MULTI USER COOPERATION SPECTRUM SENSING IN WIRELESS COGNITIVE RADIO NETWORKS

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Abstract

With the rapid proliferation of new wireless communication devices and services, the demand for the radio spectrum is increasing at a rapid rate, which leads to making the spectrum more and more crowded. The limited available spectrum and the inefficiency in the spectrum usage have led to the emergence of cognitive radio (CR) and dynamic spectrum access (DSA) technologies, which enable future wireless communication systems to exploit the empty spectrum in an opportunistic manner. To do so, future wireless devices should be aware of their surrounding radio environment in order to adapt their operating parameters according to the real-time conditions of the radio environment. From this viewpoint, spectrum sensing is becoming increasingly important to new and future wireless communication systems, which is designed to monitor the usage of the radio spectrum and reliably identify the unused bands to enable wireless devices to switch from one vacant band to another, thereby achieving flexible, reliable, and efficient spectrum utilisation.

This thesis focuses on issues related to local and cooperative spectrum sensing for CR networks, which need to be resolved. These include the problems of noise uncertainty and detection in low signal to noise ratio (SNR) environments in individual spectrum sensing. In addition to issues of energy consumption, sensing delay and reporting error in cooperative spectrum sensing. In this thesis, we investigate how to improve spectrum sensing algorithms to increase their detection performance and achieving energy efficiency.

To this end, first, we propose a new spectrum sensing algorithm based on energy detection that increases the reliability of individual spectrum sensing. In spite of the fact that the energy detection is still the most common detection mechanism for spectrum sensing due to its simplicity. Energy detection does not require any prior knowledge of primary signals, but has the drawbacks of threshold selection, and poor performance due to noise uncertainty especially at low SNR. Therefore, a new adaptive optimal energy detection algorithm (AOED) is presented in this thesis. In comparison with the existing

energy detection schemes the detection performance achieved through AOED algorithm is higher.

Secondly, as cooperative spectrum sensing (CSS) can give further improvement in the detection reliability, the AOED algorithm is extended to cooperative sensing; in which multiple cognitive users collaborate to detect the primary transmission. The new combined approach (AOED and CSS) is shown to be more reliable detection than the individual detection scheme, where the hidden terminal problem can be mitigated. Furthermore, an optimal fusion strategy for hard-fusion based cognitive radio networks is presented, which optimises sensing performance.

Thirdly, the need for denser deployment of base stations to satisfy the estimated high traffic demand in future wireless networks leads to a significant increase in energy consumption. Moreover, in large-scale cognitive radio networks some of cooperative devices may be located far away from the fusion centre, which causes an increase in the error rate of reporting channel, and thus deteriorating the performance of cooperative spectrum sensing. To overcome these problems, a new multi-hop cluster based cooperative spectrum sensing (MHCCSS) scheme is proposed, where only cluster heads are allowed to send their cluster results to the fusion centre via successive cluster heads, based on higher SNR of communication channel between cluster heads.

Furthermore, in decentralised CSS as in cognitive radio Ad Hoc networks (CRAHNs), where there is no fusion centre, each cognitive user performs the local spectrum sensing and shares the sensing information with its neighbours and then makes its decision on the spectrum availability based on its own sensing information and the neighbours' information. However, cooperation between cognitive users consumes significant energy due to heavy communications. In addition to this, each CR user has asynchronous sensing and transmission schedules which add new challenges in implementing CSS in CRAHNs. In this thesis, a new multi-hop cluster based CSS scheme has been proposed for CRAHNs, which can enhance the cooperative sensing performance and reduce the energy consumption compared with other conventional decentralised cooperative spectrum sensing modes.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

5G	5th Generation mobile networks or 5th Generation wireless systems
ADC	Analogue to Digital Converter
AOED	Adaptive Optimal Energy Detection
AP	Access Point
AWGN	Additive White Gaussian Noise
BPF	Band Pass Filter
BPSK	Binary Phase Shift Keying
BS	Base Station
CFAR	Constant False Alarm Rate
CH	Cluster Head
CR	Cognitive Radio
CRNs	Cognitive Radio Networks
CRs	Cognitive Radio users
CSMA	Carrier Sense Multiple Access
CSS	Cooperative Spectrum Sensing
DCSS	Decentralised Cooperative Spectrum Sensing
DOTED	Double Optimal Threshold Energy Detection
DSA	Dynamic Spectrum Access
EHF	Extremely High Frequency
FC	Fusion Centre
FCC	Federal Communications Commission
FFT	Fast Fourier Transform
GPS	Global Positioning System

GUESS	Gossiping Updates for Efficient Spectrum Sensing
IoT	Internet of Things
ISM	Industrial, Scientific and Medical radio band
ITU	International Telecommunication Union
LEACH-C	Centralised Low Energy Adaptive Clustering Hierarchy
LO	Local Oscillator
M2M	Machine to Machine
MAC	Media Access Control
MBB	Mobile BroadBand
MHCCSS	Multi-Hop Clustering Cooperative Spectrum Sensing
Ofcom	Office of Communications
OSA	Opportunistic Spectrum Access
Pd	Probability of Detection
Pf	False Alarm Probability
Pm	Mis-detection Probability
PU	Primary User
Qe	Global Error Rate
QoS	Quality of Service
RF	Radio Frequency
ROC	Receiver Operation Characteristic
SNR	Signal to Noise Ratio
SPTF	Spectrum Policy Task Force
SU	Secondary User
TDMA	Time Division Multiple Access

TV	Television
UK	United Kingdom
USA	United States of America
UWB	Ultra-Wide Band
VLF	Very Low Frequency
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network
WRAN	Wireless Regional Area Network
WSD	White Space Device
XOR	Exclusive-OR

List of Publications

1. Ahmed S. B. Kozal, Madjid Merabti, Faycal Bouhafs," The Key Elements of Cognitive Radio Networks: A Survey", *11th Annual Postgraduate Symposium on Convergence of Telecommunications, Networking and Broadcasting (PGNet 2010)*, Liverpool, UK, 21-22 June 2010.
2. Ahmed S. B. Kozal, Madjid Merabti, Faycal Bouhafs,"Energy Efficient Clustering Approach for Cooperative Spectrum Sensing in Cognitive Radio Networks,"*12th Annual Postgraduate Symposium on Convergence of Telecommunications, Networking and Broadcasting (PGNet 2012)*, Liverpool, UK, 25-26 June 2012.
3. Ahmed S. B. Kozal, Madjid Merabti, Faycal Bouhafs, "An Improved Energy Detection Scheme for Cognitive Radio Networks in Low SNR Region," ISCC, pp.000684-000689, 2012 IEEE Symposium on Computers and Communications (ISCC), 2012.
4. Ahmed S. B. Kozal, Madjid Merabti, Faycal Bouhafs, "Spectrum Sensing-Energy Tradeoff in Multi-hop Cluster Based Cooperative Cognitive Radio Networks," *International Workshop on Green Cognitive Communications and Computer Networking (GCCCN) (INFOCOM WKSHPS)*, pp.87,88, 27 April-2nd May 2014.
5. Ahmed S. B. Kozal, Madjid Merabti, Faycal Bouhafs, " Energy-Efficient Multi-hop Clustering Scheme for Cooperative Spectrum Sensing in Cognitive Radio," *IEEE 11thConsumer Communications and Networking Conference (CCNC)*, pp.336,344, 10-13 Jan. 2014.

Chapter 1

Introduction

Many studies predict that cities, neighbourhoods, campuses, and buildings will be smarter [1-6]. Our surroundings such as houses, cars, furniture, and cloths will be equipped with a variety of intelligent, sensing, tracking and wireless communications capabilities. Moreover, the rapid growth in cellular and wireless broadband have resulted in a tremendous increase in the number of wirelessly connected devices. Applications such e-health and vehicular systems, and Machine to Machine applications are causing a growing demand for more radio spectrum.

However, recent radio spectrum measurements undertaken by the UK regulator Office of Communications (Ofcom) have shown that most of the licensed spectrum bands are largely underutilised for significant periods of time in various geographical areas in the UK [7]. The limited available spectrum and the inefficiency in the spectrum usage have prompted the communication regulators around the world to consider a dynamic use of the available spectrum, which was later known as Dynamic Spectrum Access (DSA) technology [8], and develop a new spectrum allocation policy that enables unlicensed users to exploit the wireless spectrum opportunistically.

The key enabling technology of DSA techniques is CR technology, which is proposed as a possible solution to improve spectrum utilisation. Spectrum sensing is a key component of CR, as it plays a major role in optimising the utilisation of the radio spectrum. It has the ability to access the licensed spectrum bands without causing any harmful interference to the licensed users. To keep the collision interference minimal and at an acceptable level, secondary users must sense the spectrum to detect its availability and should be able to detect very weak primary user signals as well.

Spectrum sensing plays a major role in cognitive radio networks CRNs as it helps to reveal spectrum holes properly within the licensed spectrum that are unoccupied.

These unoccupied spectrum holes will be used by CRNs for communication without causing any harmful interference to primary users. CRNs will release these unused bands as soon as the presence of a primary user is detected.

However, there are several considerations and important requirements that must be taken into account when designing a spectrum sensing algorithm for CRNs[9]. These considerations and requirements can be summarised as following:

- *Interference Level*: To design a good spectrum sensing algorithm, the primary system should be protected against harmful interference caused by secondary user when intending to access the primary spectrum bands. The interference range depends on the secondary user's transmitted power and on the primary user's interference tolerance [10]. With the proliferation of CR systems in the future, there will be an increase of CRNs operating over the same licensed band, which will result in an interference aggregate that could be harmful to primary users even if the primary user is out of range of any secondary user. This scenario could be avoided by developing a more highly sensitive detector and a new way to reduce the aggregate interference.

- *Sensing Time and Periodicity*: During the sensing period, the secondary user should be able to identify the presence of primary users as quickly as possible, and should vacate the band immediately in the case of primary users reappearing [11]. This requires that the sensing periodicity should be short enough in order to reduce the delay and to minimise the degradation of quality of service (QoS) that is incurred by the primary users accessing the band. Generally, the sensing period depends on the capabilities of the secondary user itself and the delay sensitivity of the primary user's application, which is set by the radio spectrum regulators. For a better spectrum sensing design, and in order to maximize the time available for data transmission, it is more suitable to reduce the sensing time as much as possible.

- *Detection Sensitivity*: Realistically, most of the wireless communication channels suffer from the phenomena of fading and shadowing by obstacles, which reduce the received primary signal at the secondary user. In the case of low SNR of the sensing channel, the cognitive receiver must estimate the noise power accurately in order to distinguish between the noise signal and the primary signal [12]. In wireless networks, the noise power at each user is the result of two types of noise: the first; device noise, which comes from a nonlinearity of a receiver's components and thermal noise in these components, and second; environment noise, which is caused by transmissions of other users. CR systems may not be able to achieve higher detection sensitivity with the presence of these constraints. It is worth mentioning that the sensing performance cannot be enhanced by increasing the detection sensitivity when the SNR of the detected signal is below a certain level known as the SNR_{wall} thus a single spectrum sensing technique would be impractical. However, these issues can be tackled by allowing different secondary users to share their sensing measurements and cooperatively decide on the licensed spectrum occupancy.

- *Channel Overhead*: Improving detection sensitivity comes at the cost of additional communication overhead. In cooperative sensing mechanisms, a control channel is required to enable the exchange of information between the cooperating users and fusion centre (FC). Obviously, the cooperation overhead will increase with the increasing number of cooperating users, due to the amount of data that needs to be reported to FC [13].

- *Decision Accuracy*: A good sensing scheme should ensure a high detection probability (*Pd*) and a low false alarm probability (*Pf*), which will help to optimise spectrum usage efficiency while guaranteeing a certain level of protection to primary users [14].

1.1 Motivation and Objectives

Inefficient usage of the radio spectrum alongside the rapid growth of wireless devices and applications have led to the emergence of CR to exploit unused spectrum in opportunistic manner.CR technology is now widely expected to play a significant role in future wireless communication networks, because of its ability to adapt the operating parameters of its users according to the surrounding radio environment, and then access to the available spectrum wherever and whenever it is needed without causing any undesirable interferences. Spectrum sensing is a key component of cognitive radio, as it plays a major role in optimising the efficiency of spectrum utilisation. Designing a reliable, fast and efficient spectrum sensing algorithm has become a critical challenge in CRNs, which needs more effort in order to satisfy the aforementioned spectrum sensing requirements.

Various spectrum sensing approaches have been proposed in the literature with mitigated results as there are several issues that have not been addressed. One of the main issues in spectrum sensing is the detection of a weak primary signal at the secondary receiver. This problem is due to several phenomena such as multipath loss, multipath fading, shadowing and interference. The focus of this thesis is to design reliable and efficient spectrum sensing algorithms for CRNs. The motivation of this research thesis can be summarised as follows:

- In an energy detection based spectrum sensing scheme, selecting a suitable sensing technique to detect the primary signal is very important to guarantee a reliable detection. However, the lack of knowledge about the primary signals on the one hand and the increasing implementation complexity of the sensing algorithms on the other, have made it difficult to obtain reliable detection using the single user method [15]. In such a case, an energy detection algorithm can be considered an optimal method due to its simplicity and does not require any prior information about the detection signal. Despite the advantages of energy detection, there are still some weaknesses that need a suitable solution to improve the detection performance, including threshold detection setting, sensing delay, and noise power uncertainty. In order to deal with such issues, many improved approaches of energy detection have been proposed. In [16], a double threshold energy detection method is proposed instead of single threshold, which gives further reduction in error detection. Another way to determine the detection threshold is optimal threshold method [17-18], which is based on minimising the error detection. The effect of noise uncertainty on the performance of energy detection has been studied in [19-21]. However, all of these approaches have focused only on one of the above-mentioned issues. Therefore, there is a need for designing a new energy detection algorithm that tackles all these issues together to provide detection that is more reliable.

- In cooperative spectrum sensing (CSS) scenarios, the optimisation process of cooperative sensing can effectively improve the efficiency of cooperative detection. However, most of the existing optimisation algorithms are based on determining the optimal detection threshold numerically [22-27], leading to more time to implement because of their computational complexity. Furthermore, all these works consider that the noise power is fully known during the local sensing process, leading to more sensing errors. Therefore, there is a need for a new CSS algorithm that considers these issues in order to increase the sensing accuracy, thus improving the detection performance.

- In CSS, the power consumption issue can be of great significance when the number of cooperative users or the number of reporting results sent by CR users to FC is large. In such cases, the energy efficiency should be considered in cooperative sensing algorithms. This means that all elements of the CSS, from the local sensing to cooperation protocols must be energy efficient.

- Sensing time and reporting delay are important challenges that need to be addressed in the spectrum sensing algorithm. Sensing time depends on the sensing technique being used, which is proportional to the number of discrete samples used in the signal detection process. Typically, the sensing period is constant and depends on the cognitive user capabilities and the delay sensitivity of the primary user’s application. Accordingly, the longer the sensing time, the less time is available for transmission, thus reducing the CR user throughput. On the other hand, sharing the sensing results with a FC in centralised networks or other CR users in decentralised systems will incur reporting delay, hence, increasing the sensing time. For example, the transmitted messages from different cooperative users on the control channel may collide and thus retransmission is needed. Furthermore, sending the sensing data by multiple hops such as in the relay cooperative sensing will produce extra reporting delay. In order to improve the cooperative sensing delay, many trade-offs need to be considered, such as spectrum sensing-energy trade-off and energy-sensing delay trade-off.

- In decentralised CRNs, due to the lack of a FC, each cognitive user has its own independent and asynchronous sensing and transmission schedules, causing the cognitive user to detect the transmissions of other cognitive users as well as primary users during its local sensing period, especially when energy detection is adopted to act as local spectrum sensing, hence, degrading the efficiency of spectrum sensing.

To address the issues and limitations identified above, I have set a number of objectives that I believe will help increasing the spectrum utilisation on the one hand, and providing a good protection to the primary system against the potential interferences that may be caused by CR users on the other hand, thus, increasing the throughput of CRNs.

The objectives of this research could be summarised as following:

1. Develop a simple and efficient local spectrum sensing algorithm to reliably detect the primary signal. A reliable spectrum sensing algorithm comes at the expense of the cost and complexity, where it requires a highly sensitive detection to increase the sensing accuracy. Based on this, various individual spectrum sensing schemes have been proposed, to suit different system consideration and communication

technologies. However, there is no general sensing method available yet to fit all kinds of wireless communication systems and technologies. In terms of computational and implementation complexities, the energy detection algorithm is more suitable for CRNs due to low complexity. In contrast, existing energy detection algorithms need to improve the sensing reliability due to their bad detection accuracy, especially in low SNR. The challenge here is to determine the detection threshold that is mainly depending on the noise power and sensing channel conditions.

2. Design a simple and efficient CSS algorithm that optimises the detection performance. This design is focused on the main elements of cooperative sensing, namely local sensing, reporting, and data fusion method, and how to improve the efficiency of each element. In this work, I investigate the optimality of CSS when optimal energy detection for local sensing and optimal counting fusion rule are applied. More specifically, in the local sensing phase, we apply the same algorithm developed in paragraph 1, where the optimal detection threshold under noise uncertainty is considered, aiming at minimising the local error rate, which provides more reliable and practical detection algorithm. Furthermore, in order to make an accurate spectrum sensing decision, an appropriate fusion technique at the FC is needed; therefore, an optimal hard decision fusion strategy is adopted, which optimises the sensing performance.

3. Design a new energy efficient CSS algorithm for centralised CRNs. In CSS, each cognitive user reports its local sensing result to the FC or shares it with its neighbouring users using a control channel. However, this cooperation process presents certain problems that need to be addressed. First, the control channel may be subject to the fading effects, which may affect the quality of the reporting data and degrade its level of accuracy. Secondly, the control channel has a fixed bandwidth that limits the amount of reporting data that can be sent over it. Finally, the power consumption adds a scalability issue when increasing the number of cooperating users. Clustering is an effective approach to overcome these problems

as it helps to reduce the cooperation range and the incurred overhead. Multi-hop routing algorithms are another way to reduce the energy consumption due to reporting the sensing results through long distance reporting channels. My design is based on a combination between clustering and multi-hop techniques that aims at finding the optimal number of clusters so that the energy consumption is optimised, while providing efficient performance of spectrum sensing.

4. Develop a new approach for CSS in decentralised CRNs, such as ad hoc networks. Although Decentralised cooperative spectrum sensing (DCSS) does not require a FC to collect all local sensing data, the direct exchanges of sensing results between CR users generate more control overhead, such as bandwidth and energy overhead. The challenge here is to find a way to reduce this control overhead without affecting the accuracy of the spectrum sensing.

1.2 Key Contributions

The contributions of this thesis focus on two modes of spectrum sensing in CRNs; single-user spectrum sensing, and CSS mode. In single-user spectrum sensing mode, I propose a novel optimal energy detection based spectrum sensing algorithm that aims to increase the reliability of local sensing and mitigate interference with the primary network. In CSS mode, a novel multi-hop clustering mechanism for CSS is proposed, to reduce the energy consumption and improve spectrum-sensing performance, which can be suitable for centralised and decentralised cognitive radio networks.

The contributions of this work are summarised as follows:

1 I propose a detection method that improves the performance of the energy detection algorithm. More specifically, the performance of conventional energy detection is greatly deteriorating due to the impact of noise uncertainty, especially in low SNR environments. On the other hand, the inappropriate setting of the detection threshold could lead to a significant decline in the performance of

detection. Here, I explore these situations and I propose a new adaptive optimal energy detection (AOED) spectrum sensing algorithm. The optimal detection threshold has been derived from the basis of the trade-off between misdetection and the false alarm probabilities. I also developed an adaptive threshold factor with optimal algorithm in order to combat noise uncertainty, which is compatible with the real world communications and allows better spectrum sensing performance especially with low SNRs. This contribution has been published in [28]. In addition, I developed a new double optimal energy detection algorithm, which provides more protection to primary systems but at the expense of a small reduction in the detection probability.

2 As a CSS algorithm can give further improvements in detection reliability, where multiple cognitive users collaborate to detect the primary transmission, I extended my AOED algorithm to the case of CSS strategy. I develop a new CSS based on adaptive optimal energy detection algorithm, which gives more reliable and accurate detection decision under low SNR for cooperative CRNs. Furthermore, in this design, the optimisation of CSS is studied, where an optimal fusion strategy for hard fusion based CSS is presented, which optimises the detection performance subject to a constraint of the amount of the error rate. It is shown that the majority rule is optimal or near optimal in terms of minimising the error rates.

3 I develop a new multi-hop cluster based cooperative sensing strategy (MHCCSS)for large-scale CRNs, where the number of CR users is large and the distances between the cooperative users and the FC are long. In this design, the cluster heads will not send their cluster results directly to the FC as it is in traditional clustering approaches, which only reduce the reporting overhead, but they will send them to cluster heads in the next hop towards the FC. By dividing the total clusters into multi-levels based on distances between cluster heads and the FC, more energy can be saved during reporting the sensing results over reliable transmission channel, which leads to accurate spectrum sensing. This clustering approach extends the LEACH-C protocol [29], to enable multi-hop

transmissions between far cluster heads and the FC. In this scheme, the FC determines the optimal number of cluster heads in a centralised way, according to the best reporting channel gain, distance from the fusion centre, and the energy level of CR users. The materials presented in this work have been published in [30-31].

4 I develop a new approach for CSS in decentralised CRNs, where I adopt the same idea of (MHCCSS) in centralised networks and modify it to match with the wireless networks that do not have centralised control. By combining clustering and multi-hop communication techniques, I can maintain more energy and improve the detection performance, especially in large scale cognitive networks. In this design, all CR users that are close to each other will group into few clusters, and one of the cluster heads which has the largest energy will be elected as a FC. Instead of each CR user sending its sensing results to its neighbours, it sends its own sensing results to a related cluster head, which in turn sends the cluster results to the FC either directly (one-hop communication) or indirectly (multi-hop communications) via intermediate cluster heads.

1.3 Thesis Organisation

The reminder of this thesis is organised as follows:

- **Chapter 2**

This chapter gives background information of this work. An overview on radio spectrum allocation and wireless communication systems is presented first, and then an introduction to DSA technology is given. After that, the basic concepts and definitions of CR alongside its possible applications are presented. Finally, the spectrum sensing techniques are reviewed to introduce the state-of-art algorithms relevant to this work.

- **Chapter 3**

In this chapter, we describe the main issues of the spectrum sensing technique in CRNs, overview our proposed mechanisms that address these issues, and provide a brief description of the novel contributions in this thesis.

- **Chapter 4**

In this chapter, a new spectrum sensing based energy detection with a single user is proposed and discussed. Specifically, a closed form expression of the optimal detection threshold in energy detection algorithm with adaptive noise uncertainty factor is derived, based on minimising the local error rate under Bayesian criterion. The performance of the proposed model is analysed in terms of probability of detection and sensing time. For the purpose of comparison, the existing energy detection algorithms such as double threshold and conventional energy detection schemes are also investigated.

- **Chapter 5**

In this chapter, I extend our proposed algorithm in chapter 4 to be exploited in CSS, so that the hidden terminal issue can be tackled, and get more reliable detection. More specifically, I consider the performance optimisation of CSS by getting the optimal threshold of the local sensing based on minimising the local error, and exploiting it in CSS approach using K out N decision fusion rule, in which optimal K can be determined.

- **Chapter 6**

This chapter addresses the problems of energy consumption and spectrum sensing of centralised CSS approach. To alleviate such problems, I present a multi-hop clustering scheme. Considering the sensing errors, I first investigate the impact of false alarm and mis-detection probabilities on the sensing performance. Based on the proposed sensing strategy, I also investigate how I can reduce the energy consumption of large CRNs, while keeping the sensing delay at a reasonable level, therefore, a trade-off between performance metrics is needed based on application requirements.

- **Chapter 7**

  This chapter describes the existing issues of CSS approaches in decentralised CRNs, and presents a new multi-hop clustering based CSS for this kind of networks. In this design, since there is no central control in this type of wireless networks, as in ad hoc networks, the same proposed design of centralised CRNs is applied here, but with some modifications by employing one of cluster heads to act as a FC. The descriptions of clusters formation is illustrated in details in this chapter. The performance of the developed model in terms of energy efficiency and sensing accuracy is analysed and discussed, and for comparison, the conventional CSS approaches of decentralised CRNs are also studied here in order to validate my proposed scheme.

- **Chapter 8**

Finally, this thesis is summarized in chapter 8 and some ideas for future proposals are included based on the research carried out in this work.

Chapter 2

Background

2.1 Introduction

The radio spectrum is defined as a subset of the entire electromagnetic spectrum that carries radio waves with frequencies ranging from around 3 KHz to 300 GHz, commonly used for radio communications. These radio communications include television, radio, satellite, cellular phone, Wi-Fi, radar, and many other communication technologies [32].

Conventionally, radio frequency spectrum is often grouped in eight frequency bands based on different frequencies, starting with Very Low Frequency (VLF) that ranges between 3 KHz and 30 KHz, and extending to Extremely High Frequency (EHF) with the range of 30 GHz to 300 GHz, as shown in Figure 2.1. In general, radio signals with higher frequencies offer higher data bandwidth over a shorter communication range in comparison to lower radio frequencies. However, the performance of higher frequencies radio communication can be more affected by obstacles such as walls and trees than lower frequencies, whereas low frequencies have a capability to reach very long distances but with small data bandwidth and are less affected by obstacles and weather conditions.

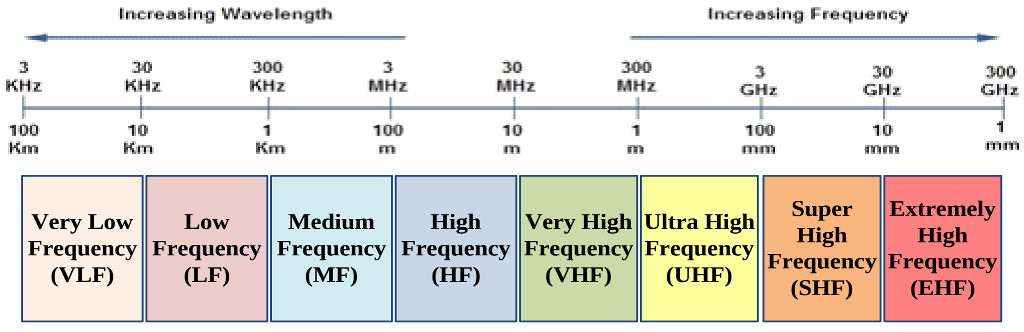


Figure 2.1 Radio spectrum frequencies

In most countries, the radio spectrum is split into bands by a government regulator of the radio spectrum, coordinated by an international regulatory body called International Telecommunication Union (ITU) [33], and national agencies such as Ofcom in the UK [34], and Federal Communications Commission (FCC) in the USA [35].

These regulations dictate that radio frequency bands are divided into two types, licensed and unlicensed bands. Over the past decades, most of the licensed spectrum has been allocated for licensed users for exclusive use, including TV broadcast, cellular communication, military services, healthcare services, and public services, while small portions of unlicensed spectrum are left open for unlicensed users such as smart devices including smartphones, smartwatches, and smart grids; which connect with other devices or networks via different wireless protocols such as Bluetooth, Wi-Fi and near field communication (NFC). Moreover, the current static spectrum allocation strategy does not give the unlicensed user the right to access the licensed spectrum, even if its transmission does not introduce any interference to the licensed service.

For decades, there has been a proportionate increase in the use of the radio spectrum with the evolution in wireless communication technology. Before 1930 the radio spectrum above 30MHz was almost free of man-made signals, where only broadcast radio was widespread at that time, on the contrary, today it has become a primary infrastructure for many wireless communications, including mobile networks.

However, some portions of the radio spectrum, which is sometimes considered to be between 100 MHz to 3 GHz, are more valuable than others, as they offer a good transmission range and data bandwidth for mobile applications and could support video broadcasting [36].

With the development in personal wireless technologies and mobile communications, both licensed and unlicensed spectrum bands have become overcrowded. However, many of the radio spectrum measurements, carried out by international organisations of the spectrum and specialized companies around the world, have shown that the conventional fixed spectrum allocation rules have resulted in low spectrum usage efficiency in almost all deployed frequency bands. For instance, recent radio frequency occupancy measurements undertaken by Ofcom in UK and the spectrum task force (SPTF) in USA have shown that some frequency bands in the licensed radio spectrum are largely unused, while some are heavily used in various geographical areas of the UK and USA [37-38]. Figure 2.2gives the average percentages of overall spectrum occupancy based on the actual measurements were made in all frequency bands in the (30-3000) MHz range over the United States and Europe [39-44]. These measurements conclude that the overall spectrum occupancy during the measuring period was 19.72% or less, which clearly confirm that some of the spectrum bands are rarely utilised continuously across time and space. Consequently, the traditional regulation of the spectrum requires reform in order to allow for more efficient use of the airwaves.

Radio spectrum is a limited natural resource, and many new developments rely on wireless connectivity, thus, radio is an important part of this connectivity. Beyond 2020, developments such as 5G, Big Data, the Internet of Things (IoT), Machine to Machine (M2M) communications, wireless internet access and smart cities will all utilise wireless connectivity that is dependent on various forms of radio mobile and fixed communications [45]. One of the possible solutions to the scarcity of radio spectrum is to enable some frequency bands to be shared for future wireless communication services. These spectrum bands include 5 GHz; which is already allocated for Wi-Fi application but it seems underutilised, below 700 MHz for future mobile services, and 60 GHz for very high data rate over very short ranges using the new Wi-Fi standard, called 802.11ad [46].

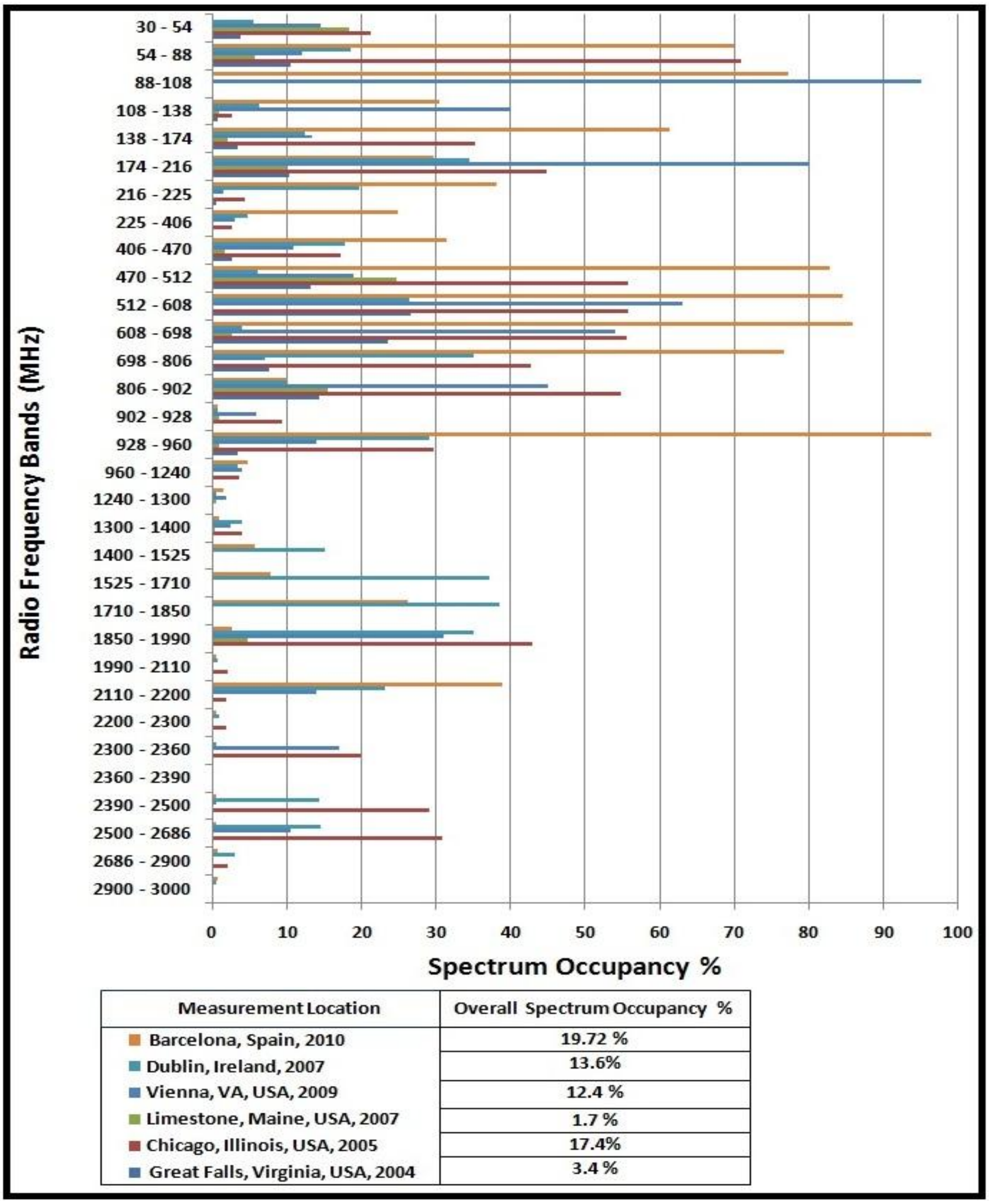


Figure 2.2 Bar graph of the radio spectrum usage over various spaces around the USA and Europe

The spectrum regulator Ofcom in the UK has already managed some new strategy to make some radio resource to support current innovation technology, including 4G wireless mobile standards and Wi-Fi broadband access [47]. The Figure 2.3 below illustrates the current spectrum usage in the UK.

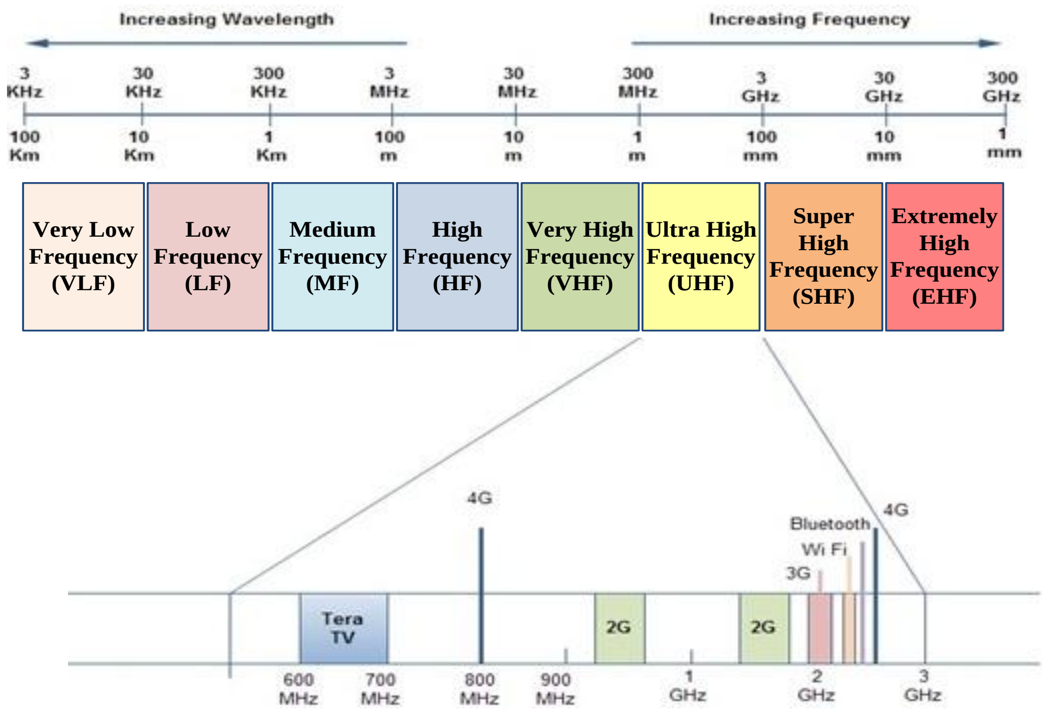


Figure 2.3 Current UHF spectrum usage in the UK.

Utilising new spectrum bands needs a new technique that enables users to identify the available spectrum bands before using them for communications. The key technologies that enable unlicensed users to utilise the licensed bands are CR and DSA technologies.

This chapter gives the reader an overview of the many topics related to this thesis, including recent evolutions in radio communication services, current and future uses of the spectrum, DSA technology, basic concepts of CR and its potential applications. In addition, the chapter encompasses a literature review on spectrum sensing techniques for CRNs, including local and CSS. The purpose of the information provided in this chapter is to enlighten readers on some of the developments in wireless communication technology and understanding the techniques that will be introduced later in this thesis.

2.2 Dynamic Spectrum Access Technology

DSA can be defined as a mechanism to adjust the spectrum resource usage in a near-real-time manner in response to the changing environment and objective (available channel and type of applications), changes of radio state, and changes in environment and external constraints. DSA is a method which can provide a flexible usage of parts of the radio spectrum, making it more efficient, thus helping service providers, and regulatory bodies like Ofcom to avoid spectrum scarcity [48]. DSA will be the pioneering technology that addresses the spectrum scarcity problem and increase the spectrum utilisation. Furthermore, DSA could play an important role in future mobile networks, such as 5G which is foreseen as the first major use of the DSA concepts [49]. This concludes that the advances in DSA technologies could enable a better quality of service to be achieved in unlicensed spectrum bands, which includes geolocation databases to manage interference between devices, cognitive sensing, carrier aggregation and smart antennas.

As shown in Figure 2.4 , DSA strategies can be broadly classified under three models, dynamic exclusive use, open sharing or spectrum commons model, and hierarchical Access model [8].

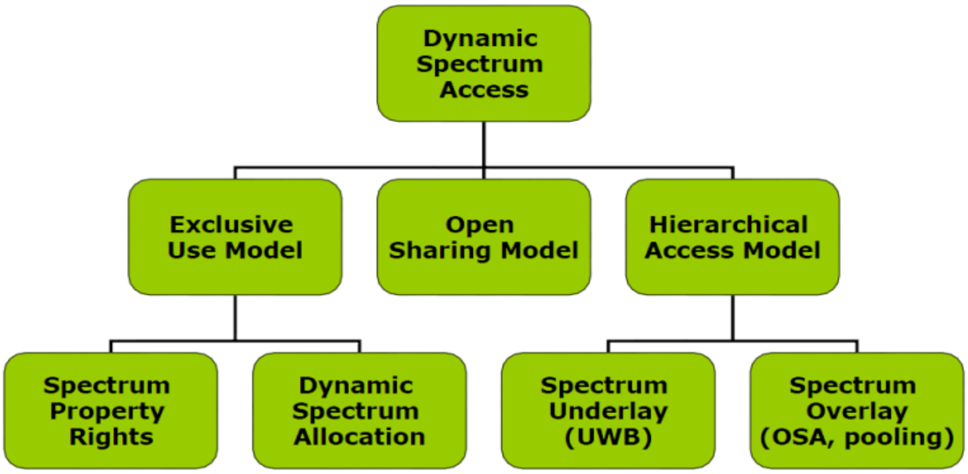


Figure 2.4 Classification of dynamic spectrum access

2.2.1 Dynamic Exclusive Use

In dynamic exclusive use, spectrum bands are licensed to services for exclusive use, where the basis of current spectrum policy is kept while providing flexibility to improve spectrum utilisation. There are two basic approaches under this model: spectrum property rights and dynamic spectrum allocation [8]. The current spectrum management policy is based on the property rights model, which gives spectrum owners an absolute right over their spectrum, and does not allow secondary users to operate in the licensed spectrum [50]. This method of spectrum allocation policy has served many successful applications, like broadcasting and cellular, which can be cited as evidence by the proponents of spectrum property rights.

On the other hand, dynamic spectrum allocation approach assigns a portion of the spectrum to services for exclusive use in a given region and at a given time [51]. Similar to the current fixed spectrum allocation policy, this strategy allocates, at a given time and region, a portion of the spectrum to a radio access network for its exclusive use. Based on an exclusive-use model, it has been established that both spectrum property rights and dynamic spectrum allocation cannot eliminate the current problem of spectrum underutilization with increasing wireless traffic.

2.2.2 Open Sharing Model

The open sharing model, which is also referred to as spectrum commons model, the spectrum is open for access to all users. This model is already in use in the unlicensed industrial scientific and medical (ISM) band. Centralised and distributed spectrum sharing strategies have been initially investigated to address technological challenges under this model.

2.2.3 Hierarchical Access Model

Hierarchical access model adopts a hierarchical access structure with primary and secondary users. The main idea is to open the licensed spectrum to secondary users while limiting the interference perceived by the primary user. There are two fundamental spectrum sharing approaches that have been proposed in CR: underlay approach, and overlay approach [8, 52-53]. Under this radio spectrum access model, the radio spectrum is viewed as having a primary or licensed user, as well as a secondary or unlicensed user. The model is considered a hybrid of the other two models previously discussed. Compared to the dynamic exclusive use and open sharing models, the hierarchical model is perhaps the most compatible with the current spectrum management policies and legacy wireless systems. Furthermore, the underlay and overlay approaches can be employed simultaneously to further improve spectrum efficiency. In [8], major challenges and recent developments in both technological and regulatory aspects of opportunistic spectrum access are provided. Based on this concept, two different approaches to radio spectrum sharing between licensed and unlicensed users have been considered, namely spectrum underlay and spectrum overlay, as illustrated in Figure 2.5.

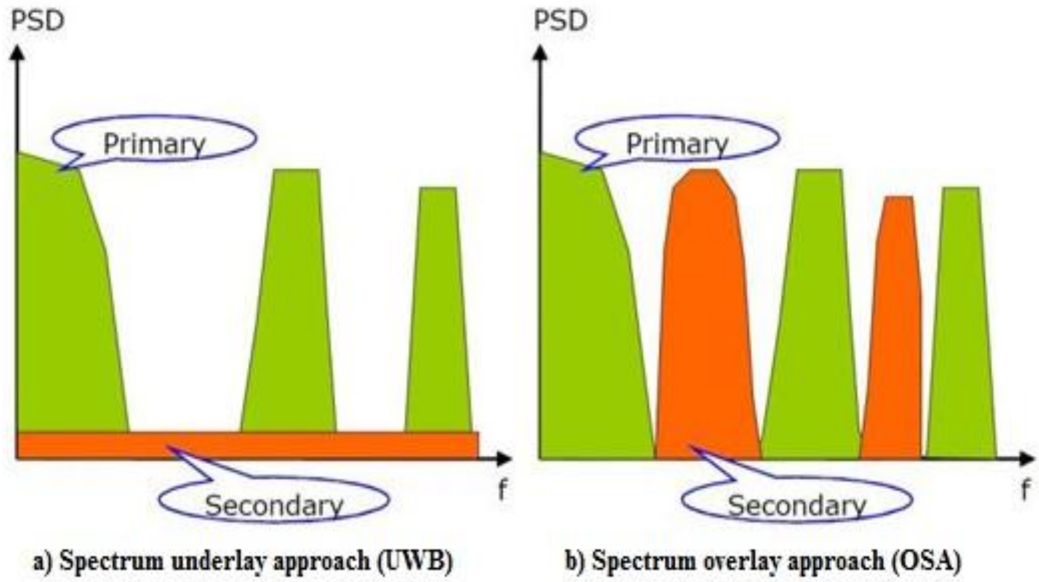


Figure 2.5 Underlay and overlay spectrum sharing approaches

A Spectrum Underlay Model

In underlay spectrum sharing, the CR user also called secondary user (SU), can transmit concurrently with a primary user (PU) by spreading transmitted signal over an ultra-wide band (UWB), and keeping their imposed interference below the interference temperature limit [54]. Although this approach does not require SUs to search for idle spectrum bands, it can only achieve short-range communication and reduce the achievable capacity of the secondary users due to the constraints of transmission power even if the licensed system is completely idle for a given time and location, which can be seen as a disadvantage of this approach. More so, in underlay access strategy, the achievable capability of the SU is further reduced during the busy periods of the PU because of the interference imposed by the primary user's activity at the secondary user's receiver. In order to tackle these aforementioned issues, overlay spectrum sharing was proposed.

B Spectrum Overlay Model

The overlay spectrum sharing approach has been proposed to address the issues of underlay spectrum sharing mode, where the secondary users can detect the spectrum holes (idle bands) and use them for transmission with high power to increase their data rates without interfering with primary systems. The spectrum overlay approach or opportunistic spectrum access (OSA) does not necessarily impose any severe restriction on the transmission power by secondary users. It allows SUs to identify and exploit the spectrum holes defined in space, time, and frequency [55]. This approach is compatible with the existing spectrum allocation, and therefore, the legacy systems can continue to operate without being affected by the SUs. However, the basic etiquettes for SUs need to be defined by the regulatory bodies to ensure compatibility with legacy systems. The spectrum overlay technique is a spectrum access system whereby a SU uses a spectrum band from a PU only when it is free. Unlike the underlay system, which hides the transmission signal under the noise level of the PU, the overlay system must have the capability of dynamic spectrum access, as it must work dynamically around the licensed system's allocation. This technique is based on a detection and interference avoidance mechanism. This mechanism requires the SUs to sense the frequency spectrum and thus, if a PU wants to access the spectrum, the SU should empty the channel.

The spectrum overlay access strategy was first envisioned by Mitola (1999) under the term spectrum pooling [56]. Unlike the spectrum underlay, this radio spectrum access strategy does not impose severe restrictions on the transmission power of SUs, but rather there are restrictions on when and where SUs can transmit. The special radios that are enablers of OSA or DSA that can use spectrum holes in an opportunistic fashion are known as cognitive radios.

2.3 The Concept of Cognitive Radio

Cognitive radio, was first coined by Mitola in 1999 [56], and can be defined as a radio frequency transceiver that provides the capability to use the radio spectrum in an opportunistic manner using DSA technique [57-59]. In a CR system, there are two types of terminals: PUs, which have the right to access the spectral resources at any time, and SUs, which exploit the unused spectrum of the primary system. More specifically, a CR system must detect unused spectra assigned to licensed users; determine the characteristics of these spectra, such as: operating frequency, transmission mode, and the transmission bandwidth. Based on these spectra parameters and according to the CR user's quality of service QoS requirements, the CR system will choose the best channel among all available spectra, and use it for communication without interfering with the transmission of the licensed user, and must vacate the spectrum or switch to another available spectrum as soon as the licensed user is detected.

The term 'cognitive' originally referred to a device's capability to sense the surrounding environment conditions and adapt its behaviour accordingly. Thus CR is based on the methodology of humans by understanding, learning and then adapting to the surrounding environment.CR is seen as the solution to the current low usage of the radio spectrum. It is the key technology that will enable flexible, efficient and reliable spectrum use by adapting the radio's operating characteristics to the real-time conditions of the environment. CR has the potential to utilise the large amount of unused spectrum in an intelligent way without interfering with other incumbent devices in frequency bands already licensed for specific uses. CR users are enabled by the rapid and significant advancements in radio technologies (software-defined radios, frequency agility, and power control), and can be characterized by the utilization of disruptive techniques such as wide-band spectrum sensing, real-time spectrum allocation and acquisition.

Cognitive radio is defined in [58] as: an intelligent wireless communications that can effectively sense and observe radio environments (RF stimuli), reliably detect the primary signals and analyses these measurements using signal processing to obtain the channel quality and interference information, learning from these and previous measurements and adaptively change the internal states according to the radio environment, then opportunistically utilise the unused bands for communications without causing any harmful interference to the primary system. Based on the above definition, we can portray the concept of CR, as in Figure 2.6.

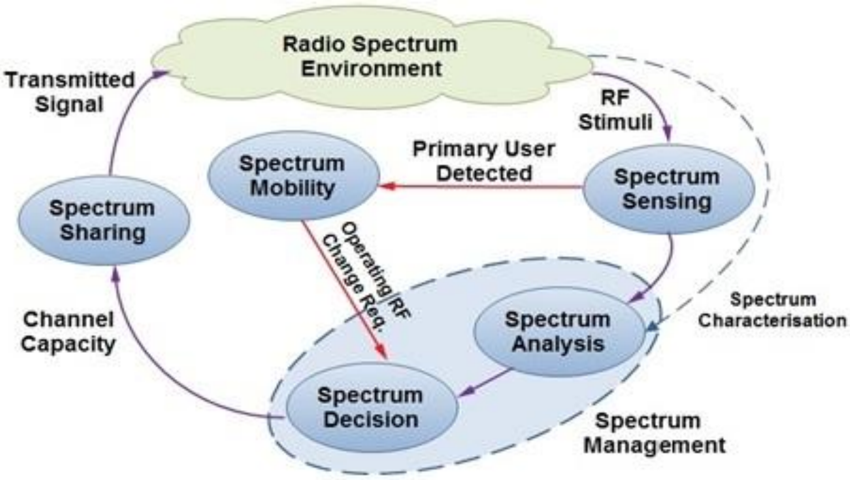


Figure 2.6 Cognitive Radio Cycle

The fundamental functionalities required for the CR systems can be summarised as follows:

- *Spectrum Sensing*: One of the most important elements in CR. Its function is sensing and monitoring the available spectrum bands reliably to detect the unused portion of the PU spectrum (spectrum holes).
- *Spectrum Management*: CR system should capture the best available spectrum to meet the user communication requirements.Spectrum management functions are classified as: spectrum analysis and spectrum decision. In spectrum analysis, the information from spectrum sensing is analysed to gain knowledge about the spectrum holes (frequency, bandwidth, modulation mode, transmit power, location, and time duration). Then, a decision to access the spectrum is made by optimising the system performance given the desired objectives (maximize the throughput of the SUs) and constraints (maintain the interference caused to PUs below the target threshold).
- *Spectrum Sharing*: After a decision is made on spectrum access based on spectrum analysis, the spectrum holes are accessed by the SUs. Spectrum access is performed based on a cognitive medium access control protocol (MAC), which intends to avoid collision with PUs and also with other SUs. The CR transmitter is also required to perform negotiation with the CR receiver to synchronize the transmission so that the transmitted data can be received successfully.
- *Spectrum Mobility*: The CR user is regarded as a visitor to the PU spectrum, and a reliable communication cannot be sustained for a long time if the primary user uses the licensed spectrum frequently. Therefore, the CR system should support mobility to continue the communication in other vacant bands. When a PU starts accessing a radio channel which is currently being used by an SU, the SU can change to a spectrum band which is idle. This change in operating frequency band is referred to as spectrum handoff. During spectrum handoff, the protocol

parameters at the different layers in the protocol stacks have to be adjusted to match the new operating frequency band. Spectrum handoff must try to ensure that the data transmission by the SU can continue in the new spectrum band.

Recently, CR has attracted a lot of attention due to its capability of vastly improving the spectrum utilisation efficiency, as it provides a dynamic mechanism for secondary users to share the radio spectrum with primary users in an opportunistic manner without disturbing the primary system.

2.4 Cognitive Radio Applications

The development of spectrum sensing and spectrum access technologies has enabled the applications of CR in many areas, ranging from smart grid network, medical network, public safety, emergency services, to military applications, and it is now widely expected to play a significant role in future wireless communication networks [11, 60]. Some of the applications that could benefit from CR are:

- **TV White Space**: The Ofcom regulatory agency in the UK has recently released the final rule to use the TV white space in 2013 [61]. By enabling cognitive devices, also called white space devices (WSD), to detect the spectrum holes and using geolocation database within TV bands, more spectrum can be gained for various application, especially Wi-Fi, rural broadband, and M2M applications.

- **Smart Grid**: In smart grid applications, such as home and office networks which are using femtocells techniques, increasing femtocells deployment and their signals can create interferences and spectrum usage problems [62-63]. By using CR femtocell technique, these interferences can be reduced to and from devices.

- **Emergency Networks**: Furthermore, the CR can play a significant role in emergency applications [60, 64]. In emergency situations of natural disasters, most times the connections fail to meet the necessary demands due to partial or full collapse in communication infrastructures due to changes in environmental conditions. CR could be used in such scenarios as it can adapt and provide reliable connections.

2.5 Spectrum Sensing Techniques

Spectrum sensing is the first function that needs to be performed in a CR system before allowing unlicensed users to access the vacant licensed spectrum. The main goal of spectrum sensing is to detect the unused frequency bands (spectrum holes) and to determine the method of accessing them without causing undesirable interference to the PU system.

Spectrum sensing for CRNs has become an active and important area in many research centres over recent years. In general, spectrum sensing techniques can be classified into four categories: transmitter detection, receiver detection, interference temperature based detection, and cooperative based sensing [9, 15, 52-53, 65-70]. The classification of these spectrum sensing categories is depicted in Figure 2.7.

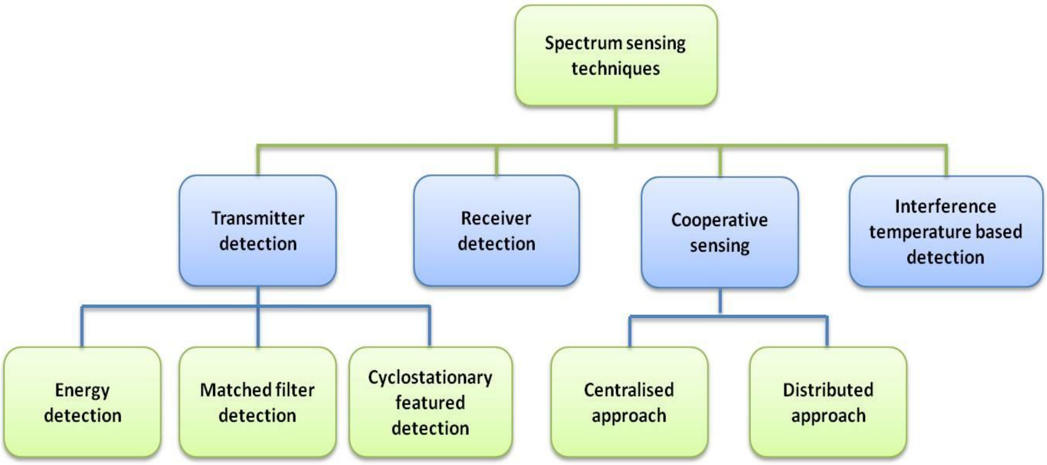


Figure 2.7 Spectrum sensing methods for CRNs

2.5.1 Transmission Detection

In the transmission detection approach, the CR user must detect the weak signal of the primary user's transmission through its local observations. Basically, there are three common schemes under this approach, which are based on detection of the energy of signal :*matched filter* [71-72], *cyclostationary feature detection* [73-74], and *energy detection* [14, 36].The first two schemes are coherent detectors that provide better detection probability but require a priori information about the primary signal, while the last one (energy detector) is a non-coherent detector that does not need a priori information about the primary signal, and is simpler to implement compared to the two first schemes, but provides poor detection performance at lower SNR; especially in the presence of noise power uncertainty.

A Matched Filter Detection

This method assumes that the PU sends a pilot signal with data. The pilot signal should be known by secondary users too allowing them to perform timing and carrier synchronisation to achieve coherence [71]. SUs should have perfect knowledge of the PUs signalling features such as modulation type, bandwidth, operating frequency packet format [72, 75]. The main advantage of this method is the less time to achieve high processing gain due to coherent detector. On the negative side, since the CR needs receivers for every kind of primary system, therefore, it increases the complexity, and result in more energy consumption to detect different primary signals.

B Cyclostationary Feature Detection

This method takes advantage of the cyclostationarity of the modulated signal. Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading or hopping sequences or cyclic prefixes, which result in built-in periodicity [73-75]. It is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. The detection algorithms can differentiate noise from primary user's signals. Therefore, this detector can perform better than the energy detector in discriminating against noise due to its robustness to uncertainty in noise power. But the disadvantage of this approach is computationally complex and requires significantly long observation time.

C Energy Detection

The energy detection approach is the most common way of spectrum sensing when the primary user signal is unknown because of its low computational and implementation complexities [15]. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. This approach has some difficulties, first of all, the threshold selection for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low (SNR) value. Moreover, the energy detector does not work efficiently for detecting spread spectrum signals.

Generally, the resolution of the energy detection scheme depends on the Signal-to-Noise-Ratio SNR of the received signal. In practical applications, the received signal at each cognitive user may suffer from the hidden primary terminal problem and uncertainty due to fading and shadowing. These issues have been solved by cooperative sensing techniques [15, 67]. However, these approaches are based on the assumption that the noise power is absolutely known. In reality, the noise power varies with the time and location of the terminal. This is called noise uncertainty and cannot be estimated accurately. The impact of the noise uncertainty on the signal detection performance has been recently studied in [76-77]. In [76], the fundamental bounds of signal detection in the presence of the noise uncertainty are analysed. This study showed that there are some SNR thresholds (SNR walls) under noise uncertainty that prevent achieving a reliable detection, and even increase the number of samples to infinity. In [20], the authors proposed a new scheme that uses dynamic threshold to overcome the noise power fluctuation problem. However, the detection threshold in this algorithm has been determined conventionally based on constant false alarm rate (CFAR) which can provide at most constant Pf rate even in a high SNR region where signal strength is much stronger than noise power, in addition, it cannot guarantee minimising the spectrum sensing error.

Basically, the performance of the energy detection algorithm depends greatly on the detection threshold setting and the SNR level of the received signal. Accordingly, an optimal threshold based energy detection scheme has been proposed in [18, 23]. In [17], the authors presented the optimisation of threshold level based on minimising the sensing error for a given sensing constraint. However, all these proposed works did not consider the effect of noise uncertainty on the detection performance. Therefore, there is a need for a new algorithm that addresses these issues together in order to increase the reliability and the efficiency of detection.

2.5.2 Receiver Detection

The receiver detection approach exploits the local oscillator (LO) leakage power emitted from the primary receiver while receiving the signal from the primary transmitter. In this approach, an external sensor node is placed nearby the PU so it can detect the presence of LO power using the energy detection technique previously described, and then transmit the information to CR users via a control channel [78]. The best feature of this approach lies in the ability to locate the PU, thus avoiding the hidden primary terminal problem and uncertainty caused by shadowing and fading. However, there is a need for a highly sensitive energy detector to detect very weak LO leakage signals.

2.5.3 Interference-Based Detection

This approach is based on a new metric called the interference temperature that has been introduced into the cognitive radio domain by the Federal Communications Commission (FCC) [79]. The interference temperature metric is a measure of the temperature equivalent of the radio frequency (RF) power available (RF power generated by other emitters and noise sources in the vicinity of the receiver) at a receiving antenna per unit bandwidth, measured in units of Kelven [80]. This metric can be used to set maximum acceptable levels of interference (interference temperature limit) for a given frequency band in a particular location. In interference-based detection strategies, the SUs are allowed to transmit in the given frequency band only if they guarantee that, their transmissions, added to the existing interference must not exceed the interference temperature limit at a licensed receiver in the same frequency band and in the same location [58, 80]. Because the CR users in this approach cannot distinguish between the actual primary signal and noise or interference, the accurate measuring of interference temperature is difficult and limited.

The following section will focus on possible cooperation strategies that increase the reliability of the spectrum detection in the CRNs.

2.5.4 Cooperative Spectrum Sensing

Cooperative communication techniques have become an attractive topic in CR research. Cooperative communication mechanisms have been developed initially to provide high diversity gain, increase channel capacity and improve transmission performance, while CR has been proposed to improve spectrum efficiency by means of dynamic and opportunistic spectrum access.

Recent works on cooperative spectrum sensing have shown that considerable network capacity and spectrum efficiency enhancements can be achieved through cooperative mechanisms such as: network coding, relaying and forwarding [81-88]. Most of the proposed work focused on exploiting cooperative sensing to improve the utilisation of the radio spectrum in order to meet the demands of new wireless communication systems. For instance, in a cognitive relay network, the SU could send data to the destination node directly, if the PU is not using the source-destination channel. In the case of the PU returning to use the channel, the SU can continue its data transmission by exploiting the relay network band as relay channel. Generally, cooperative sensing mechanisms can make CRNs more practical by enabling multiple CR users to share the spectrum bands. This can be achieved with cooperative schemes in both, spectrum sensing and sharing of CRNs.

The main drawback of the primary transmitter detection approaches earlier described in section (2.5.1), is that they cannot avoid the hidden primary user problem caused by fading and shadowing effects [15]. Figure 2.8 shows a clear perception of a hidden primary terminal problem where the shaded areas show the communication range of the PUs and the CR users.

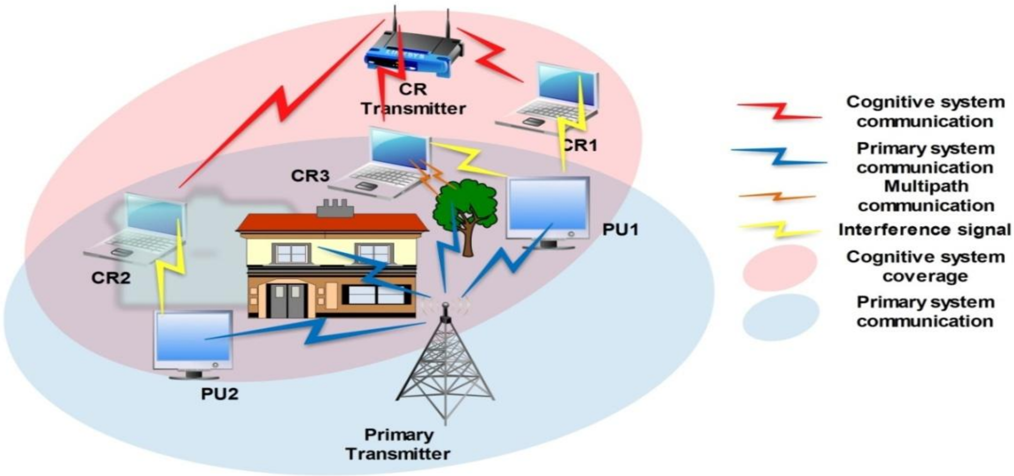


Figure 2.8 Illustration of the hidden primary user problem in CR system

As illustrated in Figure 2.8, there are many factors can cause the hidden primary problem including shadowing from obstacles affecting the wave propagation, as in the case of CR2; fading either due to multipath propagation, as in the case of CR3; or due to the location of the CR user being out of the primary transmitter range, as in the case of CR1. Here, all CR users cause unwanted interference to the PUs as the primary transmitter's signal could not be detected because of the hidden primary user problem.

Cooperative spectrum sensing CSS is considered as an alternative that could improve the sensing performance under fading and shadowing circumstances, which has attracted a lot of attention in recent years and resulted in many research efforts [89-95]. The CSS approach uses multiple spatially distributed users and transmit their observations to a fusion centre FC which fuses the local sensing information using either hard decision fusion rules or soft fusion method before issuing a final decision about whether the PU is present or not, then the final decision is sent back to all cooperative users in the network.

In addition to addressing the hidden PU problem, CSS brings many benefits to CR systems, such as: increasing the detection performance under low SNR, enhancing the agility of detection by reducing the overall sensing time (which is critical in the case of reappearing PUs), improving the global error probability using less sensitive detectors, and reducing the hardware cost and complexity. In general, CSS can be achieved using two approaches, namely: centralised CSS and distributed CSS. These approaches will be discussed in detail in the following sections.

A Centralised Cooperative Spectrum Sensing Strategies

Centralised CSS consists of primary users, cooperative users, and the fusion centre FC which represents the Access Point (AP) in the case of a wireless LAN or the Base Station (BS) in case of a cellular network. In addition to these elements, the CSS strategies include two types of wireless frequency channels for communication namely: sensing channel - the physical link between the primary transmitter and each cooperative user used to observe the primary signal, and control channel - the physical link between the cooperative users and the FC used for sending the sensing results [96]. Basically, the cooperation process between CR users consists of three main phases: local sensing, reporting, and data fusion.

- *Local sensing*: As shown in Figure 2.9, in centralised CSS the FC determines a channel band of interest (sensing channel) and asks all cooperating users to perform local sensing. Upon reception of this request, all cooperative users tune their radio transceivers to the selected channel in order to observe the primary signal.
- *Reporting*: In this phase, all cooperative users tune their radio transceivers to control channel frequency and start sending the results of their observations to the FC.

- *Data Fusion*: Finally, the FC collects the reported results and issues a final decision on whether the PU is present or not using a suitable data fusion function, and distributes the decision back to CR users over the control channel.

It has already been proven that the performance of spectrum sensing deteriorates significantly in a multi-path channel, and under shadow fading, and receiver uncertainty circumstances. As illustrated in Figure 2.9, CRU1, CRU2, CRU3, CRU4, and CRU5 users are spatially distributed within the transmission range of the primary network while CRU6 is outside the range. In the scenario depicted in this figure, CRU4 and CRU5 will not be able to detect the primary signal correctly due to multi-path and shadow fading phenomenon. Moreover, CRU6 will experience a radio uncertainty problem due to its inability to sense the primary transmission and the existence of PU1. Therefore, the transmission signal of CRU6 may overlap with the signal received by PU1. The degradation of independent measurements at each CR could be greatly improved by making a global decision derived from the collected observations in cooperative sensing strategies.

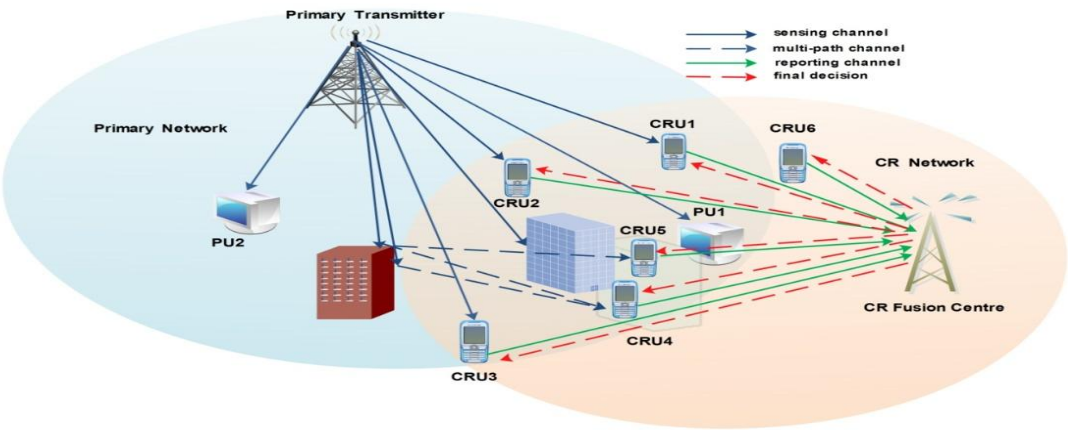


Figure 2.9 Conventional centralised cooperative spectrum sensing approach

The performance of centralised CSS depends largely on the performances offered in each phase. These performances are affected by many factors such as: the accuracy of the local sensing, reliability of the reporting channel, data fusion techniques, network overhead. Improving the performance of centralised CSS has become the main focus for many works in recent years. Some of works were aimed at enhancing the local sensing of CR user [27, 97-98], while others aimed to reduce the network overhead resulting from the large number of sensing data reports exchanged over the reporting channel [94, 99-100], with the latter problem receiving much more attention from the research community. In [101] the authors proposed to reduce the overhead by replacing observation reports by hard decision report. Thus the amount of reported data was decreased. In [100, 102] the authors proposed to use a censorship strategy where only a user that has a reliable information could report the sensing result to the FC.

Another method of network overhead reduction for CSS is to reduce the number of cooperative users, where the performance of spectrum sensing can be increased when cooperating a certain number of CR users with the highest SNR of sensing channel rather than participating all cooperative users in the network [22]. It is worth mentioning here that the detection performance and the achievable cooperative gain can be degraded due to spatially correlated shadowing when two closely located users experience similar shadowing effects [103]. Therefore, it is very important to select uncorrelated users for cooperation when designing the CSS algorithm.

In practice, the control channel used for reporting between CR users and the FC might be subject to shadowing and fading effects, hence, causing spectrum sensing degradation. Clustering technique has been recently adopted in CSS for CRNs in order to overcome the problems exhibited by CSS and there have been a number of research works that focused on using clustering methods to improve the cooperative sensing performance under imperfect channel conditions [93, 104-108], in which CR users are grouped into clusters and the user with highest reporting channel’s SNR is chosen a cluster head (CH), which in turn sends the cluster decision to FC.

In [90], a new clustering strategy was proposed to reduce the reporting channel overhead and the sensing delay, where the optimal number of clusters is obtained based on the trade-off between the communication overhead and sensing reliability. The cluster heads are elected in a centralised way by FC according to the distance from the FC and the received power signal of primary transmitter, where all members in the same cluster send their sensing measurements to the related CH which makes the cluster decision according to the largest one among them. In [109], another clustering scheme is proposed where each cluster is divided into multi groups in order to reduce the error probability caused by an imperfect reporting channel. In this scheme the optimal number of groups is determined by minimising the error rate of a cluster. The cluster based CSS under bandwidth constraints is studied in [110], where in each cluster only cognitive users with reliable information will send their observation results to the CH in order to decrease the average number of sensing bits. However, the above cluster- based sensing approaches focused mainly on the classical clustering methods which are inefficient in terms of energy consumption.

Another important problem is the energy consumption in the cooperative spectrum sensing which must pay attention to it, especially in large scale networks. Some researchers have recently focused on this problem. In [110-111], the energy consumption of cluster-based sensing is studied, where more energy can be saved by decreasing the transmission energy consumption. Although such techniques could help to overcome the issues exhibited by centralised CSS, there are certain improvements that need to be made especially considering the trade-off between the sensing performance, control overhead, and energy efficiency.

However, almost 90 % of the existing clustering algorithms as mentioned above are targeted at addressing one or two CSS issues including reporting error, sensing delay, bandwidth overheads. Furthermore, in terms of the energy consumption issue, the researchers have only focused on how to reduce the energy consumption, but they did not consider how to balance the energy within the cooperative network in order to prolong the lifetime of cooperative users. In addition, in reality, most of the clusters far from the FC have reliable local sensing decisions, but may suffer from fading and shadowing due to the low SNR of reporting channel, which may lead to further deterioration in sensing performance due to the error reporting channel, and causing more energy consumption especially in wide-range CRNs. Thus, there is a need to design a new CSS scheme that could tackle all these overhead issues.

B Distributed Cooperative Spectrum Sensing Strategies

In distributed CSS, the network is composed of CR users only, with no FC [15, 112]. In this approach each CR user performs local sensing then shares the sensing information with the others, without any central control, as depicted in Figure 2.10. The distributed CSS approach has certain advantages over the centralised CSS mode. The most important advantage is the lower implementation cost that results from the absence of backbone infrastructure. Furthermore, the communication between CR users in distributed CSS requires less power and consumes less energy than in the communication between CR users and the FC in centralised CSS.

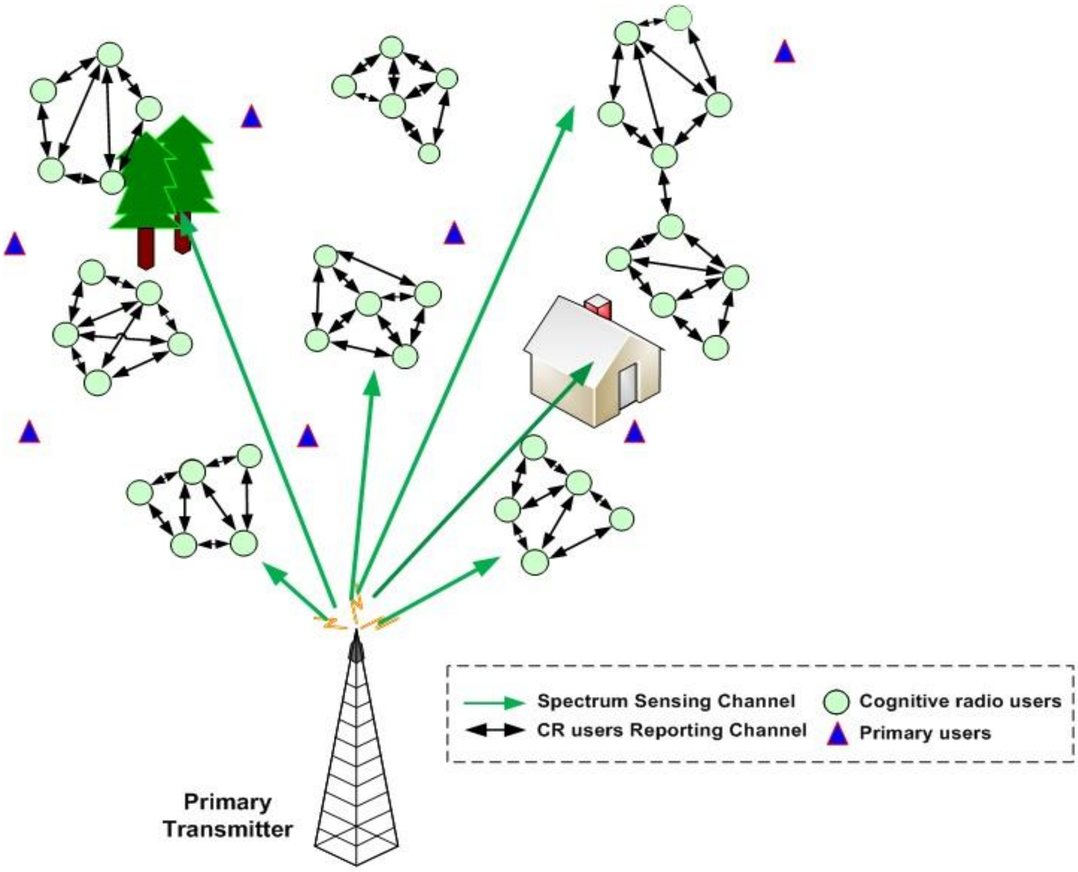


Figure 2.10 Conventional distributed cooperative spectrum sensing strategy

In distributed CSS, spectrum channels should be monitored periodically in order to detect available channels for transmission. This requires exchanging sensing data between CR users which might affect the performance of the CRN. There have been several contributions that aimed at improving the performance of distributed CSS. In [85], a distributed CSS based on network code scheme was proposed that tried to reduce the sensing data that should be transmitted. In this algorithm, each CR user detects the frequency channels firstly, encodes the occupancy information (busy or idle) of all channels into binary code and saves them in its frequency table. Then, every CR user performs a binary XOR (exclusive OR) operation for the two similar binary codes of the two randomly chosen channels in its frequency table and transmits the XOR-ed information to other CR users. By receiving the XOR-ed information, the CR users can improve their frequency table information by decoding the received XOR-ed information. After finishing all the reporting, each CR user is likely to have had sufficient and more accurate occupancy information of the frequency channels which leads to reducing potential collisions, as well as, improving the throughput of the CR users. However, this approach is based on the consideration that the reporting channel among CR users is perfect, which is practically unrealistic. Another scheme named: Gossiping Updates for Efficient Spectrum Sensing (GUESS) has been proposed in [113] to decrease the control traffic overhead in distributed CSS. In this protocol, initially each CR user performs the local measured signal at every time-step. If any CR user has a change in its local measured signal after each step, or it receives the update message from a neighbouring user, it will send its up-to-date signal to neighbouring users. In the case of the local signal change, the CR user computes the changing value and bitwise OR the result with original value. If it receives an update message, it ORs the received signal with its local value. Once all systems have converged, the CR users will have the up-to-date average signal. Thus, the communication time among CR users and the network overhead will be reduced. In [114], a fully distributed and scalable cooperative spectrum-sensing scheme based on consensus algorithms is proposed. In this approach, each cooperative user makes local measurements about primary users, then exchanges its local sensing with its own local neighbours through the possible communication links, and adopts the consensus iteration until all individual measurement at each user converge towards a common value (global measurement) which is based on the previous measurements of each user and its neighbours.

However, all the above works are based on the assumption that the communication channels between CR users are perfect, which is unrealistic. In other words, in some practical cases, some CR users may experience weak sensing and reporting channels, which leads to inaccurate decisions about spectrum availability. To overcome this issue, relay based CSS algorithms have been proposed [82, 87, 115-116], by making some users that have perfect channel conditions to relay the decisions among CR users. Although these protocols have improved the sensing performance, they add additional delay and more energy consumption.

Clustering mechanisms are another method that can be explored in this field to reduce the network overhead. In these approaches, where there is no FC, the CR user that has a favourable channel gain can be selected as a FC which collects all results from CH. Recently; a few works have been focused on the clustering method in distributed CSS. In [117-118], the authors have presented a distributed clustering approach to save the sensing energy. In these schemes, after forming the clusters, one of the members with the highest sensing gain will be selected as a CH, and a FC will be selected dynamically from all active CHs to balance energy consumption within the network. However, in order to reduce the energy consumption in these schemes, the cluster range should be short enough which leads to an increased number of clusters in the case of wide range networks. Moreover, more clusters leads to increasing the range communication between CHs and FC and more energy consumption, which are impractical. Thus, there is a need for a new reliable and efficient algorithm for CSS in distributed CRNs.

2.6 Summary

In this chapter, I presented a literature review in the field of CRNs. This includes a review of radio spectrum bands, DSA approaches, DSA and fundamental concepts of CR and its basic applications. In addition, I have reviewed some of the recent researches on spectrum sensing algorithms for CRNs, including single-user spectrum sensing and CSS approaches.

The main motivation behind CRNs is to resolve the issue of the scarcity and the underutilisation of the available radio resources. By allowing CR users to opportunistically access the spectrum bands actually licensed for PUs, the spectrum utilisation can be optimised, thus improving the efficiency of today's wireless communication systems. CR can be defined as a wireless communication method that enables CR users to effectively sense and observe radio environments, analyses these measurements and learn from these and previous measurements and adaptively change the internal states according to the radio environment, then opportunistically utilise the unused bands for communications without causing any harmful interference to the primary system.

There are many potential applications of CR, including military, leased networks, emergency situations, smart grids, wireless medical networks, and mesh networks. We can gain many benefits from CR technology such as improved spectrum utilization, enhanced link performance and high internet speed in suburban areas.

Based on the definition of CR, there are four main functions in CR that are all dependent on each other, namely spectrum sensing, spectrum management, spectrum sharing and spectrum mobility. The main objective of spectrum sensing is to determine whether portions of the spectrum are available or not, while the function of spectrum management is to select the best available channel for communication based on the analysed information of spectrum sensing. The task of spectrum sharing is to coordinate access to selected channel with other users, and finally, vacate the channel when a primary user is detected to prevent causing any interference to licensed users.

Spectrum sensing, one of the most important elements of CR, is the first task which must be carried out in CRNs. In order to design an efficient spectrum sensing algorithm, several considerations and requirements need to be taken into account, including interference level, detection sensitivity, sensing delay, sensing decision accuracy and communication overhead. Although many spectrum sensing approaches are proposed in the literature for CRNs, most of them are only focused on one or two of these spectrum sensing requirements, and are not efficient enough for practical CR applications. Basically, spectrum sensing can be conducted either locally (single-user) or collaboratively (multi-users). There are three main algorithms for local spectrum sensing, namely energy detection, matched filter and cyclostationay feature detection, where each scheme has its own advantages and disadvantages. Despite the drawbacks of energy detection, including being susceptible to noise uncertainty and threshold setting, it is still the most popular spectrum sensing technique in CRNs.

However, in fading and shadowing environments it is very difficult to obtain a reliable and accurate spectrum sensing, using single-user spectrum sensing algorithms, therefore, cooperative spectrum sensing is used to tackle this issue by exploiting the spatial diversity of CR users. Cooperative spectrum sensing can be mainly classified into two categories based on how CR users share the sensing data in the network, centralised and decentralised approaches. Although the performance of spectrum sensing can be significantly improved by using a cooperation mechanism, that comes at the cost of increasing the communication overhead with additional sensing delay.

On the other hand, several algorithms have been introduced to decrease the cooperation overhead and enhance the sensing efficiency, including censoring approach, selection of cooperative users and clustering mechanism. However, although these algorithms are energy efficient, they are based, generally, on the assumption that the reporting channels between CR users and the FC are perfect (free of error), even in clustering approaches, especially in large-scale CRNs, where some of CHs with reliable local sensing may located far away from the FC, thus causing deterioration in sensing performance in addition to more energy consumption.

The main challenge is to design new spectrum sensing that provides reliable and more accurate detection on the one hand, while satisfying the requirements of spectrum sensing on the other hand. In this thesis, we develop new spectrum sensing algorithms for CRNs based on optimisation and multi-hop clustering mechanisms, aiming at increasing the efficiency of spectrum sensing while reducing the communication overhead.

Chapter 3

Cooperative Spectrum Sensing Algorithms for Cognitive Radio Networks

Following the presentation of existing spectrum sensing algorithms for cognitive CRNs, I try in this chapter to present the outline of our proposed algorithms. The main issues and challenges related to local and CSS will be presented in section 3.1. In section 3.2 I provide the new spectrum sensing algorithms for CRN. In section 3.3 I describe the evaluation and the simulation models of my proposed algorithms. Finally, the summary of this chapter is provided in section 3.4.

3.1 Motivation and Research Challenges

The focus of this research is on the design of local and CSS algorithms for CRNs. The main objective of the spectrum sensing is to provide more accurate detection in order to increase the spectrum access opportunities to CR users without interference to the primary network. Cooperation between CR users can improve the sensing performance in fading and shadowing environments. Spectrum sensing can be implemented either using single-user transmitter detection methods or using CSS algorithms. Based on detection behaviour we consider three scenarios for spectrum sensing applications: single-user detection scenario, centralised cooperative sensing scenario and decentralised cooperative sensing scenario.

3.1.1 Local Spectrum Sensing Challenges

In single-user spectrum sensing, I consider a scenario where a wireless system consists of a primary transmitter with multiple PUs and multiple CR users that want to access the same spectrum for communication. Moreover, I assume that only the energy information of the primary transmitter signal is known at the cognitive user, therefore, I adopt the energy detection algorithm for spectrum sensing due to its simplicity and does not required any information about the primary signal.

My work aims to address the following energy detection based spectrum sensing challenges:

- In traditional energy detection algorithms, which are commonly used when only energy information of the primary signal is available, inappropriate selection of the detection threshold λ could make it difficult to obtain an accurate spectrum sensing, especially in low SNR environment, so the detection threshold setting is a big challenge in the design of energy detection algorithms.
- Energy detection schemes are sensitive to noise, and small fluctuations in noise power may cause a sharp decline in their detection performance. So the noise power uncertainty issue will add another challenge when designing an energy detection algorithm for spectrum sensing.
- Hidden primary terminal is another challenge that cannot be avoided in the design of single-user spectrum sensing algorithms, which causes the detection performance to deteriorate as a result of fading and shadowing.

From the above mentioned issues, we can see that existing energy detection approaches for spectrum sensing are not reliable and do not give accurate detection performance, especially under low SNR of sensing channel. Therefore, it is necessary to develop a new energy detection algorithm that can provide a reliable and accurate detection performance for spectrum sensing application.

3.1.2 Centralised Cooperative Spectrum Sensing Challenges

For infrastructure CRN such as IEEE802.22 based wireless regional area network (WRAN) [119], I consider a scenario where the CRN, with stable topology and consisting of multiple users with one FC, wants to share the spectrum of primary network in an opportunistic manner. CSS mechanism can give more accurate sensing performance, but there are still some related challenges that need to be solved. My work aims to address the following centralised CSS challenges:

- Optimisation of CSS is a good way to increase the detection accuracy at the FC, but it comes at the cost of computational complexity which leads to taking a long time to implement the spectrum sensing.
- In large scale infrastructure CRNs, most CR users with reliable local sensing information will be far away from the FC, causing more deterioration in spectrum sensing performance due to reporting errors.
- Although increasing the number of cooperative users can increase the efficiency of detection, it causes more sharing of sensing information, thus increasing the overhead.
- Energy consumption and sensing delay are other important challenges, especially in large-scale CRNs, that need to be addressed in order to reduce the overhead while satisfying the user requirements.

3.1.3 Decentralised Cooperative Spectrum Sensing Challenges

In distributed CRNs, such as Ad Hoc CRN, the cooperation between CR users is implemented in a decentralised way, where there is no need for a backbone infrastructure. For this kind of application, I consider a scenario where a cognitive network with static topology and consisting of multiple users that want to coexist with the primary network, which consists of one primary transmitter with multiple users, without causing harmful interference. However, there are still some related issues and challenges that need to be solved in order to improve the detection performance of decentralised CSS algorithms.

My work aims at addressing the main challenges of CSS challenges in distributed CRNs, which can be summarised as follows:

- In a large scale decentralised network, the cooperation between users requires exchanging a huge volume of sensing data between CR users, which results in increasing the control traffic overhead and causing more energy consumption.
- In some practical scenarios, some CR users may locate close to each other, making them experience correlated shadowing, which leads to decreasing the cooperation gain.
- In the presence of fading and shading, which often happens in reality, the links between CR users and their neighbours may be adversely affected, causing a significant deterioration in the overall performance of the cooperative spectrum sensing.
- Another challenge which can be faced in the design of distributed CSS is the difficulty to get time synchronisations in sensing and transmission schedules due to the lack of a control centre, which may lead the CR user with the energy detection scheme to detect the transmissions of other cognitive users as well as primary users during its local sensing period, hence, causing false alarms in spectrum sensing.

Therefore, there is a need for a new collaboration mechanism for decentralised CSS that improves the sensing performance, taking into accounts all of these issues.

3.2 Spectrum Sensing Algorithms for Cognitive Radio Network

In order to address the above mentioned challenges of spectrum sensing, I proposed a new energy detection algorithm for local sensing and new cooperation mechanisms for CSS based on optimisation and multi-hop clustering. These solutions include four new spectrum sensing algorithms that provide reliable and energy efficient spectrum sensing while increasing the efficiency of spectrum utilisation for CRNs:

a. A novel adaptive optimal threshold energy detection algorithm for local spectrum sensing that has been published in [28]. The proposed energy detection algorithm works the same way as a traditional scheme, where the power of the transmitted signal will be detected first and then compared with a predefined threshold λ to determine whether the spectrum band is occupied or not. In our algorithm, the optimal detection threshold λ_{opt} is determined based on estimated SNR γ and the noise power σ_n. Furthermore, in the presence of noise uncertainty we determined the value of λ_{opt} based on noise uncertainty factor ρ and adaptive threshold factor α. In order to obtain more reduction in error probability *Pe* of spectrum sensing, I designed a new double-optimal energy detection algorithm in which its performance basically depends on two optimal thresholdsλ_{opt1} and λ_{opt2}.

b. A novel CSS algorithm based on optimisation algorithm. In this optimisation CSS scheme, the issues of noise uncertainty at the local sensing, and computational complexity are considered. Specifically, each CR user performs a local spectrum sensing using our proposed optimal energy detection algorithm in [28], then sends its own 1-bit sensing result to the FC via the reporting channel, and finally the FC determines the final decision using the optimal fusion rule. In my optimisation algorithm, optimal detection threshold λ_{opt} can be determined based on minimising the local error probability *Pe* using a closed-form expression, while in existing optimisation CSS schemes the implementation of spectrum sensing depends on determining the local optimal threshold λ_{opt} analytically based on minimising the total error probability Q_e which takes a long time.

c. A novel multi-hop clustering approach for centralised CSS published in [30-31]. In this approach the CRs are grouped into a few multi-level clusters based on several metrics, including distances from the FC, energy level, and SNR of the reporting channels. Each cluster member sends its own 1-bit local sensing result to related CH, which in turn combines the local sensing of all cluster members and determines the cluster sensing result using the majority decision fusion rule. Then, each CH sends its own 1-bit cluster sensing result to the FC. If the distance between the CH and the FC is greater than a predefined distance (one hop communication distance), the CH will send its result to the next level CH, which in turn sends it to the FC. Finally, the FC will fuse the results of all CHs and then determine the final decision using majority fusion rule.

d. A novel multi-hop clustering mechanism for distributed cooperative spectrum sensing. In this algorithm, all CRs that are close to each other will be grouped into clusters and one of the users at each cluster will act as a CH. Based on the residual energy level of CHs, the CH which has the highest energy level will be elected to act as a FC. Each cluster member performs a local spectrum sensing using the energy detection algorithm, and then sends its 1-bit result to the CH using its own TDMA slot time, which in turn fuses the results of all cluster members and gets the cluster decision using the majority fusion rule. Finally, each CH sends its own cluster decision to the FC directly if the distance between the CH and the FC is less than the predefined distance (one hop communication distance), otherwise it sends the cluster result via next level CH towards the FC, which in turn will combine the results of all CHs and determines the final decision using majority fusion rule.

These new algorithms will be described in detail in the following subsections.

3.2.1 Local Spectrum Sensing Scheme

I developed a new adaptive optimal threshold energy detection AOED algorithm using single-user for spectrum sensing that improves the sensing performance in low SNR environment. This scheme aims at determining the optimal threshold that minimises the error probability in the presence of the noise uncertainty, which in turn increases the spectrum utilisation efficiency while providing sufficient protection to primary users. The energy detection typically does not need any prior knowledge of the primary signal parameters; it just needs to know the power of the primary signal and the noise power. The schematic diagram of the novel optimal energy detector is described in Figure 3.1 The block diagram of the energy detection in frequency domain.

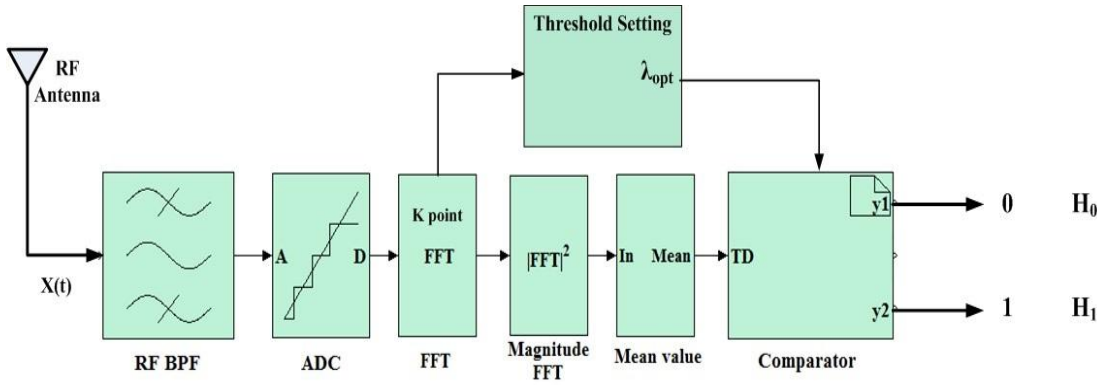


Figure 3.1 The block diagram of the energy detection in frequency domain

Based on Figure 3.1 The block diagram of the energy detection in frequency domain, in order to measure the energy signal in frequency domain, the input signal x(t), which consists of primary signal s(t) and noise signal w(t), is filtered with a band pass filter (BPF) in order to limit the noise and to select the bandwidth of interest, then sampled and converted from continuous to discrete signal with sampling rate at the analogue to digital converter (ADC), taking Fast Fourier Transform (FFT) followed by squaring the coefficients and then taking the average over an observation time window. Finally, the output signal which is usually called a decision (test) statistic T_D is compared with a predefined threshold λ to make the final decision on the presence or absence of the primary signal.

As noted in this figure, the main procedures of our algorithm are the same as in the conventional algorithm [14], but the main difference lies in the mechanism for determining the detection threshold. In our algorithm we proposed a new optimal method to set the threshold based on minimising the error probability *Pe*, and developed a new adaptive optimal threshold λ_{opt} that addresses the impact of noise uncertainty.

Furthermore, we developed a new double optimal threshold energy detection approach that provides more reduction in error probability, but at the cost of a decline in detection probability. The detection procedures in this scheme are the same as in single-optimal threshold algorithm, the difference is in the threshold setting and the comparison stages. The detection decision depends on two optimal thresholds λ_{opt1} and λ_{opt2}in which their values are basically dependent on the predetermined optimal threshold λ_{opt} and uncertainty region factor δ.

Figure3.2 shows our single and double optimal threshold energy detection methods. As shown in this figure, if the decision statistic T_D exceeds λ_{opt2}, then the energy detector indicates H_1, which means that the primary signal is present, and if T_D is less than λ_{opt1}, the energy detector decides H_0, which means that the primary signal is absent. Otherwise, if the T_D is between λ_{opt1} and λ_{opt2}, which represents uncertainty region, the energy detector indicates “no decision”. A full description of these approaches will be given in chapter 4.

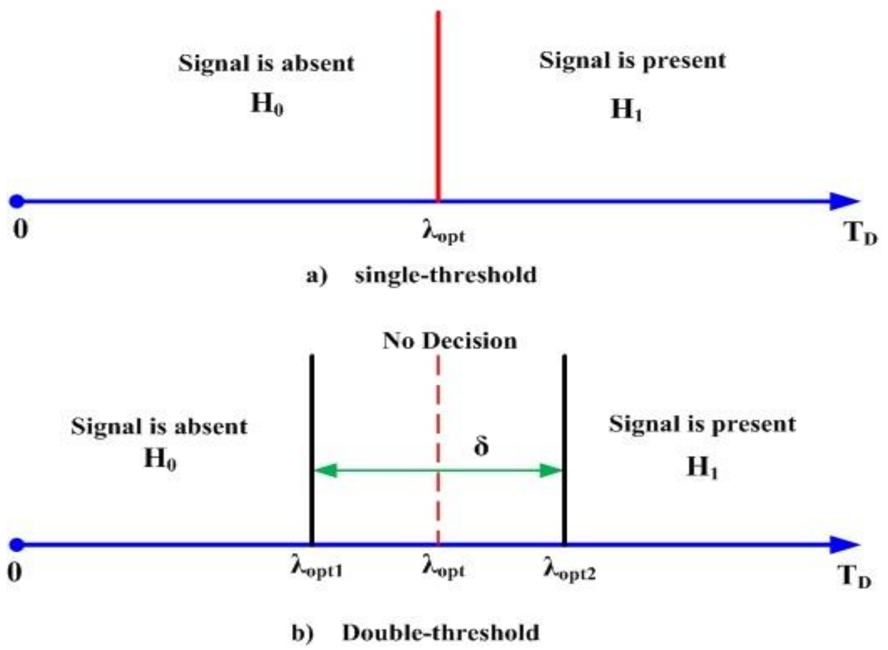


Figure3.2 a) Single-optimal threshold energy detection method. b) Double-optimal threshold energy detection method

3.2.2 Centralised Cooperative Spectrum Sensing Algorithm

For infrastructure CRN, we present two new algorithms that enhance the spectrum sensing accuracy and reduce the cooperation overheads. In the first scheme, we present a new centralised CSS based on optimisation mechanism, where the local sensing is conducted using AOED algorithm while the optimal decision fusion role is executed at the FC in order to make the final detection decision. This algorithm aims to overcome the impact of noise uncertainty at the local sensing and optimises the detection performance.

Figure 3.3 illustrates our optimisation algorithm for CSS, where each CR user performs its local spectrum sensing using our proposed adaptive optimal energy detection algorithm and based on its radio environment conditions it makes its own sensing decision b_i and sends it to the FC via the reporting channel. Then, the FC combines the decisions and makes the final decision based on optimal K out M fusion rule.

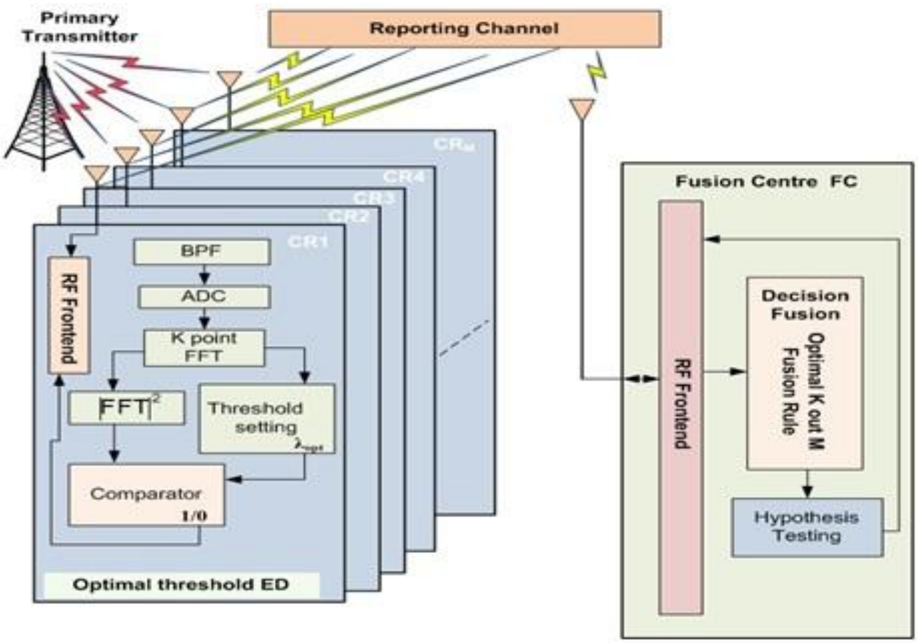


Figure 3.3 Optimisation cooperative spectrum sensing scheme

The optimal K can be determined theoretically, which depends on several parameters, including probability of occupancy, detection and false alarm probabilities, and the number of cooperative users M. The Design details of this scheme are presented in chapter 5.

The second algorithm is that proposed for centralised cooperative spectrum sensing is the multi-hop clustering approach. Figure 3.4 gives the operating procedures of this algorithm.

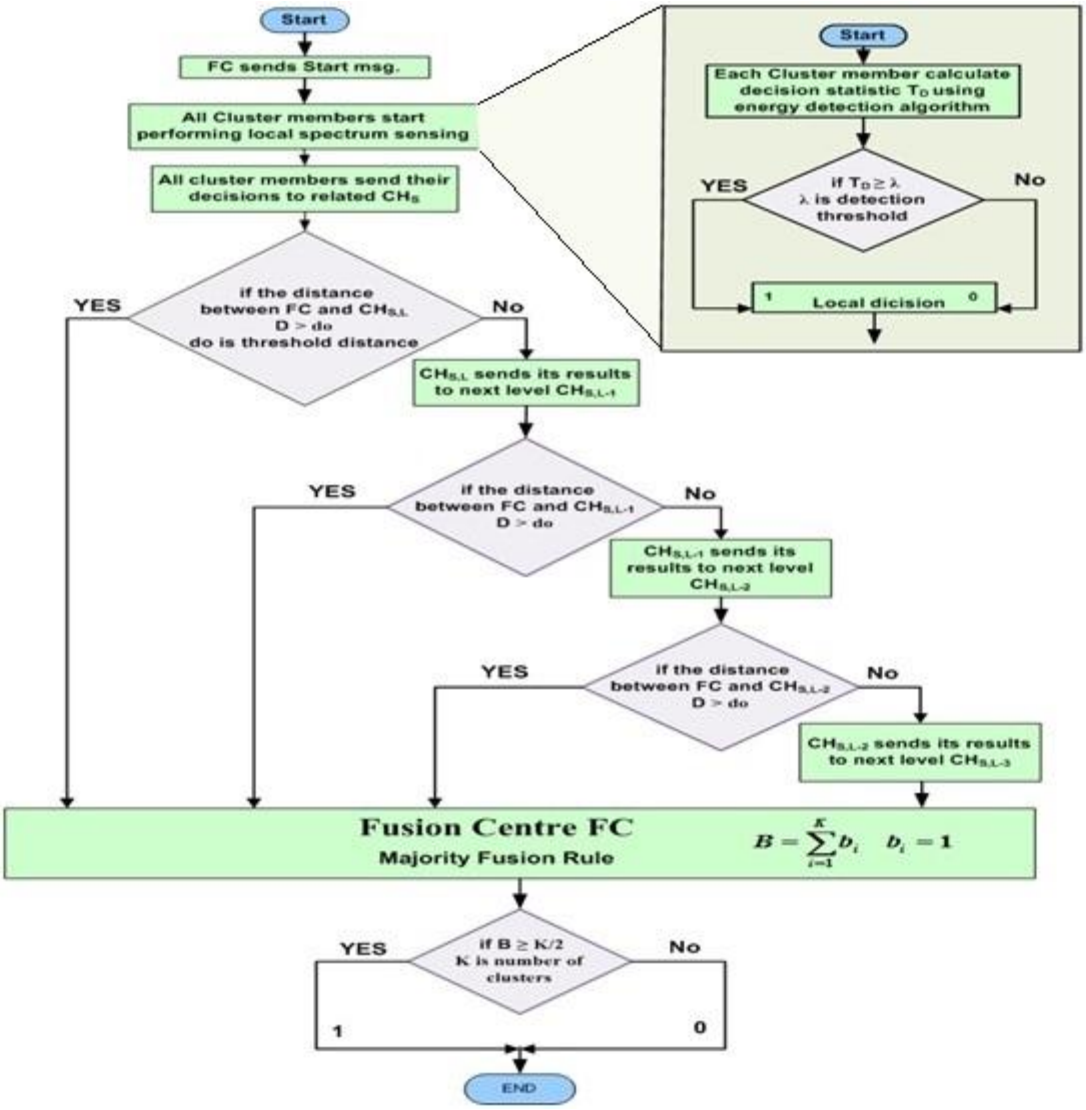


Figure 3.4 The flow chart of multi-hop cluster based centralised CSS for CRNs

The main purposes of this algorithm are to support energy efficient and reliable cooperation between CR users and the FC; especially in large scale networks, and increasing the network capacity by reducing the sensing time. The basic idea of the design is to group the CR users into a few multi-level clusters based on several metrics, including the distances from the FC, the energy level, and the SNR of reporting channels. Only the cluster heads are allowed to report the cluster result to the FC, and if the distance between the CHs and the FC is greater than a predefined threshold distance they will send the results to the nearest next level CH.

Chapter 6 provides more descriptions on how this cooperative sensing scheme works, and its performance analyses.

3.2.3 Decentralised Cooperative Spectrum Sensing Algorithm

We develop a new multi-hop clustering algorithm for distributed CSS that reduces the cooperation traffic overheads and provides a reliable communication between CR users in order to improve the global sensing efficiency. Due to the lack of a FC, the clusters are formed in a distributed manner, and one of the cluster heads will be selected as a FC based on the energy level and the SNR of the reporting channel between them. Figure 3.5 illustrates the mechanism of the multi-hop clustering algorithm in decentralised CSS.

The key advantages of this algorithm are:

- Spectrum sensing efficiency: In some practical cases, especially in large scale network, some cluster heads will be far away from the fusion centre, which leads to error reporting, thus causing a deterioration in spectrum sensing accuracy. The multi-hop clustering mechanism will increase the sensing efficiency though selecting the optimal path between the far cluster heads and the fusion centre.

- Energy consumption saving: In the case of a long distance between cluster heads and the fusion centre, multi-hop communication will be more efficient than single-hop communication, but at the cost of a small increase in the sensing time delay.

- Spectrum sensing synchronisation: the proposed clustering algorithm can solve the issue of sensing synchronisation by configuring a central control similar to infrastructure networks. In this scheme, the number of members of each cluster and the number of clusters in each level (hop) are varying, which depend on the distribution of CR users within the network.

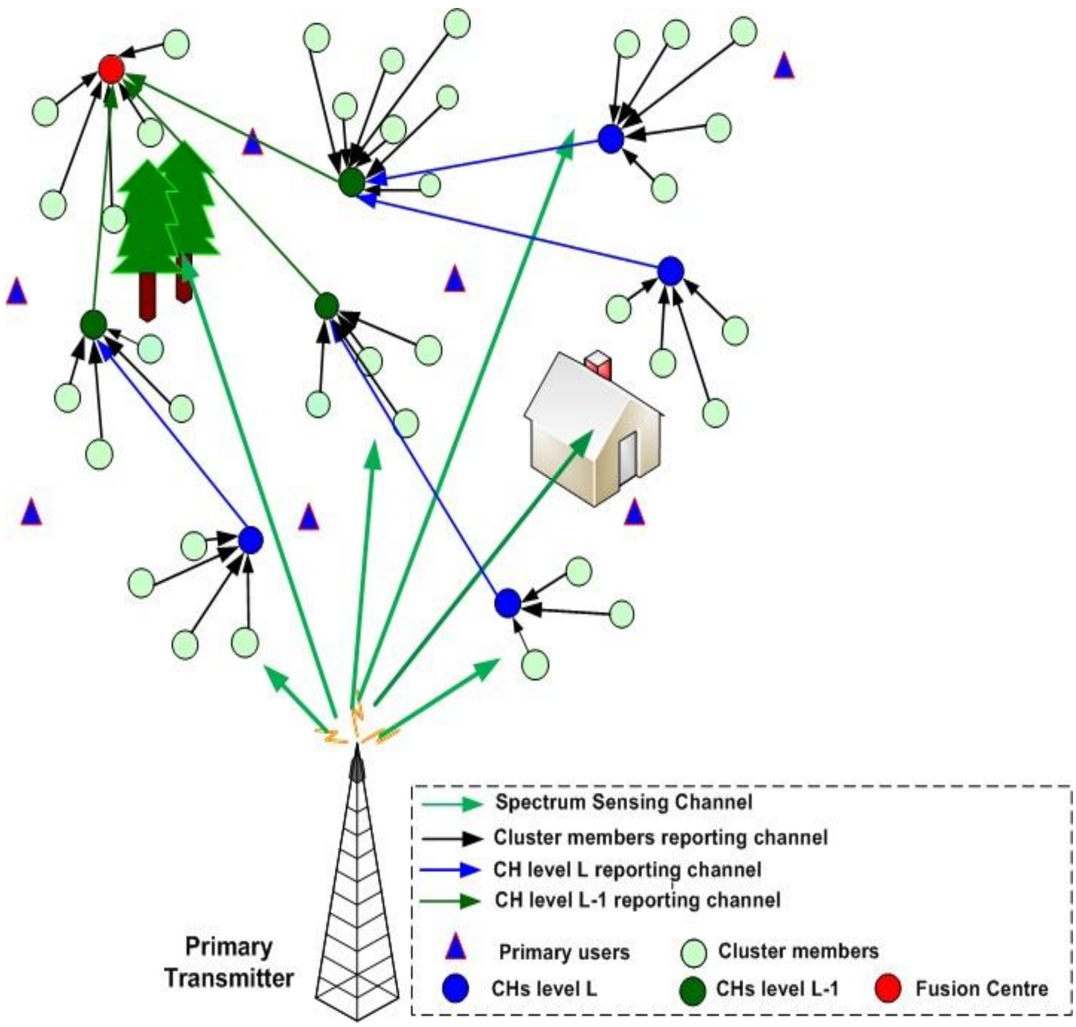


Figure 3.5 Multi-hop cluster based decentralised CSS approach for CRNs

A complete description of this multi-hop clustering algorithm for distributed cooperative spectrum sensing and its formation phases are provided in chapter 7.

3.3 Evaluation and Simulation Models

In order to evaluate the proposed algorithms and developed models of spectrum sensing for CRNs, the simulation results and the performance of spectrum sensing schemes are investigated. The simulation environment was based on MATLAB® simulator [120]. Matlab (**mat**rix **lab**oratory) is a programming language developed by MathWorks, and is widely used in academic and research institutions as well as industrial enterprises. It supports an easy interactive environment and fast mathematical algorithms, and allows matrix manipulations, and plotting of functions and data. The performance of various spectrum sensing models such as local detection model, CSS model, and reporting energy dissipation models were analysed and simulated in this simulator

The radio energy model used in the simulations described in this thesis is given in Figure 3.6. For this model we adopted the same energy parameters presented in [29], which are set as follows: the electronic energy consumption is the same for transmitting and receiving and set to E_{elec}=50 nJ/bit; the amplifier energy consumption E_{amp} can be determined in terms of E_{fs} (free space mode when R< Ro) or E_{mp} (multi-path mode when R≥ Ro) based on transmitter amplifier mode; where E_{fs}=10 pJ/ bit/ m^2; E_{mp}=0.0013 pJ /bit/ m^4 and $Ro = \sqrt{E_{fs}/E_{mp}} = 87.7\ m$; energy dissipated to collect the data E_{DC}=5 nJ /bit and the energy consumed to execute the local spectrum sensing Es=190 nJ. Here, I assumed that the energy dissipated in sleeping mode, as well as in computing the observations and making the local decision is very small compared with other energy consumption, so we can ignore this energy.

Since the thesis has dealt with several scenarios for spectrum sensing, therefore, some of the design and simulation parameters will be given separately in subsequent chapters within the simulation sections.

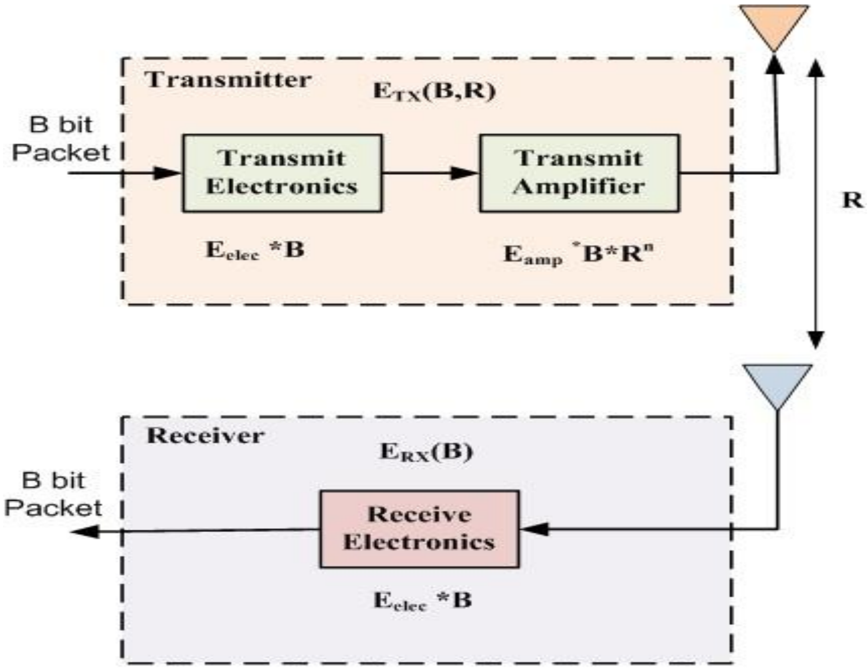


Figure 3.6 Radio energy dissipation model

3.4 Summary

The description of our proposed local and cooperative spectrum sensing algorithms for cognitive radio networks are given in this chapter. Obviously the efficiency of cognitive radio networks is mainly dependent on the performance of spectrum sensing algorithms; therefore, the need for reliable and more accurate spectrum sensing schemes is very important. Single-user spectrum sensing algorithms can provide accurate detection performance when the SNR of the detected channel is high, but in practice the problem of hidden primary terminal cannot be avoided either when the cognitive user is located outside of the range of the primary transmitter or due to fading and shadowing. Cooperative spectrum sensing mechanisms are considered to be effective ways to solve this issue and improve the detection performance. However, cooperative spectrum sensing algorithms also have some challenges that increase the burdens of the system, including energy consumption, control traffic overhead and inefficient sensing performance due to the error rate of the reporting channel.

In this thesis we have focused on the design of spectrum sensing algorithms for cognitive radio networks while considering all of these challenges. First, we designed a new single-user optimal energy detection algorithm in the presence of noise uncertainty that can provide a more reliable and accurate detection performance in a low SNR environment. In order to provide more protection for primary users we further developed a new double optimal threshold energy detection algorithm that gives more reduction in error probability with a small decrease in detection probability.

Second, as single-user spectrum sensing schemes in some cases may suffer from the primary hidden terminal problem, we developed new algorithms for cooperative spectrum sensing that improve the spectrum sensing efficiency. For infrastructure cognitive radio networks, we designed a new cooperative spectrum sensing based on optimisation mechanism. In this algorithm, our first proposed single-user optimal approach is adopted for local sensing and the sensing results of all cognitive users are combined at the fusion centre based on the optimal decision fusion rule, which provides more accurate detection performance when the sensing channel of some cognitive users suffer from fading and shadowing. In practice, both sensing and reporting channels may suffer from the fading and shadowing phenomena; leading to more deterioration in spectrum sensing performance. Therefore, a new multi-hop clustering mechanism for centralised cooperative spectrum sensing is proposed, where the optimal path between the cluster heads and the fusion centre is determined, which gives robust and efficient performance of spectrum sensing in terms of energy efficiency, sensing delay, and detection accuracy.

Finally, in decentralised cognitive radio networks we developed a new multi-hop clustering algorithm for distributed cooperative spectrum sensing, which can enhance the links between all cognitive users within the network; thus, increasing the efficiency of the spectrum sensing and reducing the energy consumption and control traffic overhead. Moreover, the proposed algorithm and through the central mechanism that is provided has helped in resolving the issue of synchronisation.

Chapter 4

Adaptive Optimal Energy Detection Based Spectrum Sensing Algorithm

4.1 Introduction

As seen in chapter 2, energy detection is among the most common spectrum sensing techniques in cognitive radio networks, as it does not need prior knowledge about the detected signal and could be implemented relatively easily. However, energy detectors exhibit some drawbacks including selection of the detection threshold, noise power uncertainty, and needing a high sensing time to achieve a given probability of detection especially in low SNR environments. Although there have been contributions in this area, none of them have addressed all these issues at the same time [16-21, 77, 121-125].

In this chapter, we propose a novel optimal energy detection algorithm that tackles all above mentioned issues. Determining the energy detection threshold is one of the biggest challenges in energy detection algorithm. Here, we present a new approach to enhance the spectrum sensing performance by focusing on some of the weaknesses of energy detection, including threshold selection and poor performance under low SNR in the presence of noise uncertainty. We propose an optimal threshold based on spectrum sensing error function to detect the available spectrum channels. We first analyse the threshold detection optimisation with the availability of sufficient information on the average noise power, then the noise uncertainty will be considered in the design of energy detection, then, we developed a dynamic optimal threshold factor in order to reduce the degradation in detection performance caused by noise uncertainty. Finally, we have expanded the single optimal threshold algorithm to include the double optimal threshold scheme, in order to reduce the spectrum decision error that may occur when the detection statistic falls near the detection threshold in single optimal mode.

4.2 General Considerations in Energy Detection Spectrum Sensing

In our approach, we assume a system model with a cognitive terminal that needs to detect a primary terminal signal using an energy detector. In this approach, only the transmitted power of the primary system is known at the CR user, therefore, this power will be detected first, and then compared to a predefined threshold to determine whether the spectrum band is available or not. When the energy of the received signal is greater than the detection thresholdλ, the detector will indicate that the primary user is present, which will be depicted by the hypothesis H_1, otherwise, the primary user is absent, which will be represented by the hypothesis H_0.

The performance of spectrum sensing is measured by two parameters:

- *The detection probability Pd*: it indicates that the primary user exists. This probability should be as big as possible to protect the primary users from interference.
- *The false alarm probability Pf*: it indicates that the primary user is present while in reality it is not. This probability should be as small as possible to increase the spectrum utilization.
- *The misdetection probability Pm*: In addition, there is another important metric that is called P_m, which stands for the collision probability between the primary user and CR user. To provide adequate protection for the primary system from harmful interference, we must ensure to decrease the P_m as much as possible.

In this section we will present a mathematical analysis that will determine these detection probabilities. The decision of spectrum availability in the energy detection method is the test of the following hypothesis [121]:

$$x(n) = \begin{cases} w(n), & H_0 \quad \text{signal absent} \\ s(n) + w(n), & H_1 \quad \text{signal present} \end{cases} \tag{4 - 1}$$

Where n = 0,1,2,3... N, which represents the number of samples (detection period). x(n)is the received signal at the secondary user, s(n) is the primary user signal, and is assumed to be independent and identically distributed random process of zero mean and variance of σ_s^2. w(n) denotes the noise signal and is also assumed to be independent and identically distributed random process of zero mean Additive White Gaussian Noise (AWGN) with variance σ_n^2.

The test statistic for the energy detector can be represented as a series of Fast Fourier Transformer (FFT) components [126]:

$$T_D = \sum_{k=1}^{N} |X[k]|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{4 - 2}$$

Here, X[k] is FFT series of signal x[n], and λ is the detection threshold value. According tocentral limit theorem and as long as N is large enough, the decision statistic in (2) can be approximated as a Gaussian distribution [121]:

$$T_D \sim \begin{cases} Normal(\mu_0, \sigma_0^2) & \mathrm{H}_0 \\ Normal(\mu_1, \sigma_1^2) & \mathrm{H}_1 \end{cases} \tag{4 - 3}$$

$$\begin{cases} \mu_0 = N\sigma_n^2 & \mathrm{H}_0 \\ \mu_1 = N\sigma_n^2(\gamma + 1) & \mathrm{H}_1 \end{cases} \tag{4 - 4}$$

$$\begin{cases} \sigma_0^2 = 2N\sigma_n^4 & \mathrm{H}_0 \\ \sigma_1^2 = 2N\sigma_n^4(\gamma + 1)^2 & \mathrm{H}_1 \end{cases} \tag{4 - 5}$$

Where ($\gamma = \sigma_s^2/\sigma_n^2$) represents the average power signal to noise ratio SNR.

Figure 4.1 depicts the Gaussian distributions of sensing metric T_D in both cases of signal present (H_1) and signal absent (H_0). Here, I considered a binary symmetric channel just for clarification, while in realistic is different; where the probability that the primary signal is absent PH_0 is greater than the probability that the primary signal is present PH_1.From this figure we can see that the probability of false alarm Pf is the probability that $T_D > \lambda$ when the primary signal is not present, while the misdetection probability Pm is the probability that $T_D < \lambda$ when the primary signal exists. The figure also illustrates that a proper setting of the detection threshold can be determined by trade-offs between Pf and Pm, thus leading to obtaining the optimal threshold.

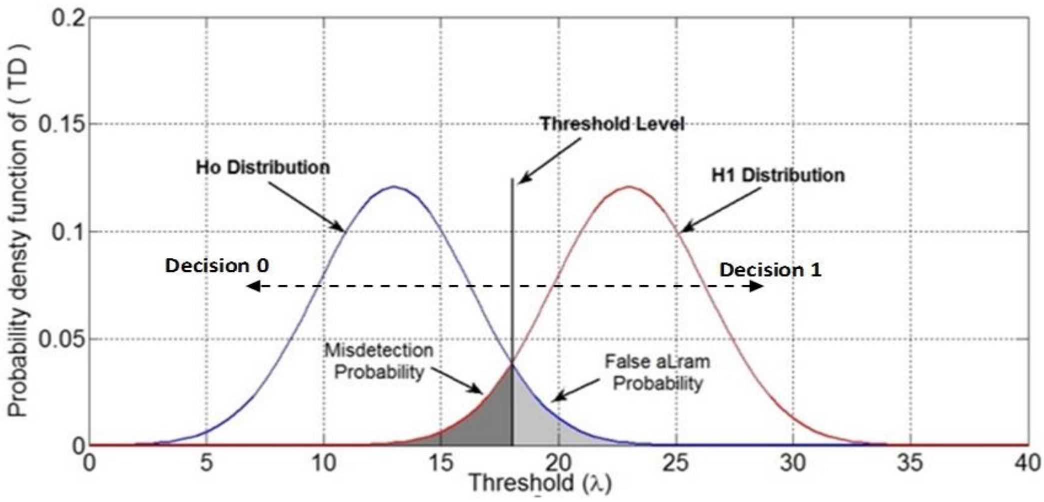


Figure 4.1 Energy Gaussian distribution of TD under threshold λ

The probability of detection Pd and the probability of false alarm Pf over AWGN channel are given respectively as follows [127]:

$$Pd = Prob\{T_D > \lambda|H_1\} = \frac{1}{2}erfc\left[\frac{\lambda-\mu_1}{\sqrt{2}\sigma_1}\right] \qquad (4 - 6)$$

$$Pf = Prob\{T_D > \lambda|H_0\} = \frac{1}{2}erfc\left[\frac{\lambda-\mu_0}{\sqrt{2}\sigma_0}\right] \qquad (4 - 7)$$

where rfc is the complementary error function which can be expressed by [128]:

$$erfc(z) = \left(\frac{2}{\sqrt{\pi}}\right)\int_z^{\infty} \exp(-x^2\ )dx \qquad (4 - 8)$$

Another important probability parameter is: mis-detection probability Pm which is the probability that the energy detector indicates that the primary user is absent while it is actually is present. This probability can be expressed as follows [127]:

$$Pm = 1 - Pd \qquad (4 - 9)$$

If a priori information of the spectrum occupancy is available and given by PH_1, PH_0, which represents the probabilities of primary user presence and absence respectively, where $PH_1+PH_0=1$, we can formulate the probability of error as follows [129]:

$$Pe = PH_0Pf + PH_1Pm \tag{4 - 10}$$

4.3 Optimal Threshold Energy Detection Model with Full Noise Knowledge

The key metric of spectrum sensing performance depends on the probability of sensing error, which should be minimised as much as possible. In spectrum sensing, it is important to minimise the false alarm probability *Pf*, which leads to providing more spectrum access opportunities, and to provide more protection for the primary user, the lower mis-detection probability *Pm* is desired. In this section, we investigate the minimisation of the total error probability *Pe* in functions of the threshold parameter, where the noise uncertainty problem is not considered. In this model, we assume that the detection period *N* is big enough, so we can approximate the distribution of decision statistic as Gaussian distribution.

In order to meet the sensing constraint (Pf^*, Pm^*), we consider the optimisation threshold level which minimises *Pe* under spectrum sensing constraint, and can be represented as:

$$\lambda^{opt} = \arg min_{\lambda}\,(PH_0Pf + PH_1Pm) \tag{4 - 11}$$
$$\text{s.t. } Pf(\lambda) \le Pf^* and Pm(\lambda) \le Pm^*$$

then,

$$\frac{PH_0\partial Pf}{\partial\lambda} + \frac{PH_1\partial Pm}{\partial\lambda} = 0 \quad and\, \frac{\partial^2 P_e}{\partial^2\lambda} > 0 \tag{4 - 12}$$

from the equations (4 – 6), (4 – 7), (4 – 8), and (4 – 9) we can get

$$\frac{\partial Pf}{\partial \lambda} = -\frac{1}{\sqrt{2\pi}\sigma_0} e^{-\left(\frac{\lambda-\mu_0}{\sqrt{2}\sigma_0}\right)^2} \qquad (4 - 13)$$

$$\frac{\partial Pm}{\partial \lambda} = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\left(\frac{\lambda-\mu_1}{\sqrt{2}\sigma_1}\right)^2} \qquad (4 - 14)$$

By substituting the parameters in (4-13) and (4-14) into (4-12), we can obtain the closed form expression of the optimal detection threshold (λ^{opt}) as follows:

$$\lambda^{opt} = \frac{-B + \sqrt{B^2 - AC}}{A} \qquad (4 - 15)$$

where

$$A = \sigma_1^2 - \sigma_0^2 (4 - 16) \qquad (4 - 16)$$

$$B = \sigma_0^2 \mu_1 - \sigma_1^2 \mu_0 \qquad (4 - 17)$$

$$C = \sigma_1^2 \mu_0^2 - \sigma_0^2 \mu_1^2 - 2\sigma_1^2 \sigma_0^2 \ln((PH_1 * \sigma_1)/(PH_1 * \sigma_0)) \qquad (4 - 18)$$

Based on the assumption that the noise power is fully known at the cognitive user, and the samples number N is large enough, the minimum samples required to satisfy the sensing constraint (Pf^*,Pm^*) can be expressed as [130]:

$$N_{min} = 2[erfc^{-1}(2Pf^*) - (1+\gamma)erfc^{-1}(2(1 - Pm^*))]^2 \gamma^{-2} \qquad (4 - 19)$$

According to (4-19), the minimum number of samples N_{min} required to satisfy the spectrum sensing constraints will be very large especially in low SNR, which is practically infeasible. In other words, for a given number of samples N and SNR, the optimal threshold algorithm can minimise the error probability Pe but does not guarantee that the mis-detection probability Pm to be below maximum allowable mis-detection probability ($Pm(\lambda) \leq Pm^*$). In such a case, the spectrum sensing performance will depend on two thresholds ($\lambda^* and\ \lambda^{opt}$), where λ^* represents the detection threshold that meets the spectrum sensing constraint ($Pm(\lambda) \leq Pm^*$) and $\lambda^{opt}$is the optimal threshold. The λ^*can be represented as [17]

$$\lambda^* = \mu_1 + \sqrt{2}\sigma_0 Q^{-1}(2Pd^*) \qquad (4 - 20)$$

where $Pm^* = 1 - Pd^*$.

In low SNR environment, the λ^{opt} is greater than the λ^{*} in most cases even when the number of samples exceeds *Nmin*, making $Pm(\lambda_{opt})$ overtake the allowable mis-detection probability Pm^{*}. Therefore, the adaptive optimal threshold that minimises spectrum sensing error while providing a sufficient protection for primary users can be given as

$$\bar{\lambda} = \min(\lambda_{opt}, \lambda^{*}) \tag{4 - 21}$$

4.4 Optimal Threshold Scheme under Noise Uncertainty

As in most communication systems, the noise is an error or undesired disturbance of a useful information signal. It is a summation of various independent sources including thermal noise, and interferences due to weak signals from transmitters very far away, and so on. However, the noise power may fluctuate over time and location, which yields noise uncertainty [131]. It is very clear from the equations; (4-15) and (4-18); described in the previous section that the optimal detection threshold λ^{opt} is proportional to nominal noise power σ_n^2. As a result, the performance of the optimal threshold scheme will be degraded and thus the scheme will not be effective. To reduce the impact of the noise uncertainty, the equations (4-6); (4-7); and (4-15) have to be modified.

In order to study the effect of noise uncertainty on the detection performance, we modelled the distributional uncertainty of noise as $\sigma^2 \in (\sigma_{min}^2, \sigma_{max}^2)$, where σ^2 is the actual noise power, $(\sigma_{min}^2 = \sigma_n^2/\alpha)$ is the lower bound of the noise uncertainty, $(\sigma_{max}^2 = \alpha\sigma_n^2)$ is the upper bound of the noise uncertainty, $(\alpha \geq 1)$ is the noise uncertainty factor, and σ_n^2 is the expected or nominal noise power. Based on central limit theorem [36], the decision statistic under noise uncertainty can be approximated as Gaussian distribution and given as following:

$$T_D \sim \begin{cases} Normal(\mu_0, \sigma_0^2) & \mathrm{H}_0 \\ Normal(\mu_1, \sigma_1^2) & \mathrm{H}_1 \end{cases} \tag{4 - 22}$$

$$T_D \sim \begin{cases} Normal(N\alpha\sigma_n^2, 2N\alpha^2\sigma_n^4) & \mathrm{H}_0 \\ Normal\left(N\sigma_n^2(\frac{1}{\alpha}+\gamma), 2N\sigma_n^4(\frac{1}{\alpha}+\gamma)^2\right) & \mathrm{H}_1 \end{cases} \qquad (4 - 23)$$

Thus, the equations (4-6) and (4-7) are modified to obtain

$$Pd = \frac{1}{2}erfc\left[\frac{\lambda-\mu_1}{\sqrt{2}\sigma_1}\right] = \frac{1}{2}erfc\left(\frac{\lambda - N\sigma_n^2(1/\alpha+\gamma)}{\sqrt{4N}\sigma_n^2(1/\alpha+\gamma)}\right) \qquad (4 - 24)$$

$$Pf = \frac{1}{2}erfc\left[\frac{\lambda-\mu_0}{\sqrt{2}\sigma_0}\right] = \frac{1}{2}erfc\left(\frac{\lambda - N\alpha\sigma_n^2}{\sqrt{4N}\alpha\sigma_n^2}\right) \qquad (4 - 25)$$

The optimal threshold level can be calculated using the equation (4-15) after substituting the modified parameters in equations (4-22) and (4-23) into equations (4-16), (4-17), and (4-18). Under noise uncertainty, to meet the pair sensing constraints (Pf^*, Pm^*), the least number of samples required can be determined by

$$N_{min} = \frac{2\left[\alpha erfc^{-1}(2Pf^*) - \left(\frac{1}{\alpha}+\gamma\right)erfc^{-1}(2Pd^*)\right]^2}{\left[\gamma - (\alpha - \frac{1}{\alpha})\right]^2} \qquad (4 - 26)$$

From equation (4-26), we can see that the samples number N approaches infinity as SNR (γ) decreases to $(\alpha - 1/\alpha)$. It can also be found that, there are SNR_{walls} that prevent the detection from being robust, and cannot achieve a reliable detection even increasing the sample number to infinity. Thereby, the SNR_{walls} can be defined as

$$SNR_{walls} = \alpha - \frac{1}{\alpha} \qquad (4 - 27)$$

4.5 Dynamic Optimal Threshold Detection Scheme

In order to provide a guarantee of adequate protection for primary users against secondary user interferences, it is very important to choose a suitable detection threshold. The optimal threshold algorithm can provide this condition. However, as mentioned above, the detection performance of this scheme could decline sharply due to noise uncertainty. In this section, we present a dynamic optimal threshold algorithm that tackles this issue.

According to the noise uncertainty factor α, we assume that the dynamic threshold is distributed within the range $(\lambda/\alpha^* \leq \lambda^* \leq \alpha^*\lambda)$, where $\alpha^* \geq 1$, is dynamic threshold factor. In the case of noise uncertainty and dynamic threshold mode, the mean and variance of the decision statistic under two hypotheses are given respectively, as follows:

$$T_D \sim \begin{cases} \mathcal{N}(\mu_0, \sigma_0^2) = \mathcal{N}(N\alpha\sigma_n^2, 2N\alpha^2\sigma_n^4) & \mathrm{H}_0 \\ \mathcal{N}(\mu_1, \sigma_1^2) = \mathcal{N}\left(N\sigma_n^2(\gamma + \frac{1}{\alpha}), 2N\sigma_n^4(\gamma + \frac{1}{\alpha})^2\right) & \mathrm{H}_1 \end{cases} \quad (4 - 28)$$

then, the probability relationships are expressed as

$$Pd = \min_{\lambda^* \in (\lambda/\alpha^*, \alpha^*\lambda)} \min_{\sigma^2 \in (\sigma_n^2/\alpha, \alpha\sigma_n^2)} \frac{1}{2} erfc\left[\frac{\lambda^* - \mu_1}{\sqrt{2}\sigma_1}\right] \quad (4 - 29)$$

$$Pd = \frac{1}{2} erfc\left[\frac{\lambda/\alpha^* - \mu_1}{\sqrt{2}\sigma_1}\right] \quad (4 - 30)$$

$$Pf = \max_{\lambda^* \in (\lambda/\alpha^*, \alpha^*\lambda)} \max_{\sigma^2 \in (\sigma_n^2/\alpha, \alpha\sigma_n^2)} \frac{1}{2} erfc\left[\frac{\lambda^* - \mu_0}{\sqrt{2}\sigma_0}\right] \quad (4 - 31)$$

$$Pf = \frac{1}{2} erfc\left[\frac{\alpha^*\lambda - \mu_0}{\sqrt{2}\sigma_0}\right] \quad (4 - 32)$$

Thus, the dynamic optimal threshold can be determined using the same equation (4-15) with the new modified parameters as follows

$$A = {\alpha^*}^2\sigma_1^2 - \left(\frac{1}{{\alpha^*}^2}\right)\sigma_0^2 \quad (4 - 33)$$

$$B = (\frac{1}{\alpha^*})\,\sigma_0^2\mu_1 - \alpha^*\sigma_1^2\mu_0 \quad (4 - 34)$$

$$C = \sigma_1^2\mu_0^2 - \sigma_0^2\mu_1^2 - 2\sigma_1^2\sigma_0^2 \ln\left({\alpha^*}^2 \frac{PH_0}{PH_1}\frac{\sigma_1}{\sigma_0}\right) \quad (4 - 35)$$

Then, the minimum samples number N required under sensing constraints can be determined as

$$N_{min} = \frac{2\left[\left(\frac{\alpha}{\alpha^*}\right) erfc^{-1}(2Pf^*) - \alpha^*\left(\frac{1}{\alpha} + \gamma\right) erfc^{-1}(2Pd^*)\right]^2}{\alpha^{*2}\left[\gamma - \left(\frac{\alpha}{\alpha^{*2}} - \frac{1}{\alpha}\right)\right]^2} \tag{4 - 36}$$

And

$$SNR_{walls} = \frac{\alpha}{\alpha^{*2}} - \frac{1}{\alpha} \tag{4 - 37}$$

4.6 Double Optimal Threshold Energy Detection Algorithm

Although optimal threshold energy detection scheme has a capability to improve the detection performance by minimising the error probability, there is still a situation, when the decision statistic locates near the optimal threshold, which causes high sensing decision error. In order to overcome this issue, we proposed a new double optimal threshold energy detection (DOTED) algorithm, which can achieve more reduction in error detection with a slight decline in the efficiency of spectrum utilisation. Figure 4.2 shows the frequency domain diagram of the proposed energy detection scheme.

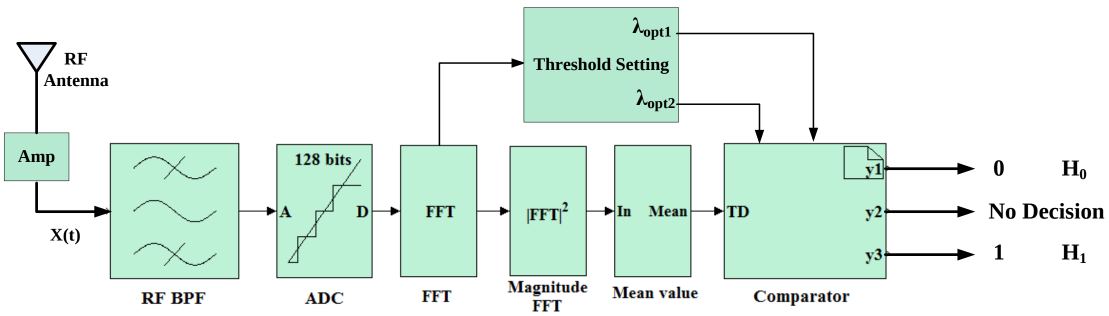


Figure 4.2 Block diagram of double threshold energy detection in frequency domain

In order to measure the primary signal energy in frequency domain, simply the received signal first selects the interesting bandwidth by a band pass filter (BPF), and samples using analogue to digital converter (ADC) with sampling frequency *fs*, then converts to frequency domain taking Fast Fourier Transformation (FFT) followed by squaring the coefficients and then taking the average over the observation band. Finally, according to a comparison between the average and determined thresholds, the presence or absence of the PU can be detected.

In the conventional energy detection method, the spectrum decision resulting in the output of the detector depends on the result of the comparison between the detection statistic and the predefined single threshold, as shown previously in Figure 4.1. In double threshold energy detection method [16], the detector employs two thresholds to make a spectrum decision based on the same hypotheses as the single threshold energy detector, in addition to an uncertain region as there is no decision to be taken in this case.

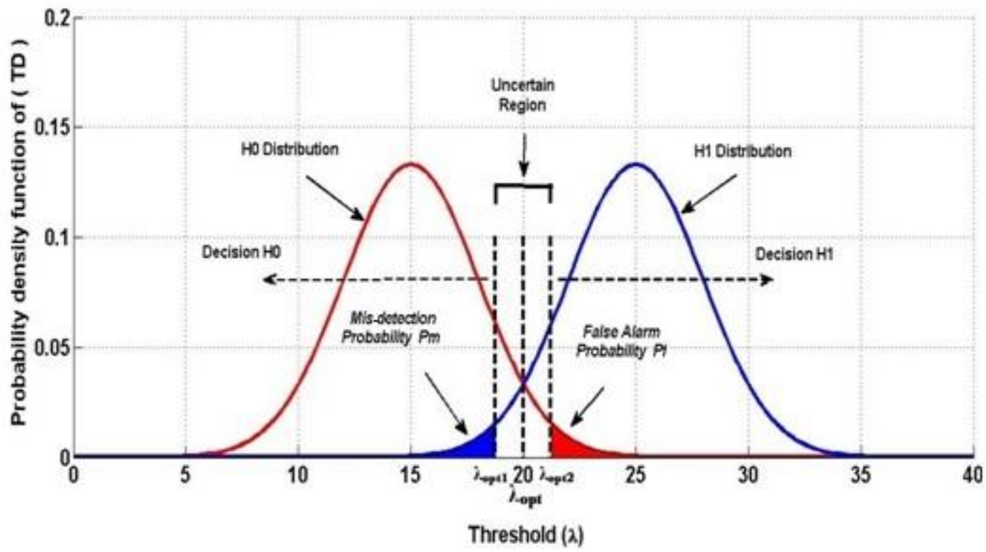


Figure 4.3 Gaussian distribution of T_D under thresholds λ_{opt1} and λ_{opt2}

Figure 4.3 depicts the Gaussian distributions of sensing metric T_D in both cases of signal present (H_1) and signal absent (H_0). From this figure we can see that the probability of false alarm *Pf* is the probability that $T_D > \lambda_{opt2}$ when the primary signal is not present, while the mis-detection probability *Pm* is the probability that $T_D < \lambda_{opt1}$ when the primary signal exists. The figure also illustrates that there is a region of uncertainty between the upper optimal thresholds λ_{opt2} and lower optimal threshold

λ_{opt1}, and whenever the received energy falls in this region, no decision is taken and the detector waits until the next sensing frame.

In the rest of the section, we will go through a mathematical analysis to determine the sensing parameters of the DOTED algorithm. In general, the values of sensing metrics (*Pd*, *Pm* and *Pf*) rely basically on detection threshold settings, which need to be optimally selected. As shown in Figure 4.2, the output decision of the DOTED has three cases depending on the value of sensing decision statistic T_D

$$Y = \begin{cases} 0 & H0 & T_D < \lambda_{opt1} \\ No\ Decision & & if\ \ \lambda_{opt1} \leq T_D \leq \lambda_{opt2} \\ 1 & H1 & T_D < \lambda_{opt1} \end{cases} \quad (4\text{ - }38)$$

In order to get the probability parameters, we first need to determine the optimal detection threshold λ_{opt}, which can be found in the same manner as in our single-optimal threshold algorithm. So, we can use the previous equations (4-11) to (4-18) to determine the optimal threshold λ_{opt}. The upper λ_{opt2} and lower λ_{opt1} optimal thresholds can be calculated as follows

$$\lambda_{opt2} = \delta * \lambda_{opt} \quad (4\text{ - }39)$$

$$\lambda_{opt1} = 2 * \lambda_{opt} - \lambda_{opt2} \quad (4\text{ - }40)$$

Where δ denotes uncertainty region factor, and these equations were adjusted to make the uncertainty region symmetrical around the optimal threshold λ_{opt}.

The equations of different probabilities are given below for AWGN channel. Under hypothesis H_1, probability of detection (probability of deciding “1”, probability of misdetection or probability of deciding “0” and probability of “no decision” are represented by Pd_1, *Pm* and Pnd_1, respectively.

$$Pd_1 = P\{T_D > \lambda_{opt2} | H_1\} = \frac{1}{2} erfc\left[\frac{\lambda_{opt2} - \mu_1}{\sqrt{2}\sigma_1}\right] \quad (4\text{ - }41)$$

$$Pm = P\{T_D < \lambda_{opt1} | H_1\} = 1 - \frac{1}{2} erfc\left[\frac{\lambda_{opt1} - \mu_1}{\sqrt{2}\sigma_1}\right] \quad (4\text{ - }42)$$

$$Pnd_1 = P\{\lambda_{opt1} \le T_D \le \lambda_{opt2} | H_1\} = Pd(\lambda_{opt1}) - Pd_1$$
$$= \frac{1}{2}\left[erfc\left[\frac{\lambda_{opt1} - \mu_1}{\sqrt{2}\sigma_1}\right] - erfc\left[\frac{\lambda_{opt2} - \mu_1}{\sqrt{2}\sigma_1}\right]\right] \quad (4 - 43)$$

Similarly, under hypothesis H_0, the probability of deciding "0", probability of false alarm (probability of deciding "1") and the probability of "no decision" are given by Pd_0, Pf and Pnd_0, respectively.

$$Pd_0 = P\{ T_D < \lambda_{opt1} | H_0\} = 1 - \frac{1}{2} erfc\left[\frac{\lambda_{opt1} - \mu_0}{\sqrt{2}\sigma_0}\right] \quad (4 - 44)$$

$$Pf = P\{T_D > \lambda_{opt2} | H_0\} = \frac{1}{2} erfc\left[\frac{\lambda_{opt2} - \mu_0}{\sqrt{2}\sigma_0}\right] \quad (4 - 45)$$

$$Pnd_0 = P\{\lambda_{opt1} \le T_D \le \lambda_{opt2} | H_0\} = Pf(\lambda_{opt1}) - Pf$$
$$= \frac{1}{2}\left[erfc\left[\frac{\lambda_{opt1} - \mu_0}{\sqrt{2}\sigma_0}\right] - erfc\left[\frac{\lambda_{opt2} - \mu_0}{\sqrt{2}\sigma_0}\right]\right] \quad (4 - 46)$$

where $Pd(\lambda_{opt1})$ and $Pf(\lambda_{opt1})$ represent the detection and false alarm probabilities with respect to lower optimal threshold λ_{opt1}, respectively.

4.7 Throughput Performance Analysis

In previous sections, the sensing performance of the proposed energy detection algorithms has been presented. The analytical expressions of the probability parameters (*Pd*, *Pf* and *Pm*) for both single and double optimal threshold algorithms have been given. In this section, we try to examine the throughput performance of single user channel using our proposed single and double optimal threshold based spectrum sensing algorithms. In order to formulate the throughput expressions, we will go through mathematical analysis to determine the final throughput expression for each type of proposed energy detection algorithm.

According to Shannon capacity theorem, the upper bound on the achievable throughput of the cognitive radio network when it operates in the absence C_o and the presence C_1 of the primary users can be represented, respectively, as follows [132]

$$C_o = B\log_2(1+\gamma_s) \qquad (bit/s) \qquad (4 - 47)$$

$$C_1 = B\log_2\left(1+\frac{\gamma_S}{1+\gamma_P}\right) \qquad (bit/s) \qquad (4 - 48)$$

Where B denotes the bandwidth of the AWGN channel, $\gamma_S = \frac{S}{N_o}$ and $\gamma_P = \frac{P}{N_o}$ are the SNR of cognitive radio link and the SNR of primary transmission link at cognitive user, respectively. Denote S as the received power of the cognitive user, P as the received power of the primary transmitter at the cognitive user, and N_o as the noise power.

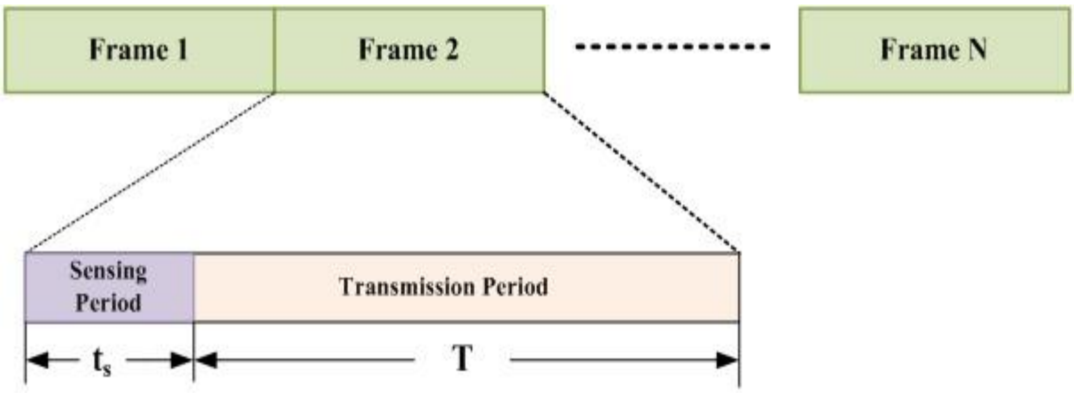


Figure 4.4 Frame structure of single-user periodic spectrum sensing

As shown in Figure 4.4, if the probability for which the primary spectrum band is occupied (PH_1), and the probability for which the band is empty (PH_0) are available, and based on the sensing period (T_S) and total Frame time of the periodic spectrum sensing (T), we define the average achievable throughput of the cognitive radio network R by [133]

$$R(\lambda, T_S) = C_0\, PH_0\left(1 - \frac{T_S}{T}\right)[1 - Pf(\lambda, T_S)] \\ + C_1 PH_1\left(1 - \frac{T_S}{T}\right)[1 - Pd(\lambda, T_S)] \qquad (4 - 49)$$

Obviously, from (4-49) we can see that the throughput of the single user based spectrum sensing algorithms is generally reliant on several parameters, some of these parameters such as detection threshold λ and sensing period T_S can be controlled, and others like (C_0, C_1, PH_0 and PH_1) are out of control and depend on the surrounding environment. In the following, we will formulate the throughput of the cognitive radio network for each energy detection based spectrum sensing algorithm.

In conventional constant detection rate based energy detection (CDR-ED) algorithm, the detection threshold λ_T is predefined based on the desirable protection level for primary users $\overline{Pd}$, then the false alarm probability Pf will be minimised for a given SNR and certain sensing period T_S. Therefore, the throughput of the CRNs with CDR-ED based spectrum sensing can be represented as:

$$R(\lambda_T, T_S) = C_0\, PH_0\left(1 - \frac{T_S}{T}\right)[1 - Pf(\lambda_T, T_S)] \\ + C_1 PH_1\left(1 - \frac{T_S}{T}\right)[1 - \overline{Pd}] \qquad (4 - 50)$$

In conventional double-threshold energy detection based spectrum sensing algorithm, the detection performance depends on two fixed thresholds (λ_1, λ_2), where λ_1 is set based on the desirable level of probability collision P_{m1} between primary user and cognitive user, while $\lambda_2 = \lambda_1 - \Delta$, which depends on the uncertain region factor Δ. The throughput of the CRN under this detection scheme can be defined as

$$R(\lambda, T_S) = C_0\, PH_0\left(1 - \frac{T_S}{T}\right)[1 - Pf_2(\lambda_2, T_S)] \\ + C_1 PH_1\left(1 - \frac{T_S}{T}\right)[1 - P_{d1}(\lambda_1, T_S] \qquad (4 - 51)$$

In single-optimal threshold energy detection algorithm, the maximum average throughput R can be achieved by minimising both false alarm $Pf\left(\lambda_{opt}, T_S\right)$ and mis-detection $Pd(\lambda_{opt}, T_S)$ probabilities. In this case, the achievable throughput of the CRN can be given as

$$R(\lambda_{opt}, T_S) = C_0\, PH_0 \left(1 - \frac{T_S}{T}\right)\left[1 - Pf(\lambda_{opt}, T_S)\right] \\ + C_1 PH_1 \left(1 - \frac{T_S}{T}\right)\left[1 - P_d(\lambda_{opt}, T_S)\right] \tag{4 - 52}$$

In the case of Double-optimal threshold energy detection approach, more reduction in Pf and P_m can be achieved, and the throughput of the CRN can be formulated as

$$R(\lambda, T_S) = C_0\, PH_0 \left(1 - \frac{T_S}{T}\right)\left[1 - Pf_2(\lambda_{opt2}, T_S)\right] \\ + C_1 PH_1 \left(1 - \frac{T_S}{T}\right)\left[1 - P_{d1}(\lambda_{opt1}, T_S)\right] \tag{4 - 53}$$

In the following section, we will evaluate our proposed algorithms by simulating the analytical analyses described in this chapter, and comparing the simulation results with existing algorithms.

4.8 Simulation Results

This section provides the simulation results of the performance evaluation of single-user energy detection algorithms that are proposed and described in this chapter. The simulation includes the spectrum sensing performance of the proposed algorithms and their throughput performance for CRN. The simulation has been conducted using the MATLAB®2009a simulator. In our numerical analysis, we assumed that the noise power is completely known and set it as ($\sigma_n^2 = 1$), also the desired pair sensing constraints are set as Pf^*=0.1, Pm^*= 0.1, (Pd^*=0.9).

In the following subsections, the performance of each proposed algorithm will be presented and discussed. The single-optimal threshold algorithm will be given first, and then followed by the performance of the double-optimal threshold mode, and finally the throughput performance of the CRN under all proposed and conventional algorithms is presented and discussed for comparison.

4.8.1 Single-Optimal Threshold Energy Detection Performance

First, we study the impact of SNR of the sensing channel; the number of samples N and the detection threshold on the error probability level using single-optimal threshold energy detection algorithm, as shown in Figure 4.5.

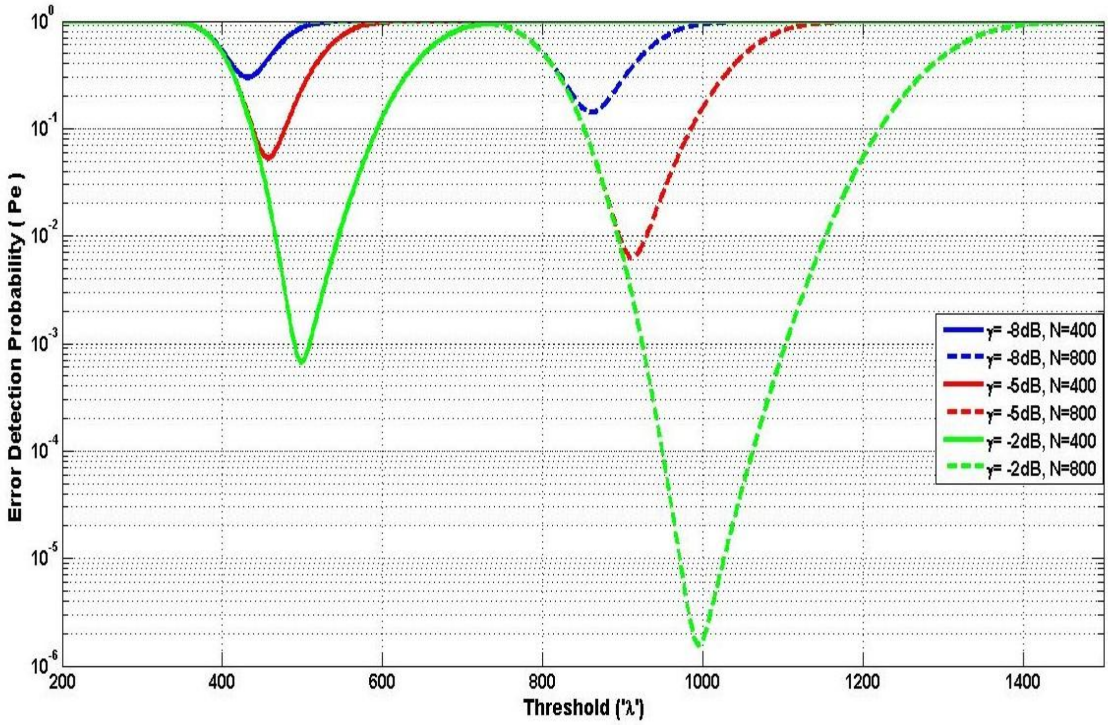


Figure 4.5 Performance of error probability with detection threshold

It can be seen from the figure that increasing the SNR and the number of samples can lead to more reduction in the error probability. Moreover, it can be also observed that, there is only one optimal threshold that minimises the error rate, and the value of the optimal threshold increases with the increase of both SNR and the number of samples. Another important point that can be seen here is, for low SNR, the level of the error rate may be large and increasing the number of samples may not lead to a significant improvement in the error rate. For instance, at SNR=-8 dB; increasing the number of samples from 400 to 800 will reduce the error rate from 0.298 to 0.142, while at SNR=-2 dB; the error rate will decrease from 0.674*10^-3 to 1.567*10^-6, indicating that the reduction rate at SNR=-8 dB is 50% while at SNR=-2 dB is 99.7%.

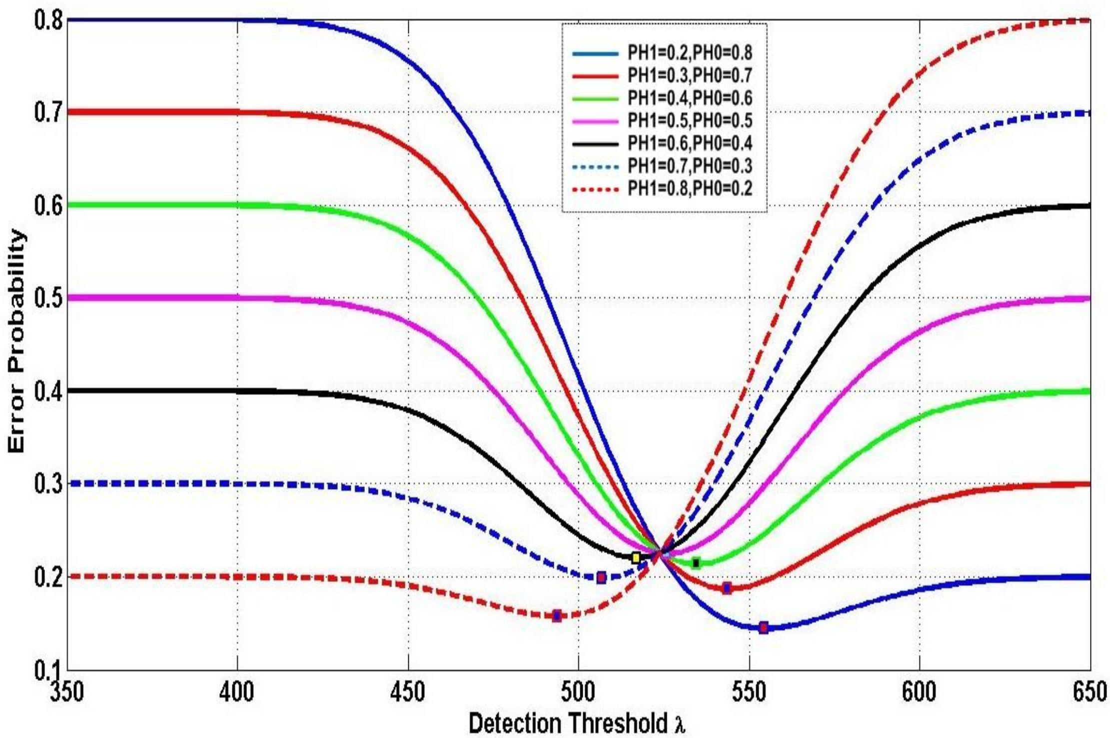


Figure 4.6 Performance of error probability versus detection threshold with different *PH1/PH0*

The relation between the probability of spectrum occupancy PH1/PH0 and the error rate is investigated in Figure 4.6. The figure shows that, increasing the probability of occupancy PH_1 (probability for which the primary user is active) leads to a reduction in the value of optimal detection threshold. On the other hand, increasing PH_1 from 0.2 to 0.5 leads to an increase in the value of minimum error rate, and then begins to decline with the continued increase of PH_1 from 0.5 to 0.8. As shown in the figure, the lowest value of the optimal error rate can be obtain at PH_1=0.2 and PH_0=0.8.

Figure 4.7 illustrates the sensing probability error versus average SNR with different N values. It is obvious to find that under different values of N and for a given low SNR, the value of P_e decreases dramatically with increasing the value of N. In addition, it can also be observed that at low SNR values the optimal scheme under sensing constraints outperforms that with fixed N, where the probability of error has been improved and kept constant to (0.2) even in cases of very low SNR, but this is at the expense of increasing the samples number N, where $N \propto 1/SNR^2$ according to equation (4-19), and thus increasing the sensing time T for a fixed bandwidth W, where N equal time-bandwidth product (TW).

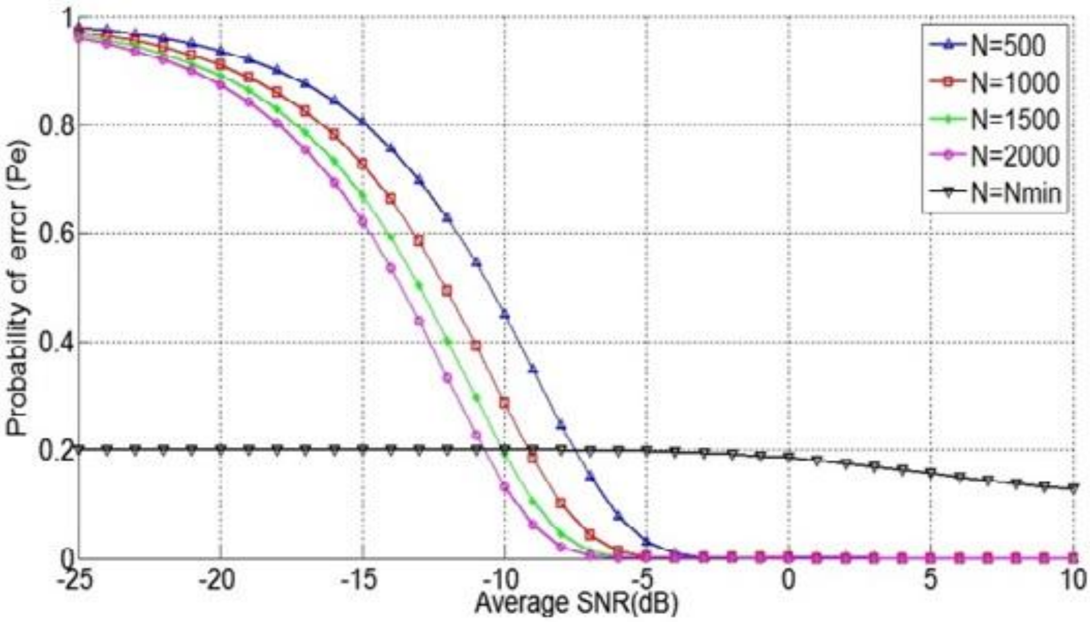


Figure 4.7 Probability of sensing error according to an average SNR

In real world communications, the noise power fluctuates over time and space, thus, causing significant degradation in sensing performance. Figure 4.8 depicts the effect of noise uncertainty on probability of error, and shows that a tiny fluctuation of average noise power could cause performance to drop seriously.

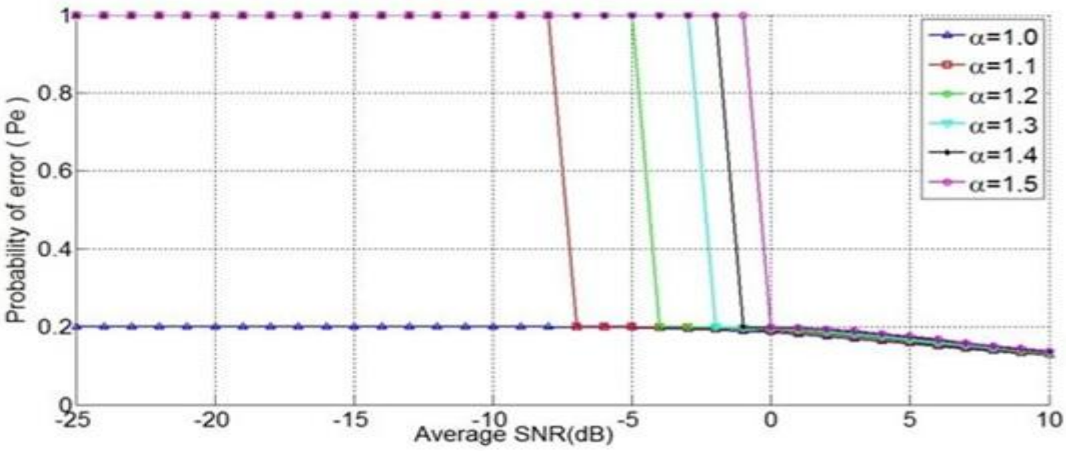


Figure 4.8 Probability of error according to the average SNR with different noise uncertainty factor α

The results presented in Figure 4.8show the impact of the noise uncertainty on detection performance for different values of the noise uncertainty factor α. These results show that the noise uncertainty factor ($\alpha = 1.0$), and for a given SNR range (-25,10) dB, the probability of sensing error will increase slightly with decreasing the value of SNR, and keep constant on the value of (0.2) even in very low SNR. For other values of a noise uncertainty factor $\alpha > 1$ the sensing error increases proportionally to the value of α. For instance, when the value of noise uncertainty factor $\alpha = 1.3$, the probability of error will increase slightly, while the SNR will decrease until approaching the SNR_{wall}, where (SNR_{wall}= 0.53) which is equivalent to (-2.75 dB) according to equation (25), then the probability of error will increase sharply and reach to (Pe=1) when $SNR \geq SNR_{wall}$even samples number N increased to infinity.

The results in Figure 4.8 also show that when the value of noise uncertainty factor α increases, the value of SNR_{wall} increases which makes the detection unreliable and impractical even in normal values of SNR. From these results we can also conclude that the optimal threshold detection method cannot detect the signal with SNR below SNR_{wall}. Therefore, it is necessary to modify the optimal threshold in order to tackle the effect of the noise uncertainty on detection performance.

Figure 4.9 gives the probability of sensing error against average SNR for different values of noise uncertainty factor α and dynamic threshold factor α^*.

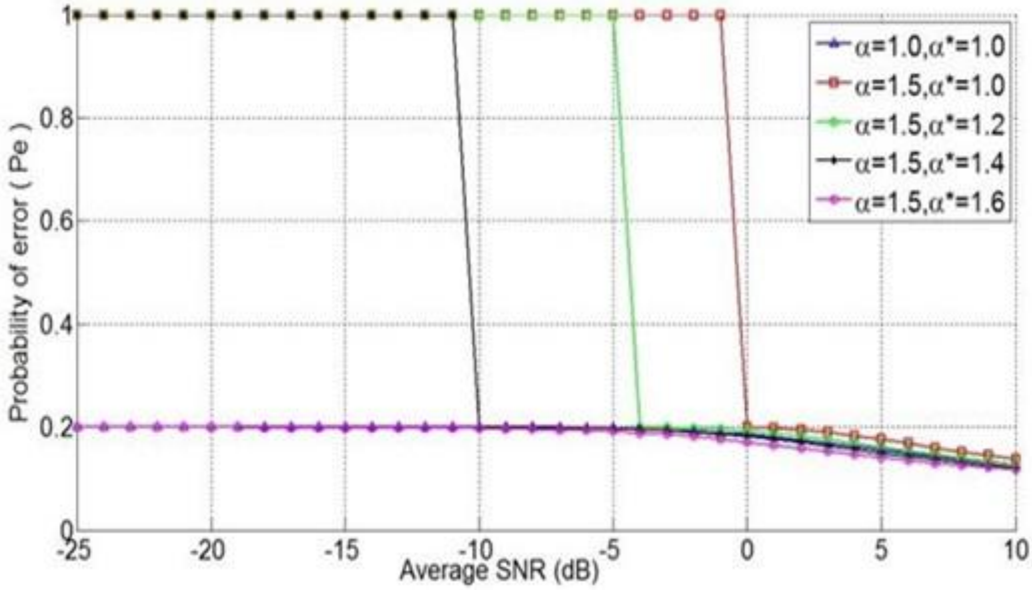


Figure 4.9 Probability of error according to an average SNR with different uncertainty factors α, α^*.

The results in Figure 4.9 show that the detection performance can effectively improve as long as the dynamic threshold factor α^* is equal to or greater than the noise uncertainty factor α. From these results we can see that for a given noise uncertainty factor $\alpha = 1.5$, and with a gradual increase of the dynamic threshold factor α^* 0.2, from an initial value of 1.0 to a final value of 1.6, the total error probability could be decreased significantly, and the value of SNR_{wall} could be reduced drastically, especially, when $\alpha^* \geq \alpha$. For instance, for $\alpha = 1.5$ and $\alpha^* = 1.0$, the value of SNR_{wall} is -0.833 (-0.79dB), while for $\alpha = 1.5$; $\alpha^* = 1.4$, the value of is SNR_{wall} -0.098 (-10dB). The results presented in this figure show that the influence of the noise uncertainty disappears completely when $\alpha = 1.5\ and\ \alpha^* = 1.6$.

Figure 4.10 illustrates the performance of the error probability as a function of sensing time for both proposed and traditional energy detection algorithms. In this simulation, we set the target *Pf**=0.05, SNR=-15 dB, PH_1=PH_0=0.5, and the bandwidth BW=1MHz. The results presented in this figure show the superiority of single-optimal threshold algorithm compared with the conventional scheme. The negative impact of noise uncertainty on the sensing time is clearly visible in this figure.

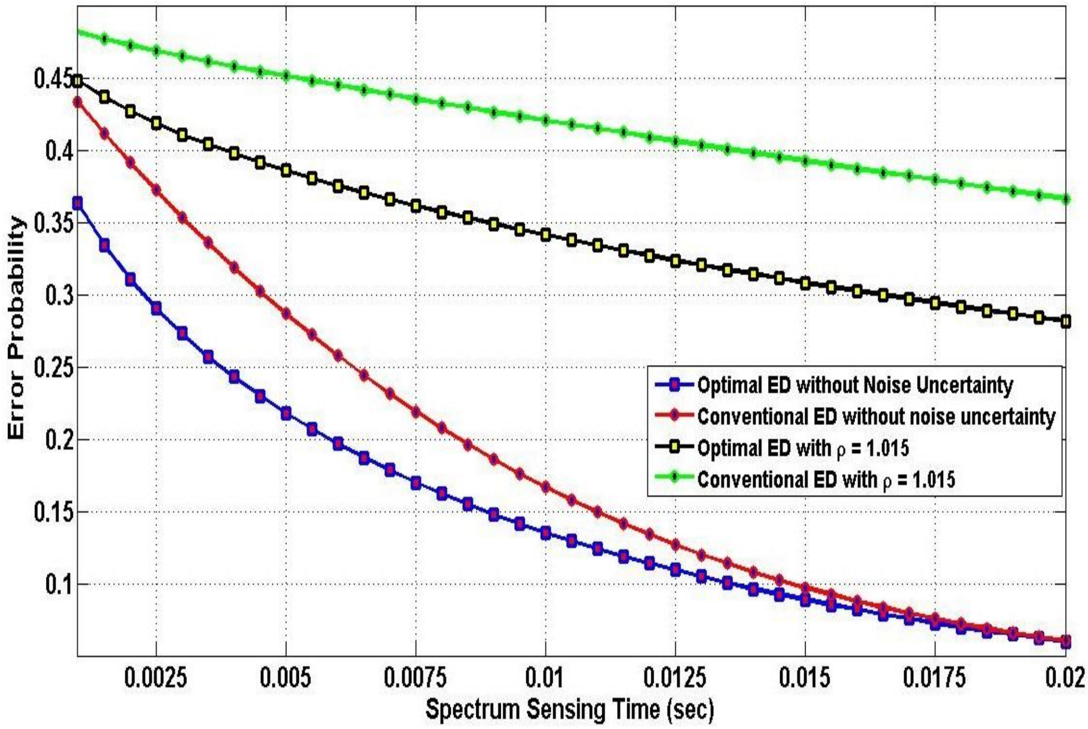


Figure 4.10 Comparison of sensing time with and without noise uncertainty

More specifically, there are two important points that could be noted here, the first point is that, regardless of the presence or absence of noise uncertainty, the proposed method gives better performance than the traditional method in terms of reducing the time of detection. For instance, in the case of absence of noise uncertainty (full noise knowledge), the sensing time that needs to meet the target error probability P_e= 0.35 in single-optimal threshold mode, which is almost (1.22ms), is less than that using conventional single-threshold mode, which is almost (3.11ms). The second important point is that for the case of noise uncertainty, the sensing time will be increased significantly due to noise uncertainty factor α. For instance, for a given target error rate P_e= 0.35, the sensing time that is required to meet this target will be almost

(8.9ms) using optimal mode, while in conventional mode the sensing time will be (23.4ms) in order to satisfy the same level of error probability.

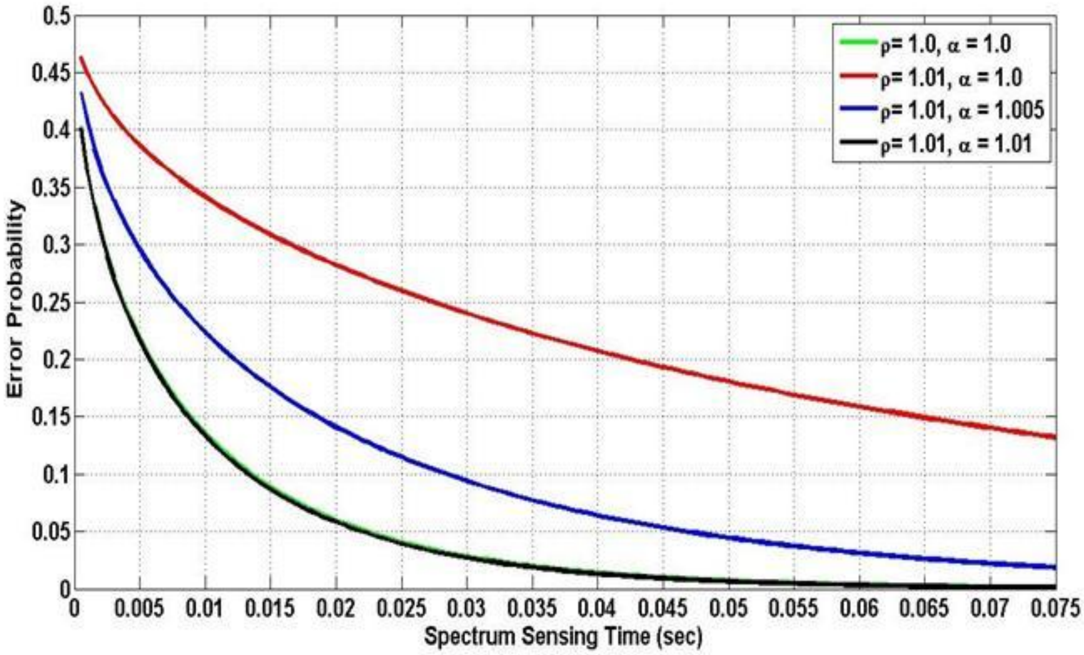


Figure 4.11 Performance of error probability versus sensing time with different values of adaptive threshold factor α and noise uncertainty factor $\boldsymbol{\rho}$

Figure 4.11 shows the advantage of adaptive optimal threshold mechanism to overcome the impact of noise uncertainty. It can be seen that the sensing time can be greatly reduced when using the proposed algorithm. For example, to satisfy the required error probability P_e=0.15; we need (64.5ms) sensing time when the noise uncertainty factor is $\rho = 1.01$, while the sensing time will be shortened to (18.5ms) when using adaptive threshold factor ($\alpha = 1.005$), and can gain more reduction down to (8.5ms) when the adaptive threshold factor equals the noise uncertainty factor. Thus, the proposed method has proved its efficiency compared to the traditional method in terms of reducing the time required for the spectrum sensing, in addition to reducing the error detection.

4.8.2 Double-Optimal Threshold Energy Detection Performance

In this subsection, the numerical results of the spectrum sensing performance using double-optimal threshold energy detection algorithm are presented. The simulation results of the single-optimal threshold algorithm and traditional energy detection algorithms are also provided for comparison. The simulation parameters for comparing performance of our proposed schemes are listed as follows: the noise power σ^2 = 1, number of samples N = 1000, SNR = -15 dB, target false alarm probability Pf^* probability of spectrum occupancy is 50%, PH_1= PH_0= 0.5.

Figure 4.12 shows the error probability in terms of detection threshold for various uncertain region factor f in double-threshold based energy detection algorithms. We can see that there is only one value of threshold that minimises the error rate, that is λ_{opt}. It can be also observed that the error rate decreases as the uncertain region factor f increases.

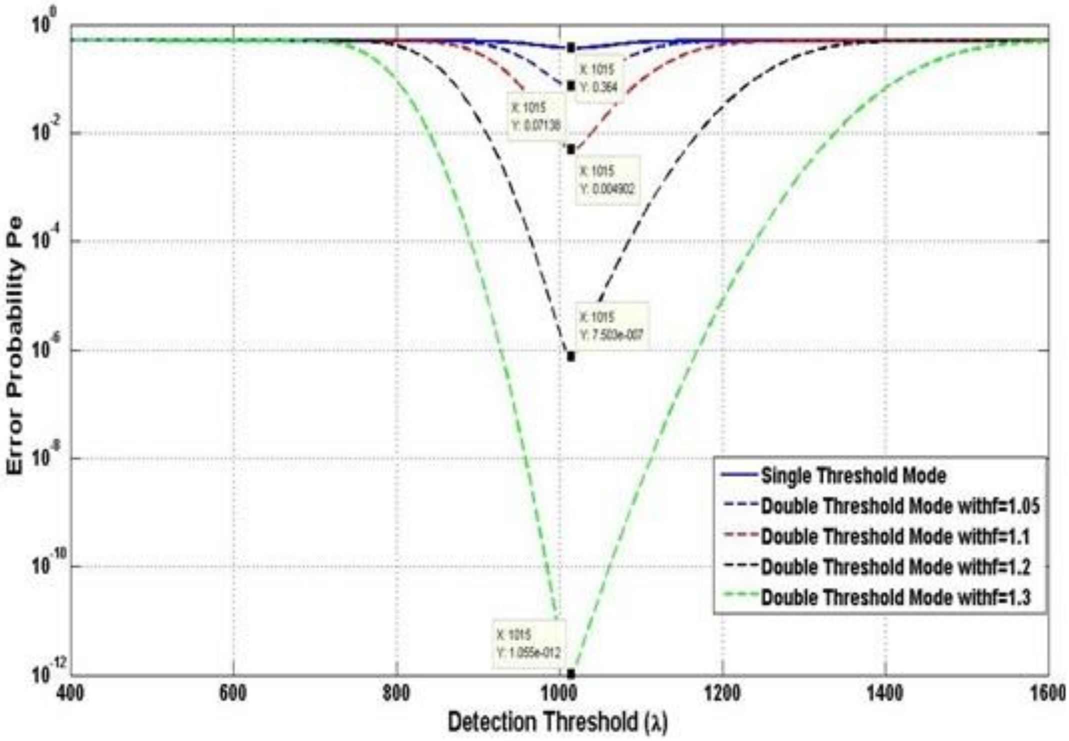


Figure 4.12 Error Probability performance versus detection threshold for different uncertain region factor f

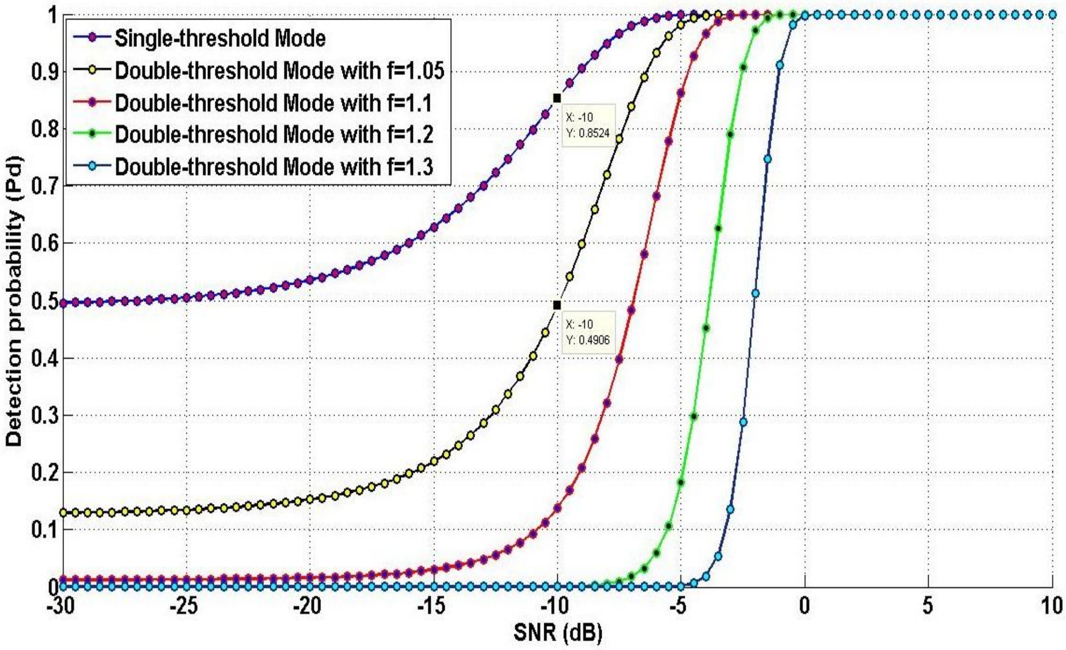


Figure 4.13 Detection performance versus SNR with various uncertain region factor f

The impact of uncertain region factor f on the detection performance of the double-optimal threshold algorithm is given in Figure 4.13. It can be seen from this figure that, increasing the factor f leads to deterioration of the detection performance. For instance, for a given value of SNR=-10 dB; the detection rate will be (0.8524) when single-optimal threshold scheme is used; while the detection rate will reduce significantly to (0.137) when double-optimal threshold with f=1.1 is used. From above, double-optimal threshold algorithm can reduce the error rate effectively, but at the cost of a further deterioration of the detection performance. Therefore, trade-off between these metrics is needed to be considered when designing the double-optimal threshold energy detection algorithm in order to meet the requirement of the application.

Figure 4.14 depicts the performance of detection rate for various energy detection algorithms, including proposed and existing schemes. The simulation parameters are assumed as: the target Pf^* =0.1, number of samples is N=100, the uncertain region factor is 1.1, PH_1=PH_0=0.5. In general, the single-threshold modes have better detection performance compared to the double-threshold mode. On the other hand, and as shown in Figure 4.14, the detection performance of the proposed optimal threshold modes is superior to the detection performance of conventional modes, especially in low SNR.

From this result, it can be concluded that the single-optimal energy detection algorithm can increase the detection accuracy and can give better detection performance compared to all other energy detection algorithms, while the double-optimal threshold scheme still gives better detection probability than other single and double threshold based conventional modes.

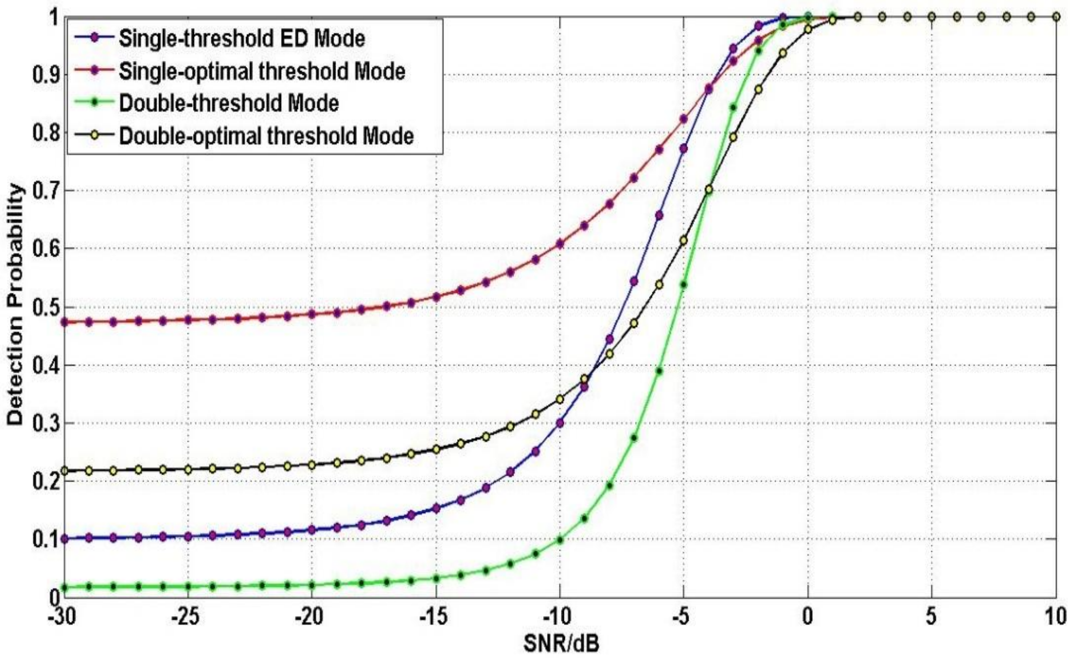


Figure 4.14 Detection probability performance versus SNR of various energy detection algorithms

Figure 4.15 illustrates the performance of error probability as a function of SNR for various energy detection algorithms. It can be shown that the error rate of double-threshold in both optimal and conventional modes are reduced greatly compared to single-threshold modes, while the double-optimal threshold mode still provides more reduction in error rate compared to the conventional double-threshold algorithm. For instance, when SNR=-10 dB, the error rates of the conventional and optimal single-threshold modes are 0.8 and 0.7341, respectively, while the levels of error rate of the conventional and optimal are decreased greatly to 0.423 and 0.2935, respectively.

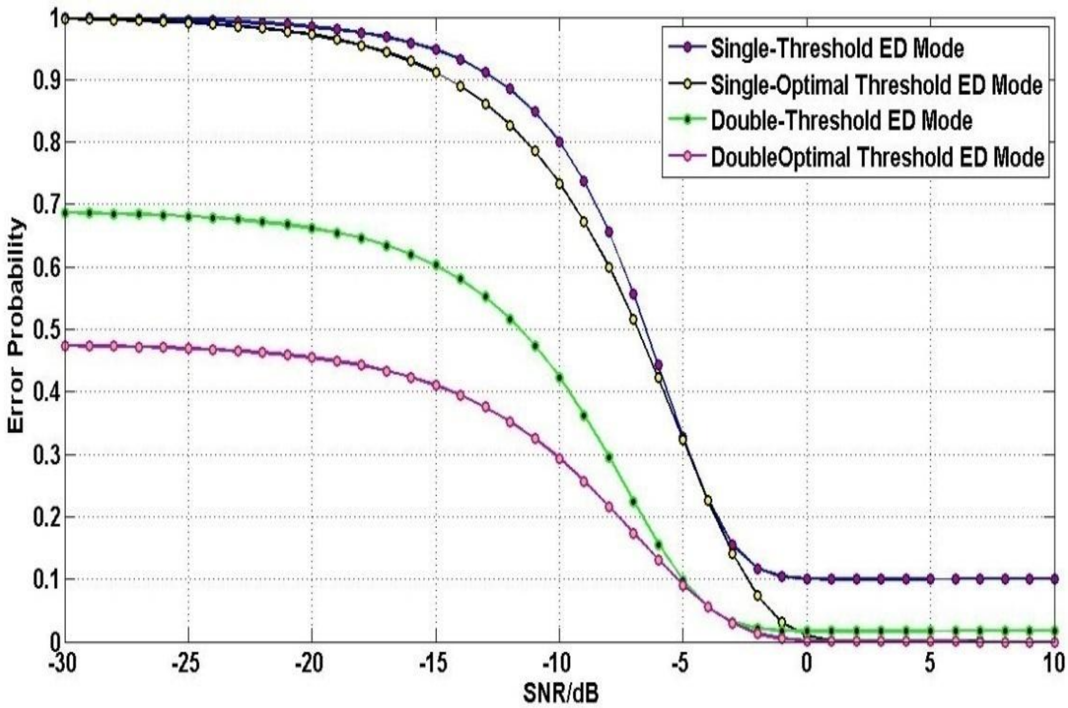


Figure 4.15 Error rate performance in terms of SNR for various energy detection schemes

The performance of the sensing time of the proposed algorithms is given in

Figure 4.16. The simulations are based on the following parameters: SNR=-20 dB; AWGN channel bandwidth BW=20MHz; uncertain factor f=1.005; PH_1=0.7; PH_0=0.3; total periodic spectrum sensing frame T=100 ms; and region uncertainty factor f=1.005. The simulation results in this figure show the superior performance of the false alarm probability of the double-threshold modes compared to those using single-threshold modes in terms of sensing time. For instance, for a given target false alarm probability Pf *=0.05, the sensing time required to meet this target using each of the conventional double threshold modes, double optimal threshold mode, conventional single threshold mode, and single optimal threshold is (1.9 ms, 2.1 ms, 4.3 ms, 7 ms), respectively. Obviously, double threshold algorithms can decrease the sensing time effectively compared to single threshold algorithms.

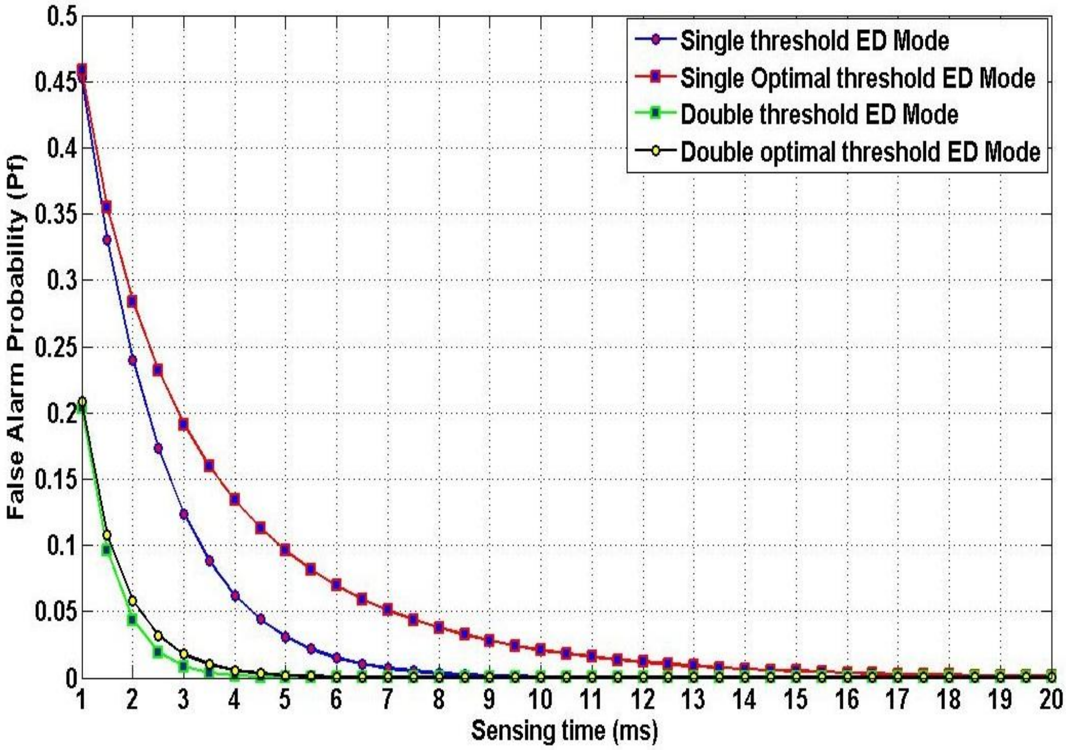


Figure 4.16 Performance of false alarm probability versus sensing time for different energy detection algorithms

4.8.3 Throughput Performance of the Proposed Algorithms

In order to verify the performance of the throughput of the proposed algorithms, we need to simulate these algorithms using a computer simulator. In our simulation, we assume the following simulation parameters and radio environment. The sensing channel SNR_S=-20 dB, cognitive radio link SNR_{Cog} =20 dB, bandwidth BW=20 MHz, desirable P_d^* =0.9, sensing period T=100 ms, and the region uncertainty factor f=1.005 in case of double threshold energy detection mode. The system diagram is illustrated in Figure 4. 17.

We aim in this evaluation to study the throughput performance of the proposed detection algorithms and compare them with existing schemes, showing the effect of both the sensing time and the probability of occupancy on the throughput values. Figure 4.18 and Figure 4.19 illustrate the achievable throughput of different energy detection based spectrum sensing algorithms for CRN, with probability of occupancy PH_1=0.4 and 0.8, respectively.

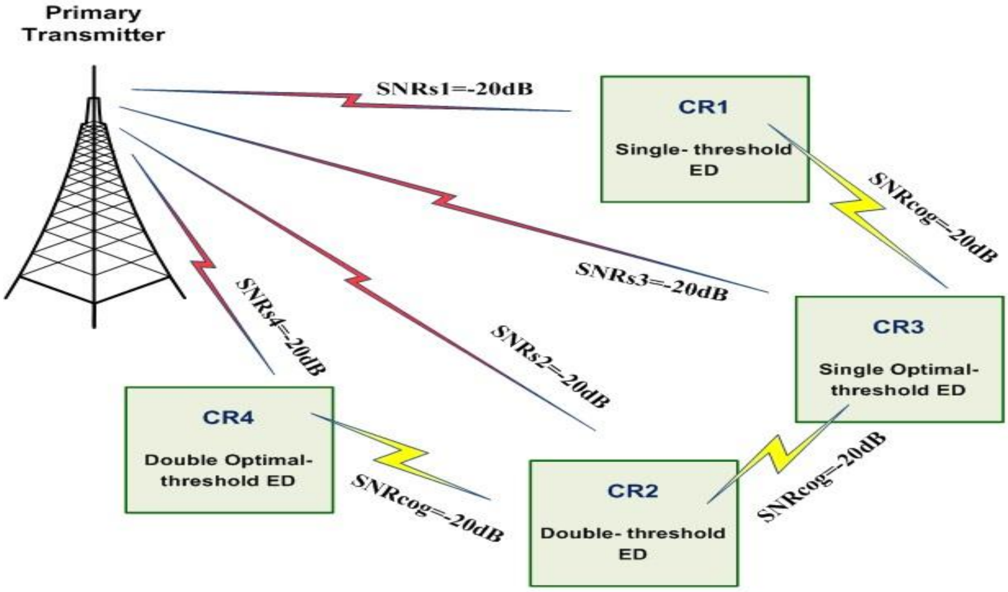


Figure 4. 17 The system diagram of the performance evaluation of proposed energy detection algorithms

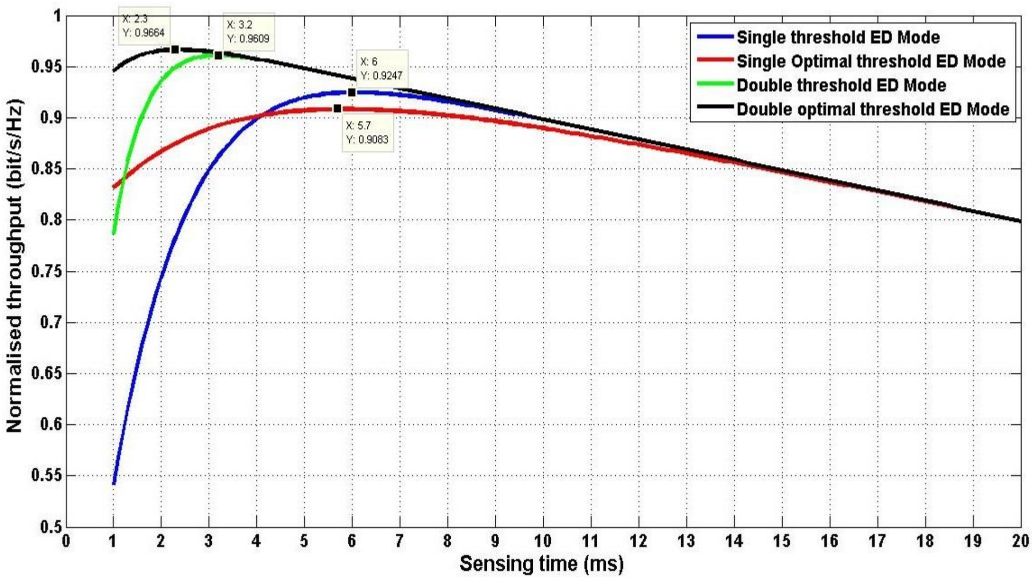


Figure 4.18 Throughput performance versus sensing time for different detection algorithms with PH_1=0.4, PH_0=0.6

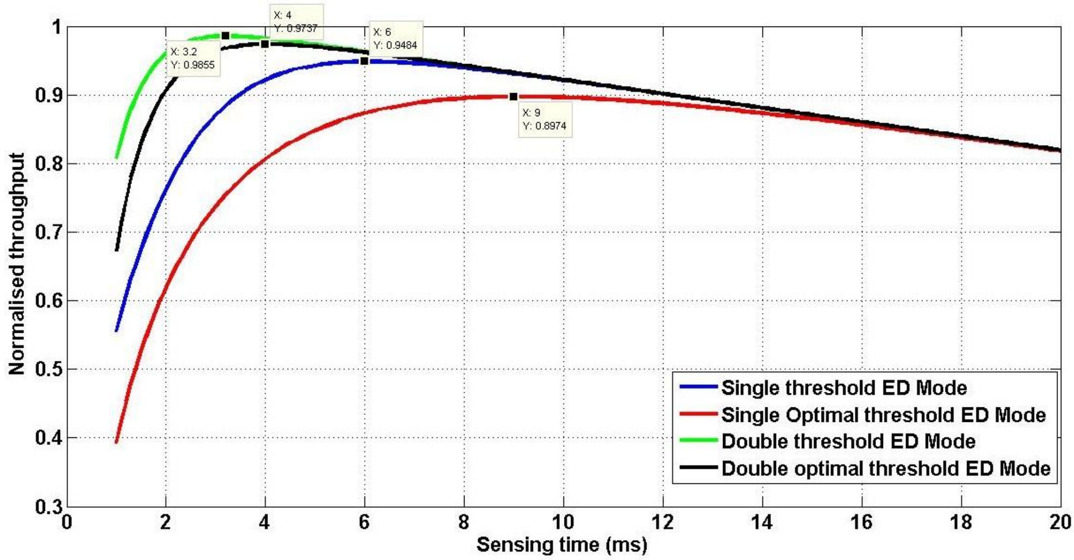


Figure 4.19 Throughput performance versus sensing time for different detection algorithms with *PH_1*=0.8, *PH_0*=0.2

As is clear from these two figures, in general, the achievable throughput of the double threshold algorithms is better than that of single threshold modes, where the maximum achievable throughput of double energy detection modes can be obtained in less sensing time compared to that in single threshold algorithms. For instance, in Figure 4.18, the maximum throughput in double optimal threshold modes can be achieved in sensing time (2.3ms), while in single optimal threshold mode the maximum throughput is obtained in sensing time almost (5.7 ms), indicating that the double optimal threshold algorithm has better performance than single optimal threshold algorithm.

We can also observe from these figures that the throughputs of the optimal energy detection algorithms can be clearly affected with the changes of probability of occupancy PH_1, while there were no significant effects in conventional energy detection modes, including single and double energy detection algorithms. For instance, the sensing time that is required to obtain the maximum achievable throughput in the single-optimal threshold algorithm can be reduced from 9 ms to 5.7 ms when the spectrum occupancy rate PH_1 changed from 0.8 to 0.4. Moreover, in double-optimal threshold modes, the sensing time that is needed to achieve the maximum throughput can also be reduced from 4 ms to 2.3 ms when PH_1 decreases from 0.8 to 0.4, showing the improvement of throughput of the optimal energy detection algorithms with the decreasing of spectrum occupancy rate.

4.9 Summary

In this chapter, novel energy detection algorithms for single user spectrum sensing have been developed. This work aims at minimising the probability of total detection error under noise uncertainty, by proposing an optimal threshold energy detection algorithm. I derived the closed form expression of the optimal detection threshold based on trade-offs between misdetection probability P_m and the probability of false alarm P_f. I discussed the effect of noise uncertainty on the performance of our optimal threshold scheme, and developed a dynamic optimal threshold factor α^* to combat the noise uncertainty. The simulation results show the advantages of this mode as long as the value of dynamic threshold factor $\alpha^*$is equal to or greater than the noise uncertainty coefficient α.In addition, the results proved the effectiveness of this method on reducing the error probability, especially in low SNR.

In order to validate the work in this chapter, the sensing performance of the proposed energy detection has been compared with that of existing energy detection algorithms [17, 20], and showed the superiority of its performance by simulation results. The results have been published in IEEE (ISCC2012) [28], which gives more confidence on obtained results.

Furthermore, I proposed a new double-optimal threshold scheme, which provides more reduction in error probability. The performance of the proposed detection algorithm has been analysed and compared with other existing approaches. The detection performance and the throughput of the cognitive network are discussed, and they demonstrated the effectiveness of the double optimal threshold method on reducing the error rate, but at the cost of decreasing the detection accuracy. Therefore, there is a need for a trade-off between error rate level and detection level when determining the detection thresholds.

Chapter 5

Cooperative Spectrum Sensing Based Optimisation Scheme

5.1 Introduction

CRNs are essentially designed to provide more spectrum resources for future wireless technologies. This requires each CR user within the network to perform spectrum sensing before utilising the spectrum in order to prevent any harmful interference to the primary network. In practice, the sensing channel between the primary transmitter and the CR user may suffer from fading and shadowing, which leads to a difficulty in obtaining an accurate spectrum sensing. CSS mechanism can solve this issue effectively by exploiting the feature of spatial diversity.

In this work, we consider an infrastructure CRN consisting of one FC and multiple CR users interested in sensing a certain spectrum channel, which is licensed for PUs to use it for communication without interfering with the primary network. For this CSS application, the optimisation method is considered as the best and most effective way to get accurate detection at the FC, but at the cost of computational complexity leading to a lot of time to implement spectrum sensing. Furthermore, most existing CSS approaches are based on using energy detection for local sensing with the assumption that noise power can be accurately estimated. However, in practice this is difficult and the noise uncertainty at the local sensing degrades the sensing performance even if CSS strategies are adopted. Therefore, this issue needs to be considered in the design of the CSS algorithm.

In this work I address these challenges by adopting adaptive optimal energy detection algorithm at the local sensing, which is presented in the previous chapter, and using an optimal decision fusion rule at the FC to get the final decision on spectrum occupancy. This offers a possibility to minimise the computational complexity by determination of the optimal detection threshold based on minimising local error probability rather than total error probability. Unlike existing optimisation algorithms for cooperative spectrum sensing in which noise uncertainty is not considered as local sensing, in this work the impact of noise uncertainty is also considered while optimising the detection performance at the FC.

The presented work in this chapter is organised as follows: Section 5.2 will give an overview of recent optimisation algorithms for cooperative spectrum sensing. In section 5.3 we will present our cooperative spectrum sensing scheme, and analyse its performance mathematically. The evaluation of our algorithm will be provided in section 5.4. Finally, in section 5.5 we will present a summary of this chapter.

5.2 Background

In practical CRNs, low SNR, fading and shadowing, and sensing time constraints, may cause a single detector to fail to sense the presence of the PU, which prompted the researchers to propose CSS. The detection performance of CSS algorithms are dependent on three main metrics, local sensing; reporting channel condition; and the fusion rules used at the FC. Energy detection algorithm is commonly used as a local sensing mechanism in CSS algorithms.

Recent research in CSS has been concentrated on one or two of the CSS metrics in order to improve the sensing efficiency [22-27, 129, 134-137]. For instance, the optimal detection threshold of local sensing has been determined numerically based on minimisation of the total error probability at the FC in [26, 136], which takes a lot of time to implement due to computational complexity. In [22], the authors presented the optimisation of CSS based on both Constant Detection Rate (CDR) and Constant False Alarm Rate (CFAR), and showed that the optimal detection performance can be obtained through the cooperation of a certain number of users with high sensing channel SNR rather than all cooperative users.

However, all above optimisation CSS approaches are grounded on an ideal wireless environment, and made upon the assumption that the noise power is totally known at each cognitive user, and the impact of noise uncertainty on the detection threshold setting has not been considered. In a realistic wireless environment, these assumptions become impractical and cause deterioration in the performance of CSS, especially in law SNR environment.

In this work, I propose a different optimisation mechanism for centralised CSS through the expansion of my previous work in [28] to encompass the CSS. Instead of determining the optimal threshold of the local sensing that minimises the total error rate at the FC, which increases the computational complexity, I determine the optimal threshold based on minimising the local error rate in the same way as [28], and then the optimum value of the total error rate can be obtained by using the optimal decision rule at the FC. I also consider the noise uncertainty at the local sensing, which increases the total detection accuracy especially in low a SNR environment.

5.3 Cooperative Spectrum Sensing Optimisation Algorithm

In my work I consider a scenario for CR application where a CRN with M of CRs and one FC wants to exploit the unused primary TV channels network, also called TV white spaces. The system framework used in our work is illustrated in Figure 5.1.

We assume the primary transmitter PT and the FC are far apart, so the relative distances between any two CRs are much smaller than their distances to the PT, then, the primary signal received by each cognitive user can be assumed to be independent and identically distributed. We also assume that the reporting channels (links between CRs and the FC) are under bandwidth limited, therefore, we employ a one-bit hard decision fusion rule at the FC rather than the data fusion rule; which needs to exchange a large number of bits with the FC.

In order to utilise the TV channels opportunistically, the CRs are required to perform cooperative spectrum sensing first, and then if the white spaces are detected they will be allowed to access the spectrum safely.

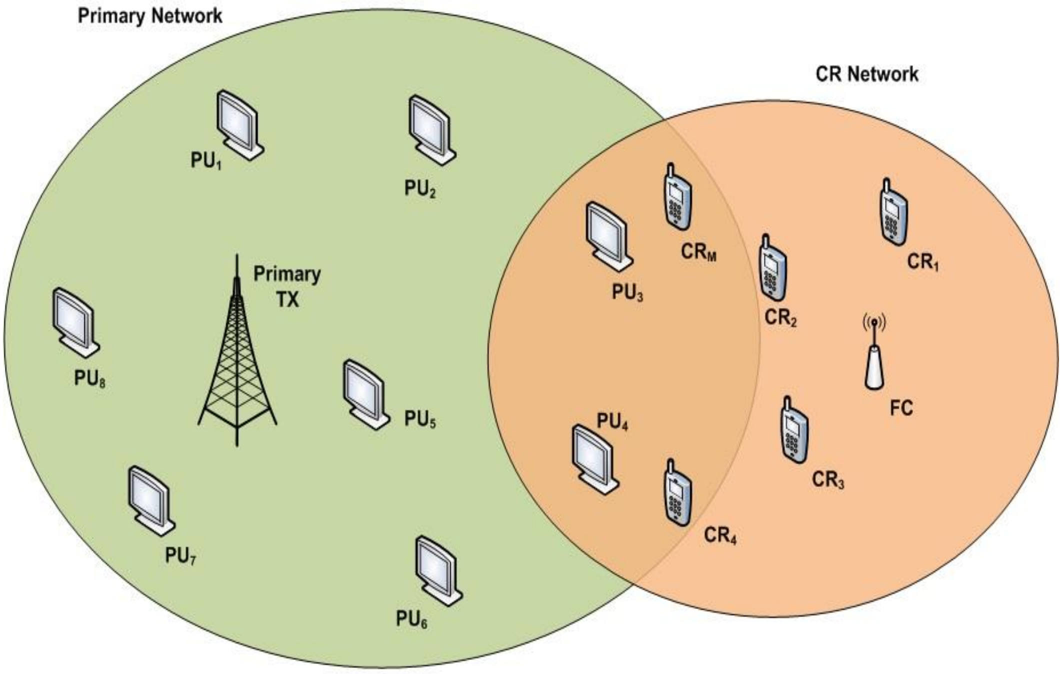


Figure 5.1 A Cognitive Radio Network Opportunistically Using the Spectrum Licensed to a primary TV broadcast network.

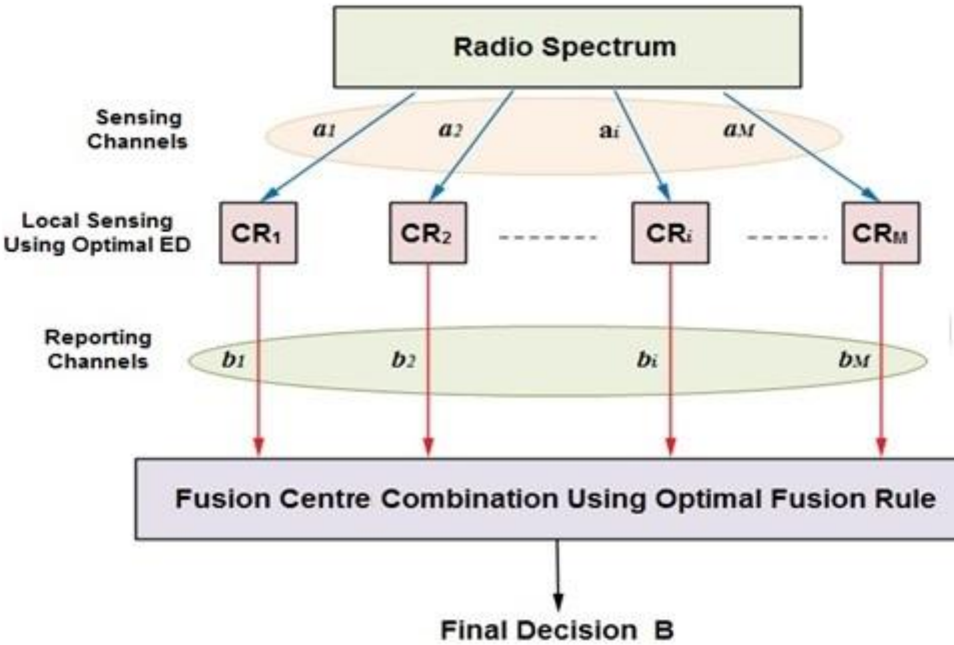


Figure 5.2 Cooperative Spectrum Sensing Optimisation Model.

In overlay spectrum access approaches, the CRs need to perform periodical and precise sensing to observe the primary system activities. In this work, we present a new cooperative spectrum sensing scheme based on adaptive optimal energy detection to increase the accuracy of spectrum sensing, especially in a low SNR environment. The procedure of our CSS scheme is given in Figure 5.2, where each CR_i (i =1,2,….,M) performs local spectrum sensing individually using the adaptive optimal energy detection algorithm [28], then makes its binary decision b_i and forwards it to the FC. Finally, the FC combines all those local decisions using the optimal decision fusion rule to make a final decision B whether the spectrum is occupied or vacant. Here, we consider the optimisation of CSS when optimal ED and optimal decision fusion are used. Furthermore, to make our detection design more practical and realistic, the impact of noise uncertainty and the reporting channel error are applied.

5.3.1 Local Spectrum Sensing

For local spectrum sensing mechanism, I adopt the adaptive optimal threshold energy detection algorithm which presented in Chapter 4. This energy detection algorithm provides more reliable and accurate detection performance [28]. In this energy detection algorithm, the optimal detection threshold was determined based on minimising the error probability *Pe*, which can increase the spectrum utilisation efficiency while providing more protection to the primary users. In order to study the detection performance of the proposed spectrum sensing scheme, we need to determine the detection metrics *Pd*, *Pf*, and *Pm*, respectively. To avoid repetition, we can use the equations derived in Chapter 4. All the mathematical analyses of these spectrum sensing metrics can be found in sections 4.3, 4.4, 4.5, and 4.6.

5.3.2 Optimisation of Cooperative Spectrum Sensing

Existing contributions in the area of cooperative spectrum sensing optimisation focus on determining the optimal detection threshold numerically, which will add more time to implement for its computational complexity. In this section, we investigate the optimality of cooperative spectrum sensing when optimal energy detection for local sensing and optimal counting fusion rule are applied.

At the FC, in order to make an accurate spectrum sensing decision, the FC needs to employ an appropriate fusion technique. Decision fusion rules are often carried out centrally at the FC as a counting (*K* out of *M*) logical functions, which include the AND, OR, and majority rule as special cases. This means that if K or more CR users decide hypothesis H_1, then the final decision B will be H_1 [138].

$$B = \begin{cases} 1 & if \sum_{i=1}^{M} b_i \geq K \\ 0 & otherwise, \end{cases} \tag{5 - 1}$$

where b_i denotes the single local decision of i^{th} CR user.

In practice, most of the reporting channels between CR users and the FC are imperfect due to fading and shadowing, thus, error may occur during sending the sensing decisions to FC. In such a case, we can model the reporting channels as binary symmetric channels with error probability *Pe*, and the detection and the false alarm probabilities at the FC can be represented, respectively, as [139]:

$$PD_i = P_{d,i}(1 - Pe_i) + \left(1 - P_{d,i}\right)Pe_i \tag{5 - 2}$$

$$Q_d = \sum_{j=k}^{M} \binom{M}{j} (PD_i)^j (1 - PD_i)^{M-j} \tag{5 - 3}$$

$$PF_i = P_{f,i}(1 - Pe_i) + \left(1 - P_{f,i}\right)Pe_i \tag{5 - 4}$$

$$Q_f = \sum_{j=k}^{M} \binom{M}{j} (PF_i)^j (1 - PF_i)^{M-j} \tag{5 - 5}$$

Where $P_{d,i}$ and $P_{f,i}$ are the probability of detection and the false alarm probability of the i^{th} CR user at local sensing, respectively, while PD_i and PF_i represent the detection and false alarm probabilities of the i^{th} CR user received at the FC, respectively.

When the reporting channels between CR users and the FC are perfect and free of error, the sensing results will be sent correctly to the FC, thus, the detection and the false alarm probabilities of each CR user will be the same at the FC. According to (5-3) and (5-5), the probabilities of detection Q_d and false alarm Q_f at FC can be written based on binomial distribution, respectively, as:

$$Q_d = \sum_{m=K}^{M} \binom{M}{m} P_{d,i}^{\ \ m} (1 - P_{d,i})^{M-m} \qquad (5 - 6)$$

$$Q_f = \sum_{m=K}^{M} \binom{M}{m} P_{f,i}{}^{m} (1 - P_{f,i})^{M-m} \qquad (5 - 7)$$

where $P_{d,i}$ and $P_{f,i}$ are the probability of detection and the false alarm probability of the i^{th} CR user, respectively.

Clearly, when K=1, the equation (5-6) represents the OR rule and written as

$$Q_{d,OR} = \sum_{m=1}^{M} \binom{M}{m} P_{d,i}^{\ \ m} (1 - P_{d,i})^{M-m} \qquad (5 - 8)$$

$$\begin{aligned} Q_{d,OR} = & \sum_{m=0}^{M} \binom{M}{m} P_{d,i}^{\ \ m} \left(1 - P_{d,i}\right)^{M-m} \\ & - \binom{M}{m} P_{d,i}^{\ \ m} \left(1 - P_{d,i}\right)^{M-m} \Big|_{m=0} \end{aligned} \qquad (5 - 9)$$

$$Q_{d,OR} = 1 - \left(1 - P_{d,i}\right)^{M} \qquad (5 - 10)$$

In the case of double-optimal ED at the local sensing, the $P_{d,i}$ can be obtained using (4-41) in chapter 4.

The equation (5-6) represents the AND rule when K=M, then it becomes

$$Q_{d,AND} = \sum_{m=M}^{M} \binom{M}{m} P_{d,i}^{\ \ m} \left(1 - P_{d,i}\right)^{M-m} \qquad (5 - 11)$$

$$Q_{d,AND} = P_{d,i}{}^{M} \qquad (5 - 12)$$

Finally, the detection probability of majority rule can be determined by setting $m = \lceil M/2 \rceil$, and then the equation (5-6) becomes:

$$Q_{d,maj} = \sum_{m=M/2}^{M} \binom{M}{m} P_{d,i}{}^{m} (1 - P_{d,i})^{M-m} \qquad (5 - 13)$$

Based on the assumption that the distance between the primary transmitter and any CR user is large compared with the distance between any two CR users, we can assume that the SNR of the sensing channel at each CR user is identical, $\gamma_1 = \gamma_2 \ldots\ldots = \gamma_M = \gamma$. Furthermore, in the case of an AWGN environment, we assume that all CR users use the same detection threshold λ_i, implying $P_{f,1} = P_{f,2} = \ldots\ldots. = P_f$, and $P_{d,1} = P_{d,2} = \ldots\ldots. = P_d$. therefore, the overall false alarm and the detection probabilities are given based on voting fusion rule, respectively, by:

$$Q_f = \sum_{m=K}^{M} \binom{M}{m} P_f{}^{m} \left(1 - P_f\right)^{M-m} \qquad (5 - 14)$$

$$Q_d = \sum_{m=K}^{M} \binom{M}{m} P_d{}^{m} (1 - P_d)^{M-m} \qquad (5 - 15)$$

There are two main criteria to assess the performance of spectrum sensing: maximizing the detection probability for a given target of false alarm probability (Neyman-Pearson criterion), or minimising the total error probability based on some optimal parameters (Bayesian criterion). Here, we consider the optimality of CSS under the Bayesian criterion, which is more practical in situations where the a priori probabilities of the two hypotheses H_1 and $H_0$are assumed to be known. For binary hypothesis test problem, four possible cases can occur: 1) decide H_0 when $H_0$is true; 2) decide H_0 when H_1 is true; 3) decide H_1 when H_0 is true; 4) decide H_1 when H_1 is true.

Another assumption, which the Bayesian paradigm is based on, is that a cost is assigned to each possible decision. The goal in the Bayesian criterion is to determine the decision rule so that the average cost, also known as Bayesian risk R, is minimised. Under this criterion, we can define the Bayesian risk of CSS as [26]:

$$R = \sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij}\, P\left(H_i \middle| H_j\right)\, PH_j \tag{5 - 16}$$

$$\begin{aligned} R = {} & C_{00}P(H_0|H_0)\, PH_0 + C_{01}P(H_0|H_1)\, PH_1 \\ & + C_{10}P(H_1|H_0)\, PH_0 + C_{11}P(H_1|H_1)\, PH_1 \end{aligned} \tag{5 - 17}$$

$$\begin{aligned} R = {} & C_{00}\left(1 - Q_f\right)PH_0 + C_{01}(1 - Q_d)P + C_{10}Q_f\, PH_0 \\ & + C_{11}Q_d\, PH_1 \end{aligned} \tag{5 - 18}$$

Where C_{00}, C_{01}, C_{10}, *and* C_{11}represent the cost of correct identification of unused spectrum, mis-detection, false alarm, and correct detection, respectively. Observe that the terms1 and 4 of the right side in (5-18) represent the correct decisions, while the terms 2 and 3 are the error decisions. Clearly, in wireless digital communications, making a wrong decision is always more costly than making a correct decision, that’s, C_{01}>C_{11}&C_{10}>C_{00}. Note that, if we choose the cost of an error decision to be “1” and the cost of a correct decision to be “0”; that is, C_{00} =C_{11}=0&C_{10} =C_{01} =1. Thus, the Bayes average risk in (5-18) can be reduced to the average error probability as [129]:

$$Q_e = Q_m PH_1 + Q_f\, PH_0 \tag{5 - 19}$$

Substituting (5-6) and (5-7) into (5-18), and since the Q_m=1-Q_d, we have the error probability represent as:

$$\begin{aligned} Q_e = {} & \left[1 - \sum_{m=K}^{M} \binom{M}{m} P_d^{\;m} (1 - P_d)^{M-m}\right] PH_1 \\ & + \left[\sum_{m=K}^{M} \binom{M}{m} P_f^{\;m} \left(1 - P_f\right)^{M-m}\right] PH_0 \end{aligned} \tag{5 - 20}$$

My goal here is to determine the optimal K that minimises the total error probability Q_e. In [136], the optimal decision fusion rule that minimises the overall probability of error was given, which proved that the half-voting rule (majority rule) is an optimal fusion rule, and the optimal K_{opt} was found to be:

$$K_{opt} = min\left(\left\lceil \frac{M\, ln\left(\frac{1-P_f}{P_m}\right)}{ln\left(\frac{P_d}{P_f}.\frac{1-P_f}{P_m}\right)} \right\rceil, M\right) \tag{5 - 21}$$

Where $\lceil . \rceil$ is the ceiling function.

In my work, I consider the optimality of CSS under Bayesian assumption, where the a priori probability of the spectrum occupancy is assumed to be known, thus, the optimisation of CSS will be represented as the following problem:

$$\min_{1 \le K \le M} Q_e(K) \tag{5 - 22}$$

We can simplify (5-16) using the fact that

$$(P_d + (1 - P_d))^M = \left[\sum_{m=0}^{M} \binom{M}{m} P_d{}^m (1 - P_d)^{M-m}\right] = 1 \tag{5 - 23}$$

We have

$$\begin{aligned} Q_e = \Bigg[1 - \sum_{m=0}^{M} \binom{M}{m} P_d{}^m (1 - P_d)^{M-m} \\ + \sum_{m=0}^{K} \binom{M}{m} P_d{}^m (1 - P_d)^{M-m} \\ + \binom{M}{m} P_{d,i}{}^m (1 - P_d)^{N-m}|_{m=K}\Bigg] PH_1 + \end{aligned} \tag{5 - 24}$$

$$\begin{aligned} \left[\sum_{m=0}^{M} \binom{M}{m} P_f{}^m (1 - P_f)^{M-m} - \sum_{m=0}^{K} \binom{M}{m} P_f{}^m (1 - P_f)^{M-m} \right. \\ \left. - \binom{M}{m} P_f{}^m (1 - P_f)^{M-m}\Big|_{m=K}\right] PH_0 \end{aligned}$$

Then,

$$Q_e(K) = \left[1 + \binom{M}{K} P_d{}^{K} (1 - P_d)^{M-K}\right] PH_1 - \left[\binom{M}{K} P_f{}^{K} \left(1 - P_f\right)^{M-K}\right] PH_0 \tag{5 - 25}$$

The minimum probability of error and the corresponding optimal K can be obtained by applying the first partial derivative for (5-21) and then find the solution of:

$$\left.\frac{\partial Q_e(K)}{\partial K}\right|_{K=K_{opt}} = 0 \tag{5 - 26}$$

$$\frac{\partial Q_e(K)}{\partial K} = \left[\ln K \binom{M}{K} P_d{}^{K} (1 - P_d)^{M-K} - \ln(M - K) \binom{M}{K} P_d{}^{K} (1 - P_d)^{M-K}\right] PH_1 - \left[\ln K \binom{M}{K} P_f{}^{K} \left(1 - P_f\right)^{M-K} - \ln(M - K) \binom{M}{K} P_f{}^{K} \left(1 - P_f\right)^{M-K}\right] PH_0 = 0 \tag{5 - 27}$$

$$PH_1\left[P_d{}^{K}(1 - P_d)^{M-K}\right] - PH_0 \left[P_f{}^{K}\left(1 - P_f\right)^{M-K}\right] = 0 \tag{5 - 28}$$

This can be simplified as follows:

$$\frac{P_d}{P_f}\left(\frac{1 - P_f}{1 - P_d}\right)^{K} = \frac{PH_0}{PH_1}\left(\frac{1 - P_f}{1 - P_d}\right)^{M} \tag{5 - 29}$$

Taking the natural logarithm for two sides of the equation, we obtain the following:

$$\mathrm{K} \ln\left[\left(\frac{1 - P_f}{1 - P_d}\right)\frac{P_d}{P_f}\right] = \ln\left[\frac{PH_0}{PH_1}\left(\frac{1 - P_f}{1 - P_d}\right)^{M}\right] \tag{5 - 30}$$

$$K = K_{opt} = \frac{\ln\left[\frac{PH_0}{PH_1}\left(\frac{1-P_f}{1-P_d}\right)^{M}\right]}{\ln\left[\left(\frac{1-P_f}{1-P_d}\right)\frac{P_d}{P_f}\right]} \tag{5 - 31}$$

5.3.3 Time Model of Optimisation CSS scheme

It is desirable in CR applications to make spectrum sensing time much lower than the transmission time that is allocated for communication, so that the throughput of CR networks can be increased. In CSS mechanisms, the sensing period within each spectrum sensing frame is divided into local sensing time and reporting time; which depends on the number of cooperative users.

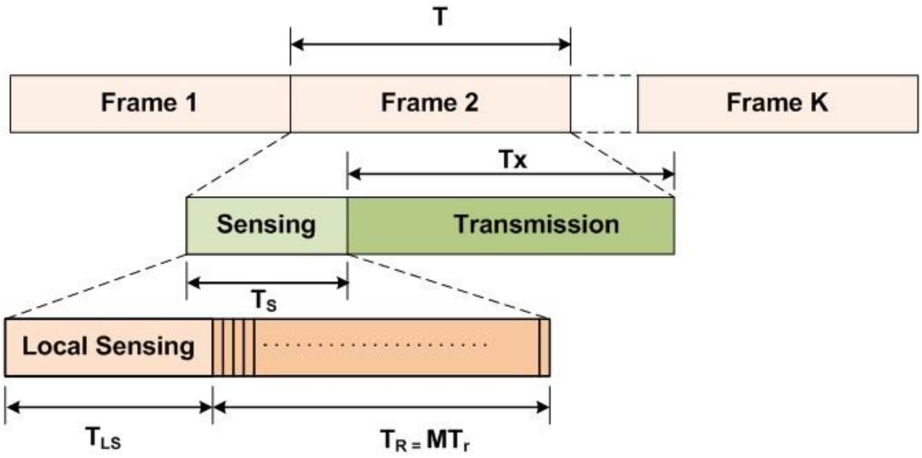


Figure 5.3 Spectrum Sensing Time Structure of Conventional CSS Scheme

As illustrated in Figure 5.3, the spectrum sensing time T_S of CSS schemes can be reduced by decreasing both local sensing time T_{LS} and reporting time T_R simultaneously. The spectrum sensing time T_S of the conventional CSS schemes can be given as :

$$T_S = T - T_X \tag{5 - 32}$$

Where T denotes the total frame time, and T_X represents the transmitting time.

Using Figure 5.3, the sensing time T_S can be given as:

$$T_S = T_{LS} + T_R \tag{5 - 33}$$

Then:

$$T_S = T_{LS} + M * T_r \tag{5 - 34}$$

Obviously, local sensing time T_{LS} = N/BW depends mainly on the number of samples N and the bandwidth BW of the sensing channel, and practically T_S is often determined to a certain value depending on the type of application. As proved in chapter four, our local optimal ED method can achieve a target error rate in less time compared to that in traditional ED algorithms. On the other hand, the reporting time T_R depends basically on the number of CR users and the time slot of each CR user T_r, which in turn relies on the BW of the sensing channel, where T_r =1/BW. However, reporting time T_R may make the spectrum sensing time unreasonably long when the number of cooperative users M is very high. Thus, cooperating a number of CR users M^* that achieves a target of detection error rate Q_e* instead of participating all CR users M can play a significant role in reducing the overall spectrum sensing time T_S.

In order to reduce the reporting time T_R, first, at each reporting slot time *Tr;* the FC calculates K_{opt} and Q_e using (5-21) and (5-20), respectively, then compares the calculated Q_e with the desired one Q_e*, where the number of cooperative users M* will be increased after each reporting slot time T_r. Finally, the number of CR users M* can be determined when $Q_e \leq Q_e$*, where $1\leq M* \leq M$.

Thus, the new expression of the sensing time T_S^* in our optimal CSS algorithm can be given as:

$$T_S^* = T_{LS}^* + M^* T_r \qquad (5 - 35)$$

Where T_{LS}^* is the sensing time of our local spectrum sensing, and M* denotes the required number of CR users to achieve a target Q_e*.

5.4 Evaluation of Optimisation CSS scheme

To further validate the above mathematical analysis, we will give the simulation of our CSS scheme in terms of detection efficiency and sensing time delay. In these simulations, our optimised CSS algorithm is compared with other centralised CSS schemes, such as the schemes in [27, 136]. The simulation of the proposed CSS optimisation scheme is conducted under the following assumptions and parameters:

- Both the cognitive radio and the primary networks are static, therefore, the wireless communication conditions during each sensing period can be considered constant.

- Only one spectrum channel is sensed over each sensing period, and the additive white Gaussian noise AWGN channel is considered.

- In all the following simulations, the number of samples at the local sensing N=500 with noise variance $\sigma_n^2 = 1$, and the number of cooperative users is M=10, and any change in the simulation parameters will be mentioned later. .

Our goals through these simulations are in two axes:

1. Study and verification of the various optimisation parameters in CSS algorithm.
2. Evaluate the performances of the proposed CSS approach in terms of detection accuracy and sensing time delay.

In our proposed CSS algorithm, the optimisation parameters for both local spectrum sensing and CSS are considered, where the optimal detection threshold at the local spectrum sensing and the optimal voting rule K_{opt} at the FC are determined based on minimising the total error rate.

5.4.1 Simulation of Optimisation Parameters in CSS Scheme

The following simulations aim to determine the optimal selections of the local sensing threshold λ and the number of voting fusion rules K in order to minimise the probability of total detection error Q_e that may occur during spectrum sensing. The obtained minimum values of Q_e for all possible values of K from K=1 to K=10 conducted in AWGN detecting channel for both cases of spectrum occupancy PH_1=0.3 and PH_1=0.5 are presented in Table 5.1 and

Table 5.2, respectively.

K	1	2	3	4	5	6	7	8	9	10
λ_{opt1}	574	557	546	537	528	520	512	503	492	476
Q_{e1}	0.0760	0.0410	0.0300	0.0260	0.0250	0.0270	0.0317	0.0414	0.0618	0.1155
λ_{opt2}	526	526	526	526	526	526	526	526	526	526
Q_{e2}	0.4500	0.3220	0.1716	0.0680	0.0273	0.0388	0.1044	0.2260	0.3690	0.4690

Table 5.1 Total detection error rates Q_e against optimal local threshold λ_{opt} and voting rule number with spectrum occupancy (PH_1=0.5, PH_0=0.5)

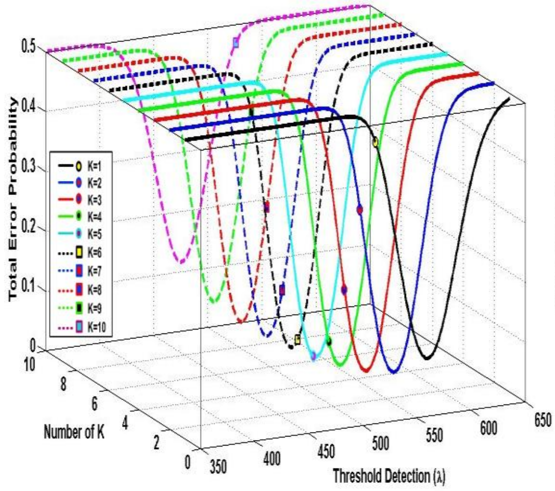
K	1	2	3	4	5	6	7	8	9	10
λ_{opt1}	580	561	549	540	531	523	515	506	495	481
Q_{e1}	0.0738	0.0387	0.0277	0.0235	0.0224	0.0237	0.0274	0.0351	0.0511	0.0912
λ_{opt2}	543.7	543.7	543.7	543.7	543.7	543.7	543.7	543.7	543.7	543.7
Q_{e2}	0.4073	0.1415	0.0371	0.0282	0.0655	0.1315	0.2055	0.2621	0.2904	0.2989

Table 5.2 Total detection error rates Q_e against optimal local threshold λ_{opt} and voting rule number K with spectrum occupancy (PH_1=0.3, PH_0=0.7)

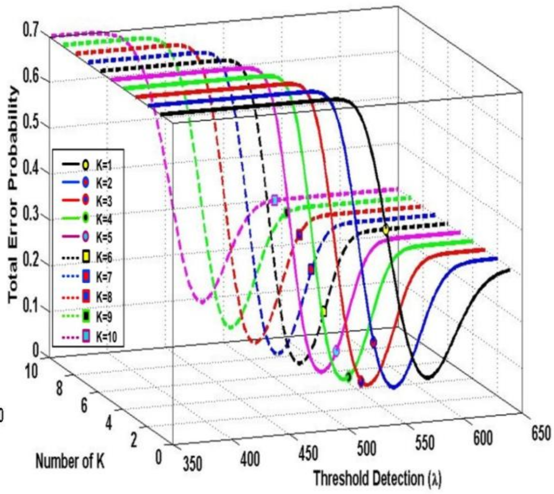
Values λ_{opt1} and Q_e represent the optimal local threshold that is determined numerically and its related total error rate, respectively, while λ_{opt2} and Q_{e2} denote the optimal local threshold which is calculated mathematically, and its related total error rate, respectively. As seen in Table 5.1, when 50% of the spectrum is occupied, the optimal fusion rule over all the examined range of local detection threshold that gives the minimum total error rate in both existing [27, 136] and proposed methods is K_{opt}=5. When the spectrum occupancy is set to PH_1=0.3 and PH_0=0.7 as shown in

Table 5.2, the optimal fusion rule remained the same without changing K_{opt}=5 under existing optimisation methods, while it reduced to K_{opt}=4 when the proposed algorithm is used.

These simulation results are illustrated in Figure 5.4 (a) and (b), where the local detection threshold is examined within the range of λ=350 and λ=650 numerically in order to get the optimal value that minimises the total error rate as the same way in existing methods. In our optimisation method we get the minimum total error rate by determining the optimal local detection threshold λ_{opt} and the optimal fusion rule K_{opt} mathematically using the equation of optimal detection threshold in (4-15); which was derived in chapter 4, and the equation of optimal fusion rule in (5-31).



(a) PH_1=0.5, PH_0=0.5



(b) PH_1=0.3, PH_0=0.7

Figure 5.4 Total detection error rate Q_e versus voting number *K* and local detection threshold λ with average SNR=-10dB

The results show in the tables and figures above that our scheme is less complex and does not incur additional time to find the optimal threshold numerically, although there is a slight difference between the values of the total error rate that have been obtained using existing methods and that using our scheme. Moreover, the difference of achieved minimum total error rates and the little shift of optimal local threshold in the results shown in Table 5.1 and

Table **5.2** imply that the selections of optimal local threshold λ_{opt} and optimal fusion rule K_{opt} depend on the particular spectrum occupancy statistics represented by PH_1 and PH_0, and the condition of sensing channels.

Figure 5.5 shows the effect of spectrum occupancy PH_1 and PH_0 on the value of optimal fusion rule K_{opt} for different SNR values. It is obvious that the optimal value of the fusion rule is greatly affect with the values of spectrum occupancy at low SNR environment, but this effected is reduced with increasing the SNR, and almost reaches a state of stability about the value of half voting $K_{opt}=M/2$ at high SNR, as it is in the purple line in this figure. Another characteristic point that can be distinguished in this figure is that for any given value of SNR and when spectrum occupancy rate $PH_1=PH_0=0.5$, the value of optimal fusion rule will be fixed on half voting value $K_{opt}=M/2$.

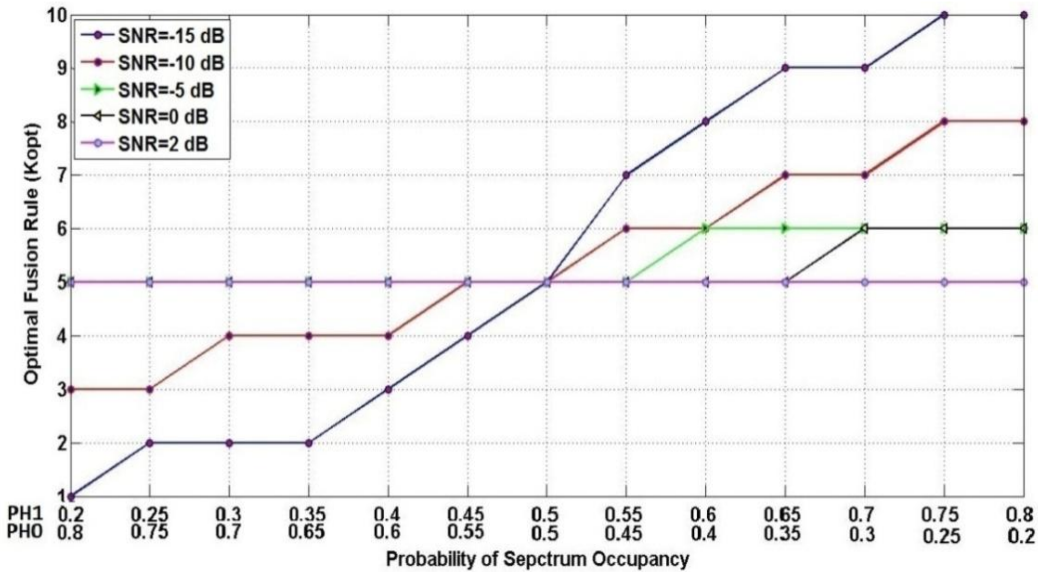


Figure 5.5 Optimal fusion rule K_{opt} versus spectrum occupancy statistics PH_1 and PH_0

Another important factor that affects the value of K_{opt} in order to minimise the total detection error rate is the local detection threshold λ. Figure 5.6 and Figure 5.7 show the relationship between K_{opt} and λ for different values of spectrum occupancy and SNR of sensing channel, respectively.

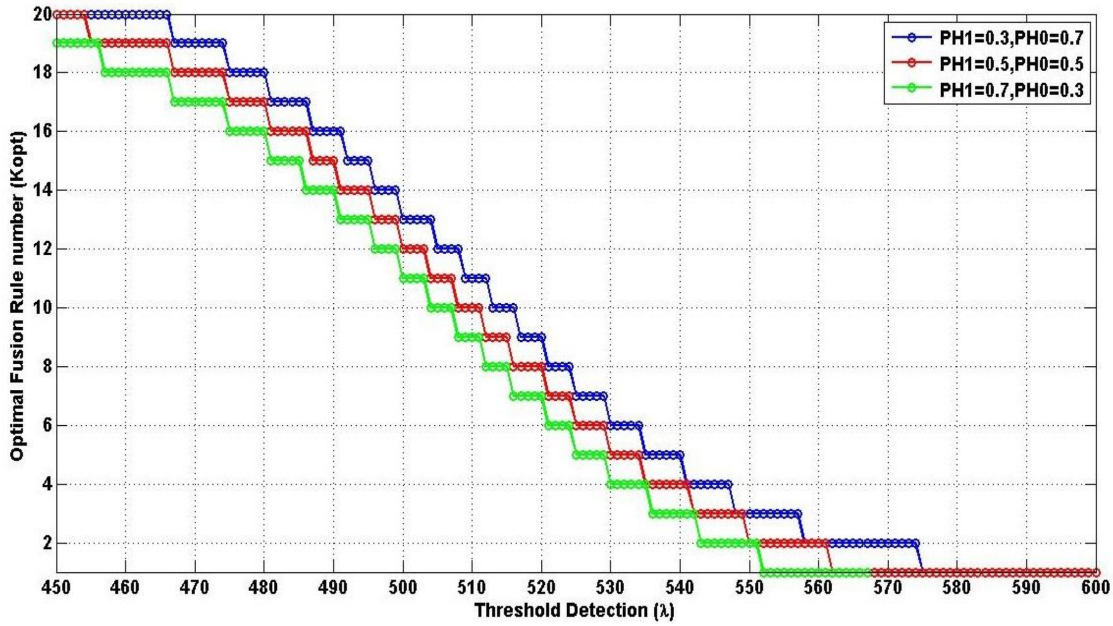


Figure 5.6 Optimal fusion rule K_{opt} against local detection threshold λ for different PH_1 values in CSS under AWGN channel with SNR=-10 and M=20.

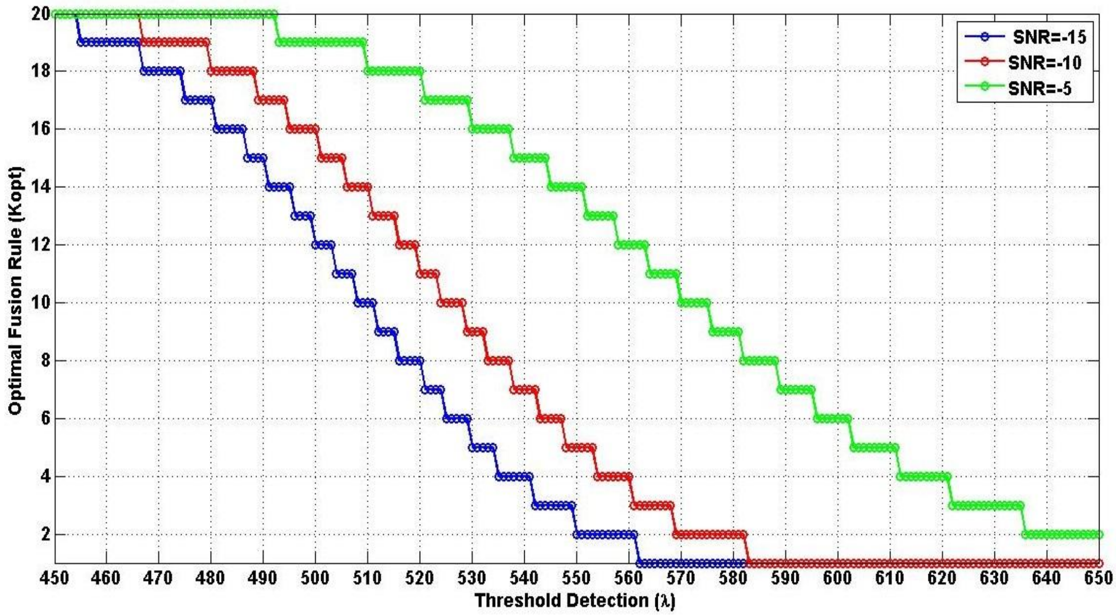


Figure 5.7 Optimal fusion rule K_{opt} against local detection threshold λ with different SNR in CSS with spectrum occupancy rate PH_1=PH_0=0.5 and M=20

As can be seen in Figure 5.6 and Figure 5.7, under different values of spectrum occupancy and SNR of sensing channel the value of K_{opt} decreases as the value of λ increases. Furthermore, at small threshold values the optimal fusion rule is AND rule, K_{opt}=20, meanwhile for large threshold values the optimal fusion rule is OR rule, K_{opt}=1. On the other hand, the value of K_{opt} also changes as the values of spectrum occupancy and SNR change. For instance, in Figure 5.6 and for a fixed local threshold (λ=510), when the values of probability of spectrum occupancy PH_1 are (0.3, 0.5, and 0.7), the values of K_{opt} that minimise the total error rate at the FC will be (11, 10, 9), respectively, indicating that the optimal fusion rule decreases while increasing the spectrum occupancy rate PH_1. Furthermore, it can be shown that in Figure 5.7 under different values of SNR (-15dB, -10dB, and -5dB), and for a given threshold value (λ=540), the values of optimal fusion rule K_{opt} are (4, 7, and 15), respectively, which implies that the K_{opt} values increases as the SNR of sensing channels increases.

From all above simulation results presented in this section we can conclude that the minimisation of total error rate at the FC occurs when optimal threshold at the local sensing and optimal fusion rule at the FC are selected. In addition, the value of optimal fusion rule K_{opt} depends basically on several factors, including spectrum occupancy rate, SNR of sensing channel, and local detection threshold λ, and all these factors are nested with each other in terms of impact on the value of K_{opt}. However, at low SNR the value of K_{opt} increases as the value of spectrum occupancy PH1 increases, while at high SNR the value of K_{opt} will fix on half voting rule $K_{opt}=M/2$ for all values of spectrum occupancy PH1. In general, increasing the value of local detection threshold λ will lead to decrease the value of K_{opt}, and for low fixed λ the optimal fusion rule will be AND rule, $K_{opt}=M$, while at large fixed λ the optimal fusion rule is OR rule, K_{opt}=1.

5.4.2 Spectrum Sensing Performance

In this subsection, we present the sensing performances of our proposed CSS algorithm, the performance of existing CSS schemes is also provided for comparison. As mentioned earlier, the spectrum sensing performance is measured by three major metrics: detection probability P_d; false alarm probability P_f; and mis-detection probability P_m. Obviously, it is very desirable when designing any spectrum sensing algorithm that P_f and P_m should be as little as possible and P_d should be as much as possible.

In the following simulations, we will provide the comparison of the sensing performance for CSS with different fusion rules. In these experimental simulations we set the total detection rate at the FC Q_d=0.99, thus, the total mis-detection probability at the FC for all conventional CSS approaches is Q_m=0.01, and the uncertainty region factor $\delta = 1.05$ for the case of double threshold energy detection scheme.

Figure 5.8 depicts the false alarm performance with average SNR for different fusion rules. It can be seen that the optimal CSS based AND algorithm has a very low false alarm probability Q_f value compared to that with majority rule, which in turn outperforms all other CSS schemes.

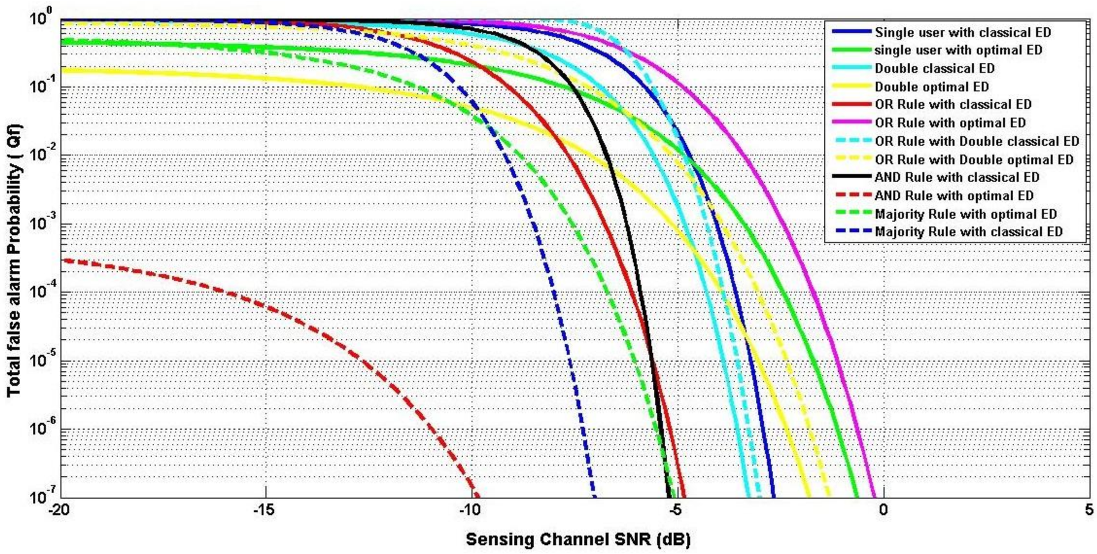


Figure 5.8 False alarm probability versus average SNR with different fusion rules

Figure 5.9 shows the mis-detection rate performance as a function of SNR for various fusion rules. As can be clearly seen, the performance of optimal CSS using OR rule is much better than other fusion rules. This is due to the characteristics of decision fusion rules, which are designed to suit the required spectrum sensing applications. In other words, for spectrum sensing applications that require very low Q_f, CSS based AND fusion rule is better, while for applications with very low Q_m, CSS based OR fusion rule is the best. However, there is no fusion rule that provides very low values of Q_f and Q_m simultaneously, therefore, for such applications a trade-off between these two sensing metrics is needed, which can be obtained by using CSS based majority fusion or optimal fusion rule algorithm.

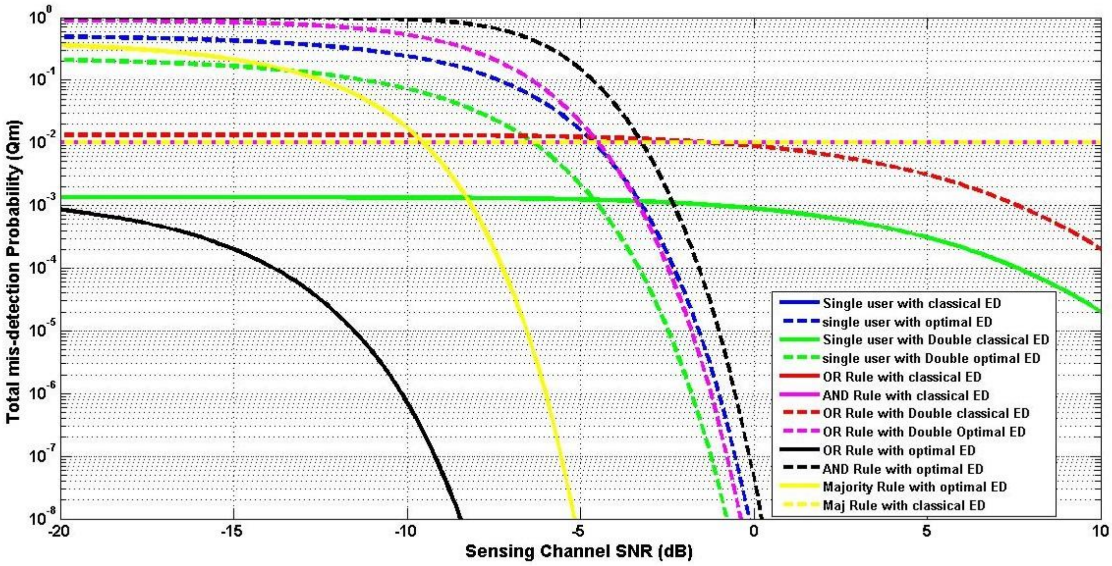


Figure 5.9 Mis-detection probability versus average SNR with different fusion rules

Figure 5.10 shows the detection error performance as a function of SNR with different decision fusion rules (AND; K_{opt}=M, OR; K_{opt}=1, Majority; K_{opt}=$M/2$). This figure gives a clear picture of that the error performance of a double-optimal ED outperforms all the rest of the cooperative and non-cooperative algorithms, especially at low SNR, indicating to the inefficiency of the double threshold Ed with cooperative spectrum sensing mechanism. This figure shows also that the conventional CSS with

OR fusion rule has better error performance than that of optimal CSS with OR fusion rule, indicating that the optimal CSS with OR and AND fusion rules are not suitable for application with very low detection error. On the other hand, the CSS with majority rule has batter error performance than of CSS with OR and AND fusion rules, which makes it more convenient in CSS systems.

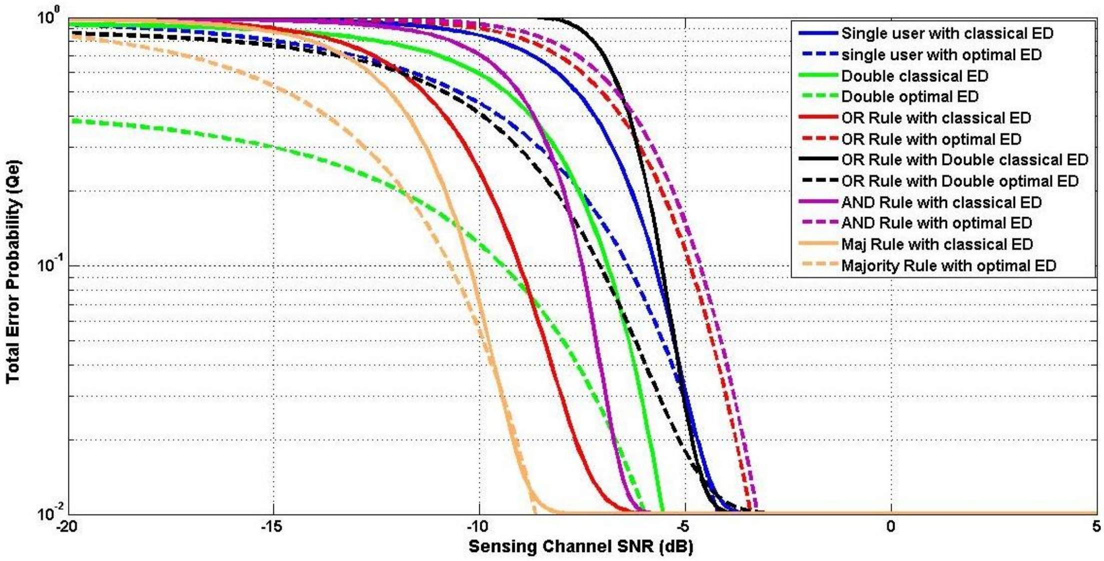


Figure 5.10 Total detection error rate versus average SNR with different fusion rules

In the following simulations, we will examine the effect of noise uncertainty on the total sensing performance at the FC, and explain the way to reduce this impact. In these simulations, for simplicity we assume that all CR users have the same SNR value of AWGN sensing channel.

Figure 5.11 illustrates the total detection error probability Q_e of the optimal CSS based majority fusion rule with different noise uncertainty values ρ. Here, we used the majority fusion rule at FC, as it represents the optimal fusion rule when the spectrum occupancy is 50%.

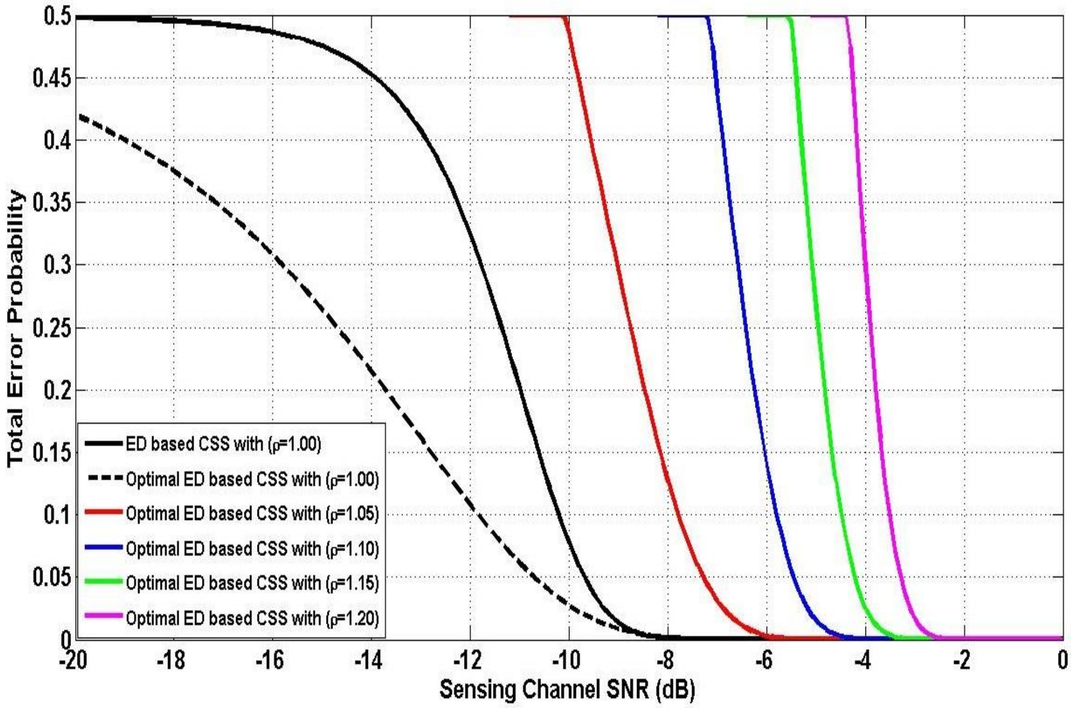


Figure 5.11 Total detection error rate against SNR with various noise uncertainty values (ρ)

As shown in Figure 5.11, there is a significant decline in detection error at the FC due to noise uncertainty at the local sensing, and the level of this decline increases as the noise uncertainty factor ρ increases. For instance, suppose that the desired error rate required at the FC is 0.05, to achieve this level, the SNR level at the local sensing should be -10.7dB in the case of without noise uncertainty ρ=1.00, while this level increases to -5.45dB and -3.3dBfor ρ=1.10 and ρ=1.20, respectively. This indicates that the cooperation gain feature of reducing the detection sensitivity at the local sensing in CSS may lose as a result of the impact of noise uncertainty. It also can be seen from the simulation that the SNR_{wall} level, a level beyond which the detector cannot detect the signals, increases as the noise uncertainty factor ρ increases. For instance, when noise uncertainty factor is ρ=1.10, the value of SNR_{wall} will be -7.2 dB, while at the value of ρ=1.20, the SNR_{wall} is -4.4 dB, which indicates that the SNR_{wall} also is affected by the noise uncertainty.

The total detection rate performance Q_d of our optimal CSS algorithm with different noise uncertainty values ρ is given in Figure 5.12. As seen in this figure, the detection performance of our optimal CSS in the event of the presence of noise uncertainty is very poor compared to that without noise uncertainty, and when the value of noise uncertainty factor ρ increases, the value of SNRwall will increase and in turn makes the detection unreliable and impractical even in normal values of SNR. For instance, in order to achieve a desired Q_d=0.9, we need a sensing channel with SNR=-12.4 dB in the case of full noise knowledge, while in the case of noise uncertainty with ρ=1.10, we need at least a sensing channel with SNR=-5.85dB.

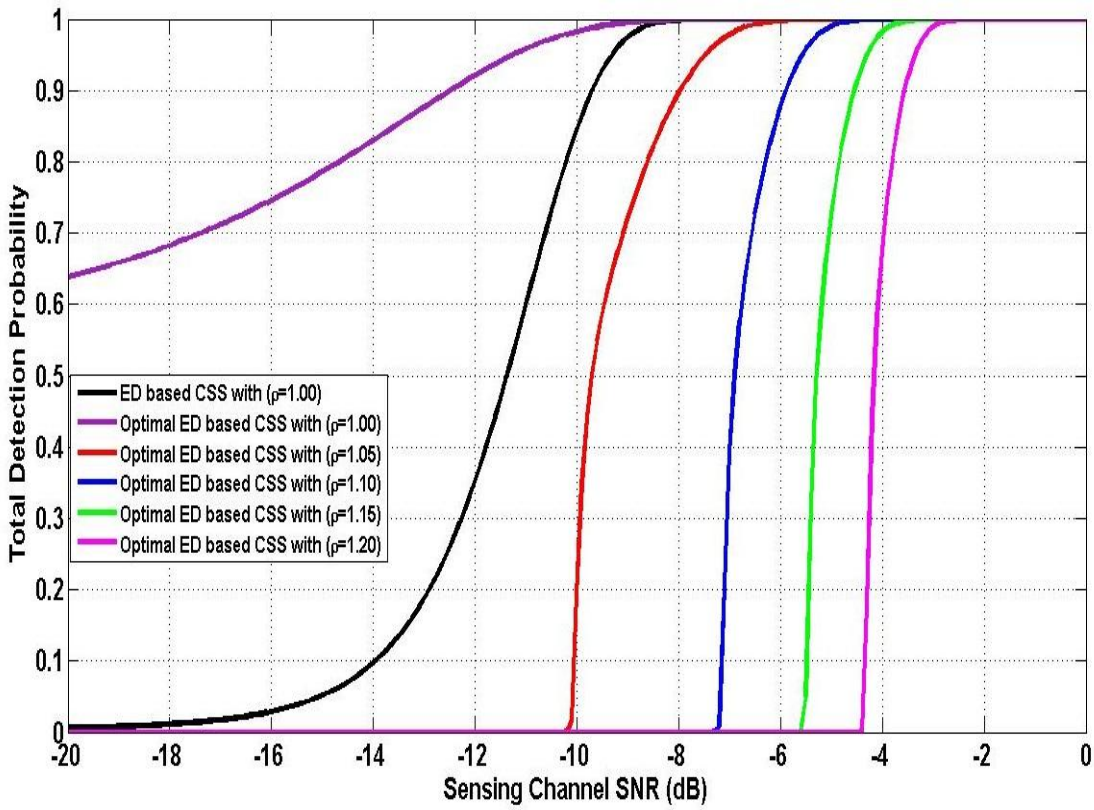


Figure 5.12 Total detection probability versus SNR with different noise uncertainty values ρ

To further validate our optimal CSS algorithm we compare the detection and error performances of our optimal CSS algorithm to other optimisation based CSS schemes presented in [27, 136].

Figure 5.13 illustrates the performance of total detection probability with SNR for various optimal CSS schemes in the presence and absence of noise uncertainty. There are several important points that can be observed in this figure. First, the detection performance of optimal CSS schemes outperforms that of conventional CSS algorithm, especially in low SNR environment. Second, the detection performance of our optimal CSS approach is very close to that of existing optimal CSS schemes, especially in the case of full knowledge noise power (without noise uncertainty). Finally, the detection performance of all spectrum sensing approaches is affected by the noise uncertainty in general, but this effect is much greater in the optimal based CSS schemes compared to the traditional CSS schemes. This is due to the SNR_{wall} that limits the ability of the detector in local sensing for detecting the signals, which in turn depends on noise uncertainty factor ρ according to (4-27) in chapter four.

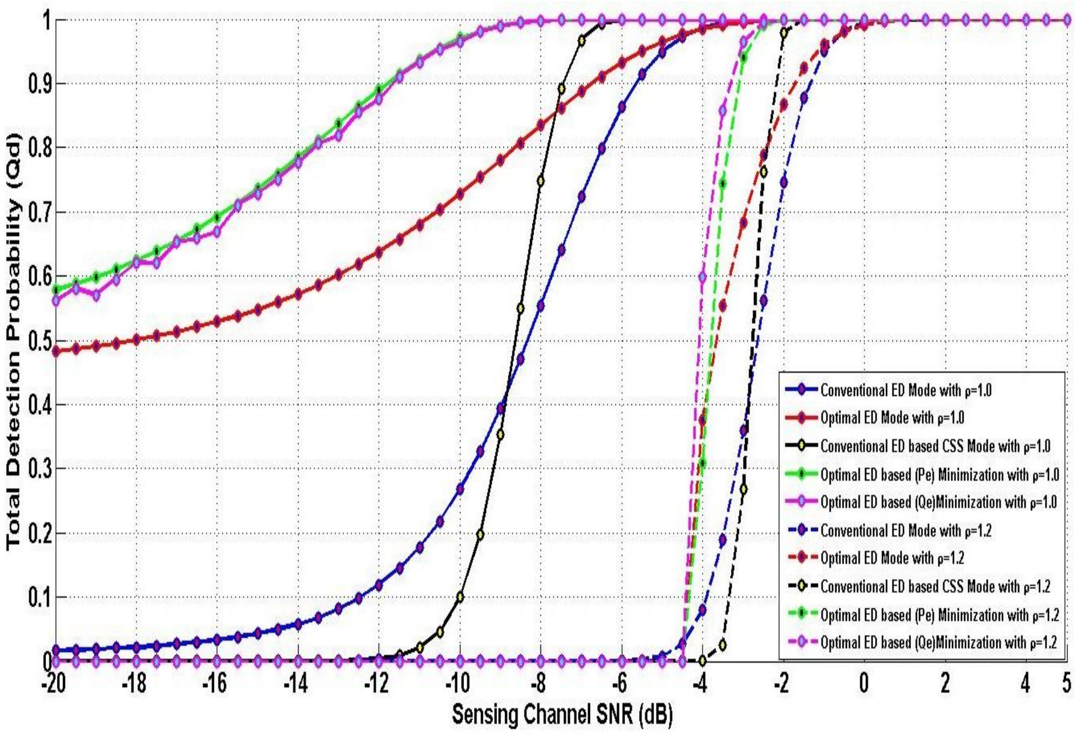


Figure 5.13 Total detection performance versus average SNR in different CSS schemes with and without noise uncertainty

Figure 5.14 describes the detection error performance with SNR in various CSS algorithms, including our optimal CSS scheme in both with and without noise uncertainty, and shows that our optimal CSS scheme has the same error performance as existing optimal CSS algorithms, which outperforms that of the conventional CSS scheme. However, despite the fact that our optimal CSS algorithm and existing optimal CSS schemes have almost the same spectrum sensing performances, our optimisation algorithm has less complexity and does not need more additional time for selecting the local detection threshold compared to existing optimal CSS algorithms.

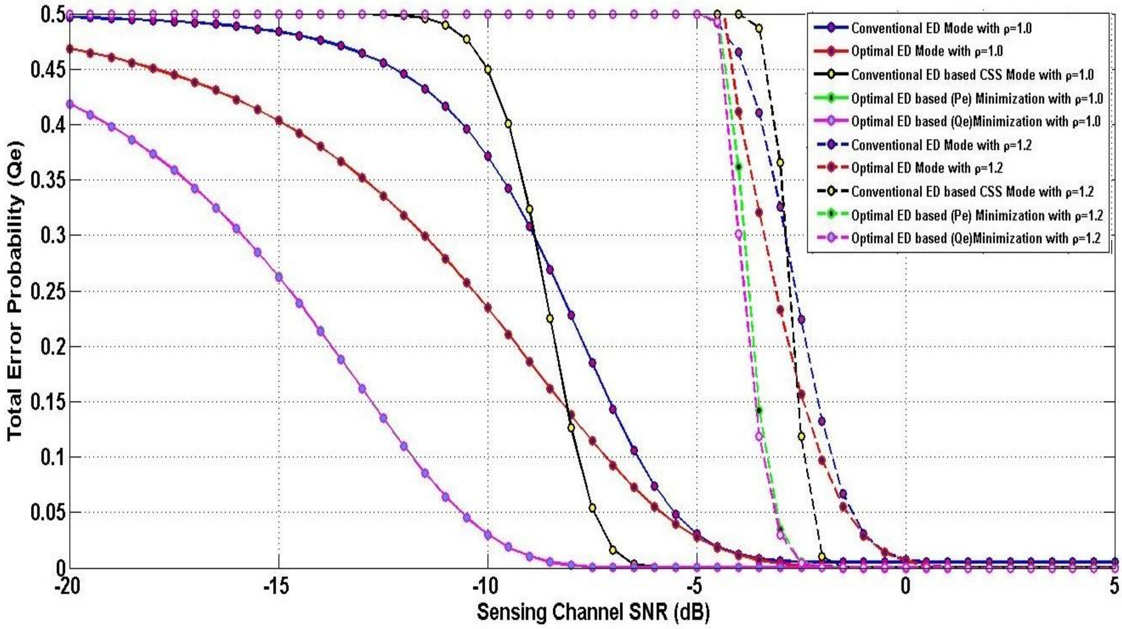


Figure 5.14 Total detection error performance against average SNR in different CSS algorithms with and without noise uncertainty

In CSS practical scenarios, the reporting channels between CR users and the FC are assumed to be imperfect due to the fading and shadowing effects. Therefore, to make our optimal CSS algorithm more practical, we need to consider this practical scenario in our optimal CSS scheme. In the following simulations, we will assess our optimal CSS algorithm when the noise uncertainty with ρ=1.2 and the reporting channel error with error rate R=0.3 are considered.

Figure 5.15 shows the performance of detection error rate of our optimal CSS algorithm with SNR in the presence of noise uncertainty and reporting channel error. As is evident in Figure 5.15, the performance of detection error rate at the FC in our optimal CSS algorithm deteriorates dramatically when both noise uncertainty with ρ=1.2 and reporting channel error with error rate R=0.3 are applied (pink line), and this deterioration is somewhat lower compared with that in traditional CSS algorithms (pink dashed line); especially within the range of SNR between -4 dB and -1 dB. However, due to the noise uncertainty the total error rate will be very high at the SNR level below SNR_{wall}, which in this simulation is equal to -4.35 dB according to noise uncertainty factor ρ=1.2. On the other hand, according to error rate R, the reporting channel error can limit the total error rate Q_e to a value, 0.1 in this simulation, even in high SNR of sensing channel.

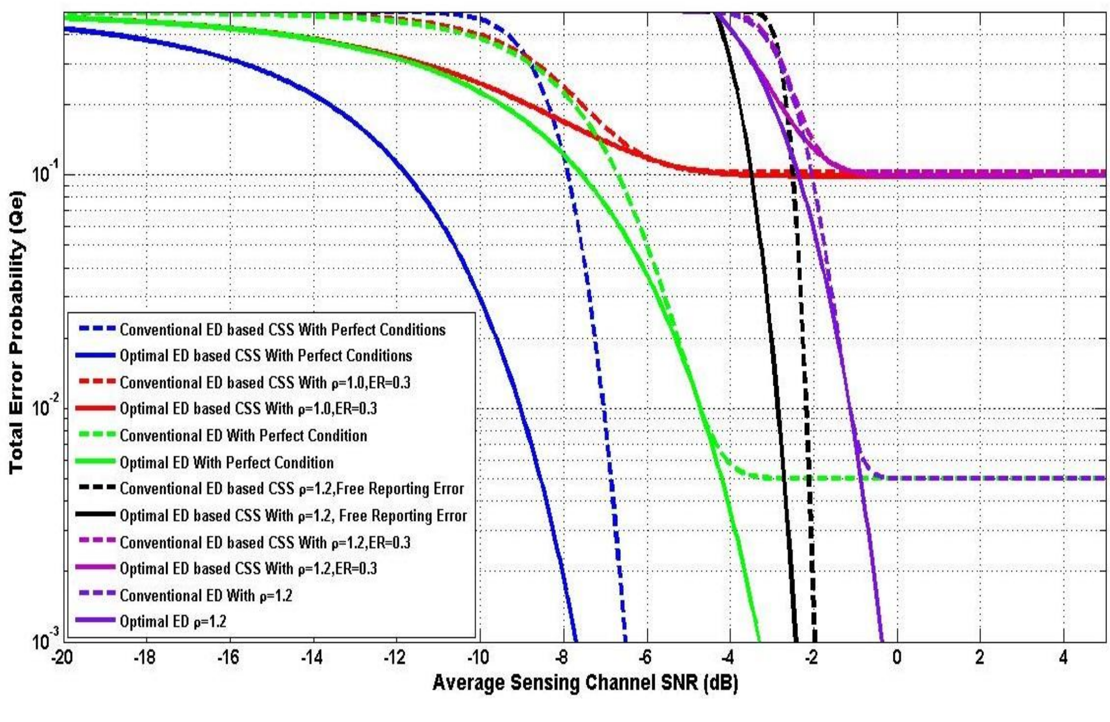


Figure 5.15 Total error performance versus SNR in CSS with noise uncertainty and reporting channel error

Figure 5.16 gives the simulation results of the total detection rate with SNR in CSS algorithms when both noise uncertainty and reporting error are considered. As is very clear, the detection rate of our optimal CSS scheme declines significantly in the presence of both noise uncertainty and reporting error. For instance, for a given SNR=-10 dB, the detection rate is 0.986 in the case of perfect conditions, while it reduces to 0.15 in the case of imperfect conditions, when both noise uncertainty with ρ=1.2 and reporting error with error factor R=0.3 are applied.

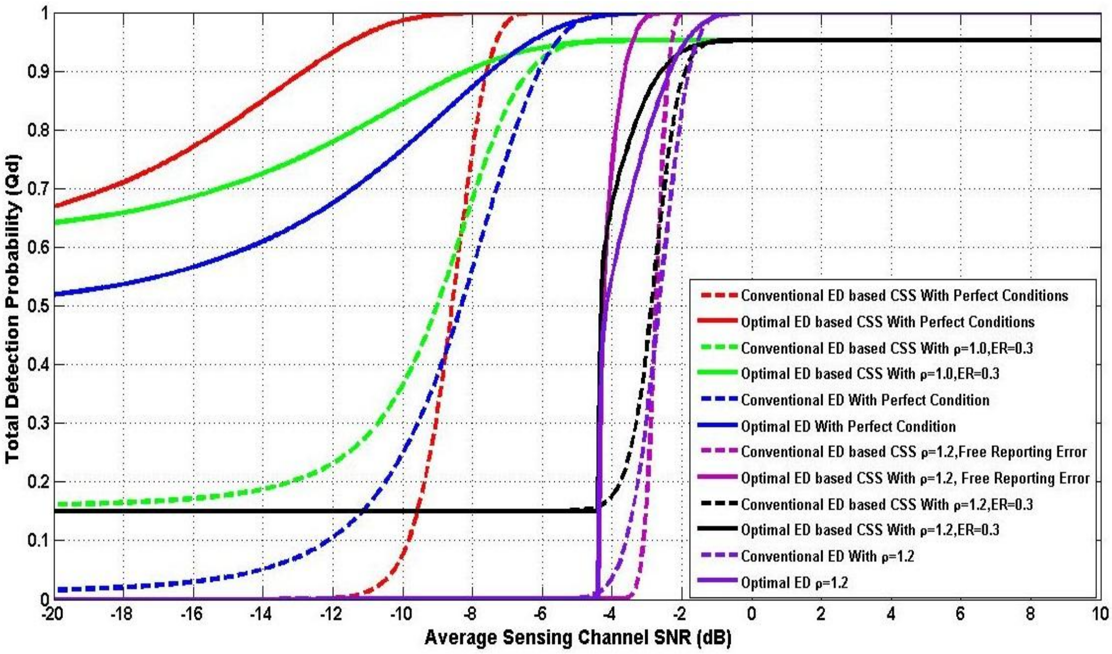


Figure 5.16 Total detection rate with average SNR in CSS with noise uncertainty and reporting channel error

After presenting the simulation results of the impacts of noise uncertainty and imperfect condition of the reporting channel on the sensing performance in our optimal CSS scheme, we need to provide a validation of our solution that tackles these effects. The issue of reporting error can be reduced by using relaying mechanisms or clustering approaches, therefore, the analysis and evaluation of the solution to this issue is postponed to the next chapter, which describes our clustering approach.

In the following simulations, we will give the simulation results that validate our analytical mathematics that were presented previously as a solution to tackle the impact of noise uncertainty on the detection performance at the FC. In these simulations, we also present the sensing performance of a conventional CSS scheme for comparison.

Figure 5.17 shows the performance of total detection probability with SNR for optimal and conventional CSS algorithms in the presence of noise uncertainty with ρ=1.2 and different values of threshold uncertainty factor α.

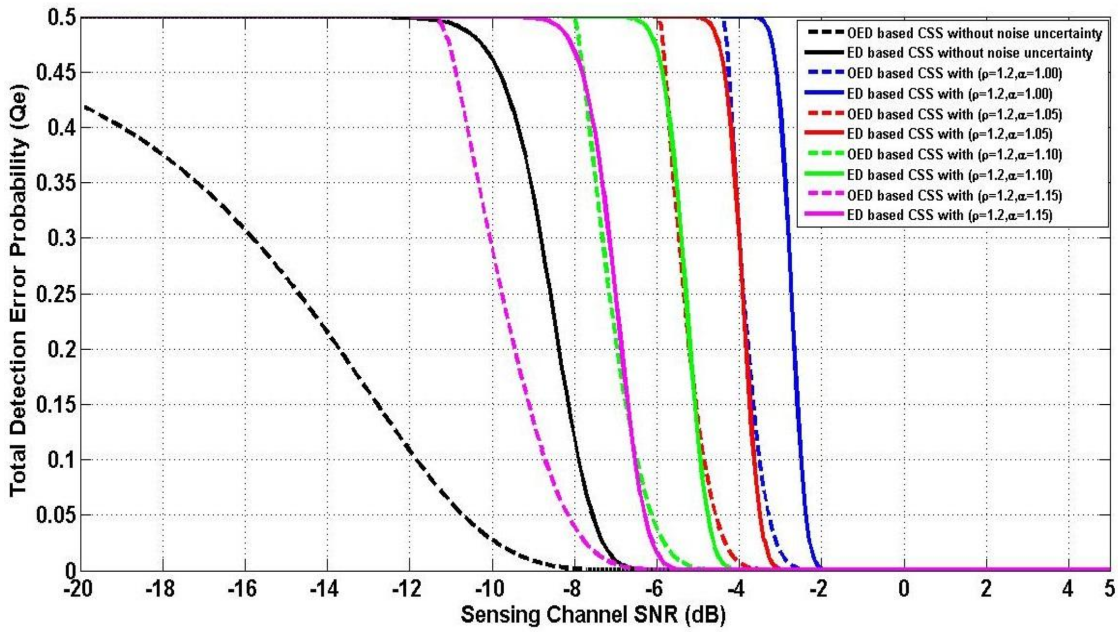


Figure 5.17 Total detection error rate versus SNR with ρ=1.2 and different α in CSS algorithms

As illustrated in this figure, there is a significant improvement in the sensing performance for both optimal and conventional CSS schemes with the use of threshold uncertainty factor α method, and this improvement increases the value of α increase towards ρ. For instance, when the value α=1.00, which represents the case of noise uncertainty without a proposed solution, the value of SNR_{wall}=-4.4 dB, while the value of SNR_{wall} will be decreased to -11.4 dB when α=1.15, which is very close to the value of ρ. Another distinctive point can be observed in Figure 5.17 is the efficiency of sensing performance of our optimal CSS compared with that in a conventional CSS scheme. For example, in the spectrum sensing application that required a detection error rate Q_e=0.05, we can see that our optimal CSS scheme can achieve this error rate with SNR=-10.7 dB in the case of full knowledge noise power, while the SNR that achieves the same error rate will be -7.55 dB when the conventional CSS algorithm is used. Furthermore, in the event of noise uncertainty with factors ρ=1.2 and α=1.15, and for the same given error rate Q_e=0.05, the SNR should be -8.15 dB in order to achieve this error rate using our optimal CSS, while this level of SNR will be increased to -6.3 dB for the same error rate when conventional CSS scheme is used.

Figure 5.18 depicts the detection probability performance as a function of average SNR for both optimal and conventional CSS schemes, and shows the advantages of using threshold uncertainty method to address the impact of noise uncertainty on the detection efficiency.

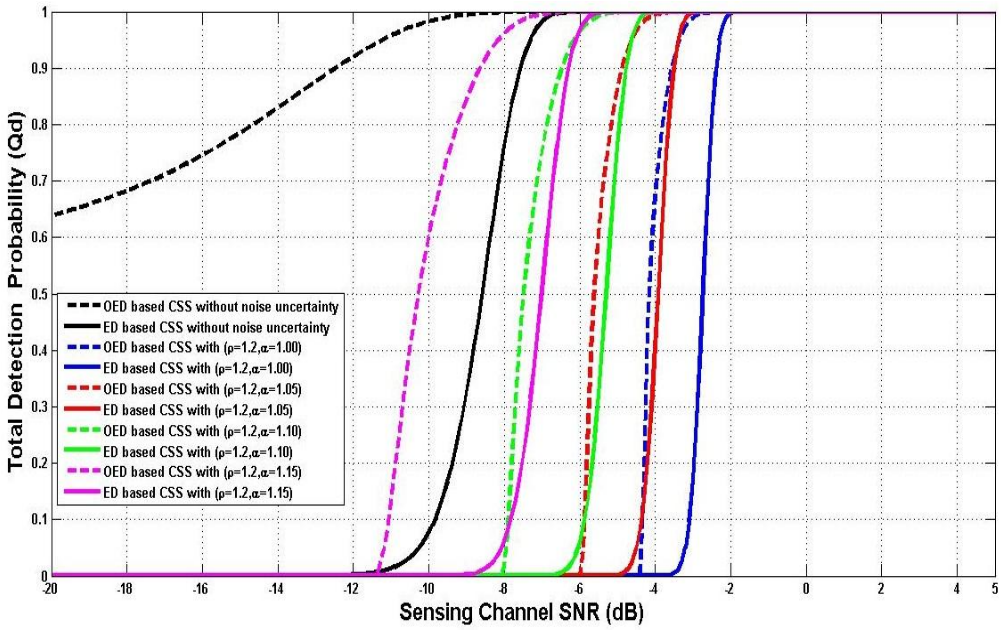


Figure 5.18 Total detection rate versus SNR with ρ=1.2 and different α in CSS algorithms

As seen in Figure 5.18, the detection probability of our optimal CSS scheme outperforms of that of conventional CSS for both with and without noise uncertainty. For instance, in the case of full knowledge noise power, for a given SNR=-10 dB the detection error rate will be 0.98 when the optimal CSS scheme is used, while in the conventional CSS algorithm it will be 0.077. Moreover, in the case of noise uncertainty with ρ=1.2 and α=1.15, and for a given SNR=-8dB, the detection probability of the optimal CSS algorithm is Q_d=0.96, whereas the achievable Q_d of the conventional CSS is 0.062. The simulation results in this figure show also that the detection performance can be improved when a suitable threshold uncertainty factor α is used at the local sensing. However, this method needs the noise uncertainty factor ρ to be known at the local sensing in order to set an appropriate threshold uncertainty factor α that tackles the impact of noise uncertainty.

5.4.3 Spectrum Sensing Time Performance

In this section we evaluate the spectrum sensing performance of our optimal CSS algorithm in terms of spectrum sensing time by comparing it with other conventional and existing CSS schemes. For that, first by fixing the number of CR users M, we investigate the effect of number of samples N on the sensing performance in the presence of noise uncertainty. Secondly, we assess the spectrum sensing performance with changing the number of CR users for different values of noise uncertainty factors ρ, while fixing the number of samples N. In our evaluation we set the simulation parameters as follows: number of CR users M=10; PH_1=PH_0=0.5; average SNR=-10 dB at each CR user; the desirable false alarm probability for all CR users is P_f =0.15; and bandwidth of sensing channel BW=6MHz. For simplicity, we assume that the reporting channels between CR users and the FC are free of error.

Figure 5.19 shows the effect of changing the number of samples N on the performance of total error rate Q_e in both optimal and conventional CSS algorithms in the presence of noise uncertainty. As shown in this figure, the performance of our optimal CSS scheme outperforms that in conventional CSS for all different values of noise uncertainty factors ρ. The simulation results also demonstrate that the number of samples N required to achieve the desired error rate Q_e increases dramatically with a slight change in the noise uncertainty factor.

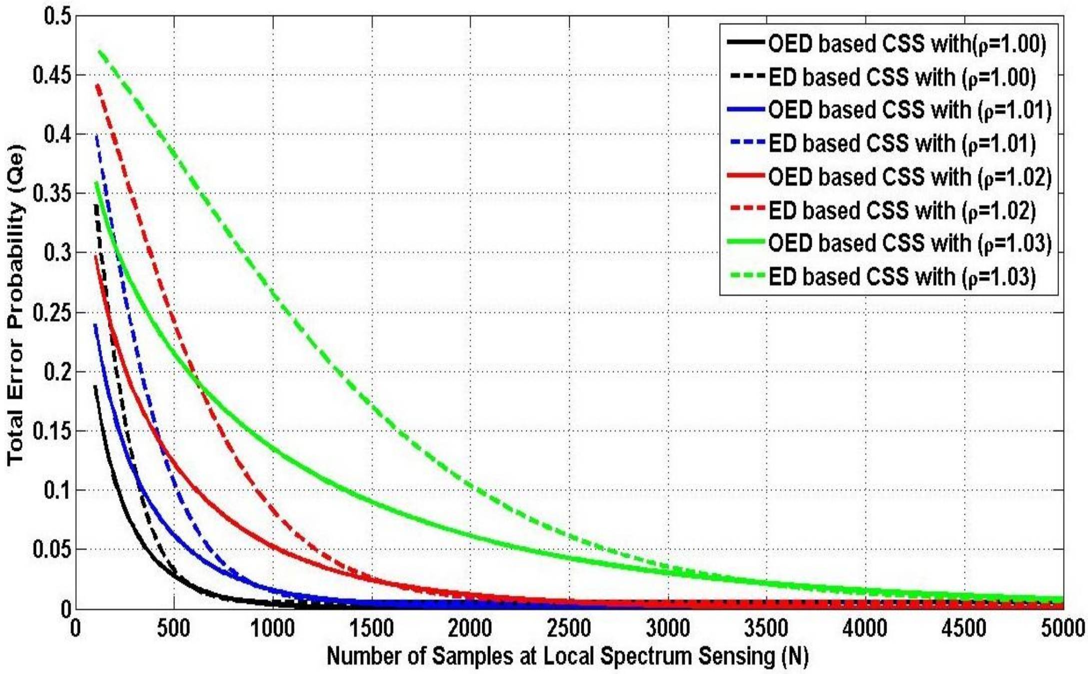


Figure 5.19 Total error probability versus number of samples in both optimal and conventional CSS schemes with different noise uncertainty factors ρ

ρ	OED based CSS		ED based CSS		OED based CSS	ED based CSS
	N	T_S= N/BW (ms)	N	T_S= N/BW (ms)	Increasing Rate %	Increasing Rate %
1.00	360	60	430	71		
1.01	570	95	680	113	58.3	59.1
1.02	1010	168	1220	203	76.8	79.6
1.03	2260	376	2660	443	123.8	118.2

Table 5.3 The impact of noise uncertainty on the number of samples N when Q_e=0.05

Table 5.3 gives the obtained results of changing the noise uncertainty factor ρ on the number of samples N required to achieve a desirable error rate Q_e=0.05. As observed in this table, for a given Q_e and ρ, the number of samples N and the corresponding sensing time T_S of our optimal CSS mode are less than those in conventional CSS mode. For instance, when the value of noise uncertainty ρ=1.02, the sensing time T_S of our optimal and conventional CSS schemes are 168μs and 203μs, respectively, indicating that the sensing time required to satisfy a given spectrum sensing performance is greater than that in our optimal CSS algorithm with the increasing rate of 20.8%.

Furthermore, for a given Q_e=0.05 and when ρ is increased from 1.02 to 1.03, the sensing time T_S will be significantly increased in both our optimal and conventional CSS algorithms with the increasing rate of 123.8% and 118.2%, respectively. This is due to the fact that increasing the noise uncertainty factor will cause more deterioration in the performance of local spectrum sensing, which leads to increasing the total error rate Q_e, thus we need to increase the number of samples in order to satisfy the target error rate.

In Figure 5.20 we simulate the total error rate performance of our adaptive optimal CSS algorithm when different threshold factors are applied in order to reduce the impact of noise uncertainty.

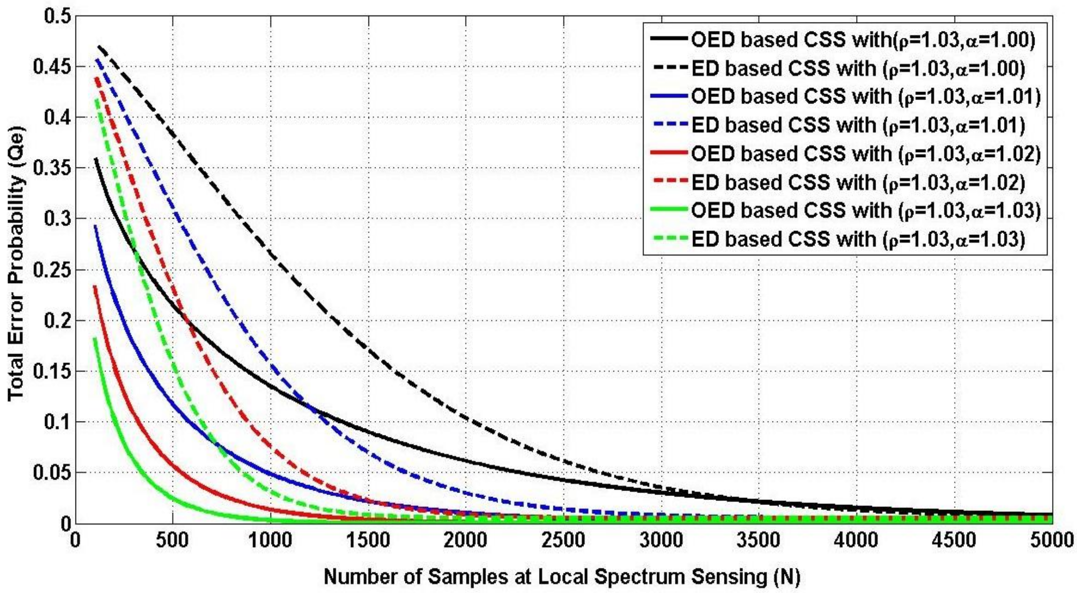


Figure 5.20 Total error probability versus number of samples in optimal and conventional CSS schemes with noise uncertainty factor ρ=1.025 and different adaptive threshold factors α

As shown in Figure 5.20, the detection error rate can be improved significantly as the adaptive threshold factor α increases. For instance, when ρ=1.03 and α=1.00; which represents the event of noise uncertainty, and for a given desired error rate

Q_e= 0.05, the number of samples N will be 2260 and 2660 for both our adaptive optimal and conventional CSS algorithms, respectively. On the other hand, the values of N for both our optimal and conventional CSS schemes are decreased dramatically to 340 and 850, respectively, when the value of adaptive threshold factor α increases to 1.03.

In the following simulations, we will evaluate the performance of the sensing time of our optimal CSS algorithm and compare it with conventional and existing algorithms. In these simulations, the number of samples N is fixed at 500, while the number of CR users was made variable in order to examine the effect of reporting time slots on the performance of overall spectrum sensing time.

Figure 5.21 shows the performance of total error rate with number of CR users in the presence of noise uncertainty in different type of CSS schemes.

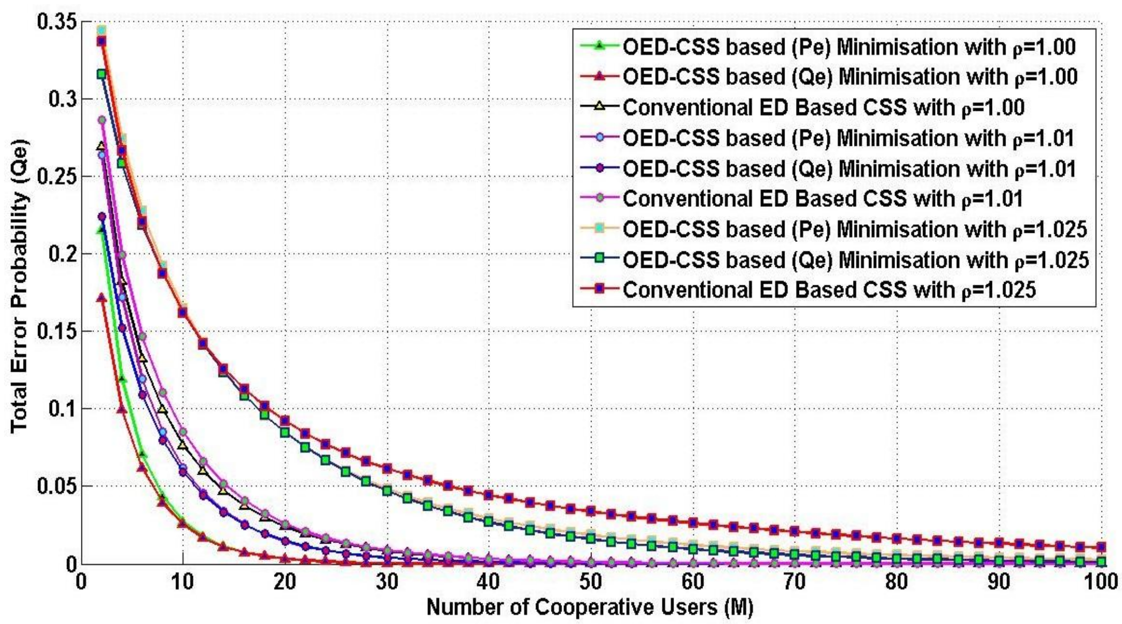


Figure 5.21 Total error probability versus number of samples in optimal CSS scheme with different noise uncertainty factors ρ and threshold uncertainty factors α

As shown in Figure 5.21, in general, the performance of total error rate improves significantly with the increase in the number of CR users in all CSS schemes. We can also observe that the sensing performance of optimal based CSS algorithms outperforms that in the conventional CSS scheme. In addition, the simulation results show that a slight increase in the noise uncertainty factor will lead to increase the number of CR users required to achieve the desired error rate, and this number will be less in optimal CSS schemes compared to the conventional CSS scheme. For instance, in the event of ρ=1.00 (without noise uncertainty), the required number of CR users M to satisfy a target error rate Q_e=0.05 will be 7 and 14 in optimal and conventional CSS algorithms, respectively, whereas when the noise uncertainty factor increases by 0.025, the number of CR users M will be increased to 30 and 36 in optimal and traditional CSS schemes, respectively, indicating that the noise uncertainty can increase the reporting time in order to satisfy quality of service.

Figure 5.22 illustrates the performance of error rate with the number of CR users M in different CSS schemes, and showing the advantages of using our adaptive threshold factor α in order to reduce the impact of noise uncertainty.

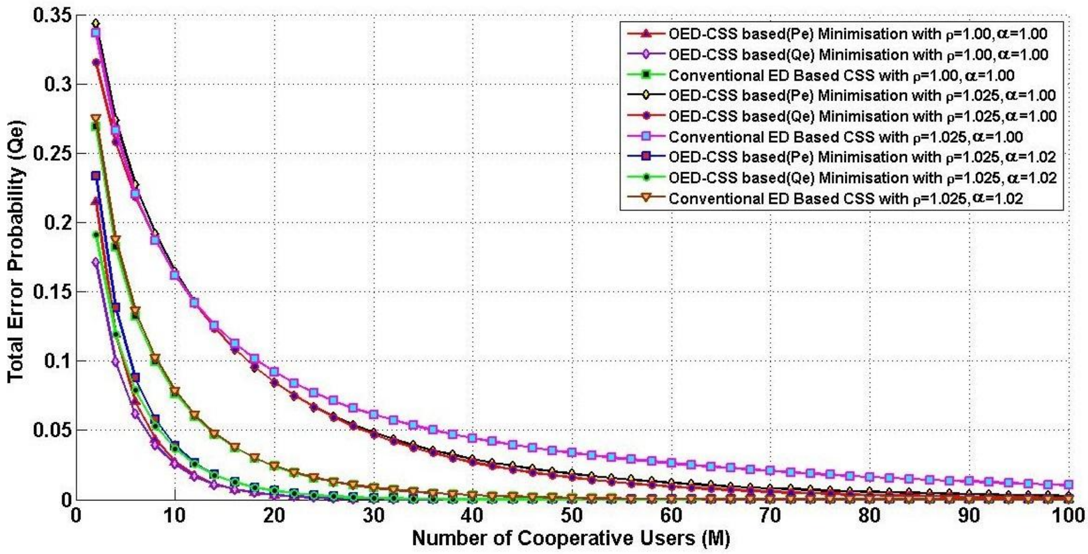


Figure 5.22 Total error probability versus number of samples in optimal CSS scheme with different noise uncertainty factors ρ and threshold uncertainty factors α

As clearly observed from this figure that the error rate performance of all CSS approaches can be improved effectively when increasing the adaptive threshold factor

α, and the impact of noise uncertainty can be reduced almost entirely when α=ρ. For instances, in case of noise uncertainty with ρ=1.025 and α=1.00, the number of CR users M are 30 and 36 in both optimal and conventional CSS algorithms, respectively, whereas these numbers will be reduced to 8 and 14, respectively, when the adaptive threshold factor α increases to 1.02.

The performance of error rate Q_e with spectrum sensing time T_S in different CSS schemes is presented in Figure 5.23. In this simulation, we assume that the number of samples M=500; bandwidth BW=5MHz; SNR=-10dB; reporting slot time of i^{th} CR user T_r= 10μs; while the number of CR users M is supposed to be variable within the range of 2 to 100.

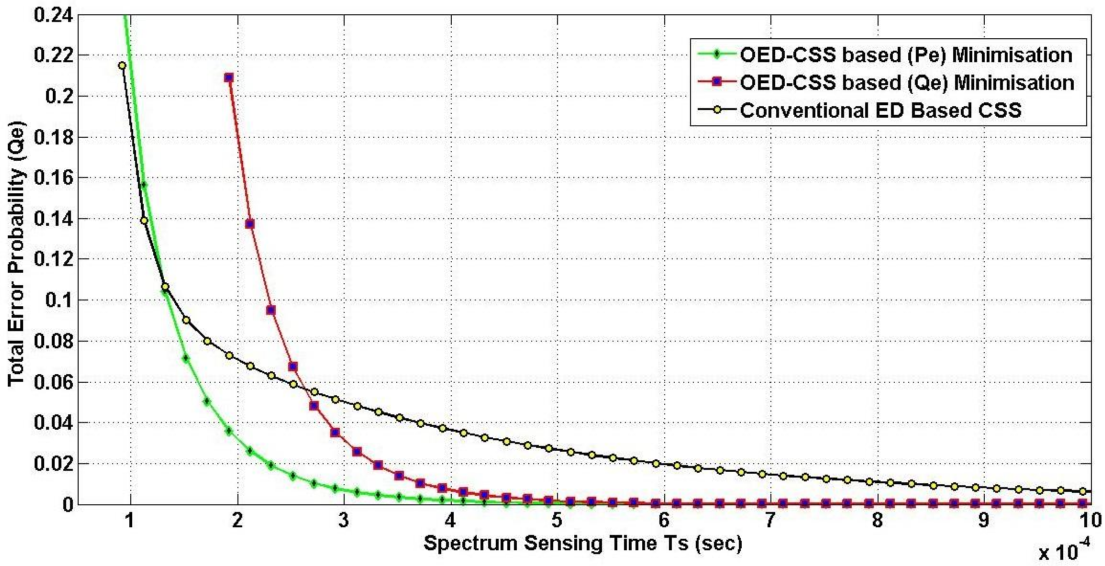


Figure 5.23 Detection error probability Q_e as a function of sensing time T_S in of different CSS scheme

It can be seen from the figure that the error rate performance of our optimal CSS scheme outperforms that in other existing CSS schemes. Although existing optimal CSS schemes have the same sensing performance of our optimal CSS scheme, as shown, they need extra time in order to achieve the same target error rate. For instance, when the value of desired error rate Q_e=0.02, the sensing time T_S required to achieve this target is 232 μs using our optimal CSS scheme, whereas in other existing optimal and conventional CSS schemes the values of T_S will be 332 μs and 592 μs, respectively. Through these results we can conclude that our optimal CSS algorithm can achieve any target error rate in less sensing time T_S compared to other existing CSS schemes, thus, increasing the throughput of the cognitive radio network.

5.5 Summary

In this chapter, we study and examine the optimisation of CSS, and proposed a new optimal CSS algorithm based on adaptive optimal ED algorithm proposed in chapter 4 [28]. This scheme uses the optimal ED algorithm that minimises the error rate at the FC, and then the local sensing results will be combined at the FC using optimal fusion rule, thus the total error rate Q_e can be minimised very easily. We also investigated the impact of noise uncertainty ρ on the detection error rate, and developed an adaptive threshold factor α that reduces the effect of ρ, and the results demonstrated that the impact of noise can be reduced effectively when the threshold factor $\alpha = \rho$.

To validate the proposed optimisation CSS algorithm, the sensing performance of the proposed scheme is compared with that of existing optimisation CSS approaches [26, 136]. We observed through simulation that our optimal CSS algorithm achieves better performance than conventional approaches, especially in low SNR environment. Although that the existing optimal CSS schemes have almost the same sensing performance of our proposed optimal CSS scheme, they still required additional time to determine the optimal local threshold numerically. We showed also through simulations that our optimal CSS algorithm achieves the target error rate in much lower sensing time than other existing CSS schemes.

Chapter 6

Multi-hop Clustering Approach for Centralised CSS

6.1 Introduction

In conventional centralised CSS, each CR user detects the presence of PU independently and then sends its local sensing observation or own decision over control channel to the cognitive fusion centre FC, which in turn makes a final decision on the spectrum availability either by collecting all the local observations using one of the data fusion methods (Soft Data Fusion) or by combining the local decisions using one of the decision fusion methods (Hard Decision Fusion) [13]. In this way, the impact of multipath fading and shadowing on the sensing channel can be addressed.

Basically, the cooperation process between CR users in CSS consists of three main phases: local sensing, reporting, and data fusion. The performance of centralised CSS depends largely on the performances offered in each phase. These performances are affected by many factors such as the accuracy of the local sensing, reliability of the reporting channel, data fusion techniques, and network overhead. It is well known that the benefits of CSS come at the cost of control channel overhead and more transmission data, requiring more power consumption and introducing additional transmission delay.

Clustering has been recently adopted in CSS for CRNs in order to overcome the problems exhibited by CSS. There are a number of research works that have focused on using clustering methods to improve the cooperative sensing performance under imperfect channel conditions [90, 93, 105-106, 108, 140], in which CR users are grouped into clusters and the user with highest reporting channel's SNR is chosen as cluster head CH, which in turn sends the cluster decision to FC.

However, the existing cluster-based spectrum sensing approaches have been focused mainly on the classical clustering methods, which are inefficient in terms of energy consumption. Furthermore, in reality, most clusters far from the FC have reliable local sensing decisions, but may suffer from fading and shadowing due to low SNR of reporting channel, which may lead to further deterioration in sensing performance due to error reporting channel, and causing more energy consumption especially in large-scale CRNs. This chapter proposes a new method to deal with the above issues, considering the trade-offs among these problem.

6.2 Multi-hop Cluster Based CSS Scheme

In this chapter, we develop a multi-hop cluster based cooperative spectrum sensing algorithm. By dividing the total cooperative users into multi-level clusters based on the distance between the CHs and the FC, the issues of power consumption and the degradation of spectrum sensing performance can be solved, more energy can be saved, and the performance of the spectrum detection and sensing delay can be also improved.

6.2.1 Description of Multi-hop Cluster Based CSS Scenario

In this model, we consider a wireless CRN with M CR users, which act as local sensing devices, and are assumed to be organised into clusters. Each cluster has a cluster head CH that makes a cluster decision based on the local decisions received from its cluster members and reports the result to the cognitive base station that acts as a FC. We also consider that the PU signal at CR users is not initially known, therefore, we adopt an energy detector to conduct the local sensing, which is suitable for any signal type. In this detection algorithm, only the transmitted power of the primary system is known. Therefore, this power will be detected firstly, and then compared with a predefined threshold to determine whether the spectrum band is available or not [121]. When the energy of the received signal is greater than the detection threshold λ, the detector will indicate that the PU is present, which will be depicted by the existing hypothesis H_1, otherwise, the primary user is absent, which will be represented by null hypothesis H_0.

The system structure of a CRN according to our clustering approach is illustrated in Figure 6.1. First, all CRs are grouped into clusters using LEACH-C protocol [29]. In this protocol, the optimal number of cluster heads CHs is determined by the FC in a centralised way, according to the best reporting channel gain, distance from the FC, and the energy level of the CRs. Based on the multi-hop routing mechanism, the FC will determine multi-level CHs according to their distances from the FC. For instance, the FC will determine a set of level-1 CHs whenever the distance of CRs is greater than a certain energy level predefined by the FC.

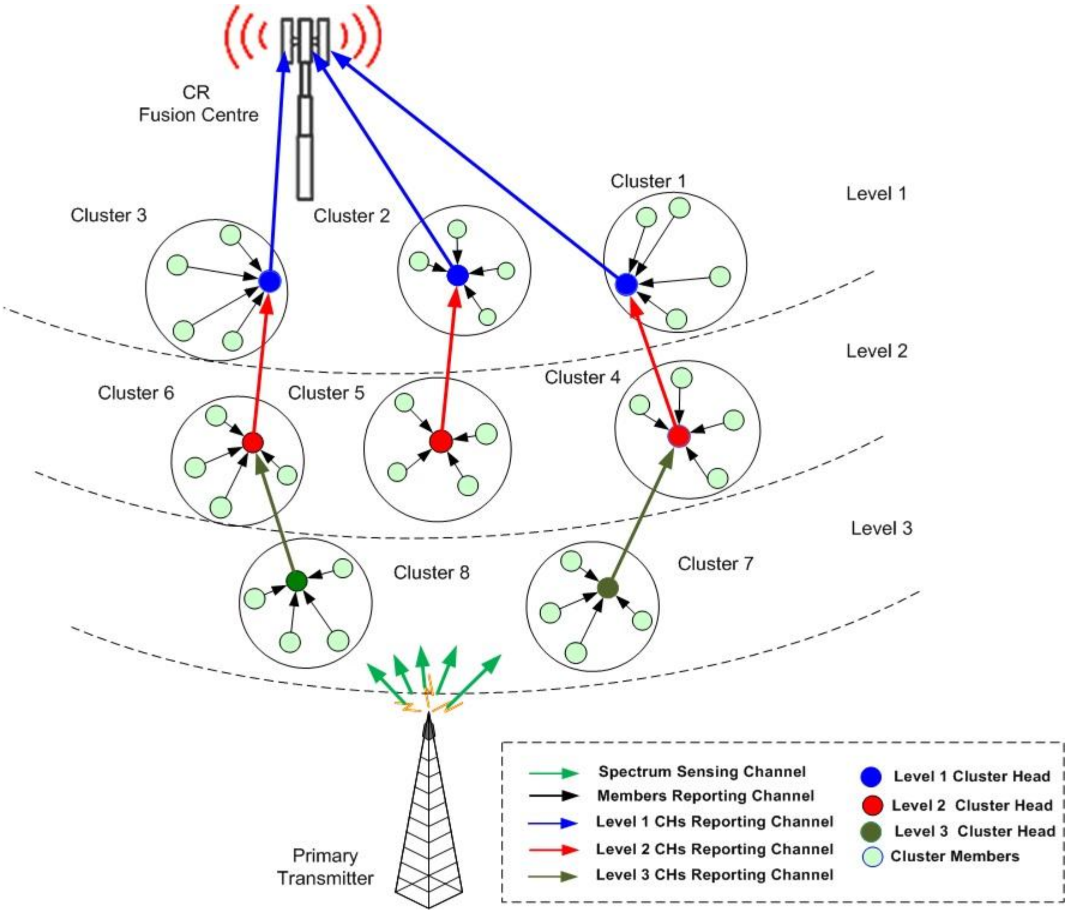


Figure 6.1 Multi-hop cluster-based cooperative spectrum sensing

Here, we make the following assumptions:

a. We assume that a CRN topology is stable and consists of one fusion centre FC, one primary transmitter, and M of cognitive radio users CRs.

b. The cognitive users either are location aware, equipped with Global Positioning System (GPS), or location unaware. In such a case, the FC broadcasts an advertisement signal to all CRs at a certain power level, and each CR user computes its approximate distance to the FC according to the received signal strength.

c. CRs can use power control to tune the amount of sending power according to the transmission distance.

d. The instantaneous channel state information of the reporting channel is available at the CRs.

e. The channel between any two CRs in the same cluster is perfect since they are close to each other.

The process of our proposed cluster-based CSS algorithm is conducted through the following steps:

1. CR j in cluster i conducts spectrum sensing individually and makes a local decision Dij for i =1,…,K, j =1,…,Ni , where K is the number of clusters, Ni is the number of CR in cluster i and $M = \sum_{i=1}^{K} N_i$, where M is the total number of CRs in the network.

2. Then, each $CRij$ will report its results to the CHi to make a cluster decision Ci based on Majority data fusion method.

3. Afterwards, all CH_{Li+1}will send their results Ci to the FC via intermediate cluster heads CH_{Li} based on inter-cluster tree routing at FC.

4. Finally, the fusion centre will collect all sensing results from cluster heads and make the final decision based on majority fusion rule, and then broadcast it back to CRs via cluster heads.

6.2.2 Multi-hop Cluster Formation

The Multi-hop LEACH-C is a centralised clustering scheme, which operates in rounds, and each round consists of two phases: setup phase when the cluster heads and clusters are organised, followed by a steady state phase when cluster members begin to send their data to CH and on to the FC, as shown in Figure 6.2.

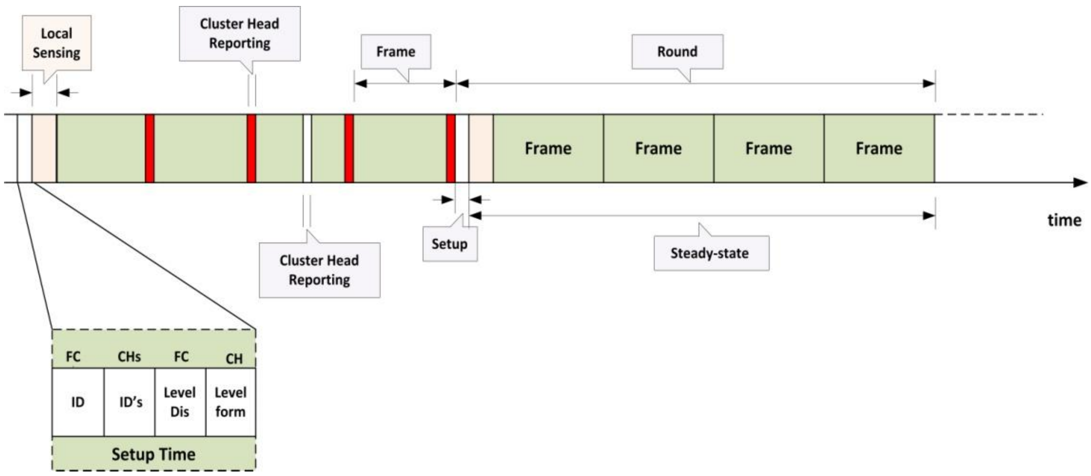


Figure 6.2 Time line of Leach-C protocol

A Setup Phase

During the setup phase of our clustering protocol, each CR user sends information about its current location or its distance from the FC, current energy level, and SNR of reporting channel to the FC. We assume that the FC can reach all CRs in one hop over a common control channel.

Firstly, the FC divides the CRs into different levels according to their distances from the FC. In order to reduce the energy consumption during the reporting phase, a predefined distance threshold (*dhop*) will be determined according to default power level required for one hop communication. In the multi-hop scenario, if we assume that there are L hops, where there are (L-1) predefined distance thresholds ($dhop_1$,$dhop_2$,….,$dhop_{L-1}$), where $dhop_1$=$dhop$; $dhop_2$=2*$dhop_1$; $dhop_{U-1}$ = (L-1)*$dhop$. Any CR user that has a distance less than *dhop* will be set in level 1, otherwise, if it has a distance less than $dhop_2$it will be set in level 2, and so on. After discovering CRs at different levels, the FC sorts CRs in descending order according to the SNR of reporting channel and to their residual energy. Then, FC computes the average energy level of each CR user, and whichever CR users have energy above this average level will be listed under the list of candidates as a CH_L for current round, while the remaining CR users will act as cluster members. The FC determines the optimal number of clusters based on minimising the energy consumed by cluster members to transmit their results to the CH_L, by minimising the total sum of squared distances between the cluster members and the closest CH_L [29].

In this proposed multi-hop clustering algorithm, depending on the spatial distribution of CRs and their distances from the FC, I have two main possibilities for the number of clusters in each hop. The first possibility may be an equal number of clusters in each hop with a different number of members in each cluster, and the second possibility is the number of clusters may be unequal in every hop with an equal number of members in all clusters. In this thesis, I have adopted in the design of the multi-hop routing algorithm on the equal sized clusters, in which the number of cluster members is equal in all clusters. In order to discover clusters at different levels, the FC broadcasts its Identifier (ID) over the common control channel, and all cluster heads, which receive this broadcast, will record the FC ID. Then, all CHs send a message with their own ID's to the FC using their default power level (the required power for intra-cluster communication). Based on a single hop distance, CHs that are near to the FC will form level one hop CH_{L1}s. Afterwards FC will send a new control packet with all level one CH_{L1} ID's in it. As the same, all CHs will reply to this message at default low power level with their own ID's as well as ID's of level one CH_{L1} (CH_{L1} will not reply to this message, since their ID's are present in the control packet). In this case, CHs cannot send their reply directly to the FC, where they will send at lower power level. Since CH_{L1} are at the distance of one hop from CH_{L2}, therefore, these replies will be received by level one CH_{L1} whose ID's are present in the reply message, which in turn relays them to the FC. Similarly, the FC will repeat broadcast control message with ID's of all CHs that have been discovered. This process continues until completing all CHs in the network.

B Cluster Formation Phase

The cluster formation is done by CHs, where each CH broadcasts an advertisement message (ADV) using a carrier-sense multiple access (CSMA) MAC protocol, which instructs the CR users to select their CHs. After receiving the messages from all CHs, each CR user sorts the received power signal of each message and selects the largest one as its selected CH. Then, each CR user should inform the CH that it would be a member of the cluster by sending back a join-request message to the selected CH using CSMA MAC technique. This join message contains the cluster head's ID and the CR user's ID. Each CH compares its ID with the received one, and if the cluster head's ID matches its own ID, the CH will accept the join request; otherwise, the request is rejected.

After completing the cluster formation, each CH knows which CRs are in its cluster and creates a TDMA schedule assigning each member a time slot to transmit its sensing result, and then informs all members in its cluster of a CSMA code which is used for communication among them. After the TDMA schedule is known by all members in the cluster, the set-up phase is complete and the data transmission can start.

C Steady State Phase

In this phase, the CRs start to transmit their results to the CH during their allocated time slots. As shown in Figure 6.2, this phase is divided into frames, which depend on the number of clusters. The time to send a frame of data is constant and depends on the number of cluster members. During each frame, all the cluster members send their results to the CH in respect to the TDMA schedule, and then the CH collects the local decisions, makes the cluster decision about the presence of the primary signal, and sends it to the FC via intermediate cluster heads within different levels in accordance to its time slot. Afterwards, the FC combines the received clustering decision to make the final decision then broadcasts it back to all CHs, which in turn send it to their cluster members.

6.3 A Mathematical Model of the Proposed Algorithm

In this section we introduce the mathematical models for analysing the energy consumption and sensing delay, and computing the spectrum sensing probabilities for our proposed multi-hop clustering algorithm. These models are described in detail in the following subsections.

6.3.1 Energy Model of Cooperative Spectrum Sensing

Typically, most of energy dissipation in each single wireless device is the result of transmitting energy dissipation to run the radio electronics, the power amplifier, and receiving energy dissipation to run the radio electronics. In our analysis, we use the same radio model described in [29], where the energy required to transmit or receive one message of size *B* bits over a transmission distance *R*, is given by:

$$E_{TX}(B,R) = \begin{cases} BE_{elec} + B\epsilon_{fs}R^2 & if \quad R \le R_O \\ BE_{elec} + B\epsilon_{mp}R^4 & if \quad R > R_O \end{cases} \tag{6 - 1}$$

$$E_{RX}(B,R) = BE_{elec} \tag{6 - 2}$$

Where E_{elec} the electronic energy consumed to send or receive a message; E_{TX} represents the total energy consumed by the transmitter, while E_{RX} is energy consumed by the receiver. $\epsilon_{fs}$and ϵ_{mp} denote the energy dissipated by the transmit power amplifier to maintain an acceptable SNR in order to transfer data reliably, and depend on the channel model, and $R_O = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$ is the breakpoint or threshold distance [141]. Power control can be used to invert this loss by appropriately setting the power amplifier; if the distance R is less than a threshold R_O, the free space model $\epsilon_{fs}$is used; otherwise the multipath model ϵ_{mp} is used.

A Energy Model of Conventional CSS

In conventional cooperative spectrum sensing approaches, the FC selects a sensing channel and instructs all CRs to individually perform local sensing, also sends the Time Division Multiple Access (TDMA) schedule for each CR user transmission. Therefore, every CR user will remain in sleep state with significantly less power and will not be on until its transmit slot time. Using a direct communication route, each CR user sends its local decision directly to the FC. Therefore, if the FC is far away from the CR user, direct reporting will consume more energy.

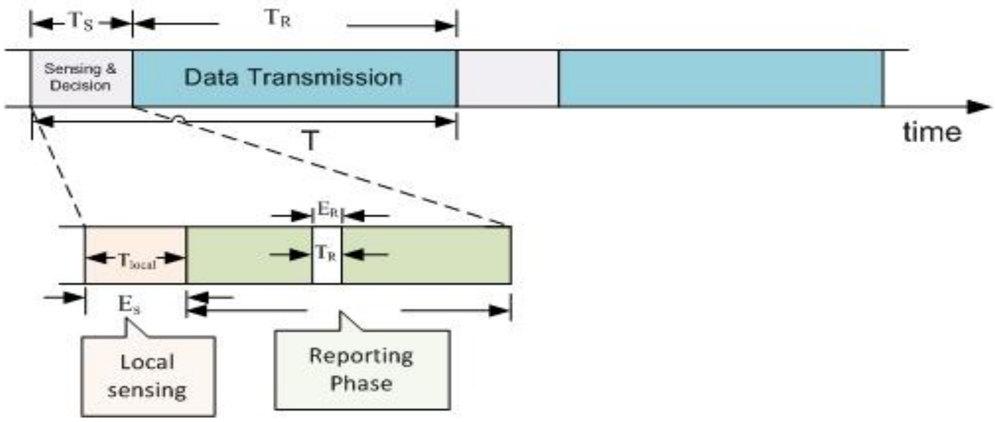


Figure 6.3 Sensing frame structure of conventional CSS

Figure 6.3 shows a general sensing frame structure of conventional CSS. In general, the energy consumption of a conventional CSS during the sensing period may include the energy consumed in sensing the channel occupancy E_s; the energy consumed in the sleeping mode E_p; the energy consumed in computing the observations and making a local decision E_c; and the energy consumed in transmitting the local decision to the fusion centre E_R. In practice, $E_p<E_c<<E_R$, then we can ignore E_p and E_c. Under these considerations, the energy consumption of M CRs can be calculated as follows:

$$E_R = \begin{cases} BE_{elec} + B\epsilon_{fs}D^2 & if \quad D \le R_O \\ BE_{elec} + B\epsilon_{mp}D^4 & if \quad D > R_O \end{cases} \tag{6 - 3}$$

where D represents the transmission distance between CR user and the FC.

$$E_{local} = E_s + E_R \tag{6 - 4}$$

$$E_{total} = ME_{local} \tag{6 - 5}$$

We can see from (6-5) that the power consumption is mainly depending on the number of CRs and the distance between the CR user and the FC.

B Energy Model of Cluster Based CSS

In one hop clustering approaches, the data transmission begins when each cluster member sends its local sensing decision to the selected CH during each frame as shown in Figure 6.4.

Presumably, the distance between each cluster member (non-CH) and the closest CH is small, so the free space model R^2 is adopted in energy dissipation. Thus, the energy consumed by each cluster member is expressed by:

$$E_{non-CH} = E_S + BE_{elec} + B\epsilon_{fs}R^2 \tag{6 - 6}$$

Assuming that the CRs are uniformly distributed in Z x Z region, and based on the approximation in [29], we can approximate the area occupied by each cluster to $\frac{Z^2}{K}$, thus, the expected R^2 becomes:

$$R^2 = 0.159\frac{Z^2}{K} \tag{6 - 7}$$

Where K is the number of clusters. Therefore, the expression (6-6) can be rewritten as:

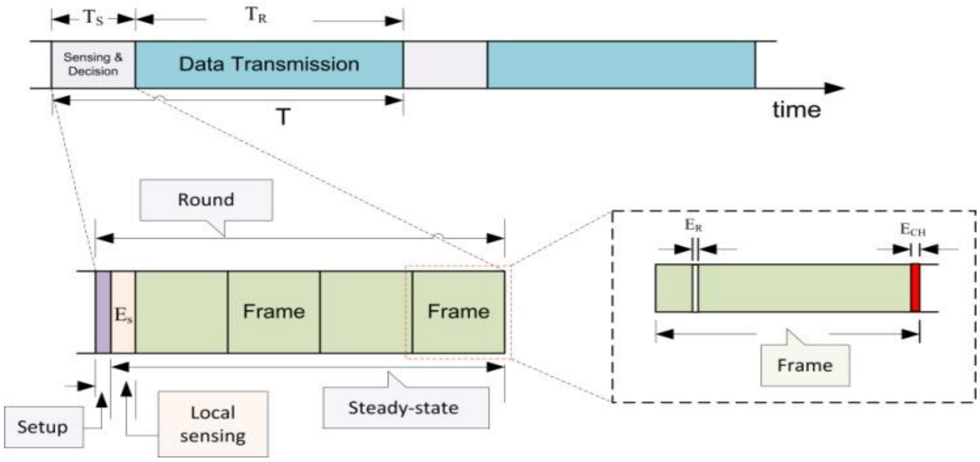


Figure 6.4 Frame structure of cluster based CSS.

$$E_{non-CH} = E_S + BE_{elec} + 0.159B\epsilon_{fs}\frac{Z^2}{K} \quad (6 - 8)$$

Also in this system, we assume that the FC is far from the CRs, thus the energy dissipation in each CH during a single frame follows the multipath model (R^4 power loss) and can be given as:

$$E_{CH} = E_{sensing} + E_{datareceiving} + E_{datacollection} + E_{datatransmission} \quad (6 - 9)$$

$$E_{CH} = E_S + BE_{elec}\left(\frac{M}{K} - 1\right) + BE_{DC}\frac{M}{K} + BE_{elec} + B\epsilon_{mp}R^4 \quad (6 - 10)$$

Here R represents the distance between CH and the FC, and E_{DC} denotes the energy dissipated in data collection. The energy dissipated in a cluster during the frame is given by:

$$E_{Cluster} = E_{CH} + \left(\frac{M}{K} - 1\right)E_{non-CH} \approx E_{CH} + \left(\frac{M}{K}\right)E_{non-CH} \quad (6 - 11)$$

and the total energy consumed by the network is

$$E_{total} = E_{setup} + KE_{Cluster} \tag{6 - 12}$$

$$\begin{aligned} E_{total} = \; & E_{setup} + K[E_S + BE_{elec}\left(\frac{M}{K} - 1\right) + BE_{DC}\frac{M}{K} \\ & + BE_{elec} + \quad B\epsilon_{mp}R^4 \; + \left(\frac{M}{K}\right)E_S \\ & + \left(\frac{M}{K}\right)BE_{elec} + 0.159(\frac{M}{K})B\epsilon_{fs}\frac{Z^2}{K}] \end{aligned} \tag{6 - 13}$$

$$\begin{aligned} E_{total} = \; & E_{setup} + (M + K)E_S + (2M)BE_{elec} + MBE_{DC} \\ & + KB\epsilon_{mp}R^4 \; + 0.159(M)B\epsilon_{fs}\frac{Z^2}{K} \end{aligned} \tag{6 - 14}$$

The optimum number of clusters K can be found by differentiating the equation (6-14) with respect to K and equating to zero as:

$$K_{opt} = \sqrt{\frac{0.159BM\epsilon_{fs}}{B\epsilon_{mp}R^4 + E_S}}Z \tag{6 - 15}$$

C Energy Model of Multi-hop Cluster Based CSS

In multi-hop cluster based CSS algorithm, the FC sets the cluster heads, and issues a TDMA schedule for each level of cluster heads. Then, each cluster head will issue its own TDMA schedule for cluster members. Based on this schedule, cluster heads not only collect the local sensing results from their cluster members, but also act as relaying users for lower level cluster heads. Thus, the cluster heads that are far away from the FC will send their sensing results to the FC through intermediate cluster heads, which leads to consuming less energy compared to direct reporting.

Here, the power consumption of each non-cluster head is the same as in the one-hop clustering algorithm. The power consumption of cluster heads will be different, because the cluster heads are divided into multi-levels depending on their distance from the FC, and only the level one cluster heads will send their results directly to the FC, while other level cluster heads will send their results through next level cluster heads until reaching the FC. As a result, the power consumption in each cluster head will be dependent on the distance from other upper level cluster heads, as well as on the length of time taken receiving and relaying the results of lower level cluster heads.

The calculation of our multi-hop clustering algorithm is as follows. The non-cluster head users only need to perform the local sensing and send their sensing results to their CH, and because they are close to each other, thus, the energy consumed by each cluster member can be expressed by:

$$E_{non-CH} = E_S + BE_{elec} + B\epsilon_{fs}R^2 \tag{6 - 16}$$

The cluster head needs to fuse the all local sensing results and relay the other level cluster heads results, so its energy consumption is:

$$\begin{aligned} E_{CH}(i) = E_{sensing} + E_{datareceiving}(i) \\ + \ E_{datacollection} + E_T(i) \end{aligned} \tag{6 - 17}$$

$$E_{sensing} = Es \tag{6 - 18}$$

$$E_{datareceiving}(i) = BE_{elec}\left[\left(\frac{M}{K} - 1\right) + Relays(i)\right] \tag{6 - 19}$$

$$E_{datacollection} = BE_{DC}\frac{M}{K} \tag{6 - 20}$$

$$E_T(i) = \begin{cases} BE_{elec} + B\epsilon_{fs}d^2_{Relays(i)} * (\mathrm{Relays(i)} + 1) \text{ if } \mathrm{d_{Relays(i)}} < \mathrm{d_O} \\ BE_{elec} + B\epsilon_{mp}d^4_{Relays(i)} * (\mathrm{Relays(i)} + 1) \text{if } \mathrm{d_{Relays(i)}} > \mathrm{d_O} \end{cases} \tag{6 - 21}$$

Where Relays(i) is number of data relay, *i* represents the cluster head, and $d_{Relays(i)}$ is the distance to its next hop CH. Finally, the total energy consumption can be written as:

$$E_{total} = E_{setup} + (M-K)E_{non-CH} + K * E_{CH}(i) \quad (6 - 22)$$

6.3.2 Sensing Model of Multi-hop Cluster Based CSS

Cooperative spectrum sensing schemes are developed to improve the detection performance and shorten the sensing time. The performance of these approaches is measured mainly by two parameters: detection probability P_d, which indicates that the primary user exists, and false alarm probability P_f, which indicates that the primary user is present while in reality it is not. Another important parameter is mis-detection probability P_m, which indicates that the primary user is absent while actually it is existing.

In our algorithm, each cluster member makes its own one bit hard decision: '0' or '1' which means absence or presence of primary activities, respectively. This one bit decision is reported independently to the FC via multiple intermediate CHs, which makes the final decision on the primary activity using one of the hard decision rules.

A Local Sensing

Spectrum sensing is essentially a binary hypothesis testing problem, assuming that cognitive users are independent of each other, and each one conducting a local sensing using a simple energy detection algorithm (ED) [121], so the model can be described as follows:

$$x_i(t) = \begin{cases} n_i(t) & , H_0 \\ h_i s(t) + n_i(t) & , H_1 \end{cases} \quad (6 - 23)$$

$x_i(t)$ is received signal of the ith cognitive user; s(t) is transmitted signal of primary transmitter; $n_i(t)$ is zero mean additive white Gaussian noise; h_i is the channel gain; H_0 and H_1 represent that the primary signal is absent and present, respectively. The main function of energy detection is to make a decision between the two hypotheses.

During local sensing process, each CR makes local sensing using the energy detection algorithm and reports its local observation to the fusion centre FC individually. The false alarm probability Pf and the detection probability Pd at each CR can be calculated as [121]:

$$Pf = Q\left[\frac{\lambda - \mu_0}{\sigma_0}\right] \qquad (6 - 24)$$

$$Pd = Q\left[\frac{\lambda - \mu_1}{\sigma_1}\right] \qquad (6 - 25)$$

where, Q represents cumulative distribution function and can be expressed as [128]:

$$Q(\mathrm{x}) = \frac{1}{\sqrt{2\pi}}\int_{\mathrm{x}}^{\infty} \exp\left(-\frac{\mathrm{u}^2}{2}\right) du \qquad (6 - 26)$$

$\mu_0 = N\sigma_n^2, \mu_1 = N\sigma_n^2(\gamma + 1),\ \ \sigma_0^2 = 2N\sigma_n^4, \sigma_1^2 = 2N\sigma_n^4(\gamma + 1)^2,$ N: number of samples, σ_n^2: is the noise power, and $(\gamma = |h\_i\ (t)\ |\text{^}2\ (\sigma s\text{^}2)/(\sigma n\text{^}2\ ))$ denotes to signal to noise ratio SNR.

Using the strategy of constant false alarm rate (CFAR) and for a given desirable Pf, the value of threshold λ can be predefined from (6-24) as: $\lambda = N\sigma_n^2 + \sqrt{2N}\sigma_n^2 Q^{-1}(Pf)$, then this value will be used to determine the value of detection probability Pd using (6-25). In non-fading environments, where $h_i(t) = h$ is deterministic, the Pf and Pd of each CR user are the same as expressed in (6-24) and (6-25) above. On the other hand, when each CR user receives the primary signal through the Rayleigh fading channel, the received signal energy and SNR at each user are location dependent. In such a case, the average probability of detection $\overline{Pd}$ may be derived by averaging (6-25) over the fading statistics as follows [103]

$$\overline{Pd} = \int_x P_d f_\gamma\,(x) dx \qquad (6 - 27)$$

Where $f_{\gamma}(x)$ is the probability density function of the received SNR at each CR user under the Rayleigh fading channel.

B Cooperative Sensing With Imperfect Reporting Channels

In practice, because of the imperfect reporting channel, errors can be occurring on the local decision bits which are transmitted by CR users to the FC. Thus, each reporting channel can be modeled as a binary symmetric channel with cross-over probability p_e which is equal to the bit error rate (BER) of the channel. Specifically, let p_e = Pr(FC receives bit'1'| CR sends bit'0') and p_e = Pr(FC receives bit'0'| CR sends bit'1'). Consider the *i*th CR user, and for binary phase shift keying modulation (BPSK) with Rayleigh fading channels, the average error probability $p_{e,i}$ can be given as [132]:

$$p_{e,i} = \frac{1}{2}\left(1 - \sqrt{\frac{\acute{\gamma}_i}{(\acute{\gamma}_i + 1)}}\right) \qquad (6 - 28)$$

Where $\acute{\gamma}_i$ is the average SNR of the reporting channel between the CR user and the FC.

Under these conditions, the FC receives a bit '1' in two cases: when a CR user sends a bit '1' with probability $pd_i(1 - p_{e,i})$; or when a CR sends a bit '0' with probability$(1 - pd_i)p_{e,i}$. On the other hand, the FC receives a bit '0' under two cases: when a CR user sends a bit '0' with probability $pf_i(1 - p_{e,i})$; or when a CR sends a bit '1' with probability$(1 - pf_i)p_{e,i}$. Thus, the detection and false alarm probability at the FC can be written, respectively, as follows [139]:

$$Pd_i' = pd_i(1 - p_{e,i}) + (1 - pd_i)p_{e,i} \qquad (6 - 29)$$

$$Pf_i' = pf_i(1 - p_{e,i}) + (1 - pf_i)p_{e,i} \qquad (6 - 30)$$

C Majority (k out of n) Hard Decision Fusion Rule

In general, there are three mean hard decision combination rules in wireless networks namely OR, AND, and Majority rules. If there are *n* cooperative users that have independent own decisions, when *k*=1, *k*=*n*, and *k*= [*n/2*], the *k* out of *n* rule represents OR rule, AND rule, and Majority rule, respectively. OR rule provides more protection to the primary system, because it allows the CRs to access the spectrum when all the reported decisions from CRs demonstrate that the primary user is absent, but it does not give us efficient spectrum utilization. On the other hand, in AND rule, the FC decides the primary user is present when all cooperative users reported that the primary user is present, thus, it gives a perfect spectrum utilization, but with poor protection to the primary system. Therefore, we adopted the majority rule in our system model, which provides a trade-off between the spectrum utilization and the interference protection.

If the reporting channels are free of errors, then the detection and false alarm probabilities can be written, respectively, as:

$$Qd = \sum_{j=k}^{M} \binom{M}{j} (pd_i)^j (1 - pd_i)^{M-j} \qquad (6 - 31)$$

$$Qf = \sum_{j=k}^{M} \binom{M}{j} (pf_i)^j (1 - pf_i)^{M-j} \qquad (6 - 32)$$

Where *M* is the total number of cooperative users, and *k* =*M/2*.

Practically, most reporting channels are imperfect; therefore, errors may occur during reporting the local sensing results to the FC. Here, we consider a BPSK signal in a CR network; error probability $p_e$can be calculated under multipath and shadowing effects according to (6-28). In our clustering approach, we assume that the cluster members are close to each other, therefore, the intra-cluster communication channels (channels between cluster members and the related cluster head) are perfect (error free). The total detection and false alarm probability at the CHs and the FC are given, respectively, as follows:

$$PD = pd(1 - pe) + (1 - pd)pe \tag{6 - 33}$$

$$PF = pf(1 - pe) + (1 - pf)pe \tag{6 - 34}$$

$$Qd = \sum_{j=k}^{M} \binom{M}{j} (PD_J)^j (1 - PD_J)^{M-j} \tag{6 - 35}$$

$$Qf = \sum_{j=k}^{M} \binom{M}{j} \left(PF_J\right)^j \left(1 - PF_J\right)^{M-j} \tag{6 - 36}$$

D Multi-hop Cluster Based CSS Mode

Consider a multi-hop clustering cognitive radio network with both identical and non-identical channels. We assume that there are L hops between the primary user and the FC. Each non identical cluster head CH_L forwards the cluster results to the next hop cluster head CH_{L-1} with probability error p_e given as [132]:

$$p_{e,i} = \frac{1}{2}\left(1 - \sqrt{\frac{\gamma_i{}'}{1 + \gamma_i{}'}}\right) \tag{6 - 37}$$

And for non-identical channels the equivalent probability error can be expressed as [139]

$$P_e = \frac{1}{2}\left(1 - \prod_{i=1}^{L-1}(1 - 2p_{e,i})\right) \tag{6 - 38}$$

Where $p_{e,i}$ is the probability error of one hop cluster.

In the event that the reporting channel is identical, (the SNR is the same for all cluster heads), the equivalent probability error will be given as

$$P_e = \frac{1}{2}(1 - (1 - 2 * p_e)^{L-1}) \quad (6 - 39)$$

Then, the total *QD*&*QF* will be expressed as:

$$QD = pd(1 - Pe) + (1 - pd)Pe \quad (6 - 40)$$

$$QF = pf(1 - Pe) + (1 - pf)Pe \quad (6 - 41)$$

6.3.3 Spectrum Sensing Delay of Multi-hop Cluster Based CSS

Another metric that is important for spectrum sensing is detection delay time. In cooperative spectrum sensing, an additional time-delay will be introduced due to the cooperation between CRs and the FC. Form Figure 6.3, the total detection delay of the conventional and the cluster based cooperative spectrum sensing, respectively, can be derived as follows.

In conventional mode, all cooperative users perform local sensing independently at the same time, and then each one will send its sensing decision according to its own TDMA schedule time. Thus, the total sensing time of the conventional cooperative spectrum sensing $T_{con.}$ can be given as:

$$Tcon. = T_{local} + M * T_R \quad (6 - 42)$$

Where T_{local} is the local sensing time, M is the number of cooperative users, and T_R denotes the reporting time of one user.

As we know, the main goal of the cluster-based algorithm is to reduce the communication overhead between the CRs and the FC, also to decrease the sensing time, thus increase the agility of the system. In the cluster based CSS scheme, after the formation of all clusters is completed, all cluster members within each cluster will start to perform the local sensing individually at the same time, and then report their decision results to their CHs using their TDMA schedule time. Afterward, each CH will send its cluster result to the FC according to its TDMA schedule time. Back to Figure 6.4, if we symbolize the setup time T_{setup}, and the number of cluster K, then, the total sensing time of the cluster based CSS $T_{clus.}$, can be written as

$$Tclus. = T_{setup} + T_{local} + \left((\frac{M}{K} - 1) + K \right) * T_R \qquad (6 - 43)$$

From the above equations (6-42) and (6-43), we can observe that the cluster based CSS has a shorter sensing time compared to the conventional approach due to the advantages of parallelism benefited from clustering, and when K=M, $Tclus. \approx Tcon.$, which is almost the same as that of the conventional scheme. When K<<M, the detection time can be decreased greatly with the clustering algorithm.

In the multi-hop clustering mechanism, relaying the sensing results from far cluster heads to the FC via intermediate cluster heads introduces an additional delay, which depends on the number of all relaying signals in the network N_{relay}. Thus, the total sensing time of the multi-hop clustering CSS approach will be the same in the equation (6-43) with adding relaying delay time T_{relay}, which can be expressed as follows.

$$T_{relay} = \sum_{i=1}^{L} \left(N_{hop,i} \right) * T_R \qquad (6 - 44)$$

$$T_{multihop} = T_{setup} + T_{local} + \left(\left(\frac{M}{K} - 1 \right) + K \right) * T_R + T_{relay} \qquad (6 - 45)$$

The optimal number of clusters K that minimises the total sensing time $T_{multihop}$ can be determined by differentiating the (6-45) with respect to K and equating the results to zero, as follows:

$$min\, T_{multihop}(K),$$

$$s.t. \quad K \in (1,2,\ldots\ldots..,M),$$

$$\frac{\partial T_{multihop}(K)}{\partial K} = (-MK^{-2} + 1) * T_R = 0$$

$$K = \sqrt{M} \tag{6 - 46}$$

6.4 Simulations and Results

The evaluation results obtained using MATLAB® software are presented in this section, which show the performance gain of the proposed method in terms of spectrum sensing and power consumption. The conventional cooperative spectrum sensing schemes, such as direct reporting and traditional cluster algorithms are also simulated for comparison. The discussion of the simulation results is presented in detail in the following subsections.

6.4.1 Energy and Sensing Delay Simulations

For our experiments, we consider a cognitive radio network with100 nodes which are randomly generated and uniformly distributed between (x=0, y=0) and (x=200, y=200) with the BS at location (x=100, y=275) as shown in Figure 6.5, and the reporting message is 1 bit long. Also we assume a simple model for the radio hardware energy dissipation and adopt the same communication energy parameters as in [29], and are given as: $Eelec$= 50 $nJ/\ bit$; Efs=10 $pJ/\ bit/\ m^2$; Emp=0.0013 $pJ\ /bit/\ m^4$; E_{DC}=5 $nJ\ /bit$.

Figure 6.5 shows the topology and the formation of our multi-hop clustering approach with 4-hops and 20 clusters, which we used in our simulation. Here, we consider that the FC can divide the CRs into 4 levels (Li), i = 1,2,3,4, based on their distances from the FC, assuming that the distance threshold of one hop communication($do = \sqrt{(\epsilon fs/\epsilon mp})$, which is here equal to (87.7 m). Thus, the FC will discover the different levels (L_1, L_2, L_3, and L_4) of CRs according to (do, $d1$, and $d2$), where $d1$=2do, and $d2$=3do, respectively.

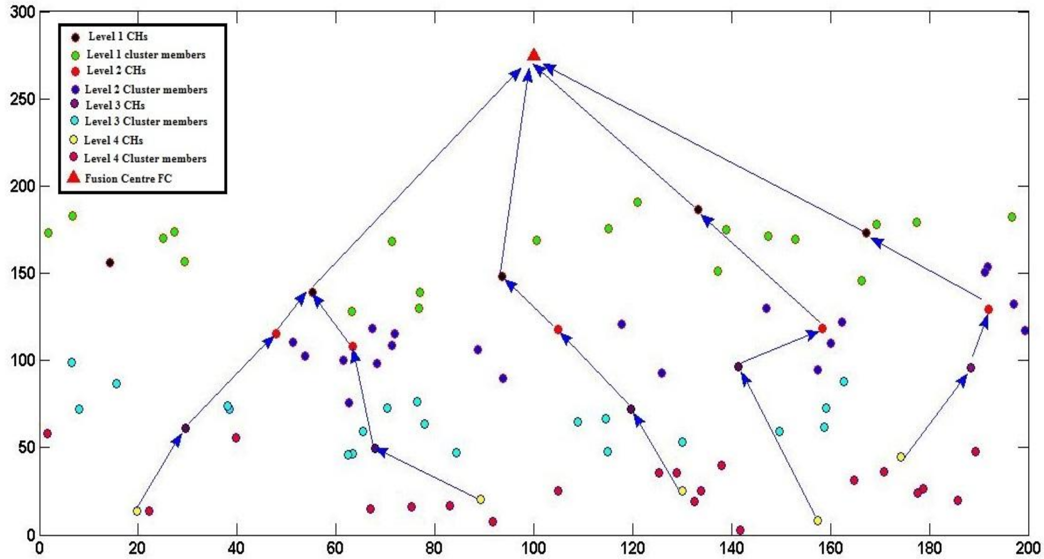


Figure 6.5 CR network deployment with Cluster formation

Here, for simplicity, we considered that the number of CRs at each level is the same and equal to 5. In practice, this is not always true, because in some cases and depending on the distances between the CRs and the FC, the number of CRs in some levels will be greater than other levels, which leads to an unequal number of clusters in each level. However, there is not much impact on the evaluation of our energy mode under all assumptions, including equal number or unequal number of CHs at each level.

Figure 6.6 illustrates the total energy dissipation in the network with different modes. We can show that the energy performance of the cluster based CSS scheme is better than the conventional mode. Furthermore, more energy reduction can be achieved when the multi-hop clustering approach is used. It can also be shown that the energy consumption of the conventional mode increases greatly with the increase of the number of CRs, while in other modes it increases slightly with the number of CRs, particularly in multi-hop clustering mode.

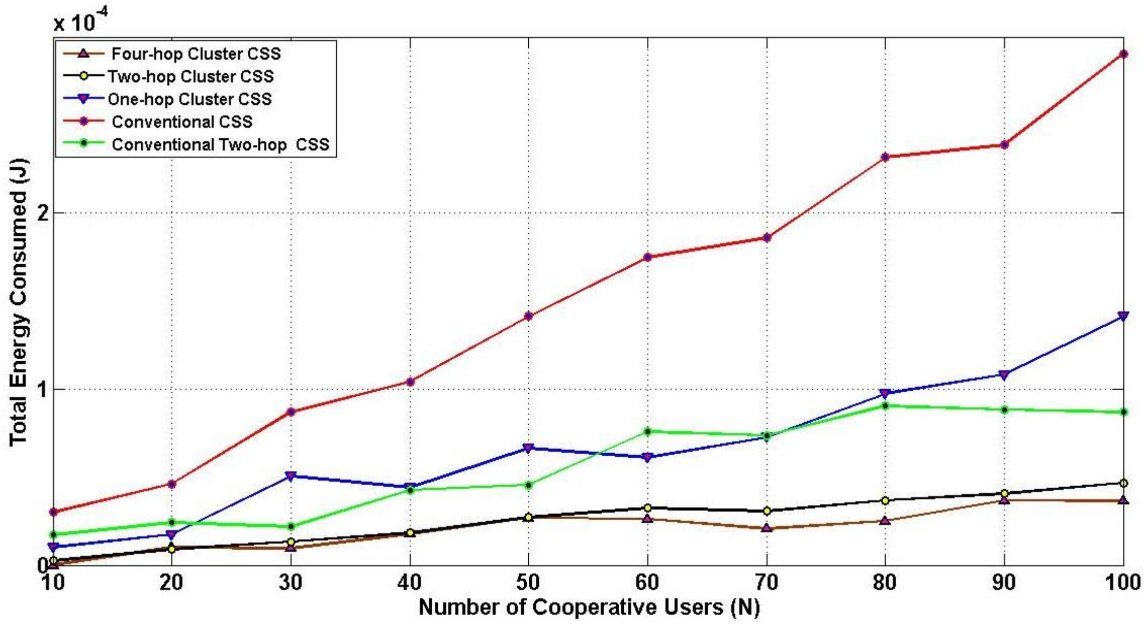


Figure 6.6Average Energy Dissipation versus number of users with different CSS modes.

The results also show that there is a slight saving in energy performance of 4-hop clustering mode compared with 2-hop mode. For instance, in the case of 100 CRs, the results show that there is a great reduction in energy dissipation and savings can reach 64% in one-hop clustering mode compared to the conventional cooperative mode, whereas the two-hop clustering mode has achieved 50% of energy savings compared with one-hop clustering approach. Furthermore, we will get a slight reduction in the energy consumed when the number of hops is increased. As shown in Figure 6.6the decline of the energy consumed in 4-hop will be 15% compared to 2-hop mode. In other words, multi-hop clustering CSS algorithm can provide a great energy efficient transmission, which is particularly true for a wide cognitive radio networks.

The optimum number of clusters that minimises energy dissipation in cognitive radio networks is studied here. According to (14), we can analytically determine the optimal number of clusters K. Using our experimental parameters, and when $(75\text{m} \leq R_{to\ FC} \leq 295\text{m})$, the value of K will be $((1 \leq K \leq 5)$. We verified this analytical result using simulations by varying K between 2 and 50.

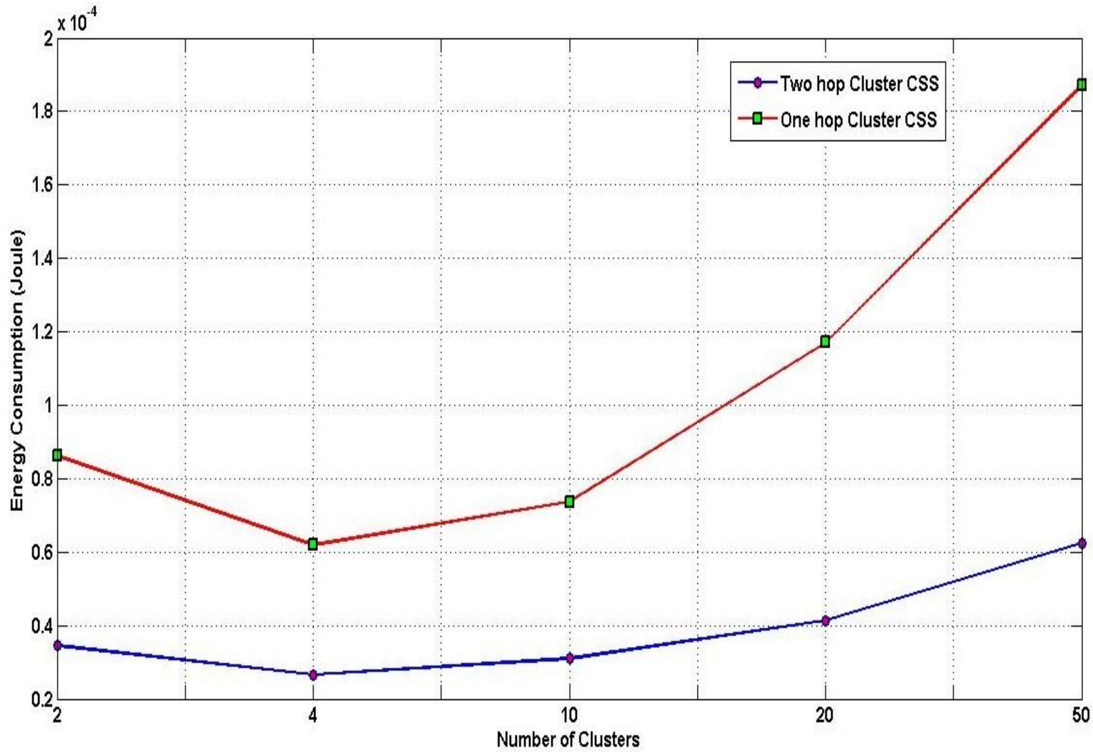


Figure 6.7 Energy dissipation versus number of clusters.

Figure 6.7,which shows the energy dissipation as a function of K for two models (one-hop and two-hop), shows that the optimal number of clusters is around 4 for 100 cooperative users, which agrees well with our analysis. As illustrated in the figure, when there are only a few clusters (less than optimal number), the cluster members need more energy to report the results to their cluster head over far distance, and when there are more clusters (greater than optimal number), the dissipated energy will increase as a result of the long distance between them and the fusion centre.

Another improvement that can be achieved by using our algorithm is the sensing agility. Figure 6.8 gives us the normalised sensing delay $\left(\frac{T_X}{T_{con.}}\right)$ in terms of the number of clusters K in different number of hops L.

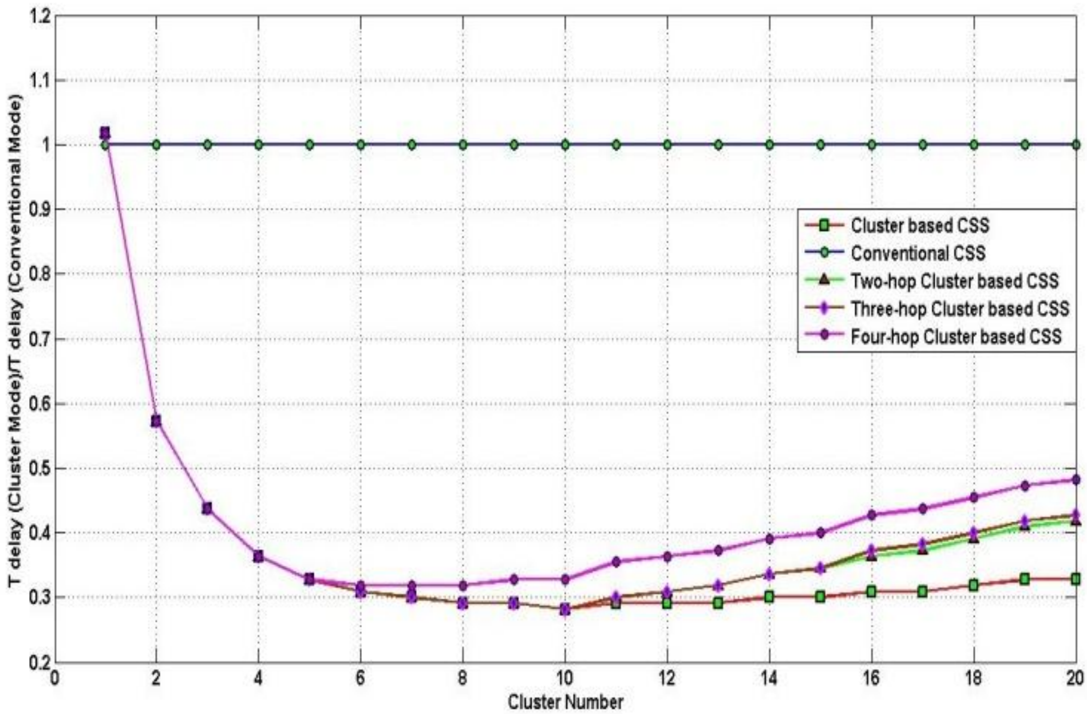


Figure 6.8 Sensing delay time performance of different cooperative mode

As we can see in Figure 6.8, the normalised sensing time of single hop and multi-hop clustering approaches have a steep decline with the increase in the number of clusters K, and then begin to increase gradually at different rates according to the number of hops L. More specifically, although the multi-hop clustering scheme reduces the sensing time significantly within the range$(2 \leq K \leq 5)$, it adds further delay time within the range$(K \geq 5)$, but is still much less than conventional mode (direct reporting).This is because more hops leads to more relaying needed to send the results to the FC, and thus, adds further delay time, according to (6-41) and (6-42). According to (6-43), we can analytically determine the value of the optimal number of clusters (K_{opt}) that gives a minimum sensing delay, which will be 10 when M = 100.

6.4.2 Spectrum Sensing Performance

In this section, the sensing performance of multi-hop cluster-based CSS scheme is investigated under the perfect and imperfect reporting channels. The numerical results of our proposed algorithm are given to verify the analytical framework that is presented in the previous section.

First, the sensing performance of the conventional CSS is presented, where CRs are reporting their local sensing results directly to the FC. Figure 6.9 shows the resulting receiver operating characteristic (ROC) curve for the decision fusion rules with the case of an Additive White Gaussian Noise (AWGN) for both sensing and reporting channels.

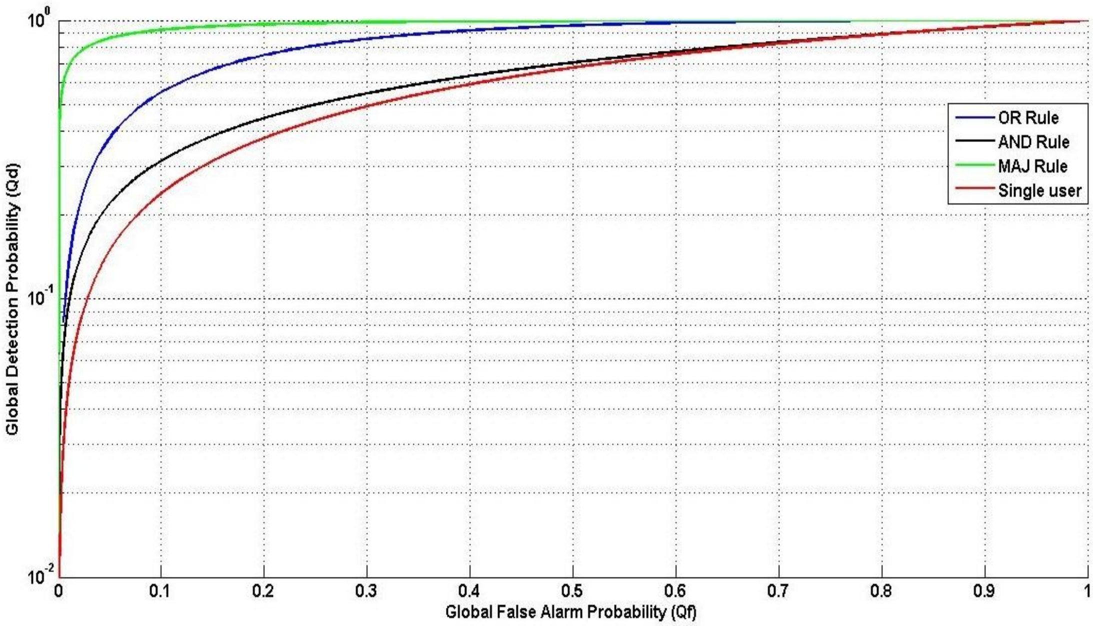


Figure 6.9 ROC curve of cooperative spectrum sensing with different fusion rules

In this simulation, we assumed that a cognitive radio network with *M*=50 cooperative users operating at an average SNR of sensing channel $\mathrm{SNR_{local}} = -10$ dB using *N*=50 samples. It can be seen from this figure that, for the same Qf the Majority rule always outperforms OR rule and AND rules, and OR has better detection capability than AND fusion rule.

Second, the effectiveness of error reporting under Rayleigh fading channels is considered, as shown in Figure 6.10. Here, we assumed that the number of samples *N*=10, and the average SNR of sensing link (between the primary transmitter and the CRs) is -10 dB. As we can see from this figure, when the number of CRs *M* increases from 50 to 100, and using the majority rule as a decision fusion rule at both the FC and the cluster head, the detection performance will improve significantly. On the other hand, with the erroneous reporting channels, and when the average SNR of the reporting channel between each CR user and the FC is-5dB, the detection capability will be degraded due to the fading phenomena.

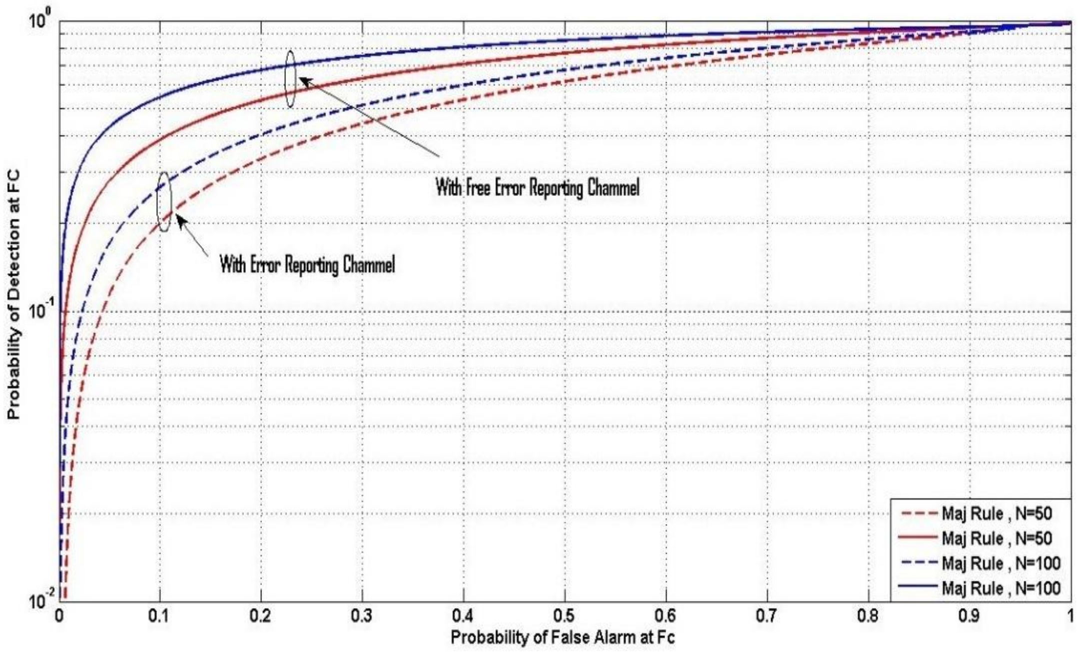


Figure 6.10. ROC curves of cooperative spectrum sensing over Rayleigh fading channels with and without error

In Figure 6.11, the ROC performance of multi-hop clustering CSS scheme over Rayleigh fading is given. In this simulation, we consider 100 CRs are deployed randomly with different average SNR of sensing and reporting channels within the ranges of (-10, -5) dB and (-25, 25) dB, respectively. For simplicity, we assume that the noise power at each CR user is equal to 1, and also the majority fusion rule at both the cluster heads and the FC is used. The results of conventional mode are also given for a comparison.

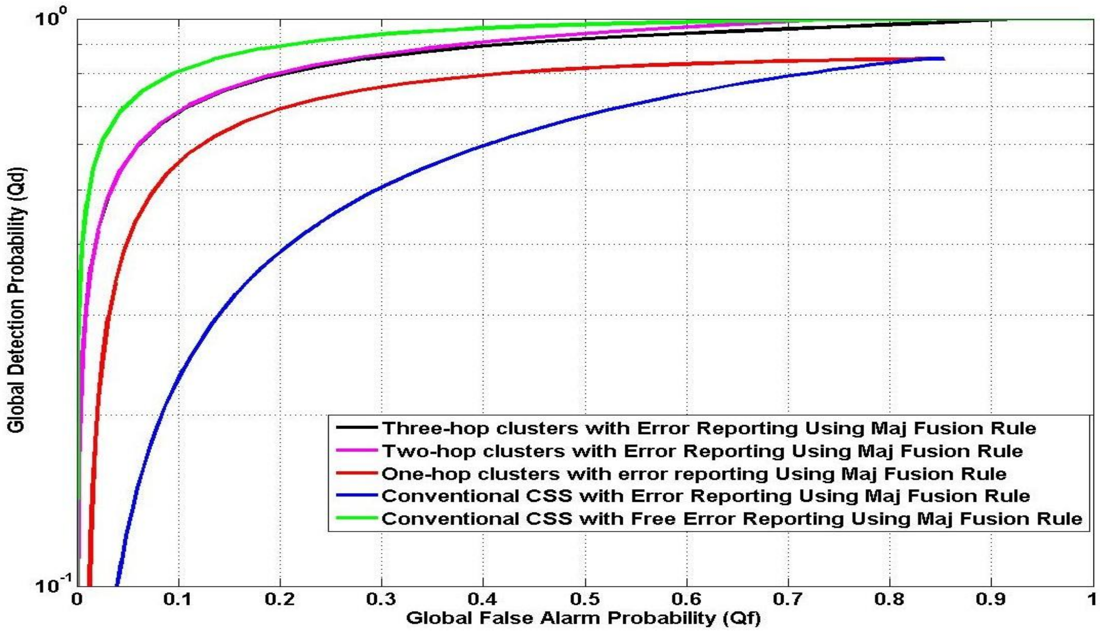


Figure 6.11. ROC curves for multi-hop Clustering CSS using Majority fusion rule.

As can be seen from this figure, the detection accuracy deteriorates as the number of error reports increases due to low SNR of the reporting channel. However, the sensing performance can be enhanced using a clustering approach. By using the clustering mechanism, the local sensing will be sent to the FC via intermediate CR user (CH) that has the largest SNR of reporting channel. In this simulation, we set the number of clusters K = 5, and the reporting SNR of CHs are (25, 8, 3, 0, -1) dB. Simulation results indicate a clear improvement in sensing performance compared to traditional detection mode even though some CHs suffer from poor SNR, especially the far CHs.

Figure 6.11 also illustrates the advantage of the detection capability of the multi-hop clustering algorithm when the SNR of multi-hop is better than one-hop. Here, we assume that the clusters (K = 5) are formed at the FC based on the CR users' distances to the FC and divided into multi-hop levels. For instance, for two levels hop scenario, 2 in level-1 and 3 in level-2. In three levels hop scenario, 2 clusters in hop level-1, 2 in hop level-2, and 1 in hop level-3. Therefore, we can exploit the channel conditions between successive hops, which are much better than between far clusters and the FC. In our simulation, the SNR of the successive three levels hop communication are chosen randomly as (25, 8, 12, 14, 15) dB, respectively. In other words, 25 dB represents the SNR of reporting channel between the first CH_{L1} and the FC, 8 dB denotes to the SNR of reporting channel between the second CH_{L1} and the FC, and so on, while 15 dB is the SNR of reporting channel between the CH_{L3} and the first or second CH_{L2}. As shown, the sensing performance of the multi-hop clustering scheme outperforms the one-hop mode, which basically depends on the channel conditions of the successive multi-hops. Although, the sensing performance of the multi-hop algorithm has not reached the ideal case (Free error case), it can be seen that there is a great improvement in the sensing performance for the 3-hop approach compared to 2-hop, resulting from good reporting channels and the short distances between CHs.

6.5 Summary

Designing a reliable and efficient detection algorithm for spectrum sensing is a major problem in cognitive radio networks. In this chapter, we proposed a new multi-hop clustering approach for cooperative spectrum sensing. In practice, most of CR users who have good local sensing information are far away from the FC, causing weakness in the reporting channel and thus reducing the detection performance. In this chapter, a new multi-hop clustering approach is developed that reports the local sensing results via a reliable reporting channel, hence increasing the detection accuracy.

In order to evaluate the proposed CSS algorithm, the performance of the proposed scheme in terms of spectrum sensing and energy consumption has been compared with that in conventional approaches. The simulation results showed that our multi-hop clustering approach achieves better energy saving and detection performance than the existing approach, at the expense of a little delay. Moreover, the proposed method can detect the spectrum availability much faster than conventional algorithms due to the characteristics of clustering, but adds a slight delay compared with the one hop clustering approach due to successive multi-hop relaying delay. Through simulation results obtained in this chapter, it can concluded that in order to design a good spectrum detector, trade-offs among the evaluation points is required, and we should balance these trade-offs according to the application requirements.

The work presented in this chapter is published in two IEEE conference proceedings [30-31], which gave more reliability of the simulation results obtained in this work.

Chapter 7

Multi-hop Clustering Approach for Decentralised CSS

7.1 Introduction

In decentralised CRNs such as cognitive ad-hoc networks and cognitive sensor networks, there is no control centre, thus the cognitive nodes have the ability to exchange their sensing information among themselves and make their own decisions as to which part of the spectrum they can use. As described in chapter 2, the existing decentralised cooperative spectrum sensing algorithms are still suffering from certain limitations. The most important issue is the large transmission bandwidth required for secondary users to share a large amount of sensing data in order to issue decisions on the spectrum availability collaboratively. Furthermore, these communications between cooperative users result in more energy consumption and further sensing delay. Another important issue is the occurrence of certain users close to each other which might lead to correlated shadowing, thus, hampering the cooperation gain. On the other hand, the lack of fusion centre implies that each cognitive user will need to perform its local sensing before transmitting the results to its neighbours without time synchronisation. The lack of synchronisation in local spectrum sensing may lead to make the cognitive user detecting not only the transmissions of primary users but also the transmission of other cognitive users, thus causing more false errors in local spectrum sensing.

Various algorithms have been proposed to improve the performance of decentralised cooperative spectrum sensing in cognitive radio networks, which can be classified as: gossiping algorithms or clustering schemes. The work presented in [85] was aimed at reducing the sensing data that should be exchanged among neighbouring cooperative users using network coding. The authors in [113] have proposed an incremental gossiping approach for efficient cooperation within a cognitive network termed as GUESS, where the cooperative users will send their sensing results only when either they have a change in their local measured signal after each step or receive the update messages from neighbouring users, thus, reducing the communication traffic overhead. Although these schemes are fast and robust to network changes, they are based on the assumption that the communication links between cooperative users are ideal, which makes them infeasible in practice.

Relay techniques can improve the detection performance of the distributed cooperative spectrum sensing in the case of imperfect communication links between cognitive users, by making some users that have perfect reporting channel conditions relay the sensing decisions among cognitive users [82-83, 87-88, 142-143]. Although these protocols have improved the sensing performance, they added additional delay and more energy consumption.

Cluster based distributed cooperative spectrum sensing mechanism is another method that can be used to reduce the network overhead. In these approaches, where there is no FC, the cognitive user that has a favourable channel gain can be selected as a FC which collects all results from CH. In [117-118], the authors have presented a distributed clustering approach to save the sensing energy. In these schemes, after forming the clusters, one of the members with the highest sensing gain will be selected as a CH, and a FC will be selected dynamically from all active CHs to balance energy consumption within network. However, in order to reduce the energy consumption in these schemes, cluster size needs to be small; however, this leads to an increase the number of clusters in the case of wide range networks. Moreover, more clusters leads to increasing the range communication between CHs and FC and more energy consumption, which are impractical. Therefore, there is a need fora new reliable and efficient algorithm for cooperative spectrum sensing in distributed cognitive radio networks.

In this chapter we present a novel hierarchical clustering algorithm for distributed CSS by combining clustering and multi-hop routing techniques. In this algorithm one of the CHs will be elected to act as a FC, while other CHs will send their cluster results to the selected FC either directly or via intermediate cluster heads based on their distances from the FC. This mechanism will bring us an increase in detection efficiency with a reduction in cooperation overhead.

7.2 Multi-hop Cluster Based Decentralised CSS Scheme

In this section, we present a multi-hop clustering approach for distributed cooperative spectrum sensing. In this approach, we have used the same idea of our multi-hop clustering algorithm presented in chapter 6 and employed it here to adapt with decentralised networks. First, we assume that all cognitive users that are close to each other are grouped into a few clusters. In this case, instead of each cognitive user sharing its sensing results with its neighbours, each cluster member will send its sensing result to a related CH, which in turn combines all the results of their members using a certain fusion rule and then sends the cluster result to FC. Unlike infrastructure based networks, due to the lack of FC in decentralised networks, one of the elected CHs will be selected as a FC. Based on the location of CH from the FC, each CH will send its result to FC either directly (one-hop communication), or indirectly via intermediate CHs (multi-hop communication).By dividing the total cooperative users into multi-levels clusters based on the distance between the CHs and the FC, the issues of energy consumption and the degradation of spectrum sensing performance can be solved, more energy can be saved, and the performance of the spectrum detection and sensing delay can be also improved.

7.2.1 Description of Multi-hop Cluster Based Decentralised CSS Scenario

In our proposed algorithm, we consider a decentralised wireless cognitive radio network with M cognitive radio users CRs, acting as local sensing devices, and aim at sensing a certain spectrum band using cooperation mechanism. In order to reduce the cooperation overhead while keeping a better spectrum sensing performance, we chose to utilise the clustering approach and multi-hop routing mechanism to conduct cooperative spectrum sensing in decentralised networks. The main idea of the clustering algorithm proposed in this work is to group cognitive users that are close to each other in clusters, where one of the cluster members will be selected as a CH based on their energy level and the SNR of reporting channel. Multi-hop routing techniques can also be exploited in decentralised CSS, which provides better transmission reliability between one user and other users in the cognitive network that may be not within direct wireless transmission range of each other.

The structure of the decentralised cognitive radio network according to our multi-hop clustering approach is given in Figure 7.1.

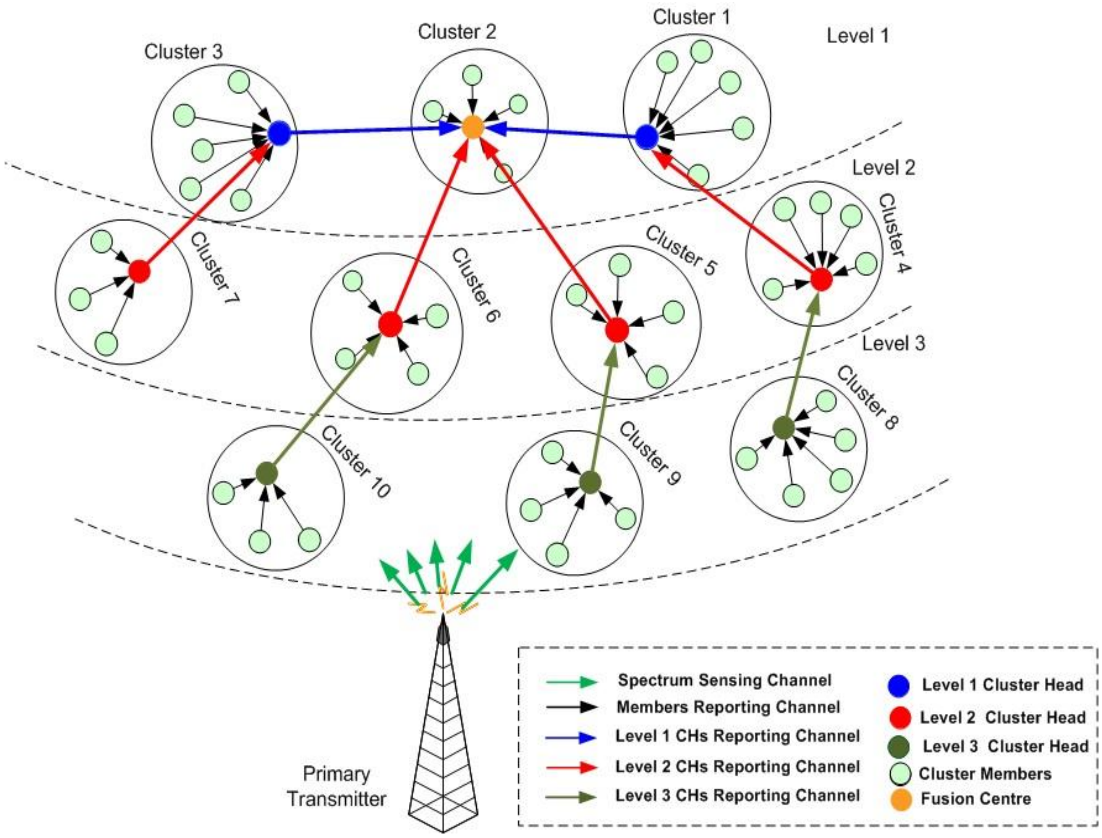


Figure 7.1 Multi-hop cluster-based decentralised cooperative spectrum sensing

In this algorithm, the CHs and clusters are formed in a distributed way, where the cognitive users who are close together form a cluster. Afterward, one of the CHs will be chosen to act as a FC based on energy level of the CHs, the CH who has the largest energy level will be acting as a FC. By considering the multi-hop reporting mechanism, the CHs in different levels will be determined with the help of FC based on the best SNR of the reporting channel among CHs of different levels. Here, the CHs and the FC will be dynamically selected in order to prolong the network lifetime.

Our decentralised algorithm is based on the following assumptions:

a. We assume that the cognitive radio network topology is stable with M of cognitive users.

b. Cognitive users can use power control to tune the amount of sending power according to the transmission distance.

c. The instantaneous channel state information of the reporting channel is available at the cognitive users.

d. The channel between any two cognitive users in the same cluster is perfect since they are close to each other.

e. We consider that all cognitive users are battery-operated devices; therefore, the CHs and FC are reselected at each round to prolong the overall average lifetime.

The process of our proposed multi-hop cluster-based decentralised CSS algorithm is conducted through the following steps:

1. CR j in cluster i conducts spectrum sensing individually using energy detection scheme, and makes a local decision Dij for i =1,…,K, j =1,…,N_i , where K is the number of clusters, N_i is the number of CRs in cluster i and $M = \sum_{i=1}^{K} N_i$, where M is the total number of CRs in the network.

2. Then, each $CRij$ will report its results to the CH_i to make a cluster decision C_i based on majority decision fusion rule.

3. Afterwards, all CH_{Li+1} will send their results C_i to FC via intermediate cluster heads CH_{Li} based on inter-cluster tree routing at the FC.
4. Finally, the FC will collect all sensing results from CHs and make the final decision based on majority fusion rule, and then broadcast it back to CRs via CHs.

7.2.2 Multi-hop Cluster Formation

Our proposed multi-hop clustering algorithm is based on rounds, where each round consists of two phases: setup phase, which includes the formation of FC, CHs, and the clusters of each level, followed by a steady state phase when the cluster members perform their local spectrum sensing, then send their data to CH and then to the FC, see Figure 7.2.

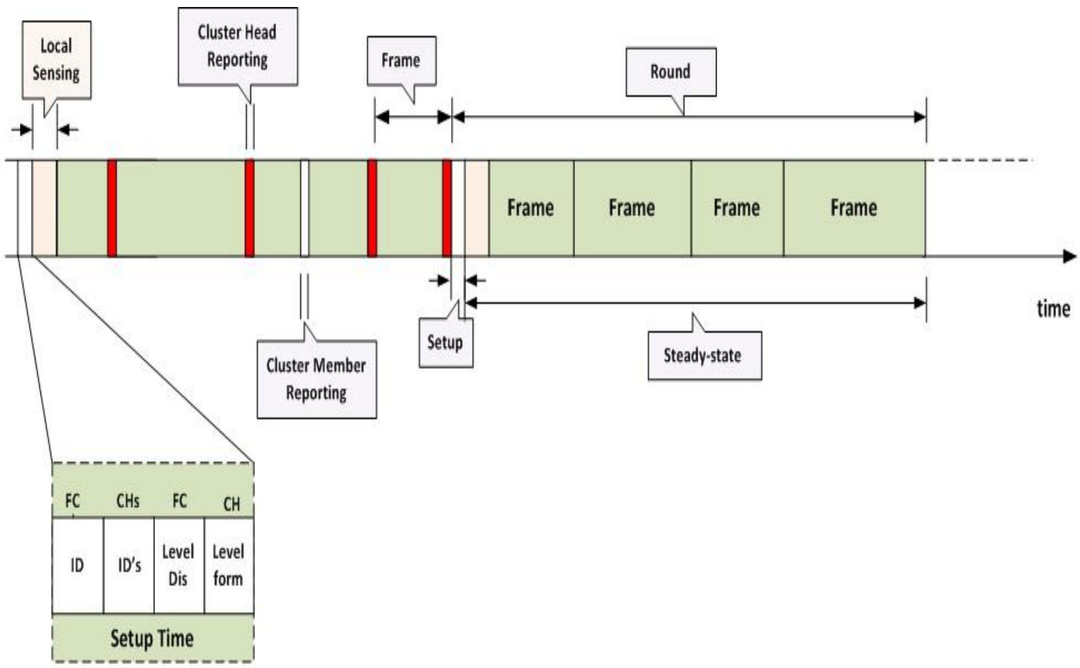


Figure 7.2 Time line of cluster based DCSS

A. Setup Phase

Our proposed multi-hop clustering approach for decentralised CSS is based on rounds, and the setup phase starts at the beginning of each round, as shown in Figure 7.2. The main goal of the setup phase is to create the infrastructure of our proposed algorithm by identifying the CHs, clusters and the FC, respectively.

B. Determination of the Cluster Heads

At the beginning of each round, each cognitive user sends an advertising message, containing its identity ID and the energy level, to all neighbours to form a cluster, using its default transmission power. Then, each cognitive user will construct a table to maintain the IDs and the energy levels of all neighbouring users. Afterwards, each cognitive user will compare its energy level with that of all neighbouring users, and whichever cognitive user has the largest energy level among its neighbours will elect itself as a CH.

C. Cluster Formation

The cluster formation is done by CHs, where each CH broadcasts an advertisement ADV message using a carrier-sense multiple access CSMA protocol, which instructs the non-CHs to select their CHs. After receiving the messages from all CHs, each non-CH sorts the received power signal of each message and selects the largest one as its selected CH. Then, each non-CH should inform the CH that it would be a member of the cluster by sending back a join-request message to the selected CH using CSMA technique. This join message contains the cluster head's ID and the non-CH's ID. Each CH compares its ID with the received one, and if the cluster head's ID matches its own ID, the CH will accept the join request; otherwise, the request is rejected.

After completing the cluster formation, each CH knows which CRs are in its cluster and creates a TDMA schedule assigning each member a time slot to transmit its sensing result, and then informs all members in its cluster a CSMA code which is used for communication among them. Here, we can determine two cases:

- Equal sized clusters, which is a special case when the users within the cognitive network are uniformly distributed. In this case, all the clusters have the same number of members CM, and since all the clusters have the same TDMA schedule, they will get the sensing results at the same time.
- Unequal sized clusters, which is a general case when the users within the cognitive network are randomly distributed. In such a case, some clusters may have small numbers of members CM, while others have large numbers, depending on the cluster size. This will make the large sized clusters have more time slots for CMs than small sized clusters, leading to delay in getting the cluster result compared with the latter.

D. Determination of the FC and Multi-level CHs

We assume that each CH can reach all cognitive users in one hop communication using maximal power. Once clusters are formed, the CHs will broadcast an ADV message that contains their ID's and energy levels, in order to choose the suitable FC and also to discover the CHs at different levels. Then, each CH constructs a table to maintain the information of other CHs, where each CH compares its energy level with that of other CHs recorded in the table, and any CH who has the largest energy level among all CHs will elect itself as a FC. To inform all the rest of the CHs, FC will broadcast the HEAD message using its maximum power, and all CHs which hear this message will record the FC ID. Afterwards, all CHs send the reply signal with their ID's to the FC using their default low transmission power. Only level-1 CHs will reply successfully to FC, since they are single hop distance from the FC. Then, FC will broadcast a control packet with all level-1 CHs ID's in it. All CHs will reply to this control packet at default transmission power with their own ID's as well as ID's of level-1 CHs, where level-1 CHs will not respond to this message, since their ID's are present in the control packet. Therefore, this reply will get to level-1 CHs, and those whose ID's are present in the reply message will relay this message to the FC. More specifically, each level-1 CH will receive the reply messages from all level-2 CHs in different power levels, then sort them and choose the largest one as an intermediate CH. Then, this intermediate CH will relay the reply message to FC. The FC will record the ID's of CHs, level of CHs and the ID's of intermediate CHs. Similarly, FC will again send control message with ID's of all CHs that have been discovered. All the rest of the CHs will reply to this messages and the processing will be done as described above. This will be continued until completing all the CHs. At this stage, the setup phase has been completed, and the steady state can start.

E. Steady State Phase

After completing the setup stage, the FC will send a START message to all cognitive users via CHs to start the local spectrum sensing. Once the local sensing is completed, each cluster member will send its own sensing results to the selected CH using its own time slot, then each CH fuses the results of all related cluster members using majority fusion rule, and sends its cluster result to FC either directly or indirectly depending on the level of cluster. For instance, level-1 CHs will send their sensing results directly to FC, while level-2 CHs send their sensing results to selected level-1 CHs, and the latter in turn will relay them to the FC, and so on. Once all the CHs results have been received by the FC, the FC will combine them using the majority fusion rule and then send back the final result to all CHs, which they in turn will send on to all related cluster members.

7.3 Mathematical Model of the Proposed Algorithm

In this section, we present the mathematical model of our multi-hop clustering algorithm for decentralised CSS. This mathematical model has been built based on the design parameters of the proposed algorithm, which includes the energy consumption model, spectrum sensing model, and sensing delay model. These models are described in details in the following subsections.

7.3.1 Energy Model of Decentralised Cooperative Spectrum Sensing

In wireless communication networks, most energy dissipation in each single wireless device is the result of transmitting energy dissipation to run the radio electronics, the power amplifier, and receiving energy dissipation to run the radio electronics. In our analysis, we use the same radio model described in [29], where the energy required to transmit or receive one message of size B bits over a transmission distance R, is given by:

$$E_{TX}(B,R) = \begin{cases} BE_{elec} + B\epsilon_{fs}R^2 & if \quad R \le R_O \\ BE_{elec} + B\epsilon_{mp}R^4 & if \quad R > R_O \end{cases} \qquad (7 - 1)$$

$$E_{RX}(B,R) = BE_{elec} \qquad (7 - 2)$$

Where E_{elec} the electronic energy consumed to send or receive a message; E_{TX} represents the total energy consumed by the transmitter, while E_{RX} is energy consumed by the receiver. $\epsilon_{fs}$and ϵ_{mp} denote the energy dissipated by the transmit power amplifier to maintain an acceptable SNR in order to transfer data reliably, and depend on the channel model, and $R_O = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$ is the breakpoint or threshold distance [29]. Power control can be used to invert this loss by appropriately setting the power amplifier; if the distance R is less than a threshold R_O, the free space model ϵ_{fs} is used; otherwise the multipath model ϵ_{mp} is used.

A. Energy Model of Conventional Decentralised CSS

In conventional decentralised cooperative spectrum sensing approaches, where there is no FC, each CR user individually performs a local spectrum sensing, and then exchanges its own sensing decision with neighbouring users who are within its transmission range, and finally determines the final decision using the majority fusion rule. Here, we assume the default transmission range of each cognitive user is limited by $R_{O.}$ Therefore, only the energy consumed in the communications within this transmission range will be included in the calculation of the total energy consumption E_T. Figure 7.3 shows an example of a mechanism of calculating the total energy consumed in sending and receiving the local sensing among M=5 of cognitive users.

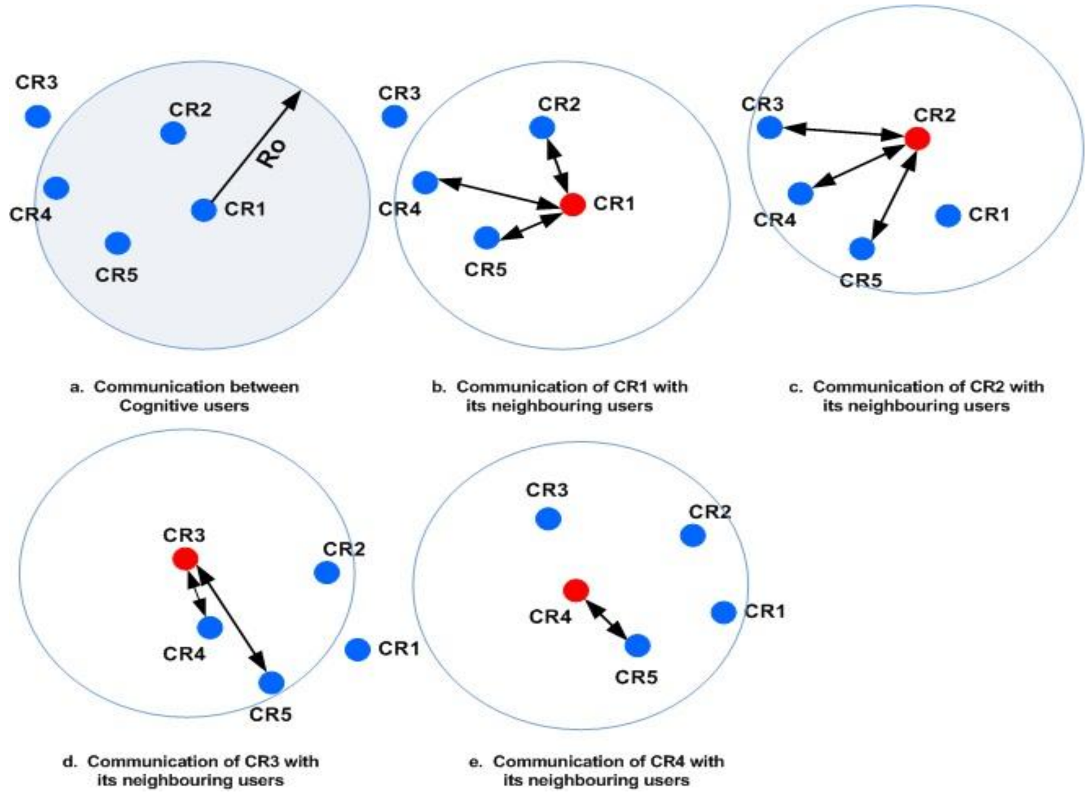


Figure 7.3 Illustration diagram for energy consumption in conventional distributed CSS

In general, the energy consumption of a conventional decentralised CSS during the sensing period may include the energy consumed in local spectrum sensing E_s; the energy consumed in the sleeping mode E_p; the energy consumed in computing the observations and making a local decision E_c; the energy consumed in transmitting the local decision to neighbour users E_{TX} and the energy consumed in receiving the local sensing E_{RX}. In practice, $E_p<E_c<E_{RX}<<E_{TX}$, then we can ignore E_p and E_c. Under these considerations, and as shown in Figure 7.3, the energy consumption of conventional decentralised CSS can be calculated as follows:

Depending on the transmission range of each CR user R=R_O, the energy consumed in transmitting and receiving the local sensing results between two cognitive neighbouring users can be given, respectively, as

$$E_{TX}(B,R) = \begin{cases} BE_{elec} + B\epsilon_{fs}R^2 & if \quad R \le R_O \\ 0 & if \quad R > R_O \end{cases} \qquad (7 - 3)$$

$$E_{RX}(B,R) = \begin{cases} BE_{elec} & if \quad R \le R_O \\ 0 & if \quad R > R_O \end{cases} \qquad (7 - 4)$$

We can see from (7-3) and (7-4) that the energy consumption is mainly depending on the number of CRs and the distance between two cognitive users.

So, the total energy consumption E_T during the cooperative spectrum sensing in conventional decentralised algorithms can be expressed as

$$E_T = MEs + \sum_{i=1}^{M-1}\sum_{k=1}^{M-i}\left(E_{TX,k} + E_{RX,k}\right) \qquad (7 - 5)$$

B. Energy Model of Cluster Based Decentralised CSS

One of the advantages of clustering is the big energy saving, especially in large scale cognitive radio networks. The data transmission begins when each cluster member sends its local sensing decision to the selected CH during their time slots. Presumably, the distance between each cluster member (non-CH) and the closest CH is small, so the free space model R^2 is adopted in energy dissipation. Thus, the energy consumed $E_{non-CH}(i)$ by i^{th} cluster member is expressed by:

$$E_{non-CH}(i) = E_S + BE_{elec} + B\epsilon_{fs}R_i^2 \qquad (7 - 6)$$

In our system, because the clusters are formed in a decentralised way and depending on the location of cognitive users, the sizes of clusters will not be equal. Therefore, each CH_j has a certain number of cluster members N_j, and needs to combine the local sensing results and then sends them to the FC. In decentralised systems one of the CHs can act as a FC, so the energy consumed by each CH_j will depend on its distance D_j from the selected FC, which follows either the free space model D^2 or the multipath model D^4 according to (7-1) and (7-2), respectively. The energy consumed by each CH_j can be given as:

$$E_{CHj} = E_{sensing} + E_{datareceiving} + E_{datacollection} + E_{datatransmission} \qquad (7 - 7)$$

$$E_{CHj} = E_S + BE_{elec}N_j + BE_{DC}N_j + BE_{elec} + \begin{cases} B\epsilon_{fs}D_j^2 & if\ D_j \leq R_O \\ B\epsilon_{mp}D_j^4 & if\ D_j \leq R_O \end{cases} \qquad (7 - 8)$$

The energy dissipated in a cluster during each round is given by:

$$E_{Clusterj} = E_{CHj} + N_jE_{non-CHi} \qquad (7 - 9)$$

and the total energy consumed by the network is

$$E_{total} = E_{setup} + KE_{Cluster} \qquad (7 - 10)$$

$$E_{total} = E_{setup} + K\left(E_{CHj} + N_jE_{non-CHj,i}\right) \qquad (7 - 11)$$

Where K represents number of clusters.

C. Energy Model of Multi-hop Cluster Based CSS

In the multi-hop cluster based CSS mechanism, after determining the CHs and forming the clusters, each CH will issue its own TDMA schedule for its cluster members. Based on this schedule, cluster heads not only collect the local sensing results from their cluster members, but also act as relaying users for lower level cluster heads. Thus, the cluster heads that are far away from the FC will send their sensing results to the FC through intermediate cluster heads, which leads to lower energy consumption compared to direct reporting.

Here, the energy consumption of each non-CH will be the same as in the one-hop clustering algorithm, while the energy consumption of CHs will be different, because the CHs are divided into multi-levels depending on their distance from the selected FC, and only the level one cluster heads will send their results directly to the FC, while other level CHs will send their results through next level CHs until reaching the FC. As a result, the energy consumption in each CH will be dependent on the distance from other upper level CHs, as well as on the length of time spent receiving and relaying the results of upper level CHs.

The mathematical equations that govern the energy consumption in our multi-hop clustering algorithm are described as follows.

The energy consumption by non-CHs will be the same as in one-hop clustering approach, so we can use the same equation in (7-6). Each CH needs to fuse all the local sensing results of its cluster members and relay the results of upper level CHs, so its energy consumption can be given as:

$$E_{CHj} = E_{sensing} + E_{datareceiving,j} + E_{datacollection} + E_{Tj} \tag{7 - 12}$$

$$E_{sensing} = Es \tag{7 - 13}$$

$$E_{datareceiving,j} = BE_{elec}\left[N_j + Relays_j\right] \tag{7 - 14}$$

$$E_{datacollection} = BE_{DC}N_j \tag{7 - 15}$$

$$E_{Tj} = \begin{cases} BE_{elec} + B\epsilon_{fs}d_{Relaysj}^2 * \left(\mathrm{Relays_j} + 1\right) & \text{if } \mathrm{d}_{Relaysj} < \mathrm{d_O} \\ BE_{elec} + B\epsilon_{mp}d_{Relaysj}^4 * \left(\mathrm{Relays_j} + 1\right) & \text{if } \mathrm{d}_{Relaysj} > \mathrm{d_O} \end{cases} \tag{7 - 16}$$

Where $Relays_j$ is the number of relays made by j^{th} CH, and $d_{Relaysj}$ is the distance between the j^{th} CH to next hop CH. Finally, the total energy consumption can be written as:

$$E_{total} = E_{setup} + N_j E_{non-CHj} + K * E_{CHj} \tag{7 - 17}$$

where K represents the number of clusters.

7.3.2 Sensing Model of Multi-hop Cluster Based Decentralised CSS

As mentioned previously, CSS mechanisms have many advantages over non-cooperative methods; one of them is enhancing the detection reliability by exploiting the spatial diversity of the cognitive users. The performance of CSS approaches is measured mainly by two parameters: detection probability Pd, which indicates that the primary user exists, and false alarm probability Pf, which indicates that the primary user is present while in reality it is not. Another important parameter is mis-detection probability Pm, which indicates that the primary user is absent while actually it is existing.

In conventional decentralised CSS algorithms, each cognitive user performs its local sensing and then shares the result with other users within its transmission range, and combines its sensing results with the received results and decides whether the spectrum is available or not using a local fusion rule. Each cluster member makes its own one bit hard decision: '0' or '1', which means absence or presence of primary activities, respectively. In the case of the decision not being satisfied, cognitive users may need to send their combined results to neighbours again and repeat this process until a cooperative decision is reached.

In our multi-hop clustering approach for decentralised CSS, all cognitive users that are close to each other will be grouped into clusters, on the assumption that the members of each cluster have almost the same sensing channel conditions as they are close to each other. Afterwards, the sensing results of each cluster will be reported to FC in order to get the final cooperative decision, where one of the CHs will act as a FC.

The mathematical equations that govern the sensing performance of our multi-hop clustering scheme in decentralised CSS are described as follows:

At first the FC sends a start signal to all cognitive users to begin their local spectrum sensing using the energy detection algorithm. The sensing performance of each cluster member depends mainly on the SNR of the sensing channel, where the false alarm probability *Pf* and the detection probability *Pd* under AWGN channels can be written as [121]:

$$Pf_i = Q\left[\frac{\lambda_i - \mu_0}{\sigma_0}\right] \tag{7 - 18}$$

$$Pd_i = Q\left[\frac{\lambda_i - \mu_1}{\sigma_1}\right] \tag{7 - 19}$$

Where, Q represents cumulative distribution function, λ is detection threshold, μ_0; μ_1; σ_0; σ_1 denote the mean and the variance parameters under H_0 and H_1 hypotheses, respectively. We consider here that the noise power is totally known at each cognitive user.

Due to the nature of wireless reporting channels between the cluster members and the CH, it is likely to get errors in receiving the local results at the CH. For instance, a reporting error may occur when a cluster member sends a single bit "0" while the CH receives "1", or may send one bit "1" but the CH receives "0". In our analysis, we assume that all the cluster members are close to each other; therefore, we can consider that the reporting channels between the CH and their cluster members are free of error.

When the CHs have received all the local sensing results from all related cluster members they combine them using the majority fusion rule, in which the radio spectrum will be decided busy when at least half of the cluster members decide it's busy. Thus, the detection and false alarm probabilities can be represented, respectively, as

$$Qd_j = \sum_{j=M/2}^{M} \binom{M}{j} (Pd_i)^j (1 - Pd_i)^{M-j} \tag{7 - 20}$$

$$Qf_j = \sum_{j=M/2}^{M} \binom{M}{j} (Pf_i)^j (1 - Pf_i)^{M-j} \tag{7 - 21}$$

In order to obtain the final cooperative decision on the spectrum occupancy, each CH needs to send its sensing results to the FC using reporting channels.In practice, because of the imperfect reporting channel, potential errors *Pe* can arise when the CHs report the clusters results to the FC.

Reporting error probability P_e can be represented by two cases: 1) FC receives a bit "1" when a bit "0" is sent by a CH. 2) FC receives "0" when a bit "1" is reported by a CH. Using the definitions of P_e, we can display the probabilities associated with detection and false alarm on the tree diagram as shown in Figure 7.4.

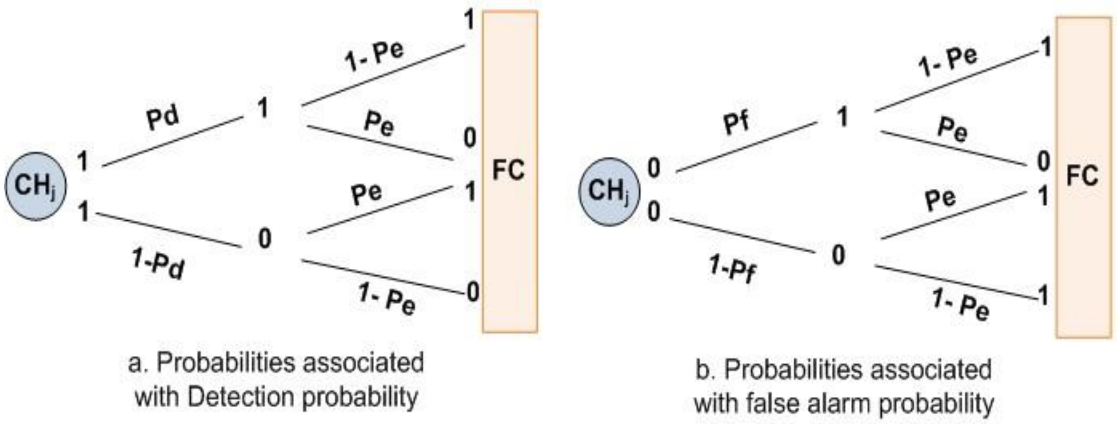


Figure 7.4 Tree diagram of the probabilities associated with the detection and false alarm probabilities

In our algorithm analysis, we model each reporting channel as a binary symmetric channel with probability P_e which is equal to the bit error rate BER of the channel. Here, we consider the binary phase shift keying modulation BPSK with Rayleigh fading channels, thus, the average error probability $P_{e,j}$ for jth CH can be given as [132]:

$$P_{e,\mathrm{j}} = \frac{1}{2}\left(1 - \sqrt{\frac{\acute{\gamma}_j}{(\acute{\gamma}_j + 1)}}\right) \qquad (7 - 22)$$

where $\acute{\gamma}_j$ is the average SNR of the reporting channel between the *jth* CH and the FC.

As shown in Figure 7.4, from the perspective of detection probability *Pd*, the possibility of the FC to receive a bit '1' when the CHs send the "1" can occur in two cases: when the CH sends a bit '1' with probability$Pd_j(1 - P_{e,j})$; or when the CH sends a bit '1' with probability $(1 - Pd_j)P_{e,j}$. On the other hand, from the perspective of false alarm probability Pf, there are two cases in which the FC can receive a bit '1' when the CH sends a bit '0' with probability $Pf_j(1 - P_{e,j})$; or when the CH sends a bit '1' with probability$(1 - Pf_j)P_{e,j}$. Thus, the detection and false alarm probabilities at the CHs and the FC can be written, respectively, as follows

$$PD_{\mathrm{j}} = \Pr\left(\text{a bit "1" received by the } FC \middle| \text{a bit "1" transmitted by the } CH_j\right) \qquad (7 - 23)$$

$$PF_j = \Pr\left(\text{a bit "1" received by the } FC \middle| \text{a bit "0" transmitted by the } CH_j\right) \qquad (7 - 24)$$

$$PD_{\mathrm{j}} = Pd_j(1 - P_{e,j}) + (1 - Pd_j)P_{e,j} \qquad (7 - 25)$$

$$PF_j = Pf_j(1 - P_{e,j}) + (1 - Pf_j)P_{e,j} \qquad (7 - 26)$$

$$Qd = \sum_{j=M/2}^{M} \binom{M}{j} (PD_j)^j (1 - PD_j)^{M-j} \qquad (7 - 27)$$

$$Qf = \sum_{j=M/2}^{M} \binom{M}{j} (PF_j)^j (1 - PF_j)^{M-j} \qquad (7 - 28)$$

The above mentioned equations are based on the assumption of direct reporting mechanism between the CHs and the FC. In large-scale cognitive radio network applications, the multi-hop clustering approaches may be more appropriate. In our multi-hop clustering algorithm, to calculate the detection and false alarm probabilities, we need to determine the P_e of multi-hop reporting channels. Here, we consider two cases of reporting channels, identical and non-identical channels. We assume that there are L hops between the primary user and the FC. Each non identical cluster head CH_L forwards the cluster results to the next hop cluster head CH_{L-1} with probability error $P_{e,i}$ given as [139]

$$P_{e,MH} = \frac{1}{2}\left(1 - \prod_{i=1}^{L-1}(1 - 2P_{e,i})\right) \qquad (7 - 29)$$

Where $P_{e,i}$ is the probability error of one-hop cluster. In the event that the reporting channel is identical, (the SNR is the same for all CHs participating in Multi-hop reporting route), $P_{e,1}=P_{e,2}=P_{e,3}=\ldots\ldots\ldots.,\ P_{e},k=P_{e}$, the equivalent probability error will be given as

$$P_{e,MH} = \frac{1}{2}(1 - (1 - 2 * P_e)^{L-1}) \qquad (7 - 30)$$

The equivalent total detection and false alarm probabilities at the FC can be determined using the same equations in (7-25), (7-26), (7-27), and (7-28).

7.3.3 Spectrum Sensing Delay of Multi-hop Cluster Based Decentralised CSS

It is obvious that the main motivation behind CSS techniques is the exploitation of spatial diversity, which leads to a significant improvement in detection performance, which is commonly termed as a cooperation gain. But the achievable cooperation gain comes at the cost of variety of overheads, one of these overheads is sensing time and delay.

In conventional decentralised CSS approaches, the cognitive users can share their sensing results, send their combined results to others and repeat this operation until a unified decision is converged. Therefore, the sensing time that is required to reach the cooperation decision depends mainly on local sensing time T_L, the number of neighbouring users, and the number of iterations that are needed to reach the final decision. Here, if we assume that the time required to integrate the results is very short and can be neglected, as well as, if we assume that there is synchronisation in the local spectrum sensing by all cognitive users, the total sensing time that is required in conventional decentralised CSS schemes can be determined as

$$Tconv = T_L + T_R * \sum_{i=1}^{M} N_i \qquad for\ D_i \le d_o \qquad (7 - 31)$$

Where N_i represents the number of neighbouring users of the ith cognitive user, T_R denotes to the time required to carry out reporting, D_i is the distance between the ith cognitive user and its neighbours, and d_O is distance threshold that determines the neighbouring users.

In cluster based decentralised CSS mechanisms, after the formation of all clusters is completed, all cluster members within each cluster will start to perform the local sensing individually, and then report their decision results to their CHs using their TDMA schedule time. Afterwards, each CH will send its cluster result to the FC according to its TDMA schedule time.

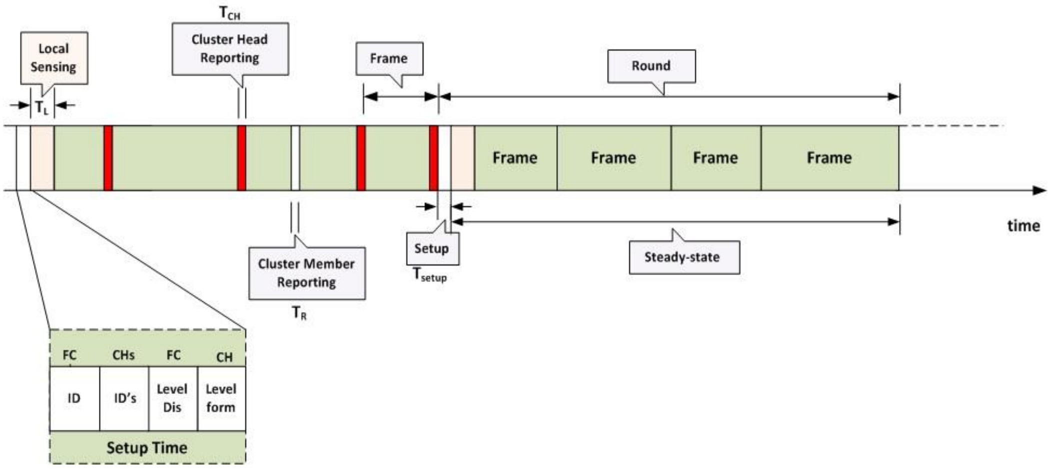


Figure 7.5 Sensing frame structure in cluster based decentralised CSS

As shown in Figure 7.5, assuming that all the cluster members perform the local sensing at same time, and the size of clusters might be not equal, so each CH may have a different number of cluster members. If we symbolize the setup time T_{setup}, number of clusters K and the number of cluster members of jth CH is N_j, then, the total sensing time of the cluster based CSS $T_{clus.}$, can be written as

$$Tclus. = T_{setup} + T_L + \left(K + \sum_{i=1}^{K} N_{j,i}\right) * T_R \qquad (7 - 32)$$

In the multi-hop clustering mechanism, relaying the sensing results from far cluster heads to the FC via intermediate cluster heads introduces an additional delay, which depends on the number of all relaying signals in the network N_{relay}. Thus, the total sensing time of the multi-hop cluster based decentralised CSS approach will be the same in the equation (7-31) with added relaying delay time T_{relay}, which can be expressed as follows

$$T_{relay} = \sum_{i=1}^{L} \left(N_{hop,i}\right) * T_R \tag{7 - 33}$$

$$T_{multihop} = T_{setup} + T_L + \left(K + \sum_{i=1}^{K} N_{j,i}\right) * T_R + T_{relay} \tag{7 - 34}$$

7.4 Simulations and Results

In this section, we provide the evaluation results of our proposed approach for decentralised CSS using MATLAB® software, which shows the performance gain of the proposed method in terms of energy consumption, sensing time delay and spectrum sensing performance. The conventional decentralised cooperative spectrum sensing schemes, such as direct exchanging results among neighbouring users and traditional cluster algorithms are also simulated for comparison. The simulation results with the discussion will be provided in detail in the following subsections.

7.4.1 Energy and Sensing Delay Simulations

In our experiment, we consider a cognitive radio network with M=200 cognitive users which are randomly generated and uniformly distributed between (x=0, y=0) and (x=200, y=200). In our simulation, we assumed that each cognitive user sends its own sensing result via the reporting channel using 1-bit reporting message. Also we assume a simple model for the radio hardware energy dissipation and adopt the same communication energy parameters described in [29], which are given as: E_{elec}= 50 nJ/bit; E_{fs}=10 $pJ/bit/m^2$; E_{mp}=0.0013 $pJ/bit/m^4$; E_{DC}=5 nJ/bit and E_s=190 nJ.

Figure 7.6 gives a 200-node random test network, showing the formation of our multi-hop clustering approach decentralised CSS with 2-hops and 7 clusters. Here, we consider that the clusters are formed in a decentralised way, where the nodes that are close to each other will group in one cluster, and the node that has highest energy will be selected as a cluster head CH. The distances between any cognitive user and its neighbours are determined here by $do = \sqrt{(}E_{fs}/E_{mp}$, which represents the default communication range and here is equal to 87.7 m. Naturally, under these considerations, each cluster will have a different number of members from the other, thus each CH has a different TDMA schedule time slot. The CH that has the highest energy level among selected CHs will be chosen as a FC. Finally, the number of CHs in each hop will be determined based on the distances from the FC.

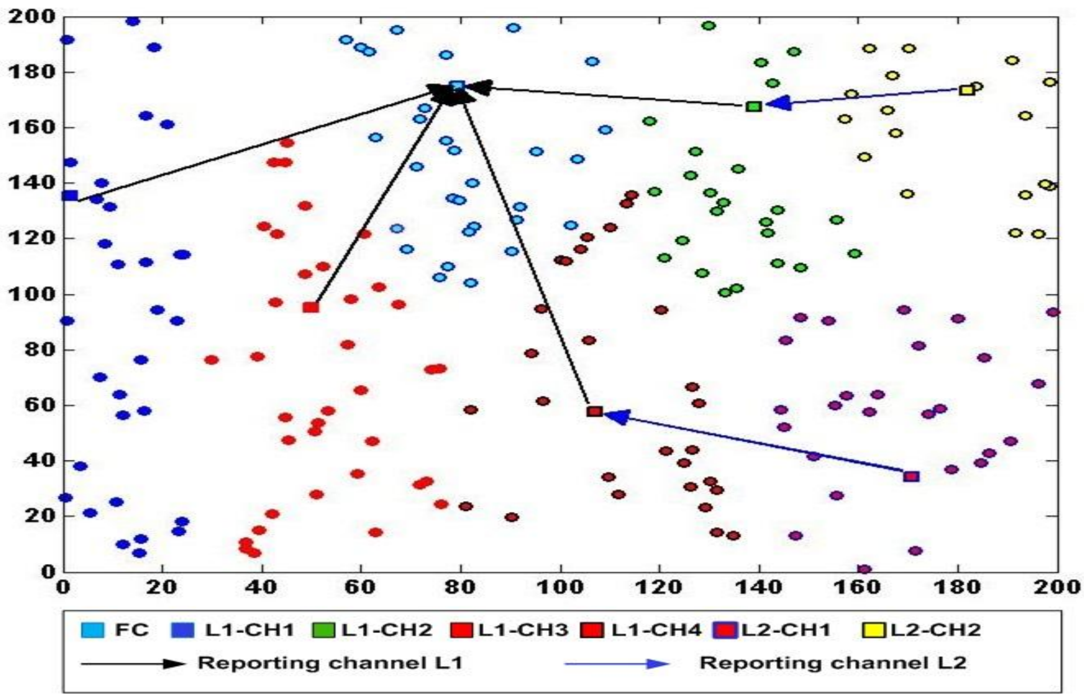


Figure 7.6 200-node random test network illustrating two-hop clustering approach for decentralised CSS

Figure 7.7 illustrates the total energy dissipation in the network with different modes. We can show that the energy performance of the cluster based CSS scheme is better than the conventional mode. Furthermore, more energy reduction can be achieved when the multi-hop clustering approach is used. In this simulation, we used the same simulation considerations as mentioned above, but we increased the dimensions of the test area to between (x=0, y=0) and (x=350, y=350) in order to make a comparison between different modes more clearly. It can be shown from the figure that the energy consumption of the conventional mode increases greatly with the increase in the number of CRs, while in cluster modes it increases slightly with the number of CRs, particularly in multi-hop clustering mode.

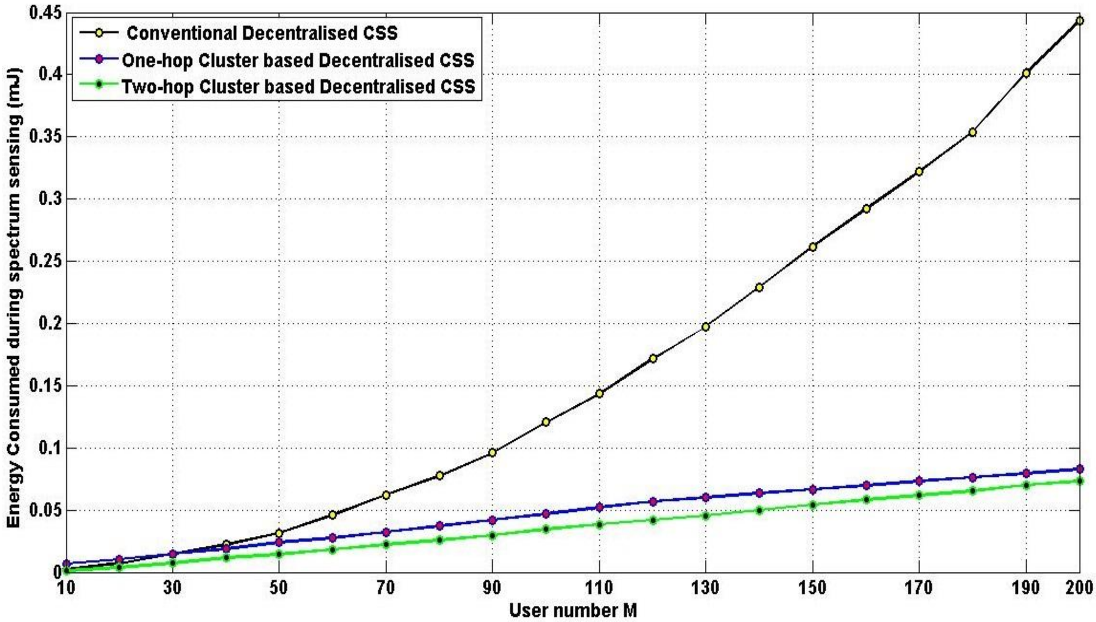


Figure 7.7 Average Energy Dissipation versus number of users with different CSS modes

The results also show that there is a slight saving in energy performance of the 2-hop clustering mode compared with the 1-hop mode. For instance, in the case of 100 CRs, the results show that there is a significant saving in energy dissipation in one-hop clustering mode compared to the conventional cooperative mode, with a reduction rate -71.4 % and this can be increased to -82.2% in the case of 200 CRs. It can also be noted that increasing the number of hops lead to a slight reduction in the energy consumption. For instance, the reduction rate in energy consumption of the two-hop clustering mechanism compared to the one-hop clustering mode is -26.7% when 100

CRs are collaborated, and it remains almost the same reduction rate for the rest of numbers of cooperative users.

Sensing time delay is another important parameter in the design of spectrum sensing algorithms, and it is desirable to be the lowest possible value. Figure 7.8 illustrates the sensing time performance of our proposed decentralised CSS scheme with different hop levels. The sensing time of conventional mode is also simulated here for comparison.

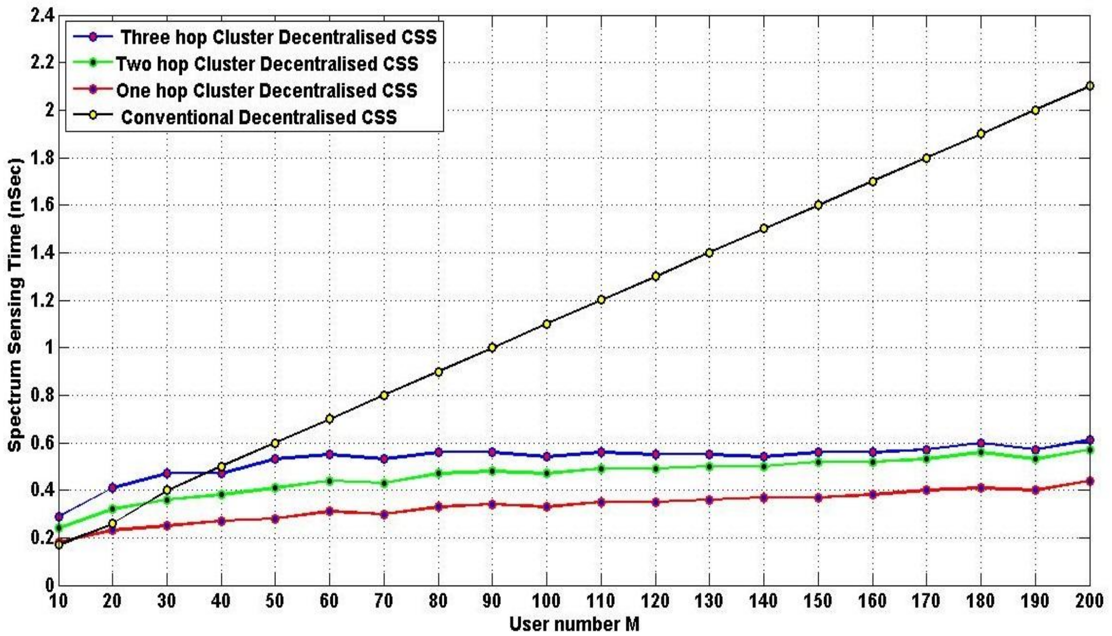


Figure 7.8 Sensing delay time performance of different decentralised CSS schemes

As shown in Figure 7.8, generally, there is a great reduction in sensing time of our proposed algorithm compared to that in conventional mode. More specifically, in conventional decentralised mode, we can see that the sensing time increases linearly with a constant increasing rate of 1% (nsec/user) with the increase of cognitive users, while this increase will be small in one-hop clustering mechanism. It can also be seen that increasing the number of hops will lead to a slight increase in the sensing time, but it is still small compared to the conventional algorithm. For instance, when 100 cognitive users are cooperating to conduct CSS, the sensing time that is required in the conventional decentralised algorithm is 1.1 ns, while in the multi-hop clustering scheme, including one-hop, two-hop, and three-hop, the sensing time will be 0.35, 0.5, and 0.58 ns, respectively. Increasing the number of cognitive users to 200 makes the sensing time of conventional and our proposed algorithm, including one-hop, two-hop, and three-hop to take the following values: 2.1, 0.41, 0.56, and 0.59 ns, respectively. In other words, our proposed one-hop clustering algorithm can give a reduction in sensing time by 68.2% and 80.5% compared to the conventional algorithm when the numbers of cognitive users are 100 and 200, respectively.

However, the multi-hop communication mechanism can incur additional delays due to the use of multiple relay communications instead of direct communication. For instance, as shown in Figure 7.8, in the case of a 70-node network, the sensing times that are required to complete the cooperative spectrum sensing using one-hop, two-hop, and three-hop clustering algorithms are 0.32, 0.46, and 0.56 nsec, respectively, which are still much less than the traditional mode.

There is another important point that can be observed in the figure, which is that in some cases the sensing time of multi-hop clustering schemes can be greater than the traditional schemes, especially when the number of users is small, as shown here, when the number of users is between 10 and 40. This is due to the fact that in the multi-hop clustering algorithm, the time required for the formation of clusters and determining the levels of CHs will have an impact and adds an extra delay compared with the conventional algorithm, but this time will remain acceptable in practical applications because it is still small.

Physically, the scientific explanations of the main results that we have obtained in Figure 7.8 can be described by two key points. First, in the case of the traditional algorithm, increasing the number of cognitive users leads to an increase in the number of neighbours, thus increasing the time required for the exchange of results among neighbours, which are mainly based on iteration to get the final result. Second, in the case of multi-hop clustering schemes, despite the fact that the increase in the number of cognitive users leads to an increase in the number of cluster members, thereby increasing the time required to get the sensing results of each clusters, these results of clusters are obtained at one time. The fact that all clusters are working in parallel, means that, the time that is required to get the results of all clusters will depend on the cluster that has the largest number of members.

7.4.2 Spectrum Sensing Performance

The most important goal to focus on when designing a spectrum sensing algorithm is the efficiency and reliability of detection, as they have a direct impact on the performance of cognitive radio networks. In this section, the sensing performance of the multi-hop cluster-based decentralised CSS scheme is investigated under the perfect and imperfect reporting channels. The numerical results of our proposed algorithm are given to verify the mathematical analyses that are presented in the previous section.

First, the sensing performance of the conventional decentralised CSS is investigated, where CRs are reporting their local sensing results directly to the neighbours that are within their default transmission ranges. Then, the sensing performance of our proposed multi-hop clustering algorithm for decentralised CSS is simulated and compared with that of the conventional scheme.

The conditions and parameters of our simulation were set as follows. We considered that 200 CRs are deployed randomly with different average SNR of sensing and reporting channels within the ranges of (-12, -10) dB and (-20, 20) dB, respectively. We also assumed that the local sensing is conducted by each CR user using the energy detection method with N=10 of samples. For simplicity, we assume that the noise power at each CR user is equal to 1, and also the majority fusion rule at both the CHs and the FC is used.

Figure 7.9 illustrates the mechanism used in the simulation of the proposed algorithm, where the CRs are grouped into K=8 clusters with different numbers of members N_j in each cluster as follows (25, 15, 30, 32, 18, 20, 36, 24). As shown in this figure, the multi-hop mechanism can be exploited efficiently so that the results of clusters are sent to the FC over the CHs with high SNR of reporting channels.

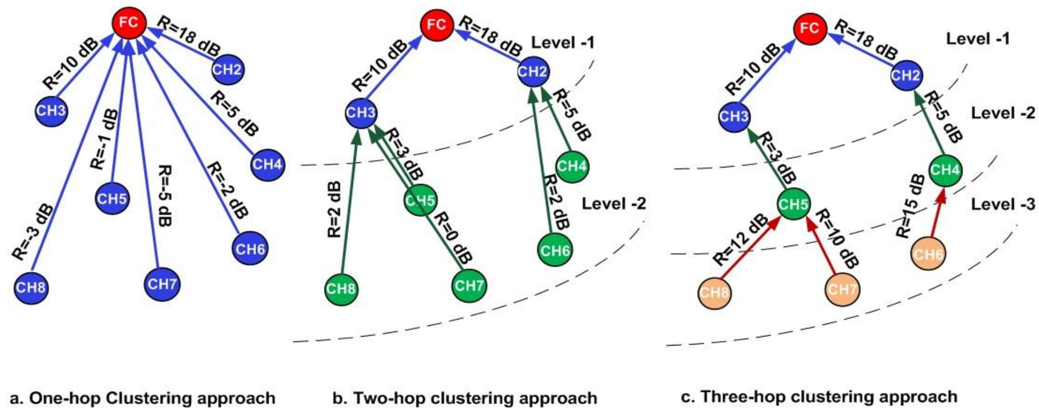


Figure 7.9 Multi-hop clustering scenarios for decentralised CSS

Figure 7.10 gives the ROC performance of the multi-hop clustering CSS scheme over Rayleigh fading channels. In this simulation, in the case of the one-hop clustering approach, where the number of clusters is K = 8, and the reporting SNR of CHs are (10, 18, 10, 5, -5, -1, -2, -3) dB, respectively. It can be observed that there is a significant improvement in the sensing performance of the one-hop clustering algorithm compared to the traditional mode even given that some CHs are suffering from poor SNR, especially the far CHs.

As can be seen from this figure, the detection accuracy deteriorates as the number of error reports increases due to low SNR of the reporting channel. However, the sensing performance can be enhanced using the clustering approach. By using the clustering mechanism, the local sensing will be sent to the FC via intermediate CHs that have the largest SNR of reporting channel.

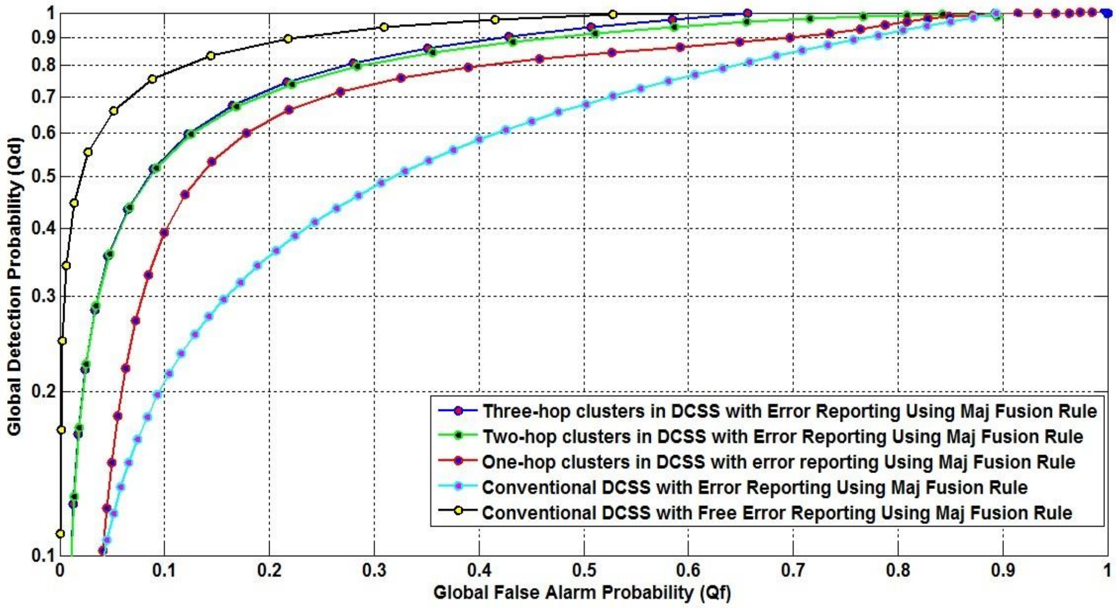


Figure 7.10 ROC curve of decentralised cooperative spectrum sensing with different fusion rules

Figure 7.10 also shows the feature of the multi-hop clustering algorithm in improving the efficiency of detection by choosing the best reporting route to the FC. In our simulation, the sensing performance of two-hop and three-hop clustering approaches have also been investigated in order to enhance the detection performance. As shown, the sensing performance of the multi-hop clustering scheme outperforms the one-hop mode, which basically depends on the channel conditions of the successive multi-hop. We can conclude that the detection performance can be greatly improved when the multi-hop clustering approach is utilised, especially in the cases of imperfect reporting channels.

7.5 Summary

In this chapter, we proposed and evaluated a multi-hop clustering approach for decentralised CSS in CRNs. By adopting the same idea of the mechanism proposed in chapter 6 [30-31], we group CRs that are close to each other into clusters and one of them that has higher residual energy will be selected as a CH, then a CH with the highest residual energy will act as a FC. Using this mechanism, the issue of synchronisation and interference problems from other CR users can be solved.

In conventional clustering approaches, most CR users who have good local sensing information are far away from the FC, thus they are sending their sensing results over imperfect reporting channels, thereby causing deteriorating detection performance. We developed a multi-hop clustering approach that provided reliable reporting routes to send the local sensing results, hence increasing the detection accuracy.

For performance evaluation, the spectrum sensing and overhead performance of the proposed algorithm have been simulated and compared with that of conventional schemes. The simulations results showed that our multi-hop clustering approach achieves better energy saving and detection performance than the existing approach, but at the expense of a little delay. Moreover, the proposed method can detect the spectrum availability much faster than conventional algorithms due to the characteristics of clustering, but adds a slight delay compared with the one hop clustering approach due to successive multi-hop relaying delays. It can concluded from the results that in order to satisfy the requirement of a certain application while reducing the overhead of the wireless network, trade-offs among these evaluation points are needed.

Chapter 8

Conclusions and Future Work

The research presented in this thesis has focused mainly on spectrum sensing techniques in cognitive radio networks. Several novel schemes and algorithms for both local and cooperative spectrum sensing have been developed and presented. In this thesis, we developed a new optimal energy detection algorithm for local spectrum sensing that aims to minimise the local sensing error in the presence of noise uncertainty. Furthermore, we developed a new cooperative spectrum sensing algorithm based on multi-hop clustering mechanisms, which can be applied for centralised and decentralised cognitive radio network applications. The new multi-hop clustering cooperative spectrum sensing scheme aims at providing reliable and more accurate spectrum sensing while reducing the cooperation overhead as much as possible.

This chapter is organised as follows: A summary of the thesis is given in section 8.1. Section 8.2 presents the key contributions of the thesis. The evaluation of the work presented in this thesis and several future research directions are summarised in section 8.3. Finally, the conclusions are given in section 8.4.

8.1 Thesis Summary

The enormous increase in the number of wireless devices has led to an increasing demand for radio spectrum, which in turn has led to the introduction of cognitive radio techniques to resolve the issue of the scarcity of spectrum. These technologies are widely expected to play a significant role in future wireless communication networks, by enabling the secondary users to share the licensed spectrum bands in an opportunistic manner without disturbing primary networks. The heart of the cognitive wireless network is the ability of cognitive users to sense the spectrum availability and the primary user activities correctly, and therefore, the spectrum sensing can be considered one of the most important elements that directly affect the performance of cognitive radio networks. While these networks provide more spectrums to meet the requirements of new wireless applications and devices, they add new constraints whichdo not exist in traditional networks. Specifically, according to the spectrum sensing process as an important component in cognitive radio networks, the cognitive user should be able to identify the presence of primary users as quickly as possible and should vacate the band immediately in the case of primary users reappearing, which requires that the sensing periodicity should be short enough in order to reduce the delay and to minimise the degradation of quality of service (QoS) that is incurred by the primary users accessing the band. Furthermore, in most practical cases it is very difficult to estimate correctly the noise ratio at the cognitive user, which adversely affects the accuracy of the spectrum sensing, and this effect increases when the SNR of the sensing channel is low. Although such issues can be alleviated through cooperating and exploiting the spatial distribution among the cognitive users, it comes at the cost of increasing the overhead of the network, including the energy consumption and sensing time with the increasing number of cooperative users.

Therefore, it is necessary to design new spectrum sensing algorithms for cognitive radio networks in order to increase the efficiency of spectrum utilisation while providing an adequate protection for primary networks, taking into account the spectrum sensing constraints. In our work, to achieve this target we have developed several algorithms for spectrum sensing in cognitive radio networks.

Chapter 1 highlighted the main considerations and important requirements that must be taken into account when designing an algorithm for spectrum sensing in cognitive radio networks as:

1) The cognitive users should accurately detect the spectrum availability in order to guarantee sufficient protection to the primary network when intending to access the available spectrum, and should vacate the band immediately in the case of primary users reappearing.

2) The sensing period should be as short as possible, while guaranteeing a reliable spectrum sensing, in order to increase the throughput of cognitive radio network.

3) In cooperative spectrum sensing mechanisms, channel overheads such as communication overhead and energy consumption is another constraint that needs to be taken into account when designing an algorithm for spectrum sensing, especially when the number of cooperative users is very high.

These considerations and requirements make the design of spectrum sensing for cognitive radio network difficult. On the one hand, the detection algorithm must provide a reliable and more accurate spectrum sensing, and on the other hand this algorithm must not incur additional overhead. Therefore, a trade-off between these design parameters is needed.

Chapter 2 presented an overview on the field of cognitive radio networks, including radio spectrum bands; dynamic spectrum access techniques; the importance and the fundamental concepts of cognitive radio alongside its possible applications. In this chapter, a state-of-the-art on spectrum sensing algorithms for cognitive radio networks found in the literature is also given, including local and cooperative spectrum sensing, pointing out the main drawbacks of existing works and the issues that need to be addressed as:

1) Energy detection algorithms are still used widely in spectrum sensing in spite of some weaknesses, including detection threshold setting, sensing delay, and noise power uncertainty. Existing energy detection based spectrum sensing algorithms are focused only on one of these issues while neglecting the others.

2) In cooperative spectrum sensing, most existing optimisation algorithms are based on determining the optimal detection threshold numerically, which

takes a lot of time, thus increasing the sensing time. On the other hand, the noise power uncertainty is not considered at the local sensing, which leads to a significant degradation in the performance of overall spectrum sensing.

3) The cooperation overhead problem in both centralised and decentralised cooperative spectrum sensing mechanisms, including detection accuracy, energy consumption, and sensing delay, especially in the case of a higher number of collaborative users, still needs more efforts in order to satisfy the requirements of future wireless networks.

Chapter 3 described in detail the above mentioned issues and presented the possible approaches to tackling these challenges. The novel contributions of this thesis are explained briefly in this chapter, which have been detailed in subsequent chapters.

Chapter 4 presented our optimal energy detection algorithm for spectrum sensing application in cognitive radio networks, including single threshold and double threshold modes. These optimal schemes have been evaluated through simulations and compared to existing energy detection algorithms.

In chapter 5, we provided with details our optimisation algorithm for centralised cooperative spectrum sensing. We evaluated our scheme through simulations and outlined its advantages over existing optimisation schemes.

Chapter 6 presented our multi-hop clustering algorithm for centralised cooperative spectrum sensing, describing its different phases, which proposed to tackle the cooperation overhead issues. This algorithm has been evaluated through simulations and compared to existing algorithms.

Finally in Chapter 7, we described in detail our multi-hop clustering approach for decentralised cooperative spectrum sensing with showing its different parts. We evaluated our multi-hop algorithm through simulations and outlined its advantages over existing works.

8.2 Thesis Contributions

Many spectrum sensing algorithms for cognitive radio network applications have been proposed in the literature, but most of them did not consider the basic requirements of spectrum sensing during the design. In order to design a good spectrum sensing scheme, it is important to clearly identify the goals and requirements of spectrum sensing application. This will help us to make good trade-offs in the design parameters to provide best support for cognitive radio network applications. Based on basic spectrum sensing design constraints we developed new detection mechanisms that suit both single and cooperative spectrum sensing applications. These detection mechanisms are based on the following developed algorithms, which represent our main contributions:

- We have developed a new energy detection algorithm for spectrum sensing application based on the single optimal threshold mechanism [28], aiming at minimising the sensing error, thus increasing the detection accuracy. We also developed an adaptive threshold factor with optimal mode in order to combat the noise uncertainty especially in a low SNR environment. In order to get more reliable detection we proposed a new energy detection scheme based on double optimal threshold with a slight decline in the efficiency of spectrum utilisation.
- For centralised cooperative spectrum sensing applications, we proposed a new cooperative spectrum sensing based on an adaptive optimal energy detection algorithm that provides more accurate detection under low SNR of sensing channel. The advantage of this scheme lies in the simplicity of its computations compared with existing schemes, which is based mainly on using the optimal

energy detection algorithm in the local sensing and optimal fusion rule at the fusion centre.

- We presented a new multi-hop clustering algorithm for centralised cooperative spectrum sensing applications that is more suitable for large scale cognitive radio networks [30-31]. In this design, the cluster heads will not send their cluster results directly to the fusion centre as it is in traditional clustering approaches, which only reduces the reporting overhead, but they will send them to cluster heads in the next hop towards the fusion centre in order to reduce the energy consumption. By dividing the total clusters into multi-levels based on distances between cluster heads and the fusion centre, more energy can be saved during reporting the sensing results over a reliable transmission channel, which leads to a more accurate spectrum sensing mechanism.
- We developed a new multi-hop clustering approach for decentralised cooperative spectrum sensing applications. This algorithm can bring several benefits, including reducing the cooperation traffic overheads; providing a reliable communication between cognitive users in order to improve the global sensing efficiency; decreasing energy consumption; and addressing the sensing synchronisation. In this design, the clusters are formed in a distributed manner, and one of the cluster heads will be selected as a fusion centre based on the energy level of the cluster head and the SNR of the reporting channel between them.

8.3 Evaluation of Contributions and Future Work

In order to develop the present work and to gain more improvements on the spectrum sensing mechanisms for cognitive radio networks, the following are possible suggestions for further work:

- ➢ Throughout this thesis we have employed energy detection as the local spectrum sensing technique, and developed a new adaptive optimal energy detection scheme that tackles the low performance of energy detection due to noise power uncertainty. However, our design of the adaptive optimal energy detection algorithm was based on the assumption that the additive white noise has a Gaussian distribution, considering only the thermal noise source, while the combined noise or non-Gaussian noise due to other noise sources has not been considered. On the other hand, the performance of our spectrum sensing algorithms was analysed and demonstrated theoretically with MATLAB R2009a simulation. To make our design more realistic, we can extend our work of local spectrum sensing in future by taking into account the effects of thermal noise and other interference sources, and instead of generating the RF signals in MATLAB, we can integrate our design in a real wireless network, where actual transmitted signals could be collected in the field, so that the sensing performance can be demonstrated under a real wireless environment. The aim of future work is to study the real effects of noise power uncertainty on the performance of local spectrum sensing in order to find an actual range $(\sigma_n^2/\rho, \rho\sigma_n^2)$ of noise uncertainty under real noise and interference sources.

- In our multi-hop clustering algorithm for cooperative spectrum sensing technique which we presented in chapter 6 and 7, we discussed the need for trade-offs between the design parameters (sensing accuracy, sensing delay, and energy consumption) while designing spectrum sensing algorithms in order to satisfy the requirement of the application. In future, we plan to treat the trade-offs issue as an optimisation issue using some professional evolution techniques such as multi-objective optimisation, where the optimal solution can be obtained in the presence of trade-offs between the above conflicting performance related parameters.

- In this thesis we presented new spectrum sensing mechanisms that are compatible with stationary wireless cognitive radio networks, while the mobility of both primary users and cognitive users were not considered.

Mobility can affect the detection performance of cooperative sensing in many directions, such as cooperation gain, cooperation overhead, and correlations among cooperative users, thus improving or degrading the spectrum sensing performance, depending on the speed and the direction of the mobility and the location of corresponding cooperative users. Our future plan is to extend our work to study the effect of primary users and cognitive users' mobility on the detection performance, taking into account the above mentioned mobility parameters.

8.4 Concluding Remarks

The tremendous development in wireless communications technology and the emergence of modern services has increased the need for more radio spectrums. Since the radio spectrum is limited and in order to provide more spectrum, the communication regulators around the world have developed a new spectrum allocation policy called dynamic spectrum access that enables the unlicensed users to exploit the unused spectrum opportunistically. Cognitive radio was proposed to enable dynamic spectrum access technology and improve the spectrum utilisation using spectrum sensing techniques. Spectrum sensing plays a major role in cognitive radio networks as it helps to optimise the efficiency of spectrum utilisation. To this end, the detection schemes that are used for spectrum sensing should have high detection probability Pd and low false alarm probability Pf, in order to increase the efficiency of spectrum usage while keeping a sufficient level of protection to primary networks. In addition, cognitive users should conduct periodical spectrum sensing with a short enough sensing period in order to reduce the delay and to minimise the degradation of quality of service (QoS) that is incurred by the primary users accessing the band. However, designing a reliable, fast and efficient spectrum sensing algorithm has become a critical challenge in CR networks, which needs more effort in order to satisfy the spectrum sensing requirements. Moreover, due to fading and shadowing phenomena the SNR of the detecting signal will be very low and therefore obtaining reliable detection is very difficult, especially in the presence of noise uncertainty. On the other hand, cooperative spectrum sensing mechanisms can significantly improve the detection performance by addressing the fading and shadowing issues, but they add other issues, including cooperation overhead; sensing delay due reporting; and energy consumption, especially when the number of cooperative users is large.

Therefore, new spectrum sensing approaches are needed to tackle these detection issues while satisfying the spectrum sensing requirements. In this thesis, we focused on the main problems and challenges in the design of spectrum sensing algorithms for cognitive radio networks, and then we presented the solutions that tackle these problems. The solutions presented in this thesis for spectrum sensing issues are composed of four novel spectrum sensing algorithms: (1) a new adaptive optimal energy detection scheme for local spectrum sensing [28], (2) a new optimisation algorithm for cooperative spectrum sensing , (3) a multi-hop clustering algorithm for cooperative spectrum sensing in centralised cognitive radio networks [30-31], and (4) a new multi-hop cluster based cooperative spectrum sensing scheme for decentralised cognitive radio networks . All these proposed algorithms were analysed and simulated using computer simulation, and their performances were evaluated by comparing them with those of existing algorithms. The evaluation of our proposed spectrum sensing algorithms was mainly based on three important parameters, namely, sensing accuracy, sensing time delay and energy consumption. Our simulation results, generally, showed the advantages of our solutions to other existing approaches. In particular, for local spectrum sensing mode, the simulation results demonstrated that our proposed algorithm can provide more accurate spectrum sensing than that of existing schemes in the presence of noise uncertainty and low SNR environment. Furthermore, for cooperative spectrum sensing scenarios, the evaluation results showed that our proposed algorithms can help to optimise the spectrum sensing performance in terms of sensing accuracy, sensing time delay and energy consumption. The experiments showed also the need for a trade-off between these designing parameters according to the spectrum sensing demands while satisfying the requirements of the certain application.

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