no. 1, pp. 13–24, Jan. 2008, doi: 10.1109/JSAC.2008.080103.

[62] W. M. Jang, “Blind cyclostationary spectrum sensing in cognitive radios,” *IEEE Communications Letters*, vol. 18, no. 3, pp. 393–396, Mar. 2014, doi: 10.1109/LCOMM.2014.012714.132507.

[63] P. Urriza, E. Rebeiz, and D. Cabric, “Multiple antenna cyclostationary spectrum sensing based on the cyclic correlation significance test,” *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 11, pp. 2185–2195, Nov. 2013, doi: 10.1109/JSAC.2013.131118.

[64] H.-S. Chen, W. Gao, and D. G. Daut, “Spectrum sensing using cyclostationary properties and application to IEEE 802.22 WRAN,” *Proceedings of IEEE GLOBECOM 2007 - IEEE Global Telecommunications Conference*, 2007, pp. 3133–3138, doi: 10.1109/GLOCOM.2007.593.

[65] G. Huang and J. K. Tugnait, “On cyclostationarity based spectrum sensing under uncertain gaussian noise,” *IEEE Transactions on Signal Processing*, vol. 61, no. 8, pp. 2042–2054, Apr. 2013, doi: 10.1109/TSP.2013.2246158.

[66] J. Lunden, V. Koivunen, A. Huttunen, and H. V. Poor, "Collaborative cyclostationary spectrum sensing for cognitive radio systems," *IEEE Transactions on Signal Processing*, vol. 57, no. 11, pp. 4182–4195, Nov. 2009, doi: 10.1109/TSP.2009.2025152.

[67] W. Ejaz, N. ul Hasan, M. A. Azam, and H. S. Kim, "Improved local spectrum sensing for cognitive radio networks," *EURASIP J. Adv. Signal Process.*, vol. 2012, no. 1, p. 242, Nov. 2012, doi: 10.1186/1687-6180-2012-242.

[68] T. Z. Oo, N. H. Tran, D. N. M. Dang, Z. Han, L. B. Le, and C. S. Hong, "OMF-MAC: An opportunistic matched filter-based MAC in cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 2544–2559, Apr. 2016, doi: 10.1109/TVT.2015.2415033.

[69] F. Salahdine, H. E. Ghazi, N. Kaabouch, and W. F. Fihri, "Matched filter detection with dynamic threshold for cognitive radio networks," *Proceedings of 2015 International Conference on Wireless Networks and Mobile Communications (WINCOM)*, 2015, pp. 1–6, doi: 10.1109/WINCOM.2015.7381345.

[70] Y. Zeng and Y.-C. Liang, "Spectrum-sensing algorithms for cognitive radio based on statistical covariances," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 4, pp. 1804–1815, May 2009, doi: 10.1109/TVT.2008.2005267.

[71] A. Bishnu and V. Bhatia, "LogDet covariance based spectrum sensing under colored noise," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6716–6720, Jul. 2018, doi: 10.1109/TVT.2018.2815693.

[72] M. Jin, Q. Guo, and Y. Li, "On covariance matrix based spectrum sensing over frequency-selective channels," *IEEE Access*, vol. 6, pp. 29532–29540, 2018, doi: 10.1109/ACCESS.2018.2842099.

[73] A.-Z. Chen, Z.-P. Shi, and J. Xiong, "Generalized real-valued weighted covariance-based detection methods for cognitive radio networks with correlated multiple antennas," *IEEE Access*, vol. 7, pp. 34373–34382, 2019, doi: 10.1109/ACCESS.2019.2903732.

[74] C. Charan and R. Pandey, “Intelligent selection of threshold in covariance-based spectrum sensing for cognitive radio networks,” *Wireless Netw*, vol. 24, no. 8, pp. 3267–3279, Nov. 2018, doi: 10.1007/s11276-017-1533-y.

[75] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Eigenvalue-based sensing and snr estimation for cognitive radio in presence of noise correlation,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 8, pp. 3671–3684, Oct. 2013, doi: 10.1109/TVT.2013.2260834.

[76] K. Bouallegue, I. Dayoub, M. Gharbi, and K. Hassan, “Blind spectrum sensing using extreme eigenvalues for cognitive radio networks,” *IEEE Communications Letters*, vol. 22, no. 7, pp. 1386–1389, Jul. 2018, doi: 10.1109/LCOMM.2017.2776147.

[77] C. Liu, J. Wang, X. Liu, and Y.-C. Liang, “Maximum eigenvalue-based goodness-of-fit detection for spectrum sensing in cognitive radio,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7747–7760, Aug. 2019, doi: 10.1109/TVT.2019.2923648.

[78] C. Guo, M. Jin, Q. Guo, and Y. Li, “Antieigenvalue-based spectrum sensing for cognitive radio,” *IEEE Wireless Communications Letters*, vol. 8, no. 2, pp. 544–547, Apr. 2019, doi: 10.1109/LWC.2018.2879339.

[79] V. Abed and A. Shahzadi, “A maximum-minimum eigenvalue detection simpler method based on secondary users locations for cooperative spectrum sensing,” *Proceedings of 2014 International Congress on Technology, Communication and Knowledge (ICTCK)*, 2014, pp. 1–4, doi: 10.1109/ICTCK.2014.7033503.

[80] S. Atapattu, C. Tellambura, and H. Jiang, “MGF based analysis of area under the roc curve in energy detection,” *IEEE Communications Letters*, vol. 15, no. 12, pp. 1301–1303, Dec. 2011, doi: 10.1109/LCOMM.2011.103111.111420.

[81] K. Cichoń, A. Kliks, and H. Bogucka, “Energy-efficient cooperative spectrum sensing: a survey,” *IEEE Communications Surveys Tutorials*, vol. 18, no. 3, pp. 1861–1886, thirdquarter 2016, doi: 10.1109/COMST.2016.2553178.

[82] K. B. Letaief and W. Zhang, “Cooperative communications for cognitive radio networks,” *Proceedings of the IEEE*, vol. 97, no. 5, pp. 878–893, May 2009, doi: 10.1109/JPROC.2009.2015716.

[83] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, “Cooperative spectrum sensing in cognitive radio networks: A survey,” *Physical Communication*, vol. 4, no. 1, pp. 40–62, Mar. 2011, doi: 10.1016/j.phycom.2010.12.003.

[84] D. Cabric, S. M. Mishra, and R. W. Brodersen, “Implementation issues in spectrum sensing for cognitive radios,” *Proceedings of Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, 2004.*, 2004, vol. 1, pp. 772-776 Vol.1, doi: 10.1109/ACSSC.2004.1399240.

[85] A. Ghasemi and E. S. Sousa, “Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs,” *IEEE Communications Magazine*, vol. 46, no. 4, pp. 32–39, Apr. 2008, doi: 10.1109/MCOM.2008.4481338.

[86] N. Noorshams, M. Malboubi, and A. Bahai, “Centralized and decentralized cooperative spectrum sensing in cognitive radio networks: A novel approach,” *Proceedings of 2010 IEEE 11th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2010, pp. 1–5, doi: 10.1109/SPAWC.2010.5670998.

[87] G. Sharma and R. Sharma, “Cluster-based distributed cooperative spectrum sensing over Nakagami fading using diversity reception,” *IET Networks*, vol. 8, no. 3, pp. 211–217, 2019, doi: 10.1049/iet-net.2018.5002.

[88] A. de Paula and C. Panazio, “Cooperative spectrum sensing under unreliable reporting channels,” *Wireless Netw*, vol. 20, no. 6, pp. 1399–1407, Aug. 2014, doi: 10.1007/s11276-013-0683-9.

[89] M. M. A. Osman, S. K. Syed-Yusof, N. N. N. Abd Malik, and S. Zubair, “A survey of clustering algorithms for cognitive radio ad hoc networks,” *Wireless Netw*, vol. 24, no. 5, pp. 1451–1475, Jul. 2018, doi: 10.1007/s11276-016-1417-6.

[90] Z. Li, F. R. Yu, and M. Huang, “A distributed consensus-based cooperative spectrum-sensing scheme in cognitive radios,” *IEEE Transactions on Vehicular Technology*, vol. 59, no. 1, pp. 383–393, Jan. 2010, doi: 10.1109/TVT.2009.2031181.

[91] A. H. Gazestani and S. A. Ghorashi, “Distributed diffusion-based spectrum sensing for cognitive radio sensor networks considering link failure,” *IEEE Sensors Journal*, vol. 18, no. 20, pp. 8617–8625, Oct. 2018, doi: 10.1109/JSEN.2018.2866429.

[92] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar, “Coalitional games for distributed collaborative spectrum sensing in cognitive radio networks,” *Proceedings of IEEE INFOCOM 2009*, 2009, pp. 2114–2122, doi: 10.1109/INFCOM.2009.5062135.

[93] Y. Huo *et al.*, “A coalition formation game based relay selection scheme for cooperative cognitive radio networks,” *Wireless Netw*, vol. 23, no. 8, pp. 2533–2544, Nov. 2017, doi: 10.1007/s11276-016-1298-8.

[94] A. El Shafie, T. Khattab, and A. El-Keyi, “Energy-efficient cooperative cognitive relaying schemes for cognitive radio networks,” *Physical Communication*, vol. 30, pp. 179–192, Oct. 2018, doi: 10.1016/j.phycom.2018.08.006.

[95] I. Souid, H. Ben Chikha, I. Dayoub, and R. Attia, “MIMO relaying networks for cooperative spectrum sensing: False alarm and detection probabilities,” *Physical Communication*, vol. 25, pp. 194–200, Dec. 2017, doi: 10.1016/j.phycom.2017.07.006.

[96] Y. Zou, Y.-D. Yao, and B. Zheng, “A selective-relay based cooperative spectrum sensing scheme without dedicated reporting channels in cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 10, no. 4, pp. 1188–1198, Apr. 2011, doi: 10.1109/TWC.2011.021611.100913.

[97] C. Sun, W. Zhang, and K. Ben Letaief, “Cooperative spectrum sensing for cognitive radios under bandwidth constraints,” *Proceedings of 2007 IEEE Wireless Communications and Networking Conference*, 2007, pp. 1–5, doi: 10.1109/WCNC.2007.6.

[98] J. Ma, G. Zhao, and Y. Li, “Soft combination and detection for cooperative spectrum sensing in cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 7, no. 11, pp. 4502–4507, Nov. 2008, doi: 10.1109/T-WC.2008.070941.

[99] H. Guo, N. Reisi, W. Jiang, and W. Luo, “Soft combination for cooperative spectrum sensing in fading channels,” *IEEE Access*, vol. 5, pp. 975–986, 2017, doi: 10.1109/ACCESS.2016.2628860.

[100] C. Sun, W. Zhang, and K. B. Letaief, “Cluster-based cooperative spectrum sensing in cognitive radio systems,” *Proceedings of 2007 IEEE International Conference on Communications*, 2007, pp. 2511–2515, doi: 10.1109/ICC.2007.415.

[101] M. Mustonen, M. Matinmikko, and A. Mammela, “Cooperative spectrum sensing using quantized soft decision combining,” *Proceedings of 2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, 2009, pp. 1–5, doi: 10.1109/CROWNCOM.2009.5188980.

[102] N. Nguyen-Thanh, P. Ciblat, S. Maleki, and V.-T. Nguyen, “How many bits should be reported in quantized cooperative spectrum sensing?,” *IEEE Wireless Communications Letters*, vol. 4, no. 5, pp. 465–468, Oct. 2015, doi: 10.1109/LWC.2015.2437879.

[103] B. A. Bastami and E. Saberinia, “A practical multibit data combining strategy for cooperative spectrum sensing,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 1, pp. 384–389, Jan. 2013, doi: 10.1109/TVT.2012.2217160.

[104] S. Nallagonda, Y. R. Kumar, and P. Shilpa, “Analysis of hard-decision and soft-data fusion schemes for cooperative spectrum sensing in rayleigh fading channel,” *Proceedings of 2017 IEEE 7th International Advance Computing Conference (IACC)*, 2017, pp. 220–225, doi: 10.1109/IACC.2017.0057.

[105] W. Han, J. Li, Z. Li, J. Si, and Y. Zhang, “Efficient soft decision fusion rule in cooperative spectrum sensing,” *IEEE Transactions on Signal Processing*, vol. 61, no. 8, pp. 1931–1943, Apr. 2013, doi: 10.1109/TSP.2013.2245659.

[106] D. Teguig, B. Scheers, and V. Le Nir, “Data fusion schemes for cooperative spectrum sensing in cognitive radio networks,” *Proceedings of 2012 Military Communications and Information Systems Conference (MCC)*, 2012, pp. 1–7.

[107] B. S. Tan, K. H. Li, and K. C. Teh, “Performance analysis of orthogonal space-time block code with minimum-selection generalized selection combining receiver over rayleigh fading,” *IEEE Transactions on Vehicular Technology*, vol. 61, no. 3, pp. 1463–1467, Mar. 2012, doi: 10.1109/TVT.2012.2185077.

[108] A. Yılmaz and O. Kucur, “Performances of transmit antenna selection, receive antenna selection, and maximal-ratio-combining-based hybrid techniques in the presence of feedback errors,” *IEEE Transactions on Vehicular Technology*, vol. 63, no. 4, pp. 1976–1982, May 2014, doi: 10.1109/TVT.2013.2267962.

[109] S. Maleki, S. P. Chepuri, and G. Leus, “Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks,” *Physical Communication*, vol. 9, pp. 193–198, Dec. 2013, doi: 10.1016/j.phycom.2012.07.003.

[110] P. Verma and B. Singh, “On the decision fusion for cooperative spectrum sensing in cognitive radio networks,” *Wireless Netw*, vol. 23, no. 7, pp. 2253–2262, Oct. 2017, doi: 10.1007/s11276-016-1285-0.

[111] S. Nallagonda, A. Chandra, S. D. Roy, S. Kundu, P. Kukolev, and A. Prokes, “Detection performance of cooperative spectrum sensing with hard decision fusion in fading channels,” *International Journal of Electronics*, vol. 103, no. 2, pp. 297–321, Feb. 2016, doi: 10.1080/00207217.2015.1036369.

[112] Z. Quan, S. Cui, H. V. Poor, and A. H. Sayed, “Collaborative wideband sensing for cognitive radios,” *IEEE Signal Processing Magazine*, vol. 25, no. 6, pp. 60–73, Nov. 2008, doi: 10.1109/MSP.2008.929296.

[113] S. Bhattacharjee, P. Das, S. Mandal, and B. Sardar, “Optimization of probability of false alarm and probability of detection in cognitive radio networks using GA,” *Proceedings of*

2015 IEEE 2nd International Conference on Recent Trends in Information Systems (ReTIS), 2015, pp. 53–57, doi: 10.1109/ReTIS.2015.7232852.

[114] R. C. D. V. Bomfin, D. A. Guimarães, and R. A. A. de Souza, "On the probability of false alarm of the power spectral density split cancellation method," *IEEE Wireless Communications Letters*, vol. 5, no. 2, pp. 164–167, Apr. 2016, doi: 10.1109/LWC.2015.2514104.

[115] Y. Y. Mihov and B. P. Tsankov, "Call-level performance evaluation and QoS provisioning in cognitive radio networks," *Proceedings of IEEE Africon '11*, 2011, pp. 1–5, doi: 10.1109/AFRCON.2011.6072183.

[116] J. Raiyn, "Spectrum efficiency improvement based on the cognitive radio management," *International Journal of Communications, Network and System Sciences*, vol. 3, no. 3, pp. 280–288, Mar. 2010, doi: 10.4236/ijcns.2010.33036.

[117] Q. Xiao, Y. Li, X. Zhong, X. Xu, and J. Wang, "A unified approach to optimal opportunistic spectrum access under collision probability constraint in cognitive radio systems," *EURASIP J. Adv. Signal Process.*, vol. 2010, no. 1, p. 148698, Dec. 2009, doi: 10.1155/2010/148698.

[118] Q. Xiao, Y. Li, M. Zhao, S. Zhou, and J. Wang, "Opportunistic channel selection approach under collision probability constraint in cognitive radio systems," *Computer Communications*, vol. 32, no. 18, pp. 1914–1922, Dec. 2009, doi: 10.1016/j.comcom.2009.06.015.

[119] Y. Chen and Z. Tang, "Effect of spectrum sensing errors on the performance of OFDM-based cognitive radio transmission," *IEEE Transactions on Wireless Communications*, vol. 11, no. 6, pp. 2342–2350, Jun. 2012, doi: 10.1109/TWC.2012.040412.111744.

[120] X. Ling, B. Wu, H. Wen, P.-H. Ho, Z. Bao, and L. Pan, "Adaptive threshold control for energy detection based spectrum sensing in cognitive radios," *IEEE Wireless Communications Letters*, vol. 1, no. 5, pp. 448–451, Oct. 2012, doi: 10.1109/WCL.2012.062512.120299.

[121] A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Fixed and dynamic threshold selection criteria in energy detection for cognitive radio communication systems,” *Proceedings of 2017 Tenth International Conference on Contemporary Computing (IC3)*, 2017, pp. 1–6, doi: 10.1109/IC3.2017.8284302.

[122] A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Performance analysis of different threshold selection schemes in energy detection for cognitive radio communication systems,” *Proceedings of 2017 Fourth International Conference on Image Information Processing (ICIIP)*, 2017, pp. 1–6, doi: 10.1109/ICIIP.2017.8313702.

[123] P. R. Nair, A. P. Vinod, and A. K. Krishna, “A fast two stage detector for spectrum sensing in cognitive radios,” *Proceedings of 2011 IEEE Vehicular Technology Conference (VTC Fall)*, 2011, pp. 1–5, doi: 10.1109/VETECF.2011.6092897.

[124] W. Prawatmuang, D. K. C. So, and E. Alsusa, “Sequential cooperative spectrum sensing technique in time varying channel,” *IEEE Transactions on Wireless Communications*, vol. 13, no. 6, pp. 3394–3405, Jun. 2014, doi: 10.1109/TWC.2014.051314.131404.

[125] S. Suwanboriboon and W. Lee, “A novel two-stage spectrum sensing for cognitive radio system,” *Proceedings of 2013 13th International Symposium on Communications and Information Technologies (ISCIT)*, 2013, pp. 176–181, doi: 10.1109/ISCIT.2013.6645845.

[126] S. Maleki, A. Pandharipande, and G. Leus, “Two-stage spectrum sensing for cognitive radios,” *Proceedings of 2010 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2010, pp. 2946–2949, doi: 10.1109/ICASSP.2010.5496149.

[127] G. Ganesan and Ye Li, “Agility improvement through cooperative diversity in cognitive radio,” *Proceedings of GLOBECOM ’05. IEEE Global Telecommunications Conference, 2005.*, 2005, vol. 5, pp. 5 pp. – 2509, doi: 10.1109/GLOCOM.2005.1578213.

[128] S. Chaudhari, J. Lunden, V. Koivunen, and H. V. Poor, “Cooperative sensing with imperfect reporting channels: hard decisions or soft decisions?,” *IEEE Transactions on Signal Processing*, vol. 60, no. 1, pp. 18–28, Jan. 2012, doi: 10.1109/TSP.2011.2170978.

[129] J. So and W. Sung, "Group-based multibit cooperative spectrum sensing for cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 12, pp. 10193–10198, Dec. 2016, doi: 10.1109/TVT.2016.2536659.

[130] G. Verma and O. P. Sahu, "Intelligent selection of threshold in cognitive radio system," *Telecommun Syst*, vol. 63, no. 4, pp. 547–556, Dec. 2016, doi: 10.1007/s11235-016-0141-y.

[131] J. Jafarian and K. A. Hamdi, "Throughput optimization in a cooperative double-threshold sensing scheme," *Proceedings of 2012 IEEE Wireless Communications and Networking Conference (WCNC)*, 2012, pp. 1034–1038, doi: 10.1109/WCNC.2012.6213925.

[132] Cong Shi, Ying Wang, Tan Wang, and Ping Zhang, "Joint optimization of detection threshold and throughput in multiband cognitive radio systems," *Proceedings of 2012 IEEE Consumer Communications and Networking Conference (CCNC)*, 2012, pp. 849–853, doi: 10.1109/CCNC.2012.6181177.

[133] L. Lu, X. Zhou, U. Onunkwo, and G. Y. Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, p. 28, Jan. 2012, doi: 10.1186/1687-1499-2012-28.

[134] M. Sadeghian Kerdabadi, R. Ghazizadeh, H. Farrokhi, and M. Najimi, "Energy consumption minimization and throughput improvement in cognitive radio networks by joint optimization of detection threshold, sensing time and user selection," *Wireless Netw*, vol. 25, no. 4, pp. 2065–2079, May 2019, doi: 10.1007/s11276-018-1797-x.

[135] Y. Pei, Y.-C. Liang, K. C. Teh, and K. H. Li, "How much time is needed for qideband spectrum sensing?," *IEEE Transactions on Wireless Communications*, vol. 8, no. 11, pp. 5466–5471, Nov. 2009, doi: 10.1109/TWC.2009.090350.

[136] X. Liu and X. Tan, "Optimization algorithm of periodical cooperative spectrum sensing in cognitive radio," *International Journal of Communication Systems*, vol. 27, no. 5, pp. 705–720, 2014, doi: 10.1002/dac.2377.

[137] A. Bhowmick, M. K. Das, J. Biswas, S. D. Roy, and S. Kundu, “Throughput optimization with cooperative spectrum sensing in cognitive radio network,” *Proceedings of 2014 IEEE International Advance Computing Conference (IACC)*, 2014, pp. 329–332, doi: 10.1109/IAdCC.2014.6779343.

[138] E. Everett, A. Sahai, and A. Sabharwal, “Passive self-interference suppression for full-duplex infrastructure nodes,” *IEEE Transactions on Wireless Communications*, vol. 13, no. 2, pp. 680–694, Feb. 2014, doi: 10.1109/TWC.2013.010214.130226.

[139] Z. Zhang, X. Chai, K. Long, A. V. Vasilakos, and L. Hanzo, “Full duplex techniques for 5G networks: self-interference cancellation, protocol design, and relay selection,” *IEEE Communications Magazine*, vol. 53, no. 5, pp. 128–137, May 2015, doi: 10.1109/MCOM.2015.7105651.

[140] E. Foroozanfard, O. Franek, A. Tatomirescu, E. Tsakalaki, E. D. Carvalho, and G. F. Pedersen, “Full-duplex MIMO system based on antenna cancellation technique,” *Electronics Letters*, vol. 50, no. 16, pp. 1116–1117, Jul. 2014, doi: 10.1049/el.2014.1650.

[141] L. T. Tan and L. B. Le, “Design and optimal configuration of full-duplex mac protocol for cognitive radio networks considering self-interference,” *IEEE Access*, vol. 3, pp. 2715–2729, 2015, doi: 10.1109/ACCESS.2015.2509449.

[142] H. Mokhtarzadeh, A. Taherpour, A. Taherpour, and S. Gazor, “Throughput maximization in energy limited full-duplex cognitive radio networks,” *IEEE Transactions on Communications*, vol. 67, no. 8, pp. 5287–5296, Aug. 2019, doi: 10.1109/TCOMM.2019.2919620.

[143] D. R. Joshi, D. C. Popescu, and O. A. Dobre, “Dynamic threshold adaptation for spectrum sensing in cognitive radio systems,” *Proceedings of 2010 IEEE Radio and Wireless Symposium (RWS)*, 2010, pp. 468–471, doi: 10.1109/RWS.2010.5434216.

[144] V. N. Kumar, K. V. Reddy, S. Geethu, G. Lakshminarayanan, and M. Sellathurai, “Reconfigurable hybrid spectrum sensing technique for cognitive radio,” *Proceedings of*

2013 IEEE 8th International Conference on Industrial and Information Systems, 2013, pp. 59–62, doi: 10.1109/ICIInfS.2013.6731955.

[145] V. Ramachandran and A. Cheeran, "Evaluation of energy efficiency of spectrum sensing algorithm for Cognitive Radio networks," *Proceedings of 2014 International Conference on Computer Communication and Informatics*, 2014, pp. 1–6, doi: 10.1109/ICCCI.2014.6921791.

[146] L. Luo, N. M. Neihart, S. Roy, and D. J. Allstot, "A two-stage sensing technique for dynamic spectrum access," *IEEE Transactions on Wireless Communications*, vol. 8, no. 6, pp. 3028–3037, Jun. 2009, doi: 10.1109/TWC.2009.080482.

[147] M. Monemi, M. Rasti, and E. Hossain, "On characterization of feasible interference regions in cognitive radio networks," *IEEE Transactions on Communications*, vol. 64, no. 2, pp. 511–524, Feb. 2016, doi: 10.1109/TCOMM.2015.2514093.

[148] S.-Q. Liu, B.-J. Hu, and X.-Y. Wang, "Hierarchical cooperative spectrum sensing based on double thresholds energy detection," *IEEE Communications Letters*, vol. 16, no. 7, pp. 1096–1099, Jul. 2012, doi: 10.1109/LCOMM.2012.050112.120765.

[149] A. Bagwari, G. S. Tomar, and S. Verma, "Cooperative spectrum sensing based on two-stage detectors with multiple energy detectors and adaptive double threshold in cognitive radio networks," *Canadian Journal of Electrical and Computer Engineering*, vol. 36, no. 4, pp. 172–180, Fall 2013, doi: 10.1109/CJECE.2014.2303519.

[150] E. Hill and H. Sun, "Double threshold spectrum sensing methods in spectrum-scarce vehicular communications," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 9, pp. 4072–4080, Sep. 2018, doi: 10.1109/TII.2018.2816580.

[151] A. Kumar, S. Saha, and K. Tiwari, "A double threshold-based cooperative spectrum sensing with novel hard-soft combining over fading channels," *IEEE Wireless Communications Letters*, vol. 8, no. 4, pp. 1154–1158, Aug. 2019, doi: 10.1109/LWC.2019.2909879.

[152] R. Stolkin and I. Florescu, “Probability of detection and optimal sensor placement for threshold based detection systems,” *IEEE Sensors Journal*, vol. 9, no. 1, pp. 57–60, Jan. 2009, doi: 10.1109/JSEN.2008.2008884.

[153] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, “Sensing-throughput tradeoff for cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008, doi: 10.1109/TWC.2008.060869.

[154] E. C. Y. Peh, Y.-C. Liang, Y. L. Guan, and Y. Zeng, “Optimization of cooperative sensing in cognitive radio networks: A sensing-throughput tradeoff view,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 9, pp. 5294–5299, Nov. 2009, doi: 10.1109/TVT.2009.2028030.

[155] L. Tang, Y. Chen, E. L. Hines, and M.-S. Alouini, “Effect of primary user traffic on sensing-throughput tradeoff for cognitive radios,” *IEEE Transactions on Wireless Communications*, vol. 10, no. 4, pp. 1063–1068, Apr. 2011, doi: 10.1109/TWC.2011.020111.101870.

[156] C. Zhao and K. Kwak, “Joint sensing time and power allocation in cooperatively cognitive networks,” *IEEE Communications Letters*, vol. 14, no. 2, pp. 163–165, Feb. 2010, doi: 10.1109/LCOMM.2010.02.092102.

[157] X. Liu, F. Li, and Z. Na, “Optimal resource allocation in simultaneous cooperative spectrum sensing and energy harvesting for multichannel cognitive radio,” *IEEE Access*, vol. 5, pp. 3801–3812, 2017, doi: 10.1109/ACCESS.2017.2677976.

[158] S. Stotas and A. Nallanathan, “Optimal sensing time and power allocation in multiband cognitive radio networks,” *IEEE Transactions on Communications*, vol. 59, no. 1, pp. 226–235, Jan. 2011, doi: 10.1109/TCOMM.2010.110310.090473.

[159] M. E. Ozfatura, S. ElAzzouni, O. Ercetin, and T. ElBatt, “Optimal throughput performance in full-duplex relay assisted cognitive networks,” *Wireless Netw*, vol. 25, no. 4, pp. 1931–1947, May 2019, doi: 10.1007/s11276-018-1692-5.

[160] P. V. Tuan and I. Koo, “Throughput maximisation by optimising detection thresholds in full-duplex cognitive radio networks,” *IET Communications*, vol. 10, no. 11, pp. 1355–1364, 2016, doi: 10.1049/iet-com.2015.1186.

[161] C. Sudhamani and S. S. R. M., “Energy efficiency in cognitive radio network using cooperative spectrum sensing,” *Wireless Pers Commun*, vol. 104, no. 3, pp. 907–919, Feb. 2019, doi: 10.1007/s11277-018-6059-9.

[162] F. Kong, Z. Jin, J. Cho, and B. Lee, “A novel spectrum sensing scheme with sensing time optimization for energy-efficient CRSNs,” *Wireless Netw*, vol. 24, no. 7, pp. 2781–2794, Oct. 2018, doi: 10.1007/s11276-017-1634-7.

[163] W. Wang, W. Zou, Z. Zhou, H. Zhang, and Y. Ye, “Decision fusion of cooperative spectrum sensing for cognitive radio under bandwidth constraints,” *Proceedings of 2008 Third International Conference on Convergence and Hybrid Information Technology*, 2008, vol. 1, pp. 733–736, doi: 10.1109/ICCIT.2008.15.

[164] S. Maleki, G. Leus, S. Chatzinotas, and B. Ottersten, “To AND or To OR: On energy-efficient distributed spectrum sensing with combined censoring and sleeping,” *IEEE Transactions on Wireless Communications*, vol. 14, no. 8, pp. 4508–4521, Aug. 2015, doi: 10.1109/TWC.2015.2422304.

[165] S. Maleki, A. Pandharipande, and G. Leus, “Energy-efficient distributed spectrum sensing for cognitive sensor networks,” *IEEE Sensors Journal*, vol. 11, no. 3, pp. 565–573, Mar. 2011, doi: 10.1109/JSEN.2010.2051327.

[166] S. Akhila and K. P. Priya, “Dynamic channel access with asynchronous sleep-wake scheduling to improve energy efficiency in CRSNs,” *Proceedings of 2017 International Conference on Intelligent Computing and Control (I2C2)*, 2017, pp. 1–6, doi: 10.1109/I2C2.2017.8321843.

[167] J. Lunden, V. Koivunen, A. Huttunen, and H. V. Poor, “Censoring for collaborative spectrum sensing in cognitive radios,” *Proceedings of 2007 Conference Record of the*

Forty-First Asilomar Conference on Signals, Systems and Computers, 2007, pp. 772–776, doi: 10.1109/ACSSC.2007.4487321.

[168] G. Ganesan and Y. Li, "Cooperative spectrum sensing in cognitive radio, Part I: Two user networks," *IEEE Transactions on Wireless Communications*, vol. 6, no. 6, pp. 2204–2213, Jun. 2007, doi: 10.1109/TWC.2007.05775.

[169] J. Ren, Y. Zhang, N. Zhang, D. Zhang, and X. Shen, "Dynamic channel access to improve energy efficiency in cognitive radio sensor networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 5, pp. 3143–3156, May 2016, doi: 10.1109/TWC.2016.2517618.

[170] N. Saeed and H. Nam, "Energy efficient localization algorithm with improved accuracy in cognitive radio networks," *IEEE Communications Letters*, vol. 21, no. 9, pp. 2017–2020, Sep. 2017, doi: 10.1109/LCOMM.2017.2712802.

[171] M. Monemian, M. Mahdavi, and M. J. Omidi, "Optimum sensor selection based on energy constraints in cooperative spectrum sensing for cognitive radio sensor networks," *IEEE Sensors Journal*, vol. 16, no. 6, pp. 1829–1841, Mar. 2016, doi: 10.1109/JSEN.2015.2503324.

[172] M. Najimi, A. Ebrahimzadeh, S. M. H. Andargoli, and A. Fallahi, "A novel sensing nodes and decision node selection method for energy efficiency of cooperative spectrum sensing in cognitive sensor networks," *IEEE Sensors Journal*, vol. 13, no. 5, pp. 1610–1621, May 2013, doi: 10.1109/JSEN.2013.2240900.

[173] X. Xu, J. Bao, H. Cao, Y.-D. Yao, and S. Hu, "Energy-efficiency-based optimal relay selection scheme with a BER constraint in cooperative cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 1, pp. 191–203, Jan. 2016, doi: 10.1109/TVT.2015.2389810.

[174] M. Monemian and M. Mahdavi, "Analysis of a new energy-based sensor selection method for cooperative spectrum sensing in cognitive radio networks," *IEEE Sensors Journal*, vol. 14, no. 9, pp. 3021–3032, Sep. 2014, doi: 10.1109/JSEN.2014.2322034.

[175] S. Maleki, S. P. Chepuri, and G. Leus, "Energy and throughput efficient strategies for cooperative spectrum sensing in cognitive radios," *Proceedings of 2011 IEEE 12th International Workshop on Signal Processing Advances in Wireless Communications*, 2011, pp. 71–75, doi: 10.1109/SPAWC.2011.5990482.

[176] M. Usman, D. Har, and I. Koo, "Energy-efficient infrastructure sensor network for ad hoc cognitive radio network," *IEEE Sensors Journal*, vol. 16, no. 8, pp. 2775–2787, Apr. 2016, doi: 10.1109/JSEN.2016.2516018.

[177] R. Deng, J. Chen, C. Yuen, P. Cheng, and Y. Sun, "Energy-efficient cooperative spectrum sensing by optimal scheduling in sensor-aided cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 2, pp. 716–725, Feb. 2012, doi: 10.1109/TVT.2011.2179323.

[178] C. Lin, G. Wu, F. Xia, M. Li, L. Yao, and Z. Pei, "Energy efficient ant colony algorithms for data aggregation in wireless sensor networks," *Journal of Computer and System Sciences*, vol. 78, no. 6, pp. 1686–1702, Nov. 2012, doi: 10.1016/j.jcss.2011.10.017.

[179] S. Althunibat, M. Di Renzo, and F. Granelli, "Optimizing the K-out-of-N rule for cooperative spectrum sensing in cognitive radio networks," *Proceedings of 2013 IEEE Global Communications Conference (GLOBECOM)*, 2013, pp. 1607–1611, doi: 10.1109/GLOCOM.2013.6831303.

[180] D. Huang, G. Kang, B. Wang, and H. Tian, "Energy-efficient spectrum sensing strategy in cognitive radio networks," *IEEE Communications Letters*, vol. 17, no. 5, pp. 928–931, May 2013, doi: 10.1109/LCOMM.2013.031913.130131.

[181] H. N. Pham, Y. Zhang, P. E. Engelstad, T. Skeie, and F. Eliassen, "Energy minimization approach for optimal cooperative spectrum sensing in sensor-aided cognitive radio networks," *Proceedings of 2010 The 5th Annual ICST Wireless Internet Conference (WICON)*, 2010, pp. 1–9.

[182] Y. Wu and D. H. K. Tsang, "Energy-efficient spectrum sensing and transmission for cognitive radio system," *IEEE Communications Letters*, vol. 15, no. 5, pp. 545–547, May 2011, doi: 10.1109/LCOMM.2011.032811.110102.

[183] M. Robat Mili, L. Musavian, K. A. Hamdi, and F. Marvasti, "How to increase energy efficiency in cognitive radio networks," *IEEE Transactions on Communications*, vol. 64, no. 5, pp. 1829–1843, May 2016, doi: 10.1109/TCOMM.2016.2535371.

[184] A. Ebrahimzadeh, M. Najimi, S. M. H. Andargoli, and A. Fallahi, "Sensor selection and optimal energy detection threshold for efficient cooperative spectrum sensing," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 4, pp. 1565–1577, Apr. 2015, doi: 10.1109/TVT.2014.2331681.

[185] S. Atapattu, C. Tellambura, and H. Jiang, "Spectrum sensing via energy detector in low snr," *Proceedings of 2011 IEEE International Conference on Communications (ICC)*, 2011, pp. 1–5, doi: 10.1109/icc.2011.5963316.

[186] W. Zhang, R. K. Mallik, and K. B. Letaief, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 8, no. 12, pp. 5761–5766, Dec. 2009, doi: 10.1109/TWC.2009.12.081710.

[187] J. J. Lehtomaki, J. Vartiainen, M. Juntti, and H. Saarnisaari, "CFAR outlier detection with forward methods," *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4702–4706, Sep. 2007, doi: 10.1109/TSP.2007.896239.

[188] A. J. Onumanyi, A. M. Abu-Mahfouz, and G. P. Hancke, "A comparative analysis of local and global adaptive threshold estimation techniques for energy detection in cognitive radio," *Physical Communication*, vol. 29, pp. 1–11, Aug. 2018, doi: 10.1016/j.phycom.2018.04.008.

[189] S. Gurugopinath, R. Akula, C. R. Murthy, P. R., and B. Amrutur, "Design and implementation of spectrum sensing for cognitive radios with a frequency-hopping primary

system," *Physical Communication*, vol. 17, pp. 172–184, Dec. 2015, doi: 10.1016/j.phycom.2015.09.001.

[190] G. Caso, L. De Nardis, G. C. Ferrante, and M.-G. Di Benedetto, "Cooperative spectrum sensing based on Majority decision under CFAR and CDR constraints," *Proceedings of 2013 IEEE 24th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC Workshops)*, 2013, pp. 51–55, doi: 10.1109/PIMRCW.2013.6707835.

[191] N. Wang, Y. Gao, and X. Zhang, "Adaptive spectrum sensing algorithm under different primary user utilizations," *IEEE Communications Letters*, vol. 17, no. 9, pp. 1838–1841, Sep. 2013, doi: 10.1109/LCOMM.2013.081313.131468.

[192] A. Mariani, A. Giorgetti, and M. Chiani, "Effects of noise power estimation on energy detection for cognitive radio applications," *IEEE Transactions on Communications*, vol. 59, no. 12, pp. 3410–3420, Dec. 2011, doi: 10.1109/TCOMM.2011.102011.100708.

[193] P. Jia, M. Vu, T. Le-Ngoc, S.-C. Hong, and V. Tarokh, "Capacity- and bayesian-based cognitive sensing with location side information," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 2, pp. 276–289, Feb. 2011, doi: 10.1109/JSAC.2011.110202.

[194] A. Singh, M. R. Bhatnagar, and R. K. Mallik, "Cooperative spectrum sensing in multiple antenna based cognitive radio network using an improved energy detector," *IEEE Communications Letters*, vol. 16, no. 1, pp. 64–67, Jan. 2012, doi: 10.1109/LCOMM.2011.103111.111884.

[195] P. P. Gandhi and S. A. Kassam, "Analysis of CFAR processors in nonhomogeneous background," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 24, no. 4, pp. 427–445, Jul. 1988, doi: 10.1109/7.7185.

[196] A. Kortun, T. Ratnarajah, M. Sellathurai, Y.-C. Liang, and Y. Zeng, "On the eigenvalue-based spectrum sensing and secondary user throughput," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 3, pp. 1480–1486, Mar. 2014, doi: 10.1109/TVT.2013.2282344.

[197] M. H. Al-Badrawi and N. J. Kirsch, “An EMD-based double threshold detector for spectrum sensing in cognitive radio networks,” *Proceedings of 2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall)*, 2015, pp. 1–5, doi: 10.1109/VTCFall.2015.7390838.

[198] C. Politis, S. Maleki, C. G. Tsinos, K. P. Liolis, S. Chatzinotas, and B. Ottersten, “Simultaneous sensing and transmission for cognitive radios with imperfect signal cancellation,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 5599–5615, Sep. 2017, doi: 10.1109/TWC.2017.2712647.

[199] M. Sarker, “Energy detector based spectrum sensing by adaptive threshold for low SNR in CR networks,” *Proceedings of 2015 24th Wireless and Optical Communication Conference (WOCC)*, 2015, pp. 118–122, doi: 10.1109/WOCC.2015.7346189.

[200] G. Verma and O. P. Sahu, “Opportunistic selection of threshold in cognitive radio networks,” *Wireless Pers Commun*, vol. 92, no. 2, pp. 711–726, Jan. 2017, doi: 10.1007/s11277-016-3573-5.

[201] H. Zhang, Y. Nie, J. Cheng, V. C. M. Leung, and A. Nallanathan, “Sensing time optimization and power control for energy efficient cognitive small cell with imperfect hybrid spectrum sensing,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 2, pp. 730–743, Feb. 2017, doi: 10.1109/TWC.2016.2628821.

[202] X. Zhai, He Haigen, and Zheng Guoxin, “Optimal threshold and weighted cooperative data combining rule in cognitive radio network,” *Proceedings 2010 IEEE 12th International Conference on Communication Technology*, 2010, pp. 1464–1467, doi: 10.1109/ICCT.2010.5688975.

[203] H.-H. Choi, K. Jang, and Y. Cheong, “Adaptive sensing threshold control based on transmission power in cognitive radio systems,” *Proceedings 2008 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom 2008)*, 2008, pp. 1–6, doi: 10.1109/CROWNCOM.2008.4562452.

[204] D. R. Joshi, D. C. Popescu, and O. A. Dobre, “Gradient-based threshold adaptation for energy detector in cognitive radio systems,” *IEEE Communications Letters*, vol. 15, no. 1, pp. 19–21, Jan. 2011, doi: 10.1109/LCOMM.2010.11.100654.

[205] J. Nasreddine, J. Riihijarvi, and P. Mahonen, “Location-based adaptive detection threshold for dynamic spectrum access,” *Proceedings 2010 IEEE Symposium on New Frontiers in Dynamic Spectrum (DySPAN)*, 2010, pp. 1–10, doi: 10.1109/DYSPAN.2010.5457863.

[206] T.-H. Yu, O. Sekkat, S. Rodriguez-Parera, D. Markovic, and D. Cabric, “A wideband spectrum-sensing processor with adaptive detection threshold and sensing time,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 58, no. 11, pp. 2765–2775, Nov. 2011, doi: 10.1109/TCSI.2011.2143010.

[207] K. Umebayashi, K. Hayashi, and J. J. Lehtomäki, “Threshold-setting for spectrum sensing based on statistical information,” *IEEE Communications Letters*, vol. 21, no. 7, pp. 1585–1588, Jul. 2017, doi: 10.1109/LCOMM.2017.2691004.

[208] G. Ding *et al.*, “Spectrum inference in cognitive radio networks: algorithms and applications,” *IEEE Communications Surveys Tutorials*, vol. 20, no. 1, pp. 150–182, Firstquarter 2018, doi: 10.1109/COMST.2017.2751058.

[209] F. Benedetto and G. Giunta, “A novel pu sensing algorithm for constant energy signals,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 1, pp. 827–831, Jan. 2018, doi: 10.1109/TVT.2017.2738331.

[210] A.-Z. Chen, Z.-P. Shi, and Z.-Q. He, “A robust blind detection algorithm for cognitive radio networks with correlated multiple antennas,” *IEEE Communications Letters*, vol. 22, no. 3, pp. 570–573, Mar. 2018, doi: 10.1109/LCOMM.2017.2789184.

[211] T. Xiong, Y.-D. Yao, Y. Ren, and Z. Li, “Multiband spectrum sensing in cognitive radio networks with secondary user hardware limitation: Random and adaptive spectrum sensing strategies,” *IEEE Transactions on Wireless Communications*, vol. 17, no. 5, pp. 3018–3029, May 2018, doi: 10.1109/TWC.2018.2805729.

[212] A. Bayat and S. Aïssa, “Full-duplex cognitive radio with asynchronous energy-efficient sensing,” *IEEE Transactions on Wireless Communications*, vol. 17, no. 2, pp. 1066–1080, Feb. 2018, doi: 10.1109/TWC.2017.2774268.

[213] A. U. Makarfi and K. A. Hamdi, “Interference analysis of energy detection for spectrum sensing,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 6, pp. 2570–2578, Jul. 2013, doi: 10.1109/TVT.2013.2244622.

[214] S. Koley, V. Mirza, S. Islam, and D. Mitra, “Gradient-based real-time spectrum sensing at low SNR,” *IEEE Communications Letters*, vol. 19, no. 3, pp. 391–394, Mar. 2015, doi: 10.1109/LCOMM.2014.2387168.

[215] P. Verma and B. Singh, “Joint optimization of sensing duration and detection threshold for maximizing the spectrum utilization,” *Digital Signal Processing*, vol. 74, pp. 94–101, Mar. 2018, doi: 10.1016/j.dsp.2017.12.001.

[216] S. L. MacDonald and D. C. Popescu, “Impact of primary user activity on the performance of energy-based spectrum sensing in cognitive radio systems,” *Proceedings 2013 IEEE Global Communications Conference (GLOBECOM)*, 2013, pp. 3224–3228, doi: 10.1109/GLOCOM.2013.6831568.

[217] C. Fu, Y. Li, Y. He, M. Jin, G. Wang, and P. Lei, “An inter-frame dynamic double-threshold energy detection for spectrum sensing in cognitive radios,” *Wireless Com Network*, vol. 2017, no. 1, p. 118, Jun. 2017, doi: 10.1186/s13638-017-0897-0.

[218] S. Pandit and G. Singh, "*Spectrum Sharing in Cognitive Radio Networks: Medium Access Control Protocol Based Approach*" Springer International Publishing, 2017.

[219] D. Cabric, A. Tkachenko, and R. W. Brodersen, “Experimental study of spectrum sensing based on energy detection and network cooperation,” *Proceedings* of the first international workshop on Technology and policy for accessing spectrum, 2006, p. 12, doi: 10.1145/1234388.1234400.

[220] S. Atapattu, C. Tellambura, H. Jiang, and N. Rajatheva, “Unified analysis of low-SNR energy detection and threshold selection,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 11, pp. 5006–5019, Nov. 2015, doi: 10.1109/TVT.2014.2381648.

[221] Z. Quan, S. Cui, and A. H. Sayed, “Optimal linear cooperation for spectrum sensing in cognitive radio networks,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 1, pp. 28–40, Feb. 2008, doi: 10.1109/JSTSP.2007.914882.

[222] F. F. Digham, M.-S. Alouini, and M. K. Simon, “On the energy detection of unknown signals over fading channels,” *IEEE Transactions on Communications*, vol. 55, no. 1, pp. 21–24, Jan. 2007, doi: 10.1109/TCOMM.2006.887483.

[223] S. K. Balam, P. Siddaiah, and S. Nallagonda, “Throughput analysis of cooperative cognitive radio network over generalized κ–μ and η–μ fading channels,” *Wireless Netw*, May 2018, doi: 10.1007/s11276-018-1758-4.

[224] Y.-J. Choi, W. Pak, Y. Xin, and S. Rangarajan, “Throughput analysis of cooperative spectrum sensing in rayleigh-faded cognitive radio systems,” *IET Communications*, vol. 6, no. 9, pp. 1104–1110, Jun. 2012, doi: 10.1049/iet-com.2010.1025.

[225] Q.-T. Vien, H. X. Nguyen, and A. Nallanathan, “Cooperative spectrum sensing with secondary user selection for cognitive radio networks over nakagami-m fading channels,” *IET Communications*, vol. 10, no. 1, pp. 91–97, 2016, doi: 10.1049/iet-com.2015.0461.

[226] Q.-T. Vien, H. X. Nguyen, R. Trestian, P. Shah, and O. Gemikonakli, “A hybrid double-threshold based cooperative spectrum sensing over fading channels,” *IEEE Transactions on Wireless Communications*, vol. 15, no. 3, pp. 1821–1834, Mar. 2016, doi: 10.1109/TWC.2015.2496598.

[227] L. Gahane, P. K. Sharma, N. Varshney, T. A. Tsiftsis, and P. Kumar, “An improved energy detector for mobile cognitive users over generalized fading channels,” *IEEE Transactions on Communications*, vol. 66, no. 2, pp. 534–545, Feb. 2018, doi: 10.1109/TCOMM.2017.2754250.

[228] H. Sun, D. I. Laurenson, and C.-X. Wang, “Computationally tractable model of energy detection performance over slow fading channels,” *IEEE Communications Letters*, vol. 14, no. 10, pp. 924–926, Oct. 2010, doi: 10.1109/LCOMM.2010.090710.100934.

[229] V. M. Patil, R. Ujjinimatad, and S. R. Patil, “Signal detection in cognitive radio networks over awgn and fading channels,” *Int J Wireless Inf Networks*, vol. 25, no. 1, pp. 79–86, Mar. 2018, doi: 10.1007/s10776-017-0376-x.

[230] F. F. Digham, A. H. Tewfik, and M.-S. Alouini, “Detection of known and unknown signals, over fading channels,” *Proceedings of GLOBECOM ’03. IEEE Global Telecommunications Conference (IEEE Cat. No.03CH37489)*, 2003, vol. 3, pp. 1756–1760 vol.3, doi: 10.1109/GLOCOM.2003.1258538.

[231] M. Cardenas-Juarez and M. Ghogho, “Spectrum sensing and throughput trade-off in cognitive radio under outage constraints over nakagami fading,” *IEEE Communications Letters*, vol. 15, no. 10, pp. 1110–1113, Oct. 2011, doi: 10.1109/LCOMM.2011.080811.111127.

[232] A. Eslami and S. Karamzadeh, “Performance analysis of double threshold energy detection-based spectrum sensing in low SNRs over nakagami-m fading channels with noise uncertainty,” *Proceedings of 2016 24th Signal Processing and Communication Application Conference (SIU)*, 2016, pp. 309–312, doi: 10.1109/SIU.2016.7495739.

[233] E. Soltanmohammadi, M. Orooji, and M. Naraghi-Pour, “Improving the sensing–throughput tradeoff for cognitive radios in rayleigh fading channels,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 5, pp. 2118–2130, Jun. 2013, doi: 10.1109/TVT.2012.2236116.

[234] G. Chandrasekaran and S. Kalyani, “Performance Analysis of cooperative spectrum sensing over K-μ shadowed fading,” *IEEE Wireless Communications Letters*, vol. 4, no. 5, pp. 553–556, Oct. 2015, doi: 10.1109/LWC.2015.2457895.

[235] P. C. Sofotasios, E. Rebeiz, L. Zhang, T. A. Tsiftsis, D. Cabric, and S. Freear, “Energy detection based spectrum sensing over K-μ and K-μ extreme fading channels,” *IEEE*

Transactions on Vehicular Technology, vol. 62, no. 3, pp. 1031–1040, Mar. 2013, doi: 10.1109/TVT.2012.2228680.

[236] M. Awasthi, M. J. Nigam, and V. Kumar, “Optimal sensing, fusion and transmission with primary user protection for energy-efficient cooperative spectrum sensing in CRNs,” *AEU - International Journal of Electronics and Communications*, vol. 98, pp. 95–105, Jan. 2019, doi: 10.1016/j.aeue.2018.10.031.

[237] B. C. Nguyen, T. M. Hoang, and P. T. Tran, “Performance analysis of full-duplex decode-and-forward relay system with energy harvesting over Nakagami-m fading channels,” *AEU - International Journal of Electronics and Communications*, vol. 98, pp. 114–122, Jan. 2019, doi: 10.1016/j.aeue.2018.11.002.

[238] S. M. Kay, "*Fundamentals of statistical signal processing*." Upper Saddle River, NJ: Prentice Hall PTR, 1993.

[239] A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: an energy detection approach,” *Wireless Netw*, vol. 25, no. 7, pp. 3917–3931, Oct. 2019, doi: 10.1007/s11276-018-01927-y.

[240] S. Nallagonda, S. D. Roy, S. Kundu, G. Ferrari, and R. Raheli, “Censoring-based cooperative spectrum sensing with improved energy detectors and multiple antennas in fading channels,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 54, no. 2, pp. 537–553, Apr. 2018, doi: 10.1109/TAES.2017.2732798.

[241] M. Li *et al.*, “Censor-based cooperative multi-antenna spectrum sensing with imperfect reporting channels,” *IEEE Transactions on Sustainable Computing*, pp. 1–1, 2019, doi: 10.1109/TSUSC.2019.2896667.

[242] Y. Lu, D. Wang, and M. Fattouche, “Cooperative spectrum-sensing algorithm in cognitive radio by simultaneous sensing and BER measurements,” *J Wireless Com Network*, vol. 2016, no. 1, p. 136, May 2016, doi: 10.1186/s13638-016-0635-z.

[243] H. Li and C. Liu, “Cross-layer optimization for full-duplex cognitive radio network with cooperative spectrum sensing,” *International Journal of Communication Systems*, vol. 32, no. 5, p. e3895, 2019, doi: 10.1002/dac.3895.

[244] R. Fan and H. Jiang, “Optimal multi-channel cooperative sensing in cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 9, no. 3, pp. 1128–1138, Mar. 2010, doi: 10.1109/TWC.2010.03.090467.

[245] W. Tang, M. Z. Shakir, M. A. Imran, R. Tafazolli, and M.-S. Alouini, “Throughput analysis for cognitive radio networks with multiple primary users and imperfect spectrum sensing,” *IET Communications*, vol. 6, no. 17, pp. 2787–2795, Nov. 2012, doi: 10.1049/iet-com.2012.0236.

[246] K. Yadav, B. Prasad, A. Bhowmick, S. D. Roy, and S. Kundu, “Throughput performance under primary user emulation attack in cognitive radio networks,” *International Journal of Communication Systems*, vol. 30, no. 18, p. e3371, 2017, doi: 10.1002/dac.3371.

[247] M. Sharifi, A. A. Sharifi, and M. J. M. Niya, “Cooperative spectrum sensing in the presence of primary user emulation attack in cognitive radio network: multi-level hypotheses test approach,” *Wireless Netw*, vol. 24, no. 1, pp. 61–68, Jan. 2018, doi: 10.1007/s11276-016-1321-0.

[248] S. Althunibat, M. Di Renzo, and F. Granelli, “Towards energy-efficient cooperative spectrum sensing for cognitive radio networks: an overview,” *Telecommun Syst*, vol. 59, no. 1, pp. 77–91, May 2015, doi: 10.1007/s11235-014-9887-2.

[249] H. Hu, H. Zhang, and Y.-C. Liang, “On the spectrum- and energy-efficiency tradeoff in cognitive radio networks,” *IEEE Transactions on Communications*, vol. 64, no. 2, pp. 490–501, Feb. 2016, doi: 10.1109/TCOMM.2015.2505281.

[250] A. Bhowmick, S. D. Roy, and S. Kundu, “Sensing throughput trade-off for an energy efficient cognitive radio network under faded sensing and reporting channel,” *International Journal of Communication Systems*, vol. 29, no. 7, pp. 1208–1218, 2016, doi: 10.1002/dac.3087.

[251] M. Najimi, “Sensing time optimisation and sensor selection in multi-channel multi-antenna wireless cognitive sensor networks,” *IET Signal Processing*, vol. 12, no. 6, pp. 795–801, Mar. 2018, doi: 10.1049/iet-spr.2017.0299.

[252] N. Zhao, F. Pu, X. Xu, and N. Chen, “Optimisation of multi-channel cooperative sensing in cognitive radio networks,” *IET Communications*, vol. 7, no. 12, pp. 1177–1190, Aug. 2013, doi: 10.1049/iet-com.2012.0748.

[253] L. Gahane and P. K. Sharma, “Performance of improved energy detector with cognitive radio mobility and imperfect channel state information,” *IET Communications*, vol. 11, no. 12, pp. 1857–1863, 2017, doi: 10.1049/iet-com.2017.0040.

[254] A. Dehghani Firouzabadi and A. M. Rabiei, “Sensing-throughput optimisation for multichannel cooperative spectrum sensing with imperfect reporting channels,” *IET Communications*, vol. 9, no. 18, pp. 2188–2196, 2015, doi: 10.1049/iet-com.2015.0097.

[255] M. Li, A. Wang, and J.-S. Pan, “CSS Technology,” *Proceedings of Cognitive Wireless Networks Using the CSS Technology*,Springer International Publishing, 2016, pp. 23–42.

[256] Ruixiang Jiang and Biao Chen, “Fusion of censored decisions in wireless sensor networks,” *IEEE Transactions on Wireless Communications*, vol. 4, no. 6, pp. 2668–2673, Nov. 2005, doi: 10.1109/TWC.2005.858363.

[257] S. Atmaca, Ö. Şayli, J. Yuan, and A. Kavak, “Throughput maximization of csma in cognitive radio networks with cooperative spectrum sensing,” *Wireless Pers Commun*, vol. 92, no. 4, pp. 1473–1492, Feb. 2017, doi: 10.1007/s11277-016-3616-y.

[258] X. Liu, W. Zhong, and K. Chen, “Optimization of sensing time and cooperative user allocation for OR-rule cooperative spectrum sensing in cognitive radio network,” *J. Cent. South Univ.*, vol. 22, no. 7, pp. 2646–2654, Jul. 2015, doi: 10.1007/s11771-015-2795-0.

[259] R. Rabiee and Kwok Hung Li, “Throughput optimization of double-threshold based improved energy detection in cooperative sensing over imperfect reporting channels,” *Proceedings of 2013 9th International Conference on Information, Communications Signal Processing*, 2013, pp. 1–5, doi: 10.1109/ICICS.2013.6782871.

[260] R. Rabiee and K. H. Li, “Performance evaluation of improved double-threshold energy detector over Rayleigh-faded sensing and imperfect reporting channels,” *Physical Communication*, vol. 17, pp. 58–71, Dec. 2015, doi: 10.1016/j.phycom.2015.08.002.

[261] S. Eryigit, S. Bayhan, and T. Tugcu, “Energy-efficient multichannel cooperative sensing scheduling with heterogeneous channel conditions for cognitive radio networks,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 6, pp. 2690–2699, Jul. 2013, doi: 10.1109/TVT.2013.2247070.

[262] R. Zhang, T. J. Lim, Y.-C. Liang, and Y. Zeng, “Multi-antenna based spectrum sensing for cognitive radios: A GLRT approach,” *IEEE Transactions on Communications*, vol. 58, no. 1, pp. 84–88, Jan. 2010, doi: 10.1109/TCOMM.2010.01.080158.

[263] L. Zhang, M. Xiao, G. Wu, S. Li, and Y.-C. Liang, “Energy-efficient cognitive transmission with imperfect spectrum sensing,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1320–1335, May 2016, doi: 10.1109/JSAC.2016.2520166.

[264] A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Intelligent threshold selection in fading environment of cognitive radio network: Advances in throughput and total error probability,” *International Journal of Communication Systems*, vol. n/a, no. n/a, p. e4175, doi: 10.1002/dac.4175.

LIST OF PUBLICATIONS

Journals:

1. A. Kumar, P. Thakur, S. Pandit and G. Singh, "Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: an energy detection approach", *Wireless Networks (Springer)*, vol. 25, no. 7, pp. 3917-3931, Jan. 2019. https://doi.org/10.1007/s11276-018-01927-y. (SCI, IF =2.405)
2. A. Kumar, P. Thakur, S. Pandit and G. Singh, "Intelligent threshold selection in fading environment of cognitive radio network: Advances in throughput and total error probability", *International Journal of Communication Systems (Wiley)*, vol. 33, no.1, Jan. 2020, https://doi.org/10.1002/dac.4175 (SCIE, IF =1.278).
3. A. Kumar, P. Thakur, S. Pandit and G. Singh, "Threshold selection and cooperation in fading environment of cognitive radio network: Consequences on spectrum sensing and throughput", AEU-International Journal of Electronics and Communications (Elsevier), vol. 117, pp.153101/1-19, Apr 2020, https://doi.org/10.1016/j.aeue.2020.153101 (SCI, IF = 2.853)
4. A. Kumar, S. Pandit and G. Singh, "Optimization of censoring based cooperative spectrum sensing approach with multiple antennas and imperfect reporting channel scenarios for cognitive radio network " *IET* Journal (June 2020), https://doi.org/10.1049/iet-com.2019.0970 **(SCI, IF = 1.779)**.
5. A. Kumar, S. Pandit and G. Singh, "Threshold Selection Analysis of Spectrum Sensing for Cognitive Radio Network with Censoring based Imperfect Reporting Channels", *Wireless Networks* (*Springer*). (Major revision submitted in Apr, 2020). (SCI, IF =2.405).

Conferences:

1. A. Kumar, P. Thakur, S. Pandit and G Singh, "Fixed and dynamic threshold selection criteria in energy detection for cognitive radio communication systems" Proc. of *10th International Conference on Contemporary Computing*, Noida, India, Aug. 2017, pp.1-6, https://doi.org/10.1109/ic3.2017.8284302.
2. A. Kumar, P. Thakur, S. Pandit and G Singh, "Performance analysis of different threshold selection schemes in energy detection for cognitive radio communication systems" Proc. of *4th International Conference on Image Information Processing*, Waknaghat, India, Dec. 2017, pp. 1-6, https://doi.org/10.1109/iciip.2017.8313702.