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Combined Soft Hard Cooperative Spectrum Sensing in Cognitive Radio Networks

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Combined Soft Hard Cooperative Spectrum Sensing in Cognitive Radio Networks

By

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Combined Soft Hard Cooperative Spectrum Sensing in Cognitive Radio Networks

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DECLARATION OF CO-AUTHORSHIP AND PREVIOUS PUBLICATION

I. Co-Authorship Declaration

I hereby declare that this thesis incorporates material that is result of joint research, as follows: This thesis also incorporates the outcome of a joint research undertaken in collaboration with Dr. Faroq Awin and Abeer Alqawasmeh under the supervision of Professor Esam Abdel-Raheem. The collaboration is covered in parts of Chapter 3 of the thesis. In all cases, the key ideas, primary contributions, data analysis and interpretation, were performed by the author, and the contribution of co-authors were primarily through the provision of discussing the simulation results in Chapter 3. I am aware of the University of Windsor Senate Policy on Authorship and I certify that I have properly acknowledged the contribution of other researchers to my thesis, and have obtained written permission from each of the co-author(s) to include the above material(s) in my thesis. I certify that, with the above qualification, this thesis, and the research to which it refers, is the product of my own work.

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Thesis Chapter	Publication title/full citation	Publication status
Chapter 3	N. Salout, F. A. Awin, A. F. Alqawasmeh, and E. Abdel-Raheem, "Hierarchical Cluster-Based Cooperative Spectrum Sensing in Cognitive Radio Employing Soft-Hard Combination." Electrical and Computer Engineering (CCECE), 2017 IEEE 30th Canadian Conference.	Published

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ABSTRACT

Providing some techniques to enhance the performance of spectrum sensing in cognitive radio systems while accounting for the cost and bandwidth limitations in practical scenarios is the main objective of this thesis. We focus on an essential element of cooperative spectrum sensing (CSS) which is the data fusion that combines the sensing results to make the final decision. Exploiting the advantage of the superior performance of the soft schemes and the low bandwidth of the hard schemes by incorporating them in cluster based CSS networks is achieved in two different ways. First, a soft-hard combination is employed to propose a hierarchical cluster based spectrum sensing algorithm. The proposed algorithm maximizes the detection performances while satisfying the probability of false alarm constraint. Simulation results of the proposed algorithm are presented and compared with existing algorithms over the Nakagami fading channel. Moreover, the results show that the proposed algorithm outperforms the existing algorithms. In the second part, a low complexity soft-hard combination scheme is suggested by utilizing both one-bit and two-bit schemes to balance between the required bandwidth and the detection performance by taking into account that different clusters undergo different conditions. The scheme allocates a reliability factor proportional to the detection rate to each cluster to combine the results at the Fusion center (FC) by extracting the results of the reliable clusters. Numerical results obtained have shown that a superior detection performance and a minimum overhead can be achieved simultaneously by combining one bit and two schemes at the intra-cluster level while assigning a reliability factor at the inter-cluster level.

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DEDICATION

To my beloved parents

brother and sisters

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LIST OF ABBREVIATIONS

AWGN	Additive white Gaussian noise
BPSK	Binary phase shift keying
CBCSS	Cluster based cooperative spectrum sensing
CDR	Constant detection rate
CFAR	Constant false alarm rate
CH	Cluster head
CHESS	Cluster hybrid energy aware cooperative spectrum sensing
CM	Cluster member
CR	Cognitive radio
CRN	Cognitive radio network
CSI	Channel state information
CSS	Cooperative spectrum sensing
CV	Chair-Varshney
EGC	Equal gain combining
FCC	Federal Communications Commission
FC	Fusion center
i.i.d	Identical independent distributed
LRT	Log Likelihood Ratio Test
MCMG	Multi-cluster Multi-group
MDC	Modified deflection coefficient
MH-CBSS	Multi-level hierarchal-based CSS

MRC	Maximal ratio combining
NLOS	No line of sight
OCS	Optimal soft combining
PDF	Probability density function
PU	Primary user
QOS	Quality of service
REM	Radio Environment Maps
ROC	Receiver operating characteristics
SC	Selection combining
SLS	Square law selection
SNR	Signal to noise ratio
SU	Secondary user
WSS	Wide sense stationary

LIST OF SYMBOLS

$\lceil . \rceil$	Ceiling function
α	Path loss exponent
β	spectrum utilization constraint
β_1	Design parameter of softened-Hard fusion
β_2	Design parameter of softened-Hard fusion
C	Number of clusters
D_1	Number of the clusters that employ Two-bit fusion
D_2	Total number of the remaining clusters
D_3	Number of the remaining clusters that employ Two-bit fusion
D_4	Number of the remaining clusters that employ One-bit fusion
δ	Path loss constant
η	SNR gap
$f\left(\gamma\right)$	Probability density function of the fading channel
f_s	Sampling frequency
G	Number of the groups
$\Gamma(.)$	Gamma function
$\Gamma(.,.)$	Incomplete Gamma function
γ_d	Received SNR of deterministic signal model
γ_r	Received SNR of random signal model
$\bar{\gamma}$	Average SNR
γ_{min}	Detection sensitivity

γ_m	Minimum SNR
γ_T	Average SNR of all the clusters
γ_c	Average SNR of the cluster
H_0	Hypothesis of channel being idle
H_1	Hypothesis of channel being occupied
h	Channel gain between transmitter and receiver
K	Number of users that decide the occupancy of the spectrum
L	Design parameter of softened-Hard fusion
λ	Detection threshold
M	Degrees of freedom
M_s	Total number of samples
m	Nakagami parameter
μ_i	Detection rate of the i-th cluster
N	Total number of users
N_T	softened-hard fusion threshold
p_d	Local probability of detection
p_f	Local probability of false alarm
p_e	Probability of error
$p\left(H_0\right)$	Probability of absence of the primary user
$p\left(H_1\right)$	Probability of presence of the primary user
p_i	Local probability of detection or false alarm for the $i-th$ CR
P_{PU}	PU transmit power
$p_{d,d}$	Probability of detection for deterministic signal model

$p_{d,r}$	Probability of detection for random signal model
Q_{OR}	Global probability for OR rule
Q_{AND}	Global probability for AND rule
$Q_{Majority}$	Global probability for Majority rule
Q_d	Global probability of detection
Q_f	Global probability of false alarm
$Q_u(.,.)$	Generalized Marcum Q-function
Q_e	Detection error rate
Q_{dc}	Global probability of detection of the cluster
R	Number of the CRs in the group
R_c	Cluster radius
R_p	Distance between the PU and the cluster center
S	Number of users within the cluster
σ_w^2	Noise power
σ_x^2	Signal power
σ^2	Gaussian noise variance
T	Test statistic
τ	Sensing time
u	Time bandwidth product
V	Number of fading channels
φ	Predefined threshold
ξ_{max}	Largest reporting channel gain threshold

CHAPTER 1

Introduction to cognitive radio networks

1.1 Cognitive radio overview

The plethora of emerging wireless devices and networks in recent years has proved the excessive dependency of the modern society on the radio spectrum. Conventionally, The Federal Communications Commission (FCC) allocates most of the spectrum to the licensed users, also known as primary users (PUs) and restrains the unlicensed users or (SUs) from exploiting the spectrum when it is being utilized by the PU. On the other hand, recent studies by FCC have shown that a significant portion of the spectrum remains underutilized. As a result, the cognitive radio (CR) technology has been introduced to overcome the spectrum scarcity problem caused by the inefficient spectrum allocation and to satisfy the ever-expanding demands for higher data rates [1]-[3]. The central concept of the cognitive radio is to harness the underutilized spectrum while accounting for the PU activity which accordingly defines the cognitive radio as an intelligent device that can sense the spectrum and modify its operating parameters to adapt to the environment where it operates [2].

In CR systems, the primary users are defined as the authorized users who have the precedence to access the spectrum while the secondary users or the unlicensed users are defined as the users with lower priority that can detect the spectrum hole and access the spectrum without interrupting the PU operation. The spectrum hole is defined as the portion of the frequency band that is not being used by the PU at a specific time within a specific geographical location as depicted in Figure 1.1 [3].

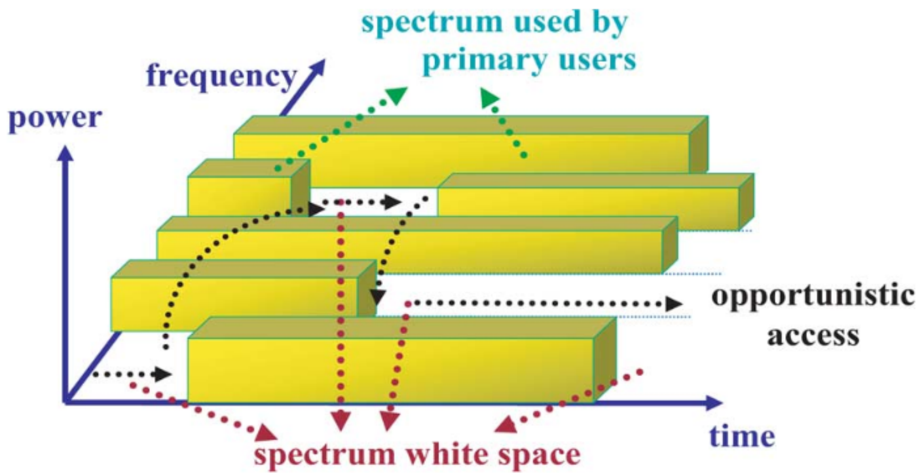


Figure 1.1: Demonstration of the spectrum hole.

Most of the access technologies of the SUs that have been developed recently either focus on spectrum utilization by exploiting the spectrum holes or on the coexistence between secondary and primary users which in turns classifies the cognitive radio networks into three broad categories: Interweave, overlay and underlay networks [4]. In Interweave networks; secondary users can only access the spectrum when the PU is absent, and they should immediately vacate the channel once the PU resumes its operation. Underlay networks are those that allow coexistence between primary and secondary users while satisfying a predefined threshold called interference temperature which is determined by the FCC. Different from underlay model, overlay networks allow the primary and secondary users to transmit simultaneously in the same band by taking advantage of the coding strategies and the knowledge of the primary user's message to eliminate the interference between the SUs and the PU [4]. Interweave network is the most favored in practical implementations among the three paradigms due to its simple application and capability to adhere to the FCC requirements by efficiently utilizing the heavily equipped bands without interfering with the PU.

The two key features of CR are outlined in [3] and [5], as cognitive capability and reconfigurability. The cognitive capability allows the CR to gather the vital information about the radio environment and thus detect the spectrum hole while the cognitive reconfigurability is the ability of the CR to change its parameters to comply with the radio environment. These two features are carried out through a cognition cycle that is regularly run by the CR to adapt to the numerous variations of the radio spectrum.

Cognitive radio cycle consists of four functions described as spectrum sensing, spectrum decision, spectrum mobility and spectrum sharing as illustrated in Figure 1.2 [5]. First, in the spectrum sensing process, the CR identifies the available portion of the spectrum that can be utilized. It can also detect the PU presence when it comes back into operation in a way that ensures an efficient track of the system. Second, in the spectrum decision process, the CR selects the proper frequency band based on the user's quality of service requirements (QoS) and spectrum characteristics. During the third process which is known as spectrum sharing, the spectrum usage is coordinated between the secondary and primary users in a way that maintains the interference below a certain threshold. Lastly, the CR vacates the channel when the PU starts using it during the spectrum mobility process [5].

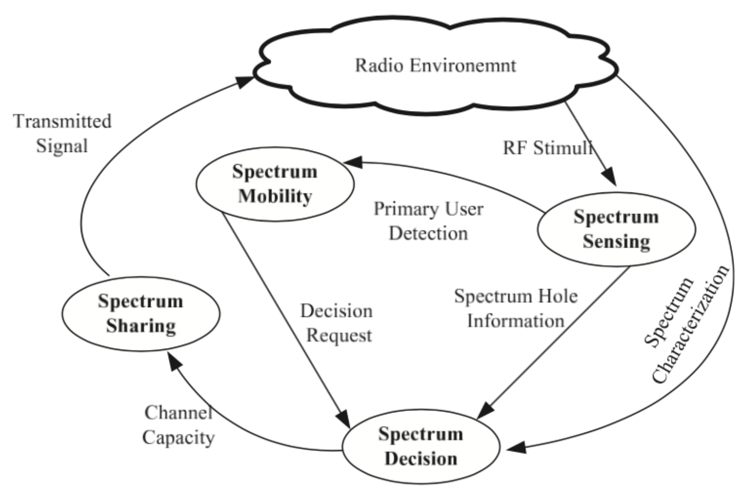


Figure 1.2: Cognitive radio cycle.

Spectrum sensing is the first step towards efficient spectrum utilization. Different techniques have been developed including energy detection, eigen value detection, cyclostationary detector and matched filter. Probability of detection (p_d) and probability of false alarm (p_f) are the common metrics used to evaluate the performance of the different techniques [1]- [13]. Cooperative spectrum sensing (CSS) was proposed to achieve a reliable detection which is a critical issue that arises in practice via local spectrum sensing in the conditions of fading, shadowing and noise uncertainty [1]-[89].

In CSS, multiple users share their observations to detect the PU signal in centralized or distributed manner. CRs share their results as either one bit or energy form regardless of the adopted technique and topology in a process known as data fusion which is a key element of CSS. A numerous research has focused on the fusion schemes in CSS [13], [15], [20], [24], [29]-[31], [38]-[41], [44], [48]-[56]. The selection of the data fusion scheme depends on the bandwidth requirement and the desired performance gain. The schemes are classified as hard combining, where the one bit binary decisions generated by the SUs are transmitted to the FC, which employs a counting rule to make a decision about the PU activity [13], [15], [20], [24], [30], [31], [38]-[41], [44], [48]-[52] ; and soft combining where the SUs forwards their entire observations to the FC that employs a soft scheme such as equal gain combining (EGC), maximal ratio combining (MRC) and selection combining (SC) or a quantized soft scheme for combining the results [29], [49], [55]-[56].

User selection is another important element that has been emphasized in the context of CSS [15], [31] [43], [71]-[82]. In spite of the detection performance gain achieved by CSS, the incurred overhead and energy consumption, particularly in the case of densely deployed areas, have motivated the design of cluster-based CSS (CBCSS). CBCSS has been developed to combat the effect of the reporting errors caused by fading channels and to reduce the number of the users reporting to the fusion center. The design of CBCSS networks has been considered to compromise between the performance and overhead.

1.2 Thesis Contributions

The main objective of this thesis is to investigate the design of CBCSS by incorporating both soft and hard combining schemes at different levels to balance between performance and overhead. The contributions of the thesis are as follows:

a) Soft and hard combining techniques are employed at two levels by grouping the users of one cluster based on an iterative algorithm that maximizes the detection gain. The users at the group level use different soft fusion schemes while a hard combining counting rule is employed at the cluster level. This scheme aims to improve the detection performance by integrating soft and hard schemes while minimizing the overhead.

b) The detection performance is enhanced by combining a 4-level quantization scheme and 2-level hard scheme in CBCSS. Clusters with low signal-to-noise-ratio (SNR) employ the 4-level quantization scheme while the clusters with high SNR employ a 2-level hard rule. This scheme enhances the performance with the minimum increase of the required bandwidth.

1.3 Thesis organization

The fundamentals of spectrum sensing including the performance metrics, hypothesis testing, and spectrum algorithms are presented in Chapter two. The chapter focuses on CSS providing a brief overview about three main elements: centralized and distributed topologies, soft and hard combining schemes and user selection algorithms. CBCSS is also outlined by addressing its primary methods and models. Combining soft data rules such as EGC and MRC by dividing the cluster into groups is considered in Chapter three while a quantized soft fusion and hard fusion is discussed in Chapter four by classifying the clusters based on their average SNR. Finally, conclusions and future works are shown in Chapter five.

CHAPTER 2

Fundamentals of spectrum sensing in cognitive radio networks and overview

2.1 Introduction

One of the most critical functions of CR is the ability to measure the spectral content of the spectrum and extract the required information about the available frequency bands which is attained by considering two approaches: spectrum sensing and database. The latter approach is considered as an alternative to spectrum sensing, the principle of this scheme is to store the information about the primary system including time, frequency, location and interference range in a centralized data base. The SUs task is to periodically check the data stored in the database to obtain the information about the channel occupancy and to circumvent the harmful interference to the PU [1]. The Radio Environment Maps (REM) is an emerging technology in the context of spectrum awareness that imposes the database approach and offers a functional facility of boosting the network functions by incorporating the environmental information and historical knowledge [6]. The former method is the most renowned in cognitive radio systems because of its simple framework architecture and wide range of applications; it allows the cognitive radio to learn, measure and be aware of the surrounding environment [1] .

In CR systems, the secondary users should achieve two objectives dynamically and efficiently; one is to find the spectrum holes when the channel is idle and the other is to detect the activity of the primary user when the channel is occupied to refrain from transmitting data and interfering with the PU. Thus, secondary users should have spectrum sensing capability to achieve these two basic purposes. The PU transmission might be detected over a particular frequency band at a specific time slot, but there might be another vacant frequency band at the same time available for use. For this reason, spectrum sensing should be performed in multiple dimensions including the time, frequency and space [1]. This chapter is dedicated to discussing the spectrum sensing preliminaries, techniques, cooperative spectrum sensing including its models, stages and reporting schemes and the clustering models and methods.

2.2 Hypothesis testing

Spectrum sensing aims to decide whether a particular part of the spectrum is being occupied or not - that is, differentiating between the presence and absence of the PU, which can be practically illustrated by formulating a binary hypothesis testing problem defined by (2.1) as described in [1]-[7]:

$$\begin{cases} H_0 : y(n) = w(n) \\ H_1 : y(n) = h(n).x(n) + w(n), \end{cases} \tag{2.1}$$

where $y\left(n\right)$ is the received signal at the CR, $x\left(n\right)$ is the primary signal transmitted over a channel with channel gain $h\left(n\right)$ and $w\left(n\right)$ represents an additive white Gaussian noise (AWGN) with zero mean and variance σ^2, that is $w\left(n\right) \sim \mathcal{N}(0, \sigma_w^2)$ where n = 0,. . . , M_s, and M_s is the total number of samples. H_0 indicates that the channel is idle while H_1 corresponds to the presence of the PU ($i.e.$, channel is occupied).

2.3 Performance metrics

The detection performance of the applied spectrum sensing algorithm is measured by two probabilities: the probability of detection (p_d) and the probability of false alarm (p_f). On one hand, the probability of detection is the probability that the secondary user successfully detects the presence of the primary user when it is present. On the other hand, the probability of false alarm is the probability that the secondary user detects the primary user presence given that the primary user is absent. Therefore, it is preferred to attain a high probability of detection as it reflects the sensing reliability ($i.e.$, primary user protection); it is also desired to achieve a low probability of false alarm to limit the spectrum underutilization and increase the gained throughput for the secondary users. P_d and P_f are defined by (2.2) and (2.3), respectively as follows [1]:

$$p_d = pr\left(T > \lambda \mid H_1\right) \tag{2.2}$$

$$p_f = pr\left(T < \lambda \mid H_0\right), \tag{2.3}$$

where λ is the detection threshold and T is the test statistic which is generated from the received data $y\left(n\right)$.

Another important performance metric to consider is the total probability of error which is defined as the probability of giving a false decision on the spectrum occupancy and it is given by the weighted sum of the probability of detection and false alarm as follows [8]:

$$p_e = p\left(H_0\right) p_f + p\left(H_1\right)\left(1 - p_d\right), \tag{2.4}$$

where $p\left(H_0\right)$ and $p\left(H_1\right)$ denote the probabilities of absence and presence of the PU, respectively and $\left(1 - p_d\right)$ represents the probability of miss detection which identifies the spectrum as idle when it is present.

2.4 Spectrum sensing techniques

As stated in the previous sections, the main goal of spectrum sensing is to be able to detect the primary user activity at very low SNR ratio and to provide an adequate level of protection to the PU. As a result, the research of spectrum sensing algorithms has been evolving, and different methods have been developed depending on the system requirements and specifications. The algorithms are categorized as blind methods that do not require any prior information about the primary user system like energy detection and eigenvalue detection and non blind methods that require some or full information about the primary user system like matched filter and cyclostationary detection [1]-[5].

Energy detection is the most attractive spectrum sensing scheme because of its meager resources requirement and simple computational analysis. Energy detector is a non-coherent detector that doesn't require any prior information about the primary user signal as well as it only needs to measure the energy of the signal to detect the presence of the primary user. Using energy detection, its output which acts as the test statistic is compared with a predefined threshold that depends on the noise power [1]-[3]. With this in mind, we can conclude that in practical situations, if the noise power is known and the primary signal features are unknown, then energy detection will be the most favorable candidate for spectrum sensing [1]-[9].

Although energy detector has the advantage of simple implementation without any primary system requirements, it is worth mentioning the significant drawbacks that make it less robust and reliable than other spectrum sensing algorithms. First, energy detector can't discriminate between the different types of signals which degrade the spectrum utilization when the received signal is combined with other interfering signals. Also, energy detector is prone to noise uncertainty which is inevitable in practical situations and leads to the phenomenon of SNR walls that is defined as the minimum SNR below which the primary signal can't be detected no matter how many samples are used or how complex the system might be [10]. Further, the threshold selection in energy detector depends on the noise variance that can not be accurately estimated in practical scenarios resulting in unreliable detection. Finally, energy detector is know to be optimal for detecting independent and identically distributed signals (i.i.d) but it can not identify correlated signals [1]-[9].

Eigenvalue detection is a blind spectrum sensing method that is developed to overcome the deficiencies of energy detection by using the minimum and maximum eigenvalues of the covariance matrix of the received signal samples [11]. In eigenvalue detection, the covariance matrix is deduced from the received signal samples, the maximum and minimum eigenvalues are extracted from the matrix where the ratio of the maximum to minimum eigenvalues serves as the test statistic that is compared to a predefined threshold to detect the PU signal. Different from energy detection, the threshold using eigenvalue detection does not depend on the noise variance and can only be computed by computer simulation or mathematical derivation, and thus eigenvalue detection can show a superior performance relative to energy detection. However, this comes at the cost of high computational complexity which is caused by covariance matrix formulation and eigenvalue decomposition of the covariance matrix [11].

The cyclostationary detector has been proposed to exploit the signal features provided that all the signals in practical situations contain cyclostationary features that are generated from modulation, coding and signaling schemes. The PU signal is detected by capturing the periodicity of the it's statistical parameters like mean and autocorrelation [1]-[4], [7]. Also, cyclostationary detectors are acknowledged to be able to differentiate between noise and PU signals and to have an optimal performance at very low SNR ratio as they deal with the periodicity of the signal and its statics when in fact the noise is wide sense stationary (WSS). Despite the outstanding performance of the cyclostationary detector under low SNR regimes, there is a high computational complexity because of the long sensing time required to extract the cyclostationary features from the signal.

The simple hardware requirement of the energy detector and the superior performance of the cyclostationary detector in low SNR regions has inspired the authors in [12] to propose a two-stage sensing. In two-stage sensing, energy detection is utilized at the first level, and cyclostationary detection is applied at the second level to harness the advantages of both schemes by increasing the reliability at low SNR while keeping the detection time as short as possible.

Matched filter can be used when a full knowledge about the primary user signal is available [1]-[7], it is known to be the optimum coherent detection method since it maximizes the received SNR and needs a short sensing time to detect the PU signal [3]. In realistic situations, most of the primary systems have pilots, preambles and synchronization signals that facilitate the PU detection. However, the estimation errors at low SNR might degrade the performance besides that the matched filter requires full knowledge about the PU signal for demodulation which leads to large incurred overhead.

A comparison between the four spectrum sensing techniques in terms of complexity, performance under noise uncertainty and prior knowledge about the PU signal is shown in Table 2.1.

Table 2.1: Comparison of the sensing algorithms.

Method	**complexity**	**performance under noise uncertainty**	**prior PU knowledge**
Energy detection	low	low	no knowledge needed
Eigenvalue detection	high	high	no knowledge needed
Cyclostationay detection	high	high	partial knowledge needed
Matched filter	high	medium	full knowledge needed

2.5 Energy detection

In spite of the merits of low complexity and simple utilization of the energy detector, it has various limitations in practical scenarios. However, energy detection remains the most feasible spectrum sensing scheme especially in the case of stringent system hardware requirements [1]. That's why extensive research strategies focus on enhancing energy detection performance by employing cooperative spectrum sensing and diversity techniques [9] and [13]. Some other works include modifications on the energy detector like the improved energy detector which is proposed in [14] by replacing the squaring operation of the received signal amplitude of the conventional energy detector with a power of (p). In energy detection, the signal passes through a bandpass filter that only allows the frequencies within a particular range to pass. Then a square law device that is followed by summation yields the energy content; in M_s samples of the received signal $y(n)$; known as the test statistic given by (2.5). The block diagram of energy detector is shown in Figure 2.1 [15].

$$T\left(y\right) = \sum_{n=1}^{M_s} \left|y\left(n\right)\right|^2 \tag{2.5}$$

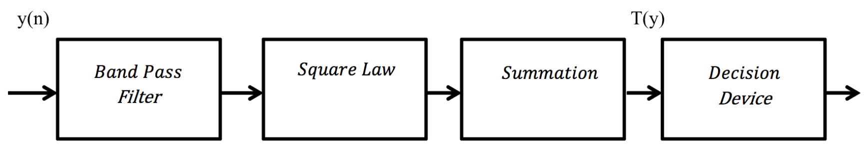


Figure 2.1: Block diagram of Energy detector.

2.5.1 Design elements

2.5.1.1 Threshold selection

A core problem in spectrum sensing is the threshold (λ) selection which stems from the fact that all the performance metrics p_d, p_f and p_e are functions of the threshold (λ). Selecting a high threshold value increases both p_f and p_d which leads to low spectrum utilization and high protection level provided to the primary user. In contrast, a low threshold value results in high spectrum utilization and low PU protection. For this reason, a trade off between spectrum usage and PU protection should be taken into account while determining the threshold value [1], [2], [9].

The IEEE standards specify the acceptable range of p_d and p_f. For example, the IEEE 802.22 which is known as the first standard based on cognitive radio, requires the detection of spectrum hole while sustaining the probability of false alarm beyond 10% and the probability of detection above 90% [16]. Consequently, several works have addressed the issue of threshold selection, in [17], an iterative algorithm has been proposed to optimize the detection threshold by minimizing the spectrum sensing error. The authors in [18] have investigated the threshold selection optimization under low SNR regime by employing a criterion that minimizes the detection error while certain levels of the probability of detection and the probability of false alarm are ensured. The problem of noise uncertainty has been analyzed in [19] as the threshold varies according to the noise power that is estimated from the covariance matrix of the received signal samples; the simulation results confirmed that the adaptive threshold has better performance than the fixed threshold value especially in realistic environments where the noise uncertainty is unavoidable. The previous recent works in [17]-[19] have considered the error probability as an optimization criterion while in practice it usually desired to determine the threshold by maximizing p_d and fixing p_f at small value which is referred as constant false alarm rate (CFAR) principle to alleviate the interference effect [1]. It is important to point out that the receiver operating characteristics (ROC) curves are widely used to examine the relationship between the reliability (p_d) and spectrum efficiency (p_f) for different threshold values which helps to choose the optimal threshold value based on the system requirements [1].

2.5.1.2 Number of samples

The number of samples is a substantial design parameter of the energy detector since its related to the sensing time. As $M = \tau f_s$ where τ is the sensing time and f_s is the sampling frequency, the longer the sensing time, the better the detection performance. However, there is always a restriction on the maximum detection time. For example, the maximum detection time specified by the IEEE 802.22 standard is two seconds [18]. Moreover, the cognitive radio can't perform simultaneous sensing and transmission. Therefore, the sensing time should be optimized to give the cognitive radio more time for data transmission and to achieve the desired throughput. It is also shown in [20] that the number of samples is a function of the SNR ratio and the equation of the minimum number of samples has been derived in terms of the targeted p_d and p_f. An experimental study was conducted by the authors in [21] to analyze the credibility of energy detection in low SNR, and it was observed that the number of samples required to meet the required specifications scales as $1/SNR^2$.

2.5.2 Fading channels

The radio channel between the receiver and transmitter is known to be affected by three main factors; path loss, multipath fading, and shadowing. These channel impediments can severely deteriorate the performance of the energy detector by introducing randomness into the received signal power [22]. Path loss refers to the decay of the received signal power with distance as it propagates from the transmitter to the receiver. On the other hand, shadowing is caused by the rapid fluctuations of the received signal power about the path loss due to obstacles in the propagation path.

While path loss and shadowing are characterized as large scale fading in that they cause the variations over comparatively large distances. Multipath fading is described as small scale fading that occurs when the signal reaches the receiver via different paths due to scattering, reflection and diffraction which results in multiple replicas with different time delays and gains [23]. Multipath fading can be modeled as AWGN, Rayleigh, Rician or Nakagami distribution according to the type of the radio channel.

Recently, energy detection over fading channels has been the focus of many research contributions [24], [25]- [27]. In [25], different multipath fading models are examined for the energy detector including the Rayleigh and Nakagami models. Further, the performance of the energy detector under log normal shadowing was assessed and compared with the non-fading case in [24]. Besides, a practical channel model that combines both multipath fading and shadowing was proposed with the analytical expressions and approximations in [26].

Some other authors derived alternate expressions to simplify the detection probability formulas that involve arduous operations of integrating the probability of detection over the probability density function of the SNR over the fading channel [27]. Before elaborating more on the various channel models, it should be stressed that under fading channels, the probability of false alarm is computed using the same formula as the AWGN case since it is independent of SNR ($i.e.$, no primary signal under H_0). Alternatively, the probability of detection is computed by averaging p_d in the AWGN channel over the SNR distribution for the corresponding fading channel with probability density function (PDF) of $f(\gamma)$ as will be shown below.

2.5.2.1 Sensing in AWGN channel

AWGN channel is the simplest model where the channel gain ($h(n)$) is deterministic and considered as unity ($h(n) = 1 \ \forall \ n$). Under this non-fading channel model, the signal is affected by the thermal noise in the channel itself. The probability of false alarm is given by (2.6) and the probability of detection is given by (2.7) for deterministic signal model or (2.8) for random signal model as [28].

$$p_f = \frac{\Gamma(u, \lambda/2)}{\Gamma(u)}, \tag{2.6}$$

$$p_{d,d} = Q_u\left(\sqrt{2u\gamma_d}, \sqrt{\frac{\lambda}{\sigma_w^2}}\right), \tag{2.7}$$

$$p_{d,r} = \frac{\Gamma\left(u, \frac{\lambda}{2\sigma_w^2(1+\gamma_r)}\right)}{\Gamma(u)}, \tag{2.8}$$

where $u = M/2$ is the time bandwidth product, λ is the threshold, $\Gamma(.)$ and $\Gamma(.,.)$ denote the Gamma function and incomplete Gamma function, respectively, σ_w^2 is the noise variance and $Q_u(a,b)$ is the generalized Marcum Q-function. The SNR of the received PU signal at the SU for the deterministic and random signal models is given by (2.9) and (2.10), respectively, as [28]:

$$\gamma_d = \frac{|h|^2 |x|^2}{\sigma_w^2}, \tag{2.9}$$

$$\gamma_r = \frac{|h|^2 \sigma_x^2}{\sigma_w^2}, \tag{2.10}$$

where x is the deterministic signal's amplitude.

2.5.2.2 Sensing in Rayleigh channel

Rayleigh fading channel model describes the worst case multipath fading with no direct line of sight (NLOS). The instantaneous SNR (γ) follows an exponential distribution given by (2.11) [25]:

$$f(\gamma) = \frac{1}{\bar{\gamma}} e^{\frac{-\gamma}{\bar{\gamma}}}. \tag{2.11}$$

2.5.2.3 Sensing in Nakagami channel

Nakagami fading is the general case that represents a broad range of multipath channels with the Nakagami parameter m which indicates the severity of fading ($i.e$, the fluctuations of the signal reduce as m increases). Nakagami channel reduces to the worst case Rayleigh when ($m = 1$) and converges to the non-fading case (AWGN) when ($m \to \infty$) [23]. The instantaneous SNR follows an exponential distribution given by [25]:

$$f(\gamma) = \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right) \gamma^{m-1} e^{\frac{-m\gamma}{\bar{\gamma}}}. \tag{2.12}$$

2.6 Cooperative spectrum sensing

As mentioned previously, the so-called local spectrum sensing which is performed by the individual CR is associated with several challenges which make it vulnerable to detection failure. The challenges include sensitivity requirements, receiver uncertainty, and hidden terminal problem [32]. Detection sensitivity (γ_{min}) was defined in [33] as the minimum SNR at which the CR can precisely detect the presence of the PU. It was also shown that γ_{min} depends on the estimated noise power which is affected by calibration errors and thermal noise fluctuations that cause noise uncertainty and introduce SNR wall problem [10]. The performance under noise uncertainty was explored in [34], and the results revealed that even the small noise uncertainty values could remarkably obstruct the detection reliability. Receiver uncertainty is another problem that occurs when the CR is outside the transmission range of the PU which creates a harmful interference if the CR is unaware of the PU transmission whereas the hidden terminal problem which is caused by multipath fading and shadowing weakens the received signal and thus hinders the detection performance as discussed earlier. Spectrum sensing challenges have been illustrated in Figure 2.2 [32]. Cooperative spectrum sensing (CSS) has been devised to resolve the aforementioned challenges of spectrum sensing.

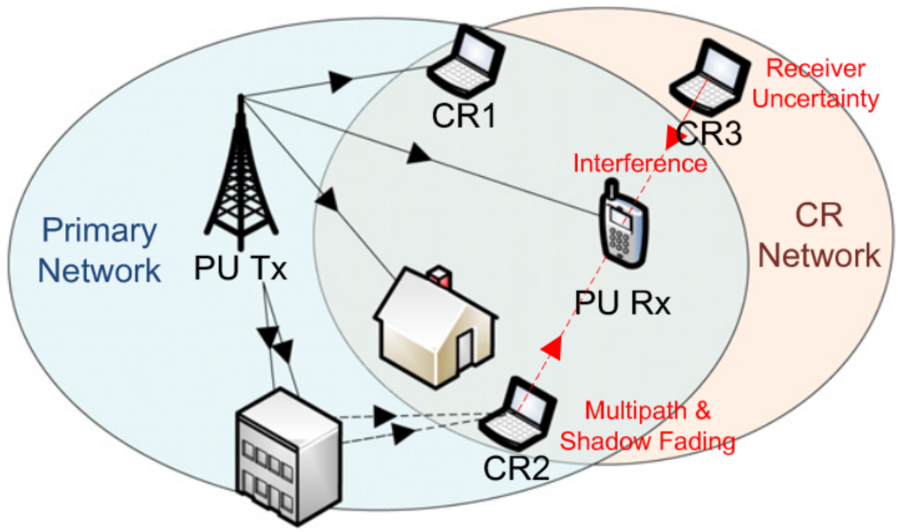
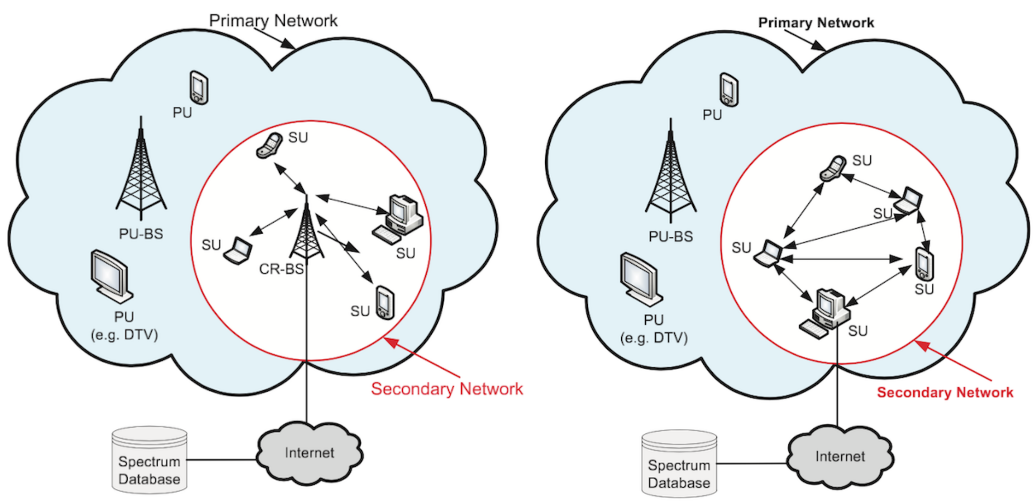


Figure 2.2: Challenges of local spectrum sensing.

In CSS, secondary users can cooperatively execute spectrum sensing to ameliorate the sensing credibility even under worst case situations. Intuitively, allowing multiple users to share their sensing results by exploiting their spatial diversity immensely improves the detection performance and ultimately increases the spectrum utilization [8], [20], [24], [29]-[32]. Numerous research efforts have been made to develop a CSS mechanism that considerably relieves the limitations of local sensing and acquire the desired gain. Some studies focused on the noise uncertainty, for example, a double threshold algorithm was applied in [35] to diminish the impact of noise uncertainty by utilizing the advantage of CSS while other studies investigated the effect of CSS in combating severe fading and shadowing [24]. An analytical CSS framework was designed in [36] to hamper the determintal effect of correlated log-normal shadowing.

2.6.1 Cooperative spectrum sensing topologies

Cooperation among cognitive radios can be classified as either centralized or distributed depending on the architecture, availability of central entity and quality of the control channel ($i.e.$, a channel used to report the data to the central entity or to exchange them with other CRs) [1]-[4], [5], [32], [37]. The process of CSS involves three main stages of local sensing, reporting, and decision making whether the network was implemented in centralized or distributed manner [32]. The two models of CSS are depicted in Figure 2.3 [5].



(a) Centralized (b) Distributed

Figure 2.3: Cooperative spectrum sensing topologies.

2.6.1.1 Centralized cooperative spectrum sensing

Centralized CSS is the most popular architecture that is composed of a central entity called the FC and a number of SUs affiliated with it [24], [31]. In centralized CSS; the FC is inherently more complicated in its hardware than all the other SUs in the network as it monitors the CSS stages and makes the final decision about the PU presence [1]-[5]. The process starts with the FC selecting the PU channel to be detected, and instructing all the SUs to start detecting it. Following this, each SU performs local spectrum sensing individually. In the subsequent stage, the SUs forward their sensing results to the FC as one bit (hard fusion) or as raw data (soft fusion). Finally, the FC gathers the local results of all the SUs and combines them according to a fusion rule to render the final decision about the PU existence [5], [32].

For an efficient execution of this process, a proper selection of the FC is required taking into account the location and security features; if the FC is heavily shadowed, the overall performance of the network will be drastically impaired [37]. Additionally, the quality of the channels is crucial in this scheme; two physical channels in this regards were defined in [32]; the sensing channel between the PU and the SU which is used for local sensing and the reporting channel between the FC and other SUs which is used for reporting the results.

Centralized CSS aims to achieve high detection performance and spectrum efficiency by combining the observations of the spatially located CRs. In spite of the attained detection gain, a number of challenges arise with the implementation of this topology. CSS requires the establishment of a complex backbone infrastructure for information exchange; dedicated reporting channels are used by the SUs for reporting the observations to the FC. Commonly, reporting channels might undergo deep multipath fading and shadowing and might be assigned with fixed bandwidth [1] besides that in the case of large number of SUs, the large distance reporting channels consume enormous energy [32]. Subsequently, a trade-off between performance and overhead ($i.e.$, time, number of users, energy consumption and complexity) should be guaranteed. To address this aim, researchers have suggested different approaches in this matter including throughput maximization, energy minimization, sensing scheduling, clustering and detection error minimization.

Throughput optimization has been considered in many works from different aspects. In [30], a throughput optimization setup that selects the optimal number of users was formulated as a problem of minimizing the total probability of false alarm while conforming to a permissible interference level. An extension of [30] was implied by the authors in [38] by imposing an additional constraint on the energy consumption. Unlike [30] and [38], in [39] the sensing time was included for optimizing the throughput. Similarly, the sensing time was optimized to maximize the throughput in [40]. Energy minimization is another approach that was adopted in [41] to counterweight the overhead and performance by selecting the optimal number of users and sensing time duration in order to minimize the total energy consumption of the network. The idea behind this approach emanated from the effect of a large number of users and long sensing duration on both the detection gain and energy consumption ($i.e.$, long sensing time increases the gain and consumes more energy).

Sensing scheduling is an approach that determines the efficiency of CSS. Sensing scheduling is known to extend the network lifetime by dividing the SUs into groups and activating one group at a time while keeping the other groups in a sleep mode given that the detection and false alarm probabilities are satisfied. In [42], greedy degradation algorithm was employed to find the optimal scheduling and to maximize the sensor lifetime. Furthermore, geographical neighboring of the users referred as clustering is a widely used approach for band-limited control channels to reduce the overhead of reporting the results to the FC [15], [43]. Recently, minimizing the error rate by finding the optimal threshold has been the focus of many researchers [8], [15], [44].

2.6.1.2 Distributed cooperative spectrum sensing

The main concept of distributed spectrum sensing is that the SUs share their observations among each other without the need for backbone infrastructure. Different from the centralized topology, SUs exchange the information among each other through multiple iterations until a consensus is reached [45]-[48]. By adopting a distributed spectrum sensing algorithm, cognitive radios should successfully complete three successive phases. In the first phase, the sensing results are generated by local spectrum sensing, they are then sent to other SUs within the transmission range of the CR, and following this, the CR fuses the received data to make a final decision based on a local criterion. Finally, if the spectrum hole is not detected, SUs iteratively repeat the process until a unanimous final decision is reached [32]. Table 2.2 highlights the advantages and disadvantages of centralized and distributed schemes.

Table 2.2: Comparison of Centralized and Distributed Topologies.

Topology	Criterion	Advantages	Disadvantages
Centralized	A central entity controls the transmission process and the final decision making	• FC collects detailed information about the network (reliable) • Less number of messages need to be transmitted compared to the decentralized approach (Bandwidth efficient)	• large number of users increases the distance of the reporting channel (energy inefficient). • one FC controls the whole network (complex)
Distributed	Each SU makes his/her own decision by interchanging the observations with other SUs	• No need for backbone infrastructure • High throughput when all users sense in every time slot	• large control bandwidth required for the transmission among all SUs • Large sensing duration

2.6.2 Reporting schemes

In both centralized and distributed CSS and regardless of the spectrum sensing technique used, each CR has to perform local spectrum sensing and to send its results to other users or to the FC as either one bit or raw data to generate a final decision for hypothesis testing [1]-[32]. The process of combining the sensing results to come up with a cooperative decision is a fundamental element of CSS known as Data fusion. In essence, for CSS, depending on the form of the sensing results reported to the FC or shared among users, we can distinguish between hard fusion and soft fusion [48]:

- Hard fusion: the sensing results are represented in one-bit form ;
- Soft fusion: the sensing results are described as either quantized or energy form.

According to the hard fusion CSS, each CR processes the sensing data locally and transmits the one-bit decision to the FC. At the FC, a decision fusion rule is employed to make the global decision. In the case of soft fusion, CRs forward their entire data to the FC to make the global decision without performing any local process [29]. It was shown in [29], [48] that the soft combining techniques yield a better performance gain as compared to the hard combing techniques in terms of the probability of detection. Meanwhile, soft combining techniques require a large control channel bandwidth that is almost comparable to the sensing channel which means that the better detection performance comes at the cost of large channel bandwidth [1]-[32]. However, recent studies showed that the bandwidth requirement of the soft techniques is relatively similar to that of hard techniques due to the overhead of transmitting the sensing results to the FC even for one-bit results. Additionally, that it is required for hard combining that each SU has the capability of complex signal processing whereas the SUs in soft schemes do not need this feature [13], [49].

2.6.2.1 Hard Fusion

In hard fusion, each SU makes a decision and forwards it to the FC which applies a linear fusion rule to incorporate the received binary data. Typically, hard combining rules wherein OR, AND and Majority rules are considered as special cases of the general *K-out-of-N* rule, are used for decision fusion [31]. Particularly, the general *K-out-of-N* which is known as the counting rule is the simplest fusion method since it only counts the number of the users that detect the presence of the PU and compares it to a predefined threshold. Assuming that the total number of users is N and the number of users that have decided that the spectrum is used is K, then the three rules are defined as below:

- Logical OR-rule: The channel is deemed to be occupied if at least one of the cognitive radios decides that it is busy ($K = 1$) [24]. Thus, this rule increases the PU protection but at the expense of inefficient spectrum utilization. The global probability is computed using (2.13) as follows:

$$Q_{OR} = 1 - (1 - p_i)^N , \tag{2.13}$$

  where p_i is the local probability of detection or false alarm for the i^{th} CR.

- Logical AND-rule: The channel is deemed to be occupied if all the cognitive radios decide that it is busy ($K = N$) [20]. Thus, this rule increases spectrum utilization but at the risk of increasing the interference with the PU. The global probability is computed using (2.14) as follows:

$$Q_{AND} = (p_i)^N . \tag{2.14}$$

- Majority *K-out-of-N*: The channel is deemed to be occupied if at least K users decide that it is occupied ($K = \lceil \frac{N}{2} \rceil$) [20]. Thus, this rule compromises between the spectrum efficiency and PU protection. The global probability is computed using (2.15) as follows:

$$Q_{Majority} = \sum_{l=K}^{N} \binom{N}{l} p_i^l \left(1 - p_i\right)^{N-l}. \tag{2.15}$$

Hard fusion schemes are vastly used in the literature of CSS [13], [15], [20], [24], [30], [31], [38]-[41], [44], [48]- [52]. Hard combining was employed in [15] to aggregate the results of multi-level CBCSS. Logical OR rule has been used in [24] to counter the detrimental effects of shadowing and fading. In [31], the number of users required to perform CSS was found based on two criteria; maximizing p_d and minimizing p_f; by using OR and AND rules. The general *K-out-of-N* has been considered in [40] where the optimal value of K and sensing time are jointly determined to maximize the throughput. An extended version that applies general *K-out-of-N* rule has been proposed in [38] to jointly optimize three parameters (K, N, p_f); to maximize the throughput ; while imposing constraints on the global probability of detection and energy consumption. Alternatively, the energy detection using the *K-out-of-N* has been studied in [44] to find the relation between the value of k and the detection threshold and the results validated that the majority rule is the optimal fusion rule to minimize the total error rate. However, it was found that the *K-out-of-N* inclines towards the AND rule when the detection threshold is very small and to the OR rule when the detection threshold is very large. Another scenario has been embraced in [50] as the optimum value of K has been derived for different setups that either target the throughput of the secondary system or the quality of service of the primary system.

Moreover, hard combining has been extensively explored in most of the works that deal with energy efficiency. For example, the *K-out-of-N* rule was optimized in [51] to maximize the energy efficiency ($i.e.$, the ratio of the throughput to energy consumption) with a constraint on the interference level. Recently, the authors in [52] developed novel energy efficient strategies based on three different hard combining rules to maximize the energy efficiency by varying the window size. Other works considered advanced fusion techniques to assure an adequate detection under practical scenarios, for instance, a linear quadratic fusion scheme that handles the issue of correlated results without requiring full knowledge of the signal's statistics was investigated in [53]. The results show that this scheme outweighs the *K-out-of-N* rule in the case of correlated shadowing while only requiring the knowledge of lower order moments of the correlated decision variables. A novel weighted decision fusion scheme that takes into account the difference in SNR between SUs was proposed in [54] where the FC applies log Likelihood Ratio Test to weight the decisions with respect to the SNR.

2.6.2.2 Soft Fusion

In soft fusion, the SUs do not make any decision, instead, they convey their entire or processed data to the FC to make the final decision [1]-[3], [32]. Several soft fusion schemes have been utilized in the context of CR [29], [49], [55] -[56]. An optimal soft combining (OCS) scheme based on the Neyman-Pearson criterion was derived in [29] in which the decision depends on the weighted summation of the collected energies from different SUs, and the threshold is calculated to meet a specified probability of false alarm. It was found that the scheme leans towards the EGC when the SNR is high and to the MRC when the SNR is low. The performance of the OCS scheme was investigated under (i.i.d) Rayleigh and Nakagami channels and was compared to the hard combining scheme. Furthermore, the results corroborated that there is no information loss in OCS, thus increasing the number of users (N) always yield a better detection performance for any value of SNR. On the contrary, information loss is a pivotal issue in the case of hard combining, thereby smaller N is better under low SNR. Motivated by the fact that the hard techniques are better regarding overhead while the soft techniques are better in terms of performance, the authors proposed a softened two-bit hard scheme which is classified as a 4-level quantization that offers an almost identical gain to the EGC with much less complexity. In the same manner, a three-bit quantization scheme was analyzed in [55] by dividing the range of observed energy into eight regions and assigning upper regions with larger weights. Inspired by the work in [20], the authors in [56] derived the optimal sensing time that maximizes the throughput for different soft fusion techniques ($i.e.$, EGC, MRC and MDC).

Quantization combining has drawn the attention of many researchers since it exhibits a fairly similar performance to the soft schemes without imposing excessive bandwidth demand on the system [57]. In [58], two multi-bit quantization combining techniques were proposed; the optimal multi-bit scheme which is based on minimum error probability and the suboptimal multi-bit method based on the general *K-out-of-N* rule. Unlike quantization over perfect channels, more quantization levels result in higher probability of error under imperfect reporting channel as emphasized in [57], [59]. In [59], numerical expressions were derived for balancing between the number of quantization levels and reporting energy. A fusion rule with multi-level quantization was designed to combat the effect of quantization noise over imperfect reporting channel, and a differential evolution algorithm was used to determine the optimization parameters [57].

An optimal linear technique was developed in [60] to optimize the detection performance and circumvent the computational complexity related to the quadratic forms of the Log Likelihood Ratio Test (LRT) fusion method. Adopting this technique requires transmitting the local test statistics to the FC where a linear combination is conducted so that the probability of detection is maximized without the exceeding the probability of false alarm limit. A modified deflection coefficient (MDC) metric was proposed to optimize the weighting factor that controls the sensing performance. In [29] and [60], the soft combining rule was derived under the assumption that the instantaneous SNR is available at each SU which is only true for slow fading channels. Lately, novel soft combining methods have been devised to consider the block fading and fast fading conditions where only the average SNR is available at each SU [61]-[63].

Other soft fusion schemes that are similar to multi antenna case and depend on the availability of the channel state information (CSI) between the CR and the PU are presented in [25] and [64]. The schemes include MRC, SC, EGC and square law selection (SLS). The performance of these schemes has been evaluated under different fading channels and compared to the hard schemes through complementary ROC according to the probability of miss detection in [65]. From an energy consumption perspective, it was shown that EGC ultimately outperforms both LRT and MRC under critical conditions including low SNR, large number of users and limited time frame [66].

Soft and hard schemes were compared in various works from different standpoints [49], [67], [68]. A comprehensive analysis of soft and hard fusion schemes where the reporting channel is imperfect was presented in [49]. It was proven that the soft schemes are more precise than the hard schemes even in the existence of the reporting channel errors. A fair comparison model between soft and hard schemes in terms of detection probability was examined in [67] by limiting the time resources; the authors extended their work and compared both schemes in terms of energy efficiency in [68]. Several works have considered combining soft and hard rules to achieve a trade off between the detection performance and bandwidth requirement as in [69], [70].

2.6.3 User selection algorithms

The user selection is one of the key elements of cooperative spectrum sensing that maintains the overall system performance regarding throughput and energy consumption [1], [32]. In [31], the authors found that it is not always necessary for all the CRs to participate in spectrum sensing due to their different locations and channel conditions. They determined the optimal number of users that either gives an optimum global probability of detection (Q_d) or global probability of false alarm (Q_f) based on two criteria; CFAR and constant detection rate (CDR). Both criteria converged to the same result that the selection of the users with highest SNR confers a better detection performance. The importance of sensor selection has been reinforced in [71], and three different centralized sensor selection algorithms were emphasized depending on the amount of available knowledge about CR locations and correlation distribution. By the same token, user selection under correlated log-normal shadowing was adopted in [72] by asserting that a few number of users collaborating over a large area is more efficient than a large number of users located close to each other in a small area. Due to the high energy consumption and bandwidth requirement affined with a large number of users, several clustering schemes were proposed to counteract this problem [32]. The literature provides an ample evidence that clustering has the potential to reduce the overhead over the control channel and the ability to cut down energy consumption [15], [43], [73]-[82].

2.7 Cluster-based CSS (CBCSS)

Cooperative spectrum sensing was introduced to enhance the detection performance by combining the decisions of spatially located CRs. However, the prospect of detection improvement gradually diminishes with the increase in the number of users that cause congestion on the control channel coupled with an added computational complexity and high energy consumption. Moreover, the reporting channels are commonly exposed to propagation effects which encompass multipath fading, path loss and shadowing. Besides that, if the user is outside the coverage range of the PU, it will only transmit the noise power inducing a negative impact on the sensing performance.

In the light of these hurdles related to the conventional CSS, cluster-based CSS (CBCSS) has been introduced because of its intrinsic attributes in reducing the control overhead and the energy consumption of the networks. This can be interpreted as clustering simultaneously reduces the reporting channels distances and the number of the users reporting to the FC, thereby consumes less energy, undergoes less propagation and requires less overhead [2], [7], [32]. In CBCSS, the available CRs are divided into groups according to the geographical locations and (SNR) values. In each cluster, the nodes are defined as either cluster heads (CHs) or cluster members (CMs) depending on their roles. The user with the largest reporting channel gain ($i.e.$, nearest to the FC) is elected as the CH where the remaining users are classified as (CMs) [73]-[75]. Unlike conventional CSS, the concept of clustering is to perform spectrum sensing on two levels where the internal level is executed among the CMs (intra-cluster) while the external level is carried out between the CHs (inter-cluster) [73]. More specifically, the CHs inform the CMs about the channel to be detected based on the FC commands, thereafter, the CMs perform local spectrum sensing and forward the results to the CH which in turn combines them and sends the final result to the BS that executes another level of fusion by combining the CHs results and disseminating the final outcome back to them.

2.7.1 Clustering methods

Multiple criteria were used to classify clustering methods [74]-[75]. For example, in [74], four clustering methods were underlined based on the availability of the CR and PU locations. First, if the location of both the CRs and PU is unknown, then random clustering is considered by randomly dividing the CRs into clusters. Second, if only the location of the CRs is known, two methods can be employed to divide the CRs into clusters: a reference based clustering based on a predefined reference and a statistical clustering that relies on the CRs relative proximities. Finally, a distance based clustering is utilized when the position of both the PU and CRs is known; only a set of users that are close to the PU is selected for clustering. A comprehensive survey was presented in [75], where clustering algorithms were classified into five categories according to their objectives, namely, dominating set based clustering, energy efficient clustering, stability based clustering, CSS based clustering and common control channel establishment based clustering. Furthermore, the works presented complexity analysis, performance evaluation and descriptions of related contributions for each category.

2.7.2 Clustering models

Clustering has been deliberately studied in literature where different clustering models are tailored for cognitive radio networks (CRNs), mainly, performance improvement oriented models, overhead reduction oriented models and combined metrics based models. The survey in [73] sheds light on these different models that are shown below:

2.7.2.1 Performance gain oriented models

In [76], a CBCSS scheme was proposed to utilize the spatial diversity of users taking into account the imperfection of the reporting channels. Both soft and hard combining fusion rules were applied to delineate the performance level. The proposed CBCSS showed a substantial performance improvement relative to the conventional CSS; the work though did not provide any information about the cluster formation design; instead, it assumed that the clustering had been already done by some distributed algorithms by the upper layers. A more consolidated version was proposed in [77] by integrating clustering formation algorithms with performance improvement model. The authors employed a greedy heuristic and graph theory techniques to build the clusters whereby the SUs within the coverage range of the PU are allowed to join the cluster. Also, the suggested CBCSS scheme aims to improve the achievable throughput while protecting the PU from harmful interference.

2.7.2.2 Overhead reduction oriented models

Under this category, CBCSS techniques are directed towards reducing the incurred overhead [43], [78]-[79]. A novel minimal dominating set algorithm based on graph theory was suggested in [43] to find the minimum number of clusters that preserves the network connectivity while reducing the number of the CRs reporting to the FC to reduce the required bandwidth. In the same manner, the authors in [78] proposed an algorithm that finds the minimum number of clusters to minimize the overhead. Although the works in [43] and [78] aim to reduce the number of clusters, they follow different approaches. In [78], the approach follows an optimization problem that balances between the system reliability and the overhead. Furthermore, the simulation results demonstrated the efficiency of the proposed model in comparison with the K-means clustering. A CBCSS approach that minimizes the energy consumption in the reporting stage was considered in [79] with the aid of frequency reuse methods.

2.7.2.3 Combined metric based models

Several works have tackled the issue of compromising between performance improvement and overhead reduction [15], [80]-[82]. Two recent works were proposed by the same authors to address this matter from different perspectives [15], [80]. In [15], a multi-level hierarchal algorithm was proposed to divide the cluster with a large number of users to multiple groups and subgroups in such a manner that improves the detection performance and minimizes the overhead. The authors also proposed another algorithm that jointly determines the sensing time and data transmission time to maximize the energy efficiency while meeting the required detection accuracy [80]. Simulation results affirmed the adequacy of the low-complexity algorithm in improving the performance of the cluster. A cluster hybrid energy aware CSS (CHESS) mechanism was introduced in [81] by coalescing the energy consumption with sensing accuracy to achieve a reliable performance and expand the network lifetime. In [82], a CBCSS scheme that reduces the required amount of cooperation resources while achieving high performance level was employed. The scheme deploys two methods within the cluster; a selective method to select the most reliable user as cluster head and a parallel mechanism that is based on frequency division to handle the synchronization and contention collision. At the FC, an optimal Chair-Varshney rule (CV rule) was employed to conclude a final decision.

2.8 Conclusions

This chapter has provided an overview of spectrum sensing including its preliminaries and techniques with an emphasis on energy detection. The design parameters and the performance under several fading channels with different signal models were briefly discussed. Furthermore, cooperative spectrum sensing has been outlined, and the main challenges of spectrum sensing were accentuated. Some of the primary advantages and drawbacks of centralized topology and distributed topology were summarized. Then, two main key elements of CSS; reporting schemes and user selection algorithms; were also presented. Finally, the three primary models of cluster based CSS were illustrated.

CHAPTER 3

Hierarchical Cluster-Based CSS in Cognitive Radio Employing Soft-Hard Combination

3.1 Introduction

Collaboration between CRs has been proposed to alleviate the adverse impact of channel impairments on the detection performance. However, the attained improvement in detection performance ($i.e.$, cooperation gain) always comes with challenges of increasing the complexity, energy consumption and delay time ($i.e.$, cooperation cost) [32]. Collaboration process has two main stages, namely, sensing stage and reporting stage. In the sensing stage, all contributing CRs independently sense the existence of the PU, whilst in the reporting stage; every single CR forwards its local observation to the FC. The FC extracts the final decision about the existence of the PU by fusing the aggregated CRs' observations [7]. Two popular schemes can be employed during the reporting stage, either hard decision or soft decision. In case of hard combining, the CRs report their observations as one bit ($i.e.$, 0 or 1) to the FC which employs a hard combining rule such as OR, AND, and k-out-of-N rules to make the cluster decision, while in case of soft combining, all CRs forward their entire test statistics to the FC which employs a soft combing technique such as EGC, SC and MRC to come out with the decision about the PU existence [83].

Soft combining schemes lead to a better detection performance compared with the hard combing schemes at the cost of large channel bandwidth [84]. In general, incurred overhead is one of the foremost challenges involved with CSS scheme. Therefore, the principle of clustering was applied to make a trade-off between the gain and the cost of the cooperation process. Tremendous research works have tackled cluster-based spectrum sensing (CBSS) schemes from distinct standpoints. The CBSS schemes can be divided into three main categories, namely, performance improvement oriented schemes, overhead reduction oriented scheme, and combined metrics scheme [73].

Multi-cluster Multi-group (MCMG) algorithm has been proposed in [85] to improve the detection performance by dividing the cluster into groups. A multi-level hierarchal-based CSS (MH-CBSS) algorithm has been developed in [15], the algorithm exploited the hierarchical structure of a cluster and employed two different fusion rules at different levels in order to attain better detection performance and lower incurred overhead. An iterative algorithm has been proposed in [80] to determine the optimal sensing time, data transmission time and number of users that maximize the energy efficiency in designing an efficient cluster-based spectrum sensing.

Inspired by the work in [15] and [85], we propose a new cluster hierarchy criterion employing soft-hard combination techniques in order to significantly improve the detection performance and to determine the required number of the hierarchical structure of the cluster. In the proposed algorithm, the soft technique is employed at the lowest level while the hard decision rule is employed at the higher levels. Moreover, the optimal number of CRs in each hierarchical level is considered.

This chapter is organized as follows: system model is presented in Section 3.2. The proposed algorithm is described in Section 3.3. Simulation results are presented in Section 3.4. Finally, conclusions are provided in Section 3.5.

3.2 System model

Assume a cluster with N CR's, each CR employs energy detection to sense PU existence independently. For an AWGN channel, p_d and p_f, are provided as in [64]

$$pd = Q_{\frac{M}{2}}\left(\sqrt{2\gamma}, \sqrt{\lambda}\right), \tag{3.1}$$

$$pf = \frac{\Gamma\left(\frac{M}{2}, \frac{\lambda}{2}\right)}{\Gamma\left(\frac{M}{2}\right)}, \tag{3.2}$$

where $\Gamma(.)$ and $\Gamma(.,.)$ denote the gamma function and the incomplete gamma function, respectively. $Q_a\left(b, c\right)$ is the generalized Marcum Q function, λ is the detection threshold, M indicates the degrees of freedom, and γ is the SNR. Note that the noise variance is assumed to be unity. Using the decision fusion rule *K-out-of-N*, Q_d, and Q_f, for a cluster with N CRs are computed as follows:

$$Q_d = \sum_{j=K}^{N} \binom{N}{j} P_d^j (1 - P_d)^{N-j}, \tag{3.3}$$

$$Q_f = \sum_{j=K}^{N} \binom{N}{j} P_f^j (1 - P_f)^{N-j}, \tag{3.4}$$

where $K = \lceil \frac{N}{2} \rceil$ with $\lceil . \rceil$ being the ceiling function. Employing data fusion rules, p_d can be determined by averaging equation (3.1) over the PDF of the employed scheme as follows:

$$p_d = \int_0^\infty Q_{\frac{M}{2}}\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) f_\gamma\left(\gamma\right) d\gamma, \tag{3.5}$$

where $f_\gamma\left(\gamma\right)$ is the PDF of the employed scheme. The three schemes over the Nakagami fading channel are described in [23], [64] as follows:

- Equal Gain Combining (EGC)

  EGC is the most popular soft fusion scheme, the FC makes the final result about the PU presence by combining the received energy values from all CRs.

  The probability of false alarm and the probability of detection are as [23]:

$$P_f^{EGC} = \frac{\Gamma\left(\frac{VM}{2}, \frac{\lambda}{2}\right)}{\Gamma\left(\frac{VM}{2}\right)}, \tag{3.6}$$

$$P_d^{EGC} = \int_0^\infty Q_{\frac{VM}{2}}\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) f_{\gamma_{EGC}}\left(\gamma\right) d\gamma, \tag{3.7}$$

where $f_{\gamma_{EGC}}\left(\gamma\right)$ is the PDF of, γ_{EGC} , for V $i.i.d$ Nakagami-m fading channels given by [23]

$$f_{\gamma_{EGC}}(\gamma) = \left(\frac{m}{\bar{\gamma}}\right)^{Vm} \frac{\gamma^{Vm-1}}{\Gamma(Vm)} e^{\frac{-m\gamma}{\bar{\gamma}}}, \tag{3.8}$$

where m is the Nakagami parameter, m = 1, 2, 3, ...

- Maximal Ratio Combining (MRC)

  Using MRC, each CR employ energy detection to obtain it's energy value and forwards the result with appropriate weighting, which is proportional to the instantaneous SNR, to the FC.

  The false alarm probability is computed as (3.2), while the probability of detection is computed as [23]:

$$P_d^{MRC} = \int_0^{\infty} Q_{\frac{M}{2}}\left(\sqrt{2}, \sqrt{\lambda}\right) f_{\gamma_{MRC}}(\gamma)\, d\gamma, \tag{3.9}$$

  where $f_{\gamma_{MRC}}(\gamma)$ is the PDF of the SNR, as [23]:

$$f_{\gamma_{MRC}}(\gamma) = \left(\frac{m}{\bar{\gamma}}\right)^{Vm} \frac{\gamma^{Vm-1}}{\Gamma(Vm)} e^{\frac{-m\gamma}{\bar{\gamma}}}. \tag{3.10}$$

- Selection Combining (SC)

  Using SC, the FC polls the CR with the maximum instantaneous SNR.

  The probability of false alarm is computed as (3.2), while the probability of detection is computed as [23]:

$$P_d^{SC} = \int_0^{\infty} Q_{\frac{M}{2}}\left(\sqrt{2}, \sqrt{\lambda}\right) f_{\gamma_{SC}}(\gamma)\, d\gamma, \tag{3.11}$$

  where $f_{\gamma_{SC}}(\gamma)$ is the PDF of SNR, as [23]:

$$f_{\gamma_{SC}}(\gamma) = \frac{Vm^m\gamma^{m-1}}{\bar{\gamma}^m\Gamma^V(m)} e^{\frac{-m\gamma}{\bar{\gamma}}} \Gamma^{V-1}\left(m, \left(\frac{m\gamma}{\bar{\gamma}}\right)\right). \tag{3.12}$$

3.3 The proposed fusion algorithm

Algorithm 1 describes the proposed soft combining technique which is employed in the inferior hierarchical level of the cluster, whilst the hard combining technique is employed in the superior levels. The optimal number of required hierarchical levels and the number of CRs in each level can be determined using the following criterion:

$$\begin{aligned} \max_{G,R,K_1} \quad & (Q_d) \\ \text{subject to} \quad & R \geq 1;\ G \geq 1 \\ & Q_f \leq \beta \end{aligned} \tag{3.13}$$

where $k_1 = \left\lceil \frac{G}{2} \right\rceil$, G is the number of the groups, R is the number of the CRs in a group and β is the spectrum utilization constraint.

The objective of the above-mentioned optimization criterion is to maximize the total attained while refraining to exceed some threshold . An iterative algorithm is developed to extract the optimal number of levels and the number of CRs in each level.

Algorithm 1 The proposed fusion iterative algorithm

1: **specify** N, β, P_f, **and then compute**, λ **using (3.2)**
2: **Find factorization of** N, **Let** $R_1 = \{1, a_1, a_2, \ldots, a_r\}$, **where** a_i **is a divisor of** N **and** $i = \{1, 2, 3, \ldots, r\}$
3: $d = 1$
FOR $i = 1 : r + 1$
$R = R_1(i)$
$G = N/R_1(i)$
compute $P_d(i),\ Q_d(i),\ Q_f(i)$
IF $Q_f(i) \leq \beta$
$A_2(d, i) = \left[Q_d(i)\ G(i)\ R(i)\right]$
$d{+}{+}$
ELSE
CONTINUE
END
END
4: $\left[i_1, i_2\right]$= $max\left(A_2\left(:, 1\right)\right)$
5: G= $A_2\left(i_2, 2\right)$ **and** R = $A_2\left(i_2, 3\right)$

3.4 Simulation Results

As a simulation setting, let N = 18 CRs, and probability of false alarm constraint β = 0.01. The simulation results of the proposed algorithm are compared with MCMG algorithm [85] and conventional algorithm [73]. Moreover, the number of required hierarchical levels and number of CRs in each level are determined by the proposed iterative algorithm as shown in Table 3.1.

Table 3.1 provides the results of selecting the best hierarchical levels for the cluster using the proposed iterative algorithm with EGC. The results show that the optimal hierarchy for the cluster with 18 CRs is to divide the cluster into three groups, each has 6 CRs. Assuming an equiprobable system with the same probability of presence and absence of the PU, then the second combination of Table 3.1 gives the minimum probability of error compared to the other combinations.

Table 3.1: Results of the proposed iterative algorithm.

i	Q_d	Q_f	G	R
1	0.9976	0.0975	2	9
2	0.9532	0.0073	3	6
3	0.8981	0.0022	6	3
4	0.6077	3.3×10^{-5}	9	2

For a thorough comparison, different scenarios are considered as follows:
Scenario one: Investigating the impact of sensing time, M , on the performance of the proposed algorithm over the Nakagami fading channel. The detection performances of the proposed algorithm employing EGC, MRC and SC schemes are illustrated in Figures 3.1, 3.2, and 3.3 respectively.

The performances of the proposed algorithm using different schemes are compared with the MCMG and the conventional algorithms. It is clear from the figures that the proposed algorithm outperforms both algorithms. Moreover, it can be inferred from the figures that increasing M adversely impacts the performances of the proposed algorithm for all employed schemes, this is because increasing M leads to increase the sensing threshold and the degree of freedom; therefore, the detection performance decreases consequently.

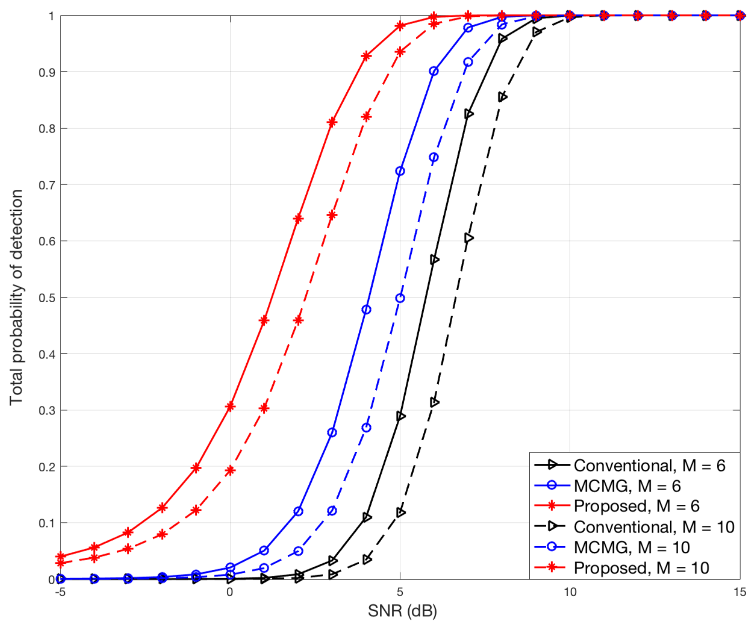


Figure 3.1: The impact of varying M on the total probability of detection of the proposed algorithm using EGC compared with the MCMG and the conventional algorithms.

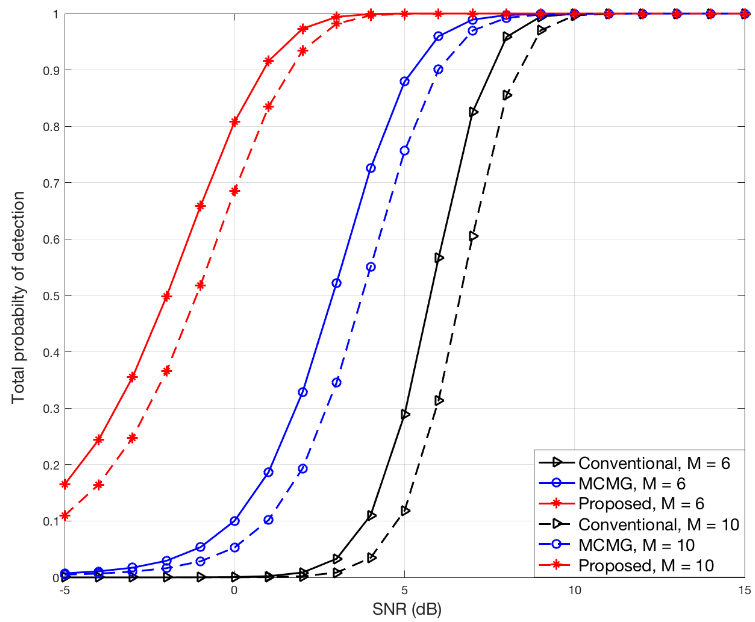


Figure 3.2: The impact of varying M on the total probability of detection of the proposed algorithm using MRC compared with the MCMG and the conventional algorithms.

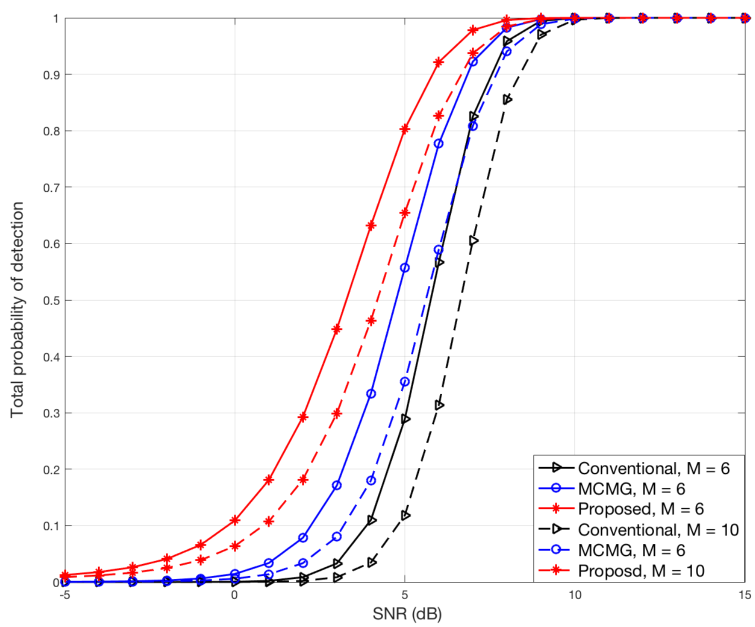


Figure 3.3: The impact of varying M on the total probability of detection of the proposed algorithm using SC compared with the MCMG and the conventional algorithms.

Scenario two: determining the best data fusion rule can be employed for the proposed algorithm. It can be seen from Figure 3.4 that MRC outperforms both EGC and SC in terms of the attained total probability of detection. However, the improvement attained by MRC scheme comes at the expense of mere complexity and more bandwidth requirements. Moreover, for a limited control channel bandwidth, EGC can be considered the best scheme.

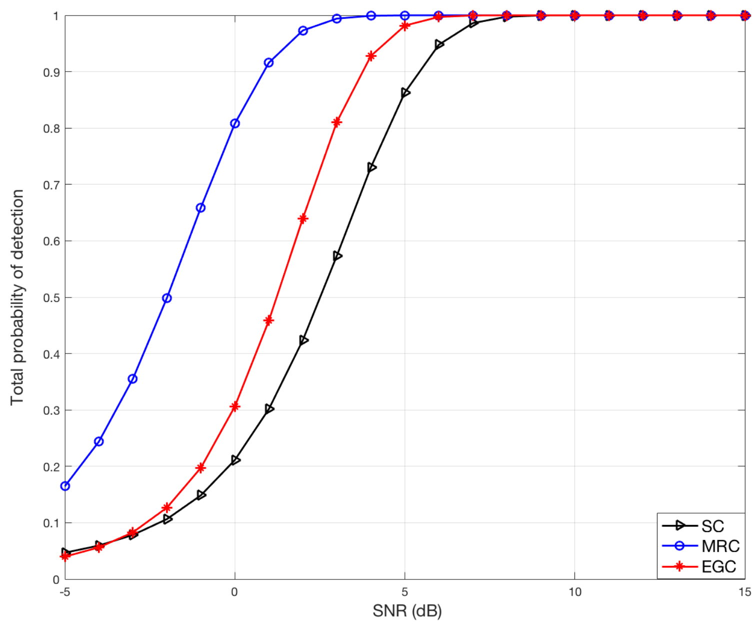


Figure 3.4: A comparison of the detection performance of the proposed algorithm employing different data fusion rules.

Scenario three: investigating the effect of varying the Nakagami parameter, , on the performance of the proposed algorithm employing different schemes. From Figure 3.5 , it can be noted that increasing Nakagami parameter, m , has a slight impact on the performance only for good SNR scenarios $(i.e., \gamma > 0\ dB)$. This can be interpreted as follows: in low SNR scenario, the effect of noise dominates over the improvement impact of spatial diversity attained by both EGC and MRC when increasing .

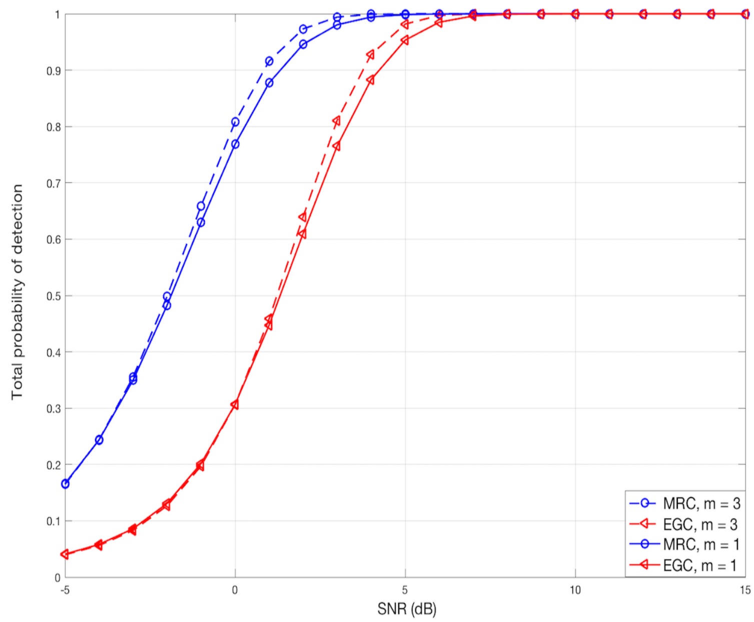


Figure 3.5: Total probability of detection of the proposed algorithm employing EGC and MRC schemes at different values of fading parameter m.

3.5 Conclusion

Balancing between detection performance and overhead in CBCSS has been considered. Optimization criterion employing soft and hard combining techniques to extract hierarchical levels for a cluster has also been developed. The simulation results have shown that using the proposed algorithm, the cluster can only have two hierarchical levels. The impact of sensing time on the performance has also been investigated. Furthermore, the effect of varying on the performance has also been examined. Finally, simulation results have shown that the proposed algorithm employing MRC technique outperforms the performance of the proposed algorithm using EGC or SC techniques.

CHAPTER 4

Combined Softened-Hard and Hard Fusion in Cluster-Based Cognitive Radio Networks

4.1 Introduction

Currently, CRN has been envisaged as a promising methodology to tackle the dilemma of spectrum scarcity by enabling the opportunistic access of the unoccupied frequency bands without interfering with the PUs. The FCC stated that the SUs should assure utilizing the spectrum with limited or no interference to the PU. Therefore, spectrum sensing is a mandatory function of cognitive radio systems as it enables the SUs to abide by this stipulation. However, the destructive effects of wireless channels including shadowing, fading and path loss might render single SU spectrum sensing as unreliable [1]. CSS is used to obviate this problem. The main idea of CSS is to make a global decision about the availability of the PU by combining the sensing results originated by multiple users [32].

Different fusion schemes, mainly the soft and hard fusion, can be applied to combine the sensing results at the FC depending on the control channel bandwidth requirements [84]. It is apparent that the detection performance achieved by the soft combining techniques is decidedly better compared with the hard combining techniques at the cost of the increasing demand for extra bandwidth of the feedback channels [49]. With Hard combining, the users transmit their local observations to the FC as one bit. Thus the traffic overhead is reduced at the cost of sacrificing the detection accuracy. The works in [44] and [52] proved that the majority *K-out-of-N* rule ($i.e.$, $K = \lceil \frac{N}{2} \rceil$) ;where N is the total number of users, k is the number of users which decide the occupancy of the spectrum and $\lceil . \rceil$ denotes the ceiling function; is the optimal hard fusion rule. It was found in [44], that the majority *K-out-of-N* is the optimal rule regarding the detection error rate. Alternatively, the work in [52], validated the optimality of the general *K-out-of-N* regarding the energy efficiency; as it compromises between the probability of detection (Q_d) and the probability of false alarm (Q_f). In [29] and [60], the cost was sacrificed for the veracity of the detection performance. Simulation results reinforced the superior detection performance of the soft combining schemes compared with the hard schemes whereas, the complexity analysis of both schemes was overlooked. The energy consumption of different soft schemes was analyzed in [66]. Researchers applied different strategies to counterbalance between the overhead and performance. In [29], a softened two-bit hard technique; classified as 4-level quantization; was proposed by dividing the range of the observed energy into four regions, the results showed that this rule is suboptimal in terms of the overhead and the detection performance. Unlike quantization strategy, the works in [69] and [70] considered combining soft and hard fusion techniques by relying on the estimation of the test statistics and the estimation of the reporting channel coefficient, respectively, to exploit the advantages of both schemes. In [86], soft and hard schemes were combined at different levels; LRT is applied at the lower level while weighted decision fusion is adopted at the higher level, further, using different fusion rules at different hierarchical levels was considered in [15] to balance between performance and overhead.

The trade off between gain and performance in CRNs can be addressed from a different aspect to confront the problems related to imperfect reporting channel and shadowing. The shadowing effect of the closely located CRs impedes the performance, and the large distances of the reporting channels require a significant amount of energy consumption and are susceptible to erroneous. The selection of the users for CSS plays a vital role in determining the overall detection performance [32]. In [31], the users with the highest SNR are selected for CSS while a small number of users over a large distance is chosen to reduce the effect of shadowing in [72]. On the other hand, clustering has been recognized to improve the detection performance especially in the case of densely deployed areas by grouping the CRs located close to each other into separate clusters [73]-[74]. CBCSS has been studied thoroughly in literature [15], [43], [73]- [82], [85]. With such a scenario, the average distance over which the observation results are sent becomes smaller compared with the centralized scheme besides that the number of the reporting users to the FC reduces significantly. Hence, CBCSS reduces the overhead in terms of bandwidth requirement and energy consumption, as well as enhances the overall detection performance.

In this chapter, two schemes are proposed to enhance the detection performance of CBCSS while reducing the system's complexity. First, a two bit softened hard scheme is combined with one bit hard scheme at the cluster level based on the average SNR of each cluster to balance between the overhead and gain while a one bit general *K-out-of-N* hard fusion is employed at the FC level to combine the results in a way that compromises between Q_d and Q_f taking into account both the imperfection of the reporting channels and the non-identical SNR of the multiple clusters. The proposed algorithm is compared with two schemes that both employ the General *K-out-of-N* hard fusion at the FC level incorporated with either softened two bit or one bit hard fusion at the cluster level. The proposed scheme is further improved by employing an adaptive iterative algorithm that selects only the reliable clusters for decision making based on their Q_d to adapt to the SNR variations of the PU which results in variations of the SNR of each cluster. In addition, the overhead analysis of different cases are presented along with the simulation results. Furthermore, the performance is analyzed in both Rayleigh and Nakagami fading channels besides that a random signal model is considered which is more appropriate for the detection of unknown PU signals.

This chapter is organized as follows: system model is briefly described in Section 4.2. Section 4.3 presents the proposed scheme and the modified proposed scheme. Simulation results are illustrated in Section 4.4. Finally, conclusions are provided in Section 4.5.

4.2 System model

Assume a cognitive radio network that consists of one PU and multiple SUs (N) which are grouped into multiple clusters (C) by a certain clustering strategy [77]-[78], [87]. Similar to [88], the SUs within the cluster are assumed to have identical average SNR of the received PU signal since they are located near each other and the distance between them is much smaller compared with their average distance to the PU. This is equivalent to a SNR variation of less than one dB within the cluster which is true since the cluster radius (R_c) is computed by (4.1) as [88]:

$$R_c = \frac{\theta - 1}{\theta + 1} R_P, \tag{4.1}$$

where R_p is the average distance between the PU and the cluster, $\theta = 10^{\frac{0.1}{\alpha}}$ and α is the path loss exponent. However, each cluster has independent and different average SNR of the PU signal due to its different location and channel conditions. It is assumed that all the nodes are stationary and that the clusters are located at different distances from the PU. Each cluster has (S) CMs and is governed by a CH which is selected based on the largest reporting channel gain and acts as a FC of the cluster. Here, two levels of fusion are considered; at the first level of fusion, the CH collects the results from the SUs which belong to it and combines them with a certain fusion rule to formulate a final decision that is to be sent to the FC through imperfect reporting channel for the second level of fusion. In such scenario, errors can occur at two levels, a perfect channel condition at the low level and an imperfect channel at the high level are considered. Each SU in the cluster employ energy detection to find its local observations. The SUs within the cluster employ either a softened hard fusion or hard fusion depending on their average SNR, $\bar{\gamma_c}$. The FC employs general *K-out-of-N* rule to find the global decision. The conventional cluster based CSS model that is used throughout this chapter is shown in Figure 4.1.

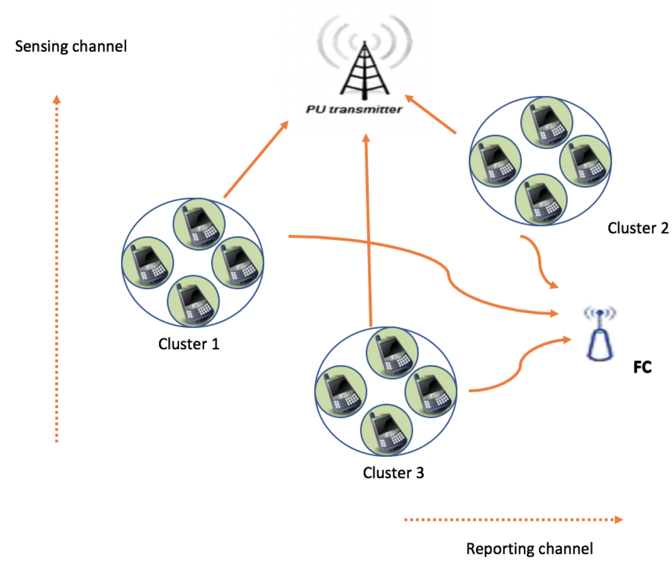
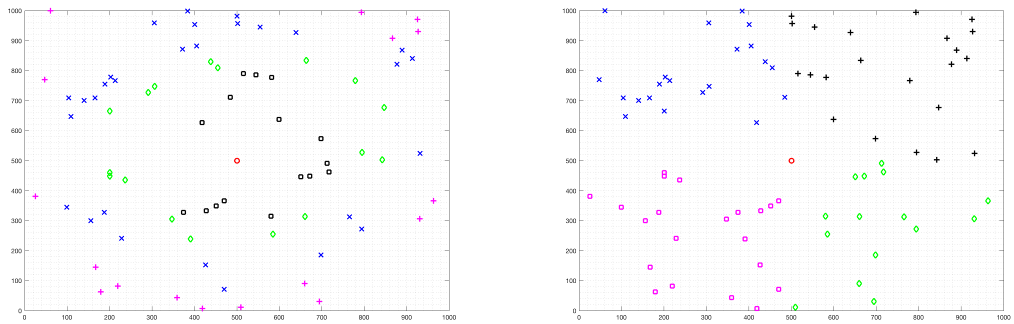


Figure 4.1: Cluster-Based CSS model.

Traditionally, in clustering, users are grouped based on their distance to the PU or the relative distance between them. The clustering topologies which are depicted in Figure 4.2 are classified as below:

- Clustering based on the distance between the cognitive radio and the primary user ($i.e.$, users that have similar distance to the primary user will be in the same cluster),
- Clustering based on the relative distance between cognitive radios ($i.e.$, users that are close to each other will be in the same cluster)

In this chapter, it is considered that the sensing channels between the SUs and the PU experience Nakagami-m fading. Therefore, a clustering topology based on the relative distance among users is adopted throughout this chapter as it achieves the best detection performance. This can be interpreted as this clustering topology reduces the distance between SUs and thus minimizes the effect of fading. However, clustering based on the relative distance to the PU increases the distance between the SUs in the cluster which is suitable if a shadowing model was considered.



(a) Relative distance to PU

(b) Relative distance between users

Figure 4.2: Different clustering methods

a) Local decision :

Suppose that each SU is employed with an energy detector to detect the PU signal. Then, for an AWGN channel and random signal model with small number of samples; p_f and p_d are computed from equations (4.2) and (4.3), respectively , as follows:

$$p_f = \frac{\Gamma\left(\frac{M}{2}, \frac{\lambda}{2}\right)}{\Gamma\left(\frac{M}{2}\right)}, \tag{4.2}$$

$$p_d = \frac{\Gamma\left(\frac{M}{2}, \frac{\lambda}{2(1+\gamma_r)}\right)}{\Gamma\left(\frac{M}{2}\right)}, \tag{4.3}$$

where M is the degrees of freedom related to the distribution of the test statistic of the energy detector ($i.e.$, $\frac{M}{2}$ is the number of samples), λ is the detection threshold, γ_r is the SNR, $\Gamma(.)$ is the Gamma function and $\Gamma(.,.)$ is the incomplete Gamma function [28].
However, when the SUs experience independent Nakagami fading channels, the expression of the local probability of false alarm is computed by (4.2) and the local probability of detection is obtained by averaging p_d in (4.3) over the PDF of the instantaneous SNR γ ($i.e.$, $f(\gamma)$) given by

$$f(\gamma) = \frac{1}{\Gamma(m)}\left(\frac{m}{\bar{\gamma}}\right)\gamma^{m-1}e^{\frac{-m\gamma}{\bar{\gamma}}}, \tag{4.4}$$

where m is the Nakagami parameter and $\bar{\gamma}$ is the average SNR.

b) Global decision at the cluster head:

Upon receiving the local decisions from each SU, the CH combines the received results by either employing a hard fusion or soft fusion rule to deduce a global decision that is disseminated back to the whole network. The control channel between the users of the cluster and the CH is assumed to be perfect ($i.e.$, error free) since the users in the clusters are in the vicinity of each other. In this chapter, we will consider two schemes for contriving a global decision at the CH, namely, one-bit hard fusion and two-bit quantized soft fusion.

1. **General *K-out-of-N* rule**

   The general *K-out-of-N* rule is the general one-bit hard fusion that includes OR ($i.e.$, $K = 1$), AND ($i.e.$, $K = N$) and majority ($i.e.$, $K = \lceil \frac{N}{2} \rceil$) rules. K can be optimized to maximize the detection accuracy. The formulas in (4.5) and (4.6) are used for independent clusters with non-identical SNR considering that the reporting channels between the SU and the CH is perfect [89].

$$Q_f = \sum_{i=K}^{N} \left\{ \sum_{j=1}^{C_k^N} \left[\prod_{l=1}^{K} p_{f,x_j,l} \prod_{l=K+1}^{N} \left(1 - p_{f,x_j,l}\right) \right] \right\}, \tag{4.5}$$

$$Q_d = \sum_{i=K}^{N} \left\{ \sum_{j=1}^{C_k^N} \left[\prod_{l=1}^{K} p_{d,x_j,l} \prod_{l=K+1}^{N} \left(1 - p_{d,x_j,l}\right) \right] \right\}, \tag{4.6}$$

   where C_k^N = $N!/\left(K!\left(N-K\right)!\right)$, $k = \lceil \frac{N}{2} \rceil$ with $\lceil . \rceil$ indicating the ceiling function, $p_{f,x_j,l}$ and $p_{d,x_j,l}$ are the local probabilities of false alarm and detection for each SU which are obtained by averaging equations (4.2) and (4.3) over (4.4), respectively.

2. **Softened-Hard fusion**

   It is known that in the conventional One-bit hard fusion, one threshold divides the whole range of observed energy into two regions in the sense that all the SUs above the threshold are equally assigned with the same weight value. Unlike the conventional one-bit hard scheme, the whole range of energy is divided by three thresholds (λ_1, λ_2, λ_3), into four regions where each region is allocated with a different weight value due to the distinction in the observed energies. Thus, each SU needs to exchange two bits to identify which region its observed energy belongs to. The detection criteria depends on the weighted summation given by $N_C = \sum_{i=0}^{3} w_i N_i$ where N_i indicates the number of observed energies falling in region i and the weight values assigned to each region are given by ($w_0 = 0, w_1 = 1, w_3 = L, w_4 = L^2$). The weighted summation is compared to a predefined threshold equivalent to ($N_C = L^2$) where L is a design parameter to be optimized. The channel is detected as occupied if $N_C \geq L^2$; otherwise, it is detected as idle. The principle of softened-hard fusion differs from the conventional one-bit Hard fusion as shown in Figure 4.3 [29].

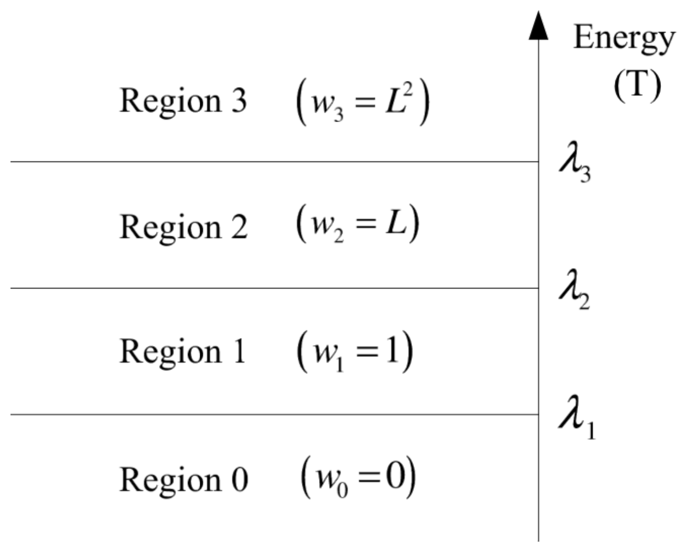


Figure 4.3: The principle of Softened-Hard scheme.

In the two-bit hard fusion rule, the three thresholds (λ_1, λ_2, λ_3) which denote three local probabilities of false alarm (p_{f1}, p_{f2}, p_{f3}), respectively, are determined to satisfy a specific global false alarm probability (Q_f). For this target to be met, N_c should be less than L^2 which can be interpreted in (4.7) where $I = L^2 - 1$ and $J_i = min\left\{\left\lfloor \frac{L^2 - iw_1}{w_2 - w_1} \right\rfloor, i\right\}$ with $\lfloor . \rfloor$ denoting the floor function. Two design parameters β_1 and β_2 are defined as $\beta_1 = \frac{p_{f2}}{p_{f1}}$, $\beta_2 = \frac{p_{f3}}{p_{f2}}$. An exhaustive search is employed to determine L, β_1 and β_2. Thereafter, the value of ρ which is given by $\rho = \frac{p_{f1}}{1-p_{f1}}$ is determined using (4.8). The total probability of detection is obtained likewise from (4.9); the values of L, β_1 and β_2 are numerically calculated to maximize the average Q_d while meeting the required Q_f. When N, Q_f, β_1,

β_2 and ρ are known, the values of p_{f1}, p_{f2} and p_{f3} can be obtained while λ_1, λ_2 and λ_3 can be determined in a subsequent manner from (4.2). Then, p_{d_1}, p_{d_2} and p_{d_3} can be obtained by averaging (4.3) over (4.4). It is worth mentioning that the exhaustive search can be done offline and the values can be stored in a look up table to reduce the computational complexity.

$$\begin{aligned} 1 - Q_f &= \sum_{i=0}^{I} \sum_{j=0}^{J_i} Pr\left(N_0 = N - i, N_1 = i - j, N_2 = j, N_3 = 0 \mid H_0\right) \\ &= \sum_{i=0}^{I} \binom{N}{i} (1 - p_{f_1})^{N-i} \left\{ \sum_{j=0}^{J_i} \binom{i}{j} \left(p_{f_1} - p_{f_1}\right)^{i-j} \left(p_{f_2} - p_{f_3}\right)^j \right\} \end{aligned} \tag{4.7}$$

$$(1 - Q_f)(1 + \rho)^N = \sum_{i=0}^{I} \binom{N}{i} \left\{ \sum_{j=0}^{J_i} \binom{i}{j} \times (1 - \beta_1)^{i-j} (\beta_1 - \beta_1\beta_2)^j \right\} \rho^j \tag{4.8}$$

$$\begin{aligned} Q_d &= 1 - \sum_{i=0}^{I} \sum_{j=0}^{J_i} Pr\left(N_0 = N - i, N_1 = i - j, N_2 = j, N_3 = 0 \mid H_1\right) \\ &= 1 - \sum_{i=0}^{I} \binom{N}{i} (1 - p_{d_1})^{N-i} \left\{ \sum_{j=0}^{J_i} \binom{i}{j} \left(p_{d_1} - p_{d_1}\right)^{i-j} \left(p_{d_2} - p_{d_3}\right)^j \right\} \end{aligned} \tag{4.9}$$

The performance of both hard and quantized schemes is validated in Figures (4.4) and (4.5) which compare the total probability of detection of quantized two bit fusion and hard one bit fusion ($i.e.$, OR-rule) for different number of users and different degrees of freedom, respectively, considering that the cognitive radios experience Rayleigh fading and the total probability of false alarm Q_f is 0.05 for both schemes. It is concluded from the figures that the softened scheme outperforms the hard scheme especially with a large number of samples and large number of users at the cost of only transmitting one more bit for each CR without jeopardizing the control channel bandwidth as EGC and MRC which feed back the entire energy observations to the FC [29].

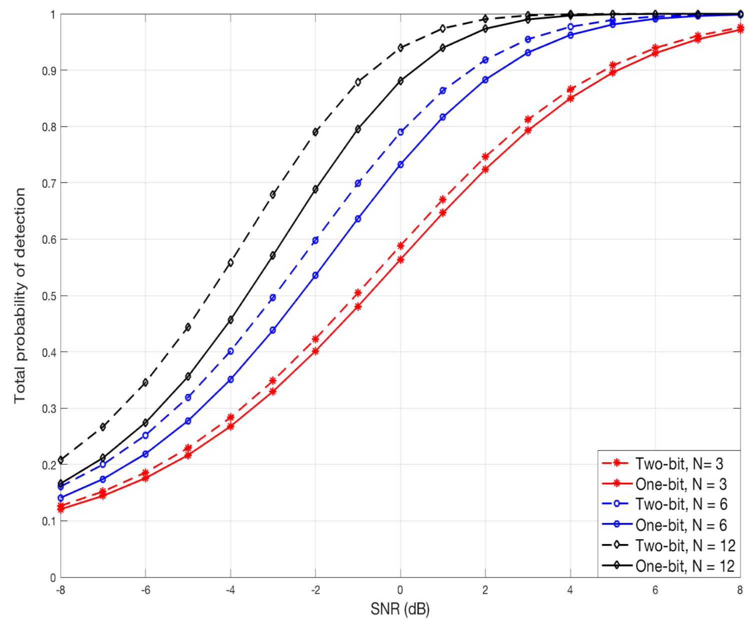


Figure 4.4: The impact of varying N on the total probability of detection of the Softened-hard fusion compared with OR-hard fusion.

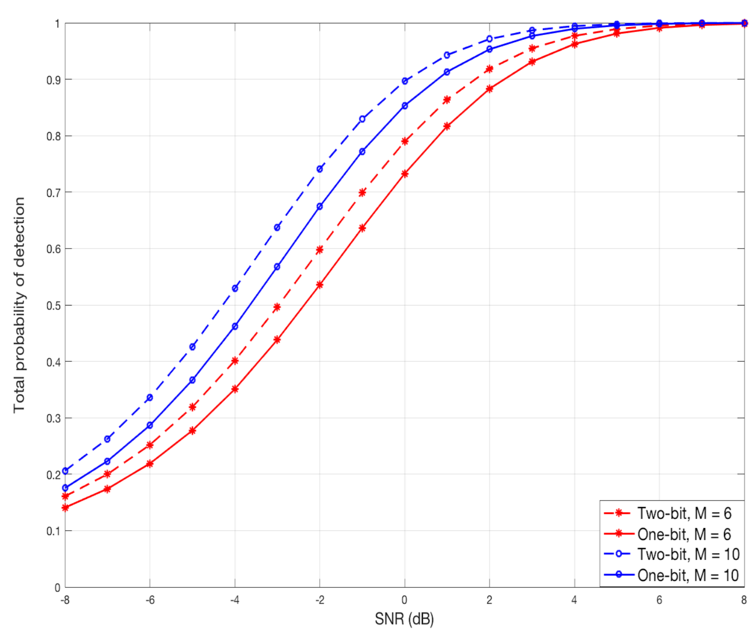


Figure 4.5: The impact of varying M on the total probability of detection of the Softened-hard fusion compared with OR-hard fusion.

c) Global decision at the Fusion center:

It is more suitable for practical scenarios to consider the effect of the imperfect reporting channel between the CH and the FC. In the case of imperfect reporting channels between the CHs and the FC and if the observations are reported as binary phase shift keying (BPSK) over fading channel with $\xi_{max,i}$ which represents the largest control channel gain between the FC and the CH, $i.e.$;

$$\xi_{max,i} = max\left(\xi_{i,1}, \xi_{i,2}, \cdots, \xi_{i,S_i}\right) \tag{4.10}$$

Where S_i is the number of the users in the i-th cluster and $\bar{\xi}_i$ is the average of $\xi_{i,j}$ ($i.e$, the SNR of the channel between the j-th user in the i-th cluster and the fusion center) since the users in the cluster are close to each other [15], [85].
The global probabilities of false alarm ($Q_{f,i}$) and detection ($Q_{d,i}$) for the i-th cluster are written as a function of the probability of error ($Q_{e,i}$) as follows:

$$Q_{f,i} = Q_{f,i}\left(1 - Q_{e,i}\right) + \left(1 - Q_{f,i}\right) Q_{e,i} \tag{4.11}$$

$$Q_{d,i} = Q_{d,i}\left(1 - Q_{e,i}\right) + \left(1 - Q_{d,i}\right) Q_{e,i} \tag{4.12}$$

where $Q_{e,i} = \int_0^\infty Q_{e|\xi_{max,i} f(\xi_{max,i}) d\xi_{max,i}}$ with error probability rate of $Q_{e|\xi_{max,i}} = Q\left(\sqrt{2\xi_{max,i}}\right)$ and the probability density function $f\left(\xi_{max,i}\right)$ of $(\xi_{max,i})$ is given by (4.13).

$$f\left(\xi_{max,i}\right) = \frac{S_i m^m \xi_{max,i}^{m-1}}{\bar{\xi}_i^m \Gamma^{S_i}(m)} e^{\frac{-m\xi_{max,i}}{\bar{\xi}_i}} \Gamma^{S_i - 1}\left(m, \left(\frac{m\xi_{max,i}}{\bar{\xi}_i}\right)\right) \tag{4.13}$$

which reduces to (4.14) under Rayleigh fading when $m = 1$

$$f\left(\xi_{max,i}\right) = \frac{S_i}{\bar{\xi}_i} e^{\frac{-\xi_{max,i}}{\bar{\xi}_i}} \left(1 - e^{\frac{-\xi_{max,i}}{\bar{\xi}_i}}\right)^{S_i - 1} \tag{4.14}$$

4.3 Proposed model

In this section, we present the proposed low complexity soft-hard combination scheme (combined scheme) which incorporates the softened hard and hard fusion schemes at the cluster level and employs a low bandwidth *K-out-of-N* at the FC level. The proposed combined scheme that selects the reliable clusters for the decision making process is also illustrated to enhance the detection performance of the combined scheme while reducing the actual overhead. Two levels of spectrum sensing are completed in both schemes; combined fusion at the low level and hard fusion at the high level.

Using the combined scheme; we assume that the FC can obtain the location information and the SNR of all users either by REM [6] or through SNR estimation methods as in [90] and thus it can determine the average SNR, $\bar{\gamma_c}$, of each cluster. The FC determines the total average SNR ,$\bar{\gamma_T}$,of all the clusters within the PU's protection range and compares $\bar{\gamma_c}$ of each cluster with $\bar{\gamma_T}$. The clusters with $\bar{\gamma_c}$ greater than or equal to $\bar{\gamma_T}$ employ hard fusion and compute the cluster's Q_{dc} by (4.6) which is equivalent to the expression in (2.15) since the SNR variation within one cluster is about 1 dB, while the clusters with $\bar{\gamma_c}$ less than $\bar{\gamma_T}$ employ a softened two bit fusion and compute Q_{dc} by (4.9). Finally, the FC employs a hard fusion and finds the global probability of detection (Q_d) by (4.6). The system's performance is mainly analyzed with Q_d since it is a function of the SNR while Q_f is independent of the SNR and varies according to the adopted fusion rule and number of users. The detection error rate (Q_e) is also used for performance analysis and is defined by (4.15) as [8]:

$$Q_{e,i} = p\left(H_0\right) Q_{f,i} + p\left(H_1\right) \left(1 - Q_{d,i}\right), \tag{4.15}$$

where $Q_{f,i}$ and $Q_{d,i}$ are the global probabilities of false alarm and detection for the i-th cluster, respectively, while $p\left(H_0\right)$ and $p\left(H_1\right)$ are the probabilities of absence and presence of the PU, respectively.

The procedure of the combined scheme is summarized as follows:

Step 1: The FC collects the location information of each SU and determines the CHs based on the reporting channel gains.

Step 2: Each SU forwards its local observations and its estimated SNR to its CH.

Step 3: The CH sends its average SNR ,γ_c, to the FC which finds SNR, γ_T, of all the clusters.

Step 4: Q_{dc} is computed using (4.6) if $\gamma_c > \gamma_T$. Otherwise Q_{dc} is calculated using (4.9).

Step 5: The global decision is made at the FC using (4.6).

Algorithm 2 illustrates the proposed combined fusion scheme which selects the reliable clusters for the decision making process. The FC allocates a reliability factor to each cluster proportional to its detection rate. The reliability factor is given by Equation (4.16)

$$\mu_i = Q_{dci}, \tag{4.16}$$

where μ_i denotes the detection rate of the i-th cluster which is compared to a predefined threshold (φ) to determine the eligible clusters for the decision making process. The threshold (φ) is initialized with a specific value to satisfy a condition of practical interest.
Algorithm 3 illustrates a proposed adaptive combined fusion scheme assuming that the clusters are located at different distances from the PU and that the PU transmit SNR varies according to a path loss model described by (4.17) as in [31]:

$$\gamma_c = \frac{P_{PU}}{\sigma^2}\frac{\delta}{R_p^{\alpha}} \tag{4.17}$$

where P_{PU} is the transmit power of the PU, δ is the path loss constant and R_p is the average distance between the cluster center and the PU. The threshold (φ) is initialized with a specific value and updated at each iteration in adaptive manner to ensure the improvement of Q_d and the reduction of Q_e, simultaneously.

Algorithm 2 The proposed combined fusion algorithm

1: **Find the estimation of SNR of each cluster** (γ_c) **and compute** (γ_T)
2: **Specify** φ **and** W **where** $W = \{W_1, W_2, \cdots, W_C\}$ **and** C **is the number of the clusters**,
3: **for** $i = 1 : C$,
4: **if** $\gamma_c(i) > \gamma_T(i)$
Using (4.6) compute $Q_{dc(i)}$
else if
Using (4.9) compute $Q_{dc(i)}$
end for
5: **if** $Q_{dc(i)} < \varphi$
$W \leftarrow W \setminus \{W_i\}$ **/* Remove cluster** W_i **from the set of clusters** W ***/**
else
continue
end if

Algorithm 3 The proposed adaptive combined fusion algorithm

1: **Initialize** $\bar{P}_{PU}$, Q_{fc} **and let Q** $\leftarrow \varnothing$
2: **Compute** Q_{dc} **for each** P_{PU}
3: **Let U** $= \left[\bar{\mathbf{Q}}_{\mathbf{dc1}}, \ldots, \bar{\mathbf{Q}}_{\mathbf{dcC}}\right]$ **where** C **is the number of the clusters**,
4: **Sort the rows of U in descending order**.
5: **for** $i = 1 : length(\mathbf{U})$
$D = U(i, :)$
6: **for** $j = 1 : length(D)$
7: **if** $D(j) > \varphi$
$\mathbf{Q} = D(j)$
else
$\varphi = D(j)$
break
end
end
Using (4.5) compute $Q_f(i)$
8: **if** $Q_f(i) < Q_{fc}$
Using (4.6) compute $Q_d(i)$
else
$Q = [Q' \ \varphi]$
Using (4.6) compute $Q_d(i)$
Using (4.5) compute $Q_f(i)$
end
end

The complexity analysis of the different fusion schemes is illustrated in Table (4.1) where C is the number of clusters, S is the number of the users in the cluster, D_1 is the number of the clusters that employ two-bit fusion, D_2 is the number of the remaining clusters after discarding the unreliable clusters, D_3 is the number of the remaining clusters that employ two-bit fusion and D_4 is the number of the remaining clusters that employ one-bit fusion.

Table 4.1: Overhead analysis for different fusion schemes.

Fusion scheme	Number of bits transmitted in intra-cluster level	number of bits transmitted in inter-cluster level	Total number of bits
Hard	$(S$-1$)C$	C	$(S$-1$)C$+C
Softened-Hard	2$(S$-1$)C$	C	2$(S$-1$)C$+ C
Combined	2$(S$-1$)D_1$+$(S$-1$)(C - D_1)$	C	2$(S$-1$)D_1$+$(S$-1$)(C - D_1)$+C
Proposed combined	2$(S$-1$)D_3$+$(S$-1$)D_4$	D_2	2$(S$-1$)D_3$+$(S$-1$)D_4$+D_2

4.4 Simulation results

In this section, the simulation results of the combined scheme and the proposed combined scheme are presented and compared with two different scenarios, namely, the conventional CBCSS with either the softened hard fusion or the hard fusion at the cluster level [76]. The results are presented for different number of users for each cluster, different number of samples, different global probability of false alarm, different fading channels and different K value of the hard scheme. Perfect and imperfect reporting channel cases are also considered. The effect of variable PU SNR ratio is considered by varying the average SNR of each cluster according to a path loss model that accounts for the average distance between the cluster and the PU. Here a simple model is used: the average SNR of all the clusters is $\bar{\gamma} = \frac{1}{C}\sum_{i=1}^{C}\gamma_i$ and the SNR of cluster i is $\eta^{i-1}\gamma_m$, where η is the SNR gap between all the clusters and γ_m is the minimum SNR among all the clusters. It is assumed that there are five clusters with SNR gap of 2 dB. The degrees of freedom M is 10, Q_{fc} is 0.05, S = 4,

C = 5, m = 1, L = 2, α = 3, δ = 1 and φ = 0.5. The overhead analysis is shown in Tables 4.2 and 4.3 for the different schemes of five clusters with four and ten users in each cluster, respectively.

Table 4.2: Overhead analysis when C = 5 and S = 4.

Fusion scheme	Number of bits transmitted in intra-cluster level	number of bits transmitted in inter-cluster level	Total number of bits
Hard	$3 \times 5 = 15$	$1 \times 5 = 5$	20
Softened-Hard	$2 \times (4-1) \times 5 = 30$	$1 \times 5 = 5$	35
Combined	$2 \times (4-1) \times 3 + (4-1) \times 2 = 24$	$1 \times 5 = 5$	29
Proposed combined	$2 \times (4-1) \times 2 + (4-1) \times 2 = 18$	$1 \times 4 = 4$	22

Table 4.3: Overhead analysis when C = 5 and S = 10.

Fusion scheme	Number of bits transmitted in intra-cluster level	number of bits transmitted in inter-cluster level	Total number of bits
Hard	$9 \times 5 = 45$	$1 \times 5 = 5$	50
Softened-Hard	$2 \times (10-1) \times 5 = 90$	$1 \times 5 = 5$	95
Combined	$2 \times (10-1) \times 3 + (10-1) \times 2 = 72$	$1 \times 5 = 5$	77
Proposed combined	$2 \times (10-1) \times 2 + (10-1) \times 2 = 54$	$1 \times 4 = 4$	58

It is clearly inferred from the tables that the required number of bits scales gradually with the number of users in the cluster. As number of the clusters or the users in the cluster increases, the combined scheme becomes a better option than the softened hard scheme with less overhead at the cost of slightly degraded performance. However, selecting the reliable clusters provides a better detection performance and less overhead compared with both the softened hard and combined schemes.

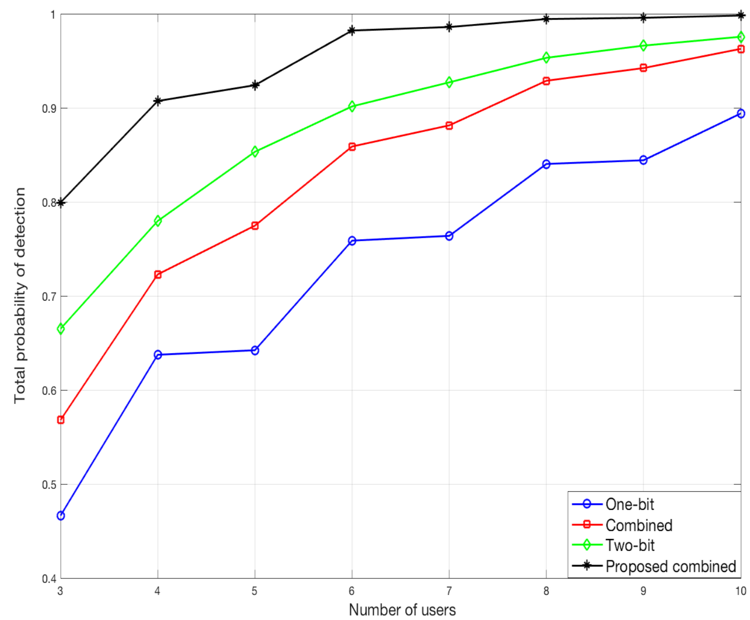


Figure 4.6: The impact of varying the number of users in the cluster on the total probability of detection for different fusion schemes.

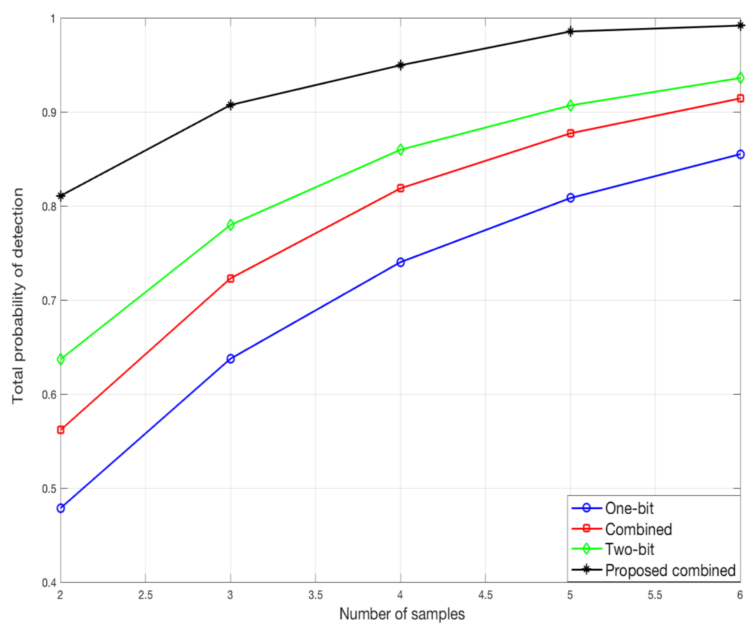


Figure 4.7: The impact of varying the number of samples on the total probability of detection for different fusion schemes.

The detection performance of the combined softened hard scheme and the proposed combined fusion scheme is evaluated and compared with the softened hard and hard fusion schemes when the number of the users in the clusters varies form 3 to 15 as shown in Figure (4.6). As expected, the total probability of detection (Q_d) will improve with the increase of the number of users in the cluster. It is shown that the combined scheme is a suboptimal solution that balances between the complexity and gain while the proposed combined fusion scheme is the best among all the schemes as it achieves high detection performance even when the number of the users in the cluster is small. Similarly, we can see from Figure 4.7 that the network total probability of detection (Q_d) of all schemes increases with the increases of the number of samples, further, the proposed combined fusion algorithm significantly enhances the performance compared with all schemes with much less complexity in terms of the number of bits required to transmit the results.

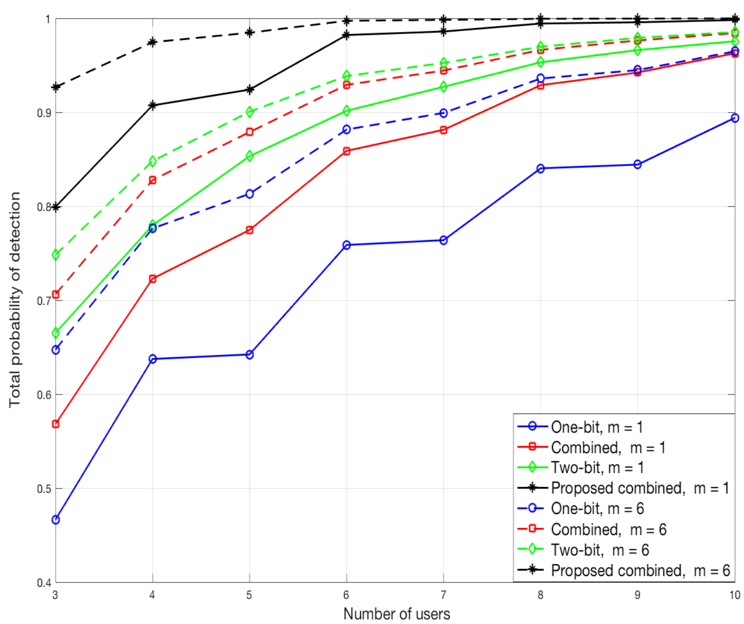


Figure 4.8: A comparison of different fusion schemes under Rayleigh and Nakagami fading channels.

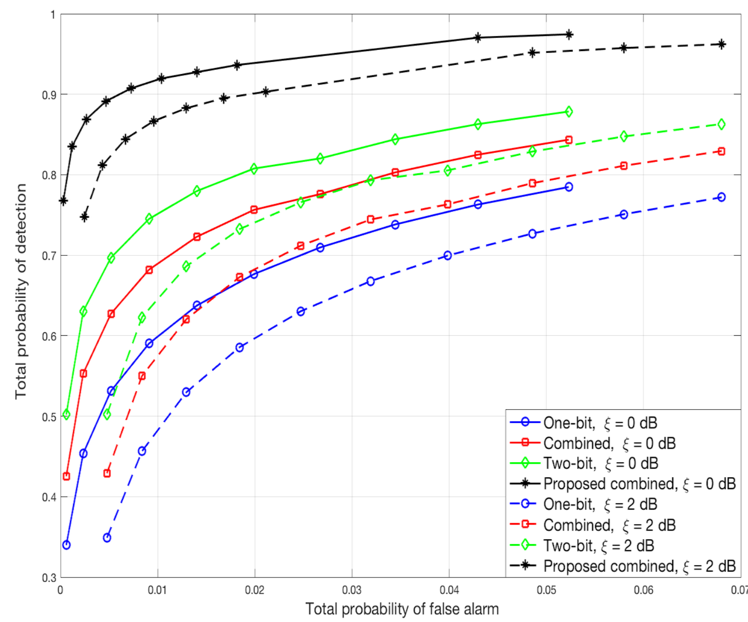


Figure 4.9: ROC curves under perfect and imperfect reporting channels.

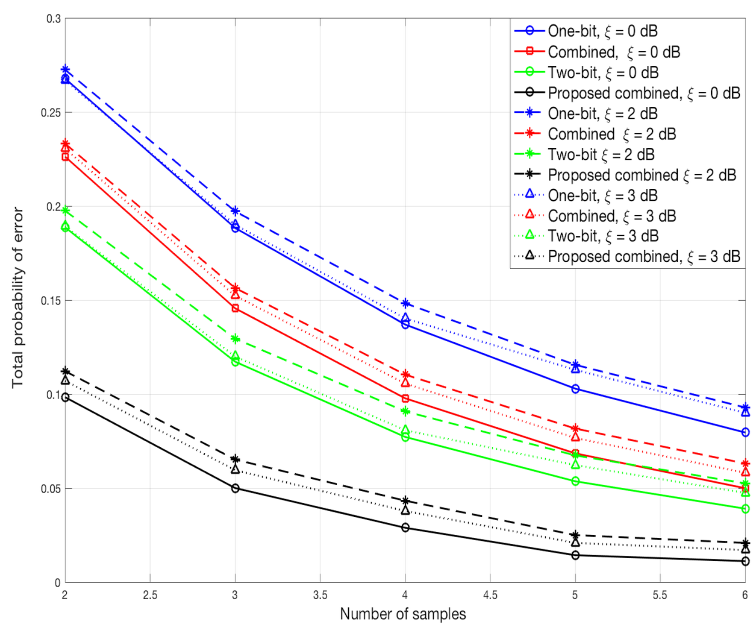


Figure 4.10: Total probability of error under perfect and imperfect reporting channels with different number of samples.

Different channel conditions are investigated in Figures 4.8, 4.9 and 4.10, respectively. Figure 4.8 investigates the effect of varying Nakagami parameter m on the system's performance. It is shown that the detection performance remarkably improves when increasing the Nakagami parameter m for both the hard and the combined schemes. However, the improvement attained by increasing m diminishes gradually as the number of users increases for both softened and proposed combined schemes. Figure 4.9 compares ROC curves of all the schemes under both perfect and imperfect reporting channels. Moreover, the effect of the imperfect reporting channel is analyzed in terms of the detection error rate in Figure 4.10; increasing the SNR of the reporting channel (ξ) decreases the error rate Q_e. The combined scheme is marginally comparable to the softened hard scheme while the proposed combined scheme exhibits a superior performance relative to the other schemes. The impact of the the value of K on the detection performance is assessed in Figure 4.11. It is shown that the value of K does not affect the softened hard scheme and only have a slight effect on the proposed combined scheme, yet it greatly affects both hard and combined schemes.

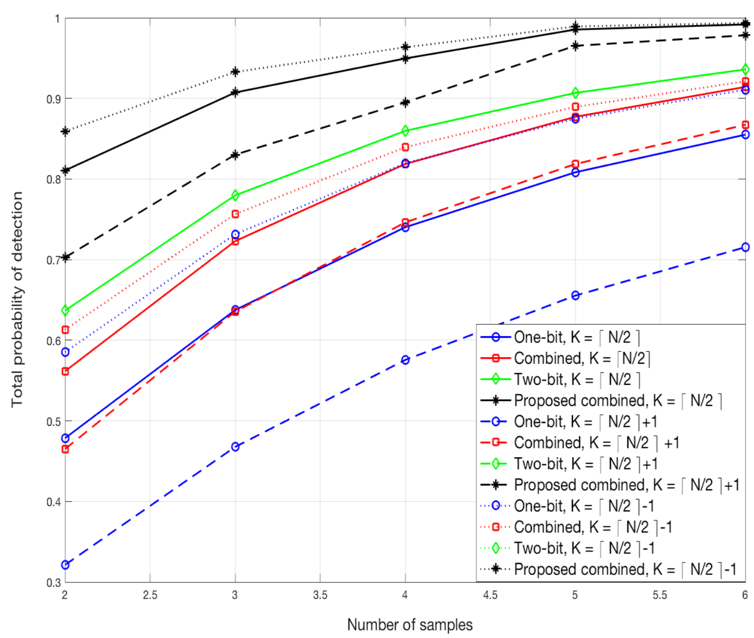


Figure 4.11: Total probability of error with different values of K for different schemes.

Varying the PU SNR which yields to variations of the SNR of all the clusters is illustrated in Figures 4.12, 4.13 and 4.14, respectively. In Figure 4.12, the proposed combined algorithm is compared with the one-bit, two-bit and combined schemes. The results show that the proposed algorithm outperforms all the schemes especially under low SNR. However, the performance improves with the increase of SNR and then degrades at moderate SNR values since the reliability of the clusters increases with the increase of SNR and more clusters are selected for the decision making process while they still are not as reliable as the case of high SNR. Therefore, an adaptive proposed algorithm was employed to ensure minimizing Q_e and attaining high Q_d as shown in Figures 4.13 and 4.14, respectively. In Figure 4.13, the schemes are compared at cluster global probability of false alarm equal to 0.05 and 0.1, respectively, and it is shown that the adaptive modified algorithm has the best detection performance among all schemes. The performance of the schemes is also compared in terms of Q_e with respect to the PU SNR and the same results are obtained.

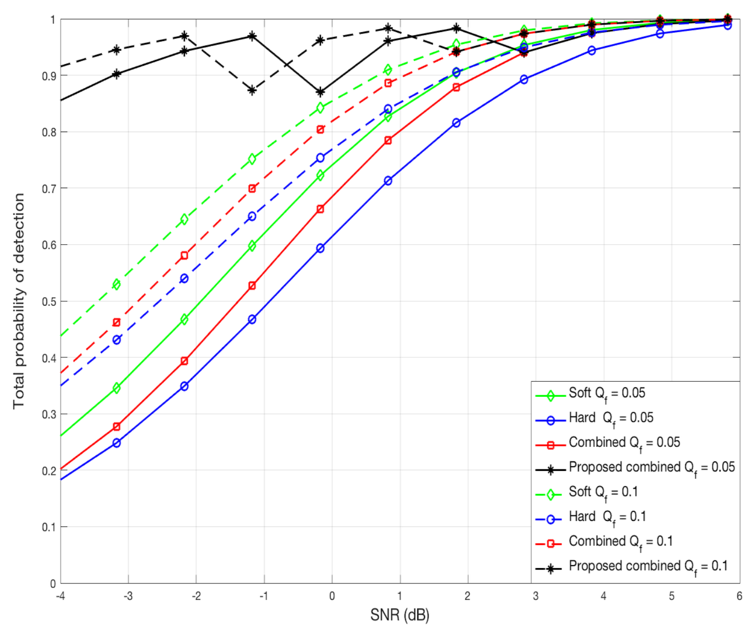


Figure 4.12: Detection performance with different PU SNR with proposed combined fusion scheme.

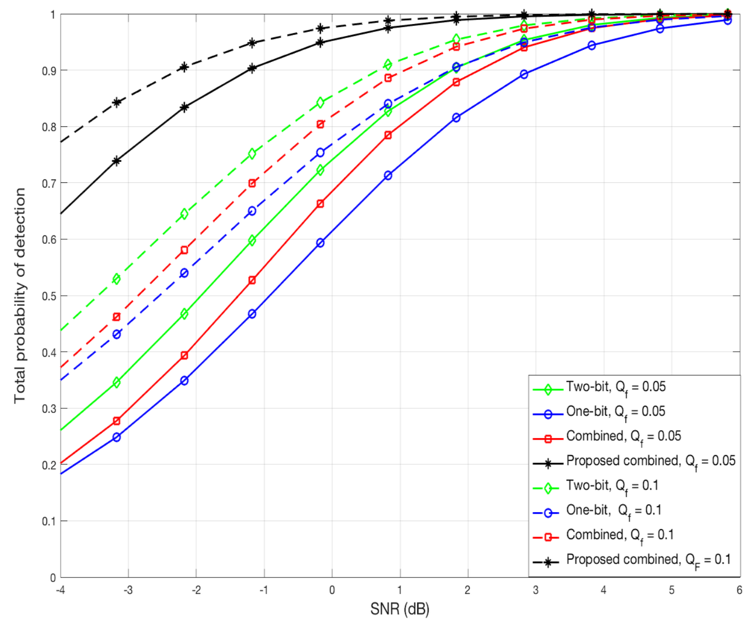


Figure 4.13: Detection performance with different PU SNR with proposed adaptive combined fusion scheme.

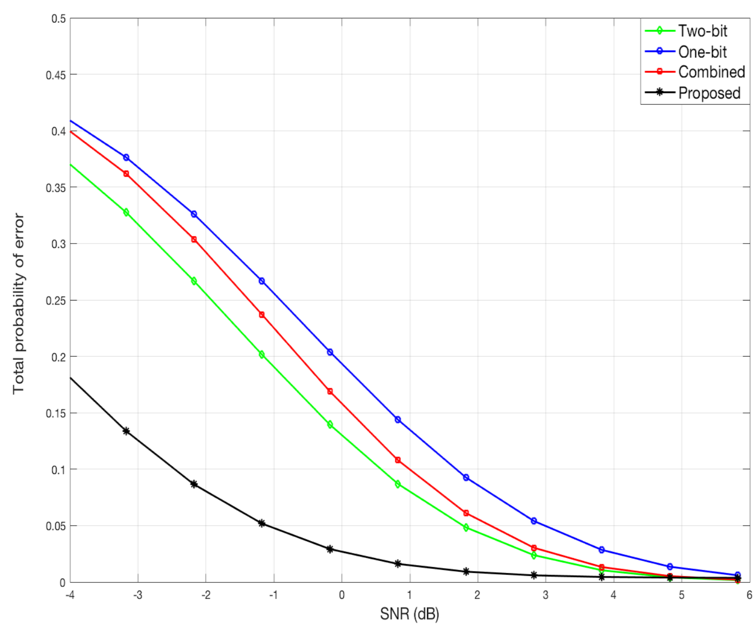


Figure 4.14: Total probability of error with different PU SNR.

4.5 Conclusion

In this chapter, a new soft-hard combined scheme in CBCSS was presented to enhance the detection performance while accounting for the system's complexity by combining the softened hard and the hard fusion at the intra-cluster level. The scheme was compared with both softened hard and hard fusion schemes. Furthermore, the scheme was improved by selecting the reliable clusters for detection by employing an adaptive iterative algorithm.

Both schemes were analyzed over imperfect and perfect reporting channels as well as different channel conditions. They were also studied with different values of K ($i.e.$, number of users that successfully detect the PU signal). Simulation results have shown that the combined scheme is suboptimal in terms of performance and overhead while it becomes a better option in the case of densely deployed areas. However, the modified combined scheme outperforms all schemes in terms of performance and overhead considering that the iterative algorithm can be done offline to reduce the complexity.

CHAPTER 5

Conclusions and Future Works

5.1 Conclusions

Compromising between the performance and complexity in CBCSS was considered in this thesis by combining soft and hard fusion techniques from two different aspects. On one hand, the cluster was divided into groups by an optimization criterion in a way that employs soft data fusion at the group level and hard fusion at the cluster level as described in chapter three. On the other hand, multiple clusters were classified based on their SNR to employ either quantized soft fusion or hard fusion while a hard fusion scheme was adopted at the FC level as delineated in chapter four.

Balancing between detection performance and overhead in CBCSS has been considered. Optimization criterion employing soft and hard combining techniques to extract hierarchical levels for a cluster has also been developed. The simulation results have shown that using the proposed algorithm, the cluster can only have two hierarchical levels. The impact of sensing time on the performance has also been investigated. Furthermore, the effect of varying on the performance has also been examined. Finally, simulation results have shown that the proposed algorithm employing MRC technique outperforms the performance of the proposed algorithm using EGC or SC techniques.

A combined performance and overhead oriented CBCSS scheme was considered by proposing a new soft hard combined scheme to enhance the detection performance while accounting for the system's complexity by combining the softened hard and the hard fusion at the intra-cluster level. The scheme was compared with both softened hard and hard fusion schemes. Furthermore, the scheme was improved by selecting the reliable clusters for the decision making process by employing an adaptive iterative algorithm. Both schemes were analyzed under imperfect and perfect reporting channels as well as different channel conditions. They were also studied with different values of K. Simulation results showed that the combined scheme is suboptimal in terms of performance and overhead while it becomes a better option in the case of large number of users. However, the modified combined scheme is superior to all schemes in terms of performance and overhead considering that the iterative algorithm can be done offline to reduce the complexity.

5.2 Recommendations for future work

Throughout this thesis, we addressed some methods based on clustering for cooperative spectrum sensing in cognitive radio networks to improve the detection performance while accounting for the system's complexity. This work can be extended in various ways. For instance, the performance of the proposed schemes is examined under Nakagami fading channels while in practice shadowing might occur if the two cognitive radios are located close to each other. In that case, the performance can be further investigated over a composite multipath fading and shadowing channel model. While we mainly studied the temporal detection assuming that all the SUs share the same spectrum access opportunities, it is beneficial to consider the spectrum heterogeneity by exploring the joint detection of spectrum holes in both spatial and temporal domains. Besides, the system is implemented using energy detector which assumes the exact estimation of the noise power. However, there exists noise uncertainty in real scenarios which significantly affects the detection performance. Therefore, it is important to analyze the performance by exploiting some techniques such as two-stage sensing to alleviate the effect of uncertainty. Practical implementations using Software Defined Radio (SDR) which is characterized by a soft ware entity and USRP (Universal Software radio Peripherals) hardware platform can also be considered. Finally, a typical PU activity model, the ON/OFF model, can be applied to study the effect of the alternate PU states on the system's performance.

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Appendices

APPENDIX A

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