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Cooperative Spectrum Sensing in Cognitive Radio Network

A Thesis

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by

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Dedication

This thesis is dedicated to my parents. Many thanks for your love,encouragement and support. A Special thanks to my siblings for countless support throughout my life, and to all my dear friends.

Acknowledgement

In the name of Allah, the Most Gracious and the Most Merciful Alhamdulillah, all praises to **Allah** for the strengths and His blessing incompleting this thesis. First of all, I would like to express my deepest thanksand sincere gratitude to my supervisor **Dr. Mohamed A. Elalem** for his continuous guidance, support, and timely feedback on every query. Also, I want to thank all the staff in the department of Electrical and computer Engineering for providing me the facilities to accomplish this work. Finally, I would like to thank the chairman and members of my thesis committee for their precious time and valuable suggestions.

Abstract

Cognitive radio is a communication technology developed to solve the problem of spectrum scarcity. Energy detection based on cooperative spectrum sensing represents a solution to enhance the throughput of CR since the information about primary signal presence are collected using many sensing nodes with different channel conditions. Each node reports its own reports to the network center which in terns, makes its decision. However, the throughput cannot be maximized unless efficient decision rules are used to combine the collected information and produce right final judgment.

In this thesis, a centralized cooperative spectrum sensing scheme is used, and basic decision rules are presented. New decision-making rule based on statistical average of the node reports is proposed (Average Rule). Closed form expressions for probability of detection and false alarm probability for the different decision rules are given. Comparison on the throughput performance of each scheme is studied using both hard and soft mechanisms. A complete sensing stage based on the proposed rules is designed and simulated via a system model and MATLAB programming. Additive White Gaussian Noise channel is assumed for data transmission, while the reporting channels are assumed to be free of errors.

Through this study, the comparison between different decision rules provesthat the proposed decision rule based on statistical measurements shows better performance. This rule provides better throughput and robust decisionfor probability of detection and false alarm. This, in turn, will improve thespectral efficiency and mitigate harmful interference on the primary users.

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List of Abbreviations

AWGN	Additive White Gaussian Noise
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSS	Cooperative Spectrum Sensing
DSA	Dynamic Spectrum Access
FC	Fusion Center
FCC	Federal Communications Commission
ED	Energy Detection
HCS	Hard Combination Scheme
ITU	International Telecommunication Union
MBMS	Multimedia Broadcast-Multicast Services
MC	Monte Carlo
MRC	Maximal Ratio Combining
MPO	Middle Plus One
PU	Primary User
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
SCS	Soft Combination Scheme
SLC	Square Law Combining
SNR	Signal to Noise Ratio
SU	Secondary User

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CHAPTER ONE
Introduction

CHAPTER ONE

Introduction

1.1 Background

In recent decades, it has been witnessed a rapid growth in wireless communications, which have been almost applied to every aspect of personal. Emerging wireless devices and applications further accelerate the development of wireless systems. Such an exponential growth of wireless communication also imposes huge demands on radio spectrum. As a natural resource, radio spectrum is scarce and limited. Nowadays, the spectrum is managed by government agencies such as the Federal Communications Commission (FCC), and assigned to licensed users on a long-term basis to avoid interference among wireless systems. Although this static allocation approach worked well in the past, it cannot serve the ever-increasing demand for wireless communication well because of the problem of spectrum scarcity. Recent studies reveal that the allocated spectrum is underutilized. Some parts of spectrum remain largely underutilized; some parts are sparingly utilized, while the remaining parts of the spectrum are heavily occupied.

It is recognized that this kind of static allocation policy has resulted in poor spectrum utilization. Furthermore, spectrum underutilization by licensed users exacerbates spectrum scarcity. The main reason of spectrum underutilization is that licensed users typically do not fully utilize their allocated bandwidths for most of the time, while unlicensed users are being starved for spectrum availability. To deal with this dilemma, cognitive radio is a paradigm created in an attempt to enhance spectrum utilization, by allowing unlicensed users to coexist with licensed users and make use of the spectrum holes. The spectrum holes are defined as the spectrum bands owned by licensed users, which are unused at a particular time and specific geographic location. Cognitive radio is the key enabling technology that enables next generation communication networks, also known as Dynamic Spectrum Access (DSA) networks, to utilize the spectrum more efficiently in an opportunistic fashion without interfering with the primary users. It is also defined as a radio that can change its transmitter parameters according to the interactions with the environment in which it operates. It differs from conventional radio devices in that a cognitive radio can equip users with cognitive capability and reconfigurability.

Cognitive capability defines the ability to sense and gather information from the surrounding environment, such as information about transmission frequency, bandwidth, power, modulation, etc. With this capability, cognitive users (which also known assecondary user (SU)) can identify the best available spectrum. Reconfigurability is the ability to rapidly adapt the operational parameters according to the sensed information in order to achieve the optimal performance. By utilizing the spectrum in an opportunistic fashion, cognitive radio allows secondary users to sense the portion of the spectrum if available, select the best available channel, co-ordinate spectrum access with other users, and leave the channel when a primary user reclaims the spectrum usage right[1].

1.2 Motivation

Spectrum sensing process is needed to achieve the detection of cognitive radio. Secondary users (SUs) must be able to detect the signal of the primary user. Individual spectrum sensing is sometimes difficult since the fundamental characteristics of wireless channels such as multipath fading, shadowing, can degrade the signal[2]. To overcome these issues of individual spectrum sensing, cooperative spectrum sensing is proposed, where SUs send their local sensing information to a (FC) where the final decision can be made [3].

Gathering these sensing information in cooperative spectrum sensing schemes can be categorized into two kinds: Soft Combination Scheme(SCS) and Hard Combination Scheme(HCS) [4].

In soft combination scheme, SUs send their sensing information to FC without making any decisions.

In hard combination scheme, SUs perform local measurement decisions and send this information to fusion center which collects this different data and decide either a licensed user is in operation or not.

The existing traditional decision rules provide modest performance in throughput and spectrum efficiency. This motivates me to adopt a new decision rule for spectrum sensing that provides better result and more utilization for network resources. This approach is based on statistical measurements for long time observations of the channel.

1.3 Problem Definition

In cooperative spectrum sensing, the cognitive cycle which include sensing operation of each cognitive user, transmits the sensing information to FC and takes a final decision about licensed users (which also known as Primary user (PU)) signal presence. All these operations should be done as fast as possible and with a high probability of correct decision. The network throughput is chosen as a performance measure in this study. The throughput of Cognitive Radio CR is defined as the ratio of the total transmission time to the total frame time after successful final decision is taken. The throughput is normally deteriorated because of the existence of Additive White Gaussian Noise AWGN and Rayleigh fading channels in the sensed spectrum and because of the use of inefficient fusion rules at FC. Therefore, there is always a need for developing efficient approaches to handle this deterioration. In this study, most fusion rules will be analyzed and evaluated, furthermore, one new fusion rule (Average Rule) is proposed, formulated and compared with the previous rules.

1.4 Literature Survey

In cooperative detection, the primary signals for spectrum opportunities are detected reliably by interacting or cooperating with other users. This method can be implemented as either centralized access to spectrum coordinated by a spectrum server or as distributed approach implied by the spectrum load smoothing algorithm or external detection.

Unlicensed users need to conduct spectrum sensing. However, spectrum sensing might be inaccurate due to multipath fading, shadowing, and primary receiver uncertainty. To address this problem the designing of energy detection requires a great care due to the relationships between, firstly,the noise power(or the accuracy of its estimation), secondly, the probability of false alarm and , finally,the probability of detection. It is shown in [5] that by allowing the cognitive radio operating in the same band to cooperate in spectrum sensing, the detection time can be reduced and thus increasing their agility. The authors in this study first consider the case of two cognitive users and show how the inherent asymmetry in the network can be exploited to increase the probability of detection. This study then is extended to multiple cognitive user networks.

In [6], an optimal cooperative spectrum has been proposed, in which the system energy efficient throughput is maximized. Subject to adequate protection to the primary user, there is a tradeoff between the sensing time and number of working sensors. As such; the authors have proposed an iterative algorithm to maximize the energy efficient throughput. The results of the propose iterative algorithm have been verified to be optimal by comparing them to exhaustive search results. It is found that significant improvement in the energy efficient throughput of cognitive radio system has been achieved when both the parameters for the sensing time and number of working sensors are jointly optimized [6].

Topics on optimal cooperation strategies for spectrum sensing have been studied in previous literatures. In [7], the study analyzes the effects of destructive channels and malfunctioning devices. This approach conducts spectrum sensing based on the linear combination of local test statistics from individual secondary users. The authors propose two optimization schemes to control the combining weights, and compare their performance. The first approach is to optimize the probability distribution function (pdf) of the global test statistics at the fusion center. For the second scheme, the global detection sensitivity is maximized under constraints on the false alarm probability. Simulation results illustrate the significant cooperative gain achieved by the proposed strategies. The proposed schemes optimize the detection performance by operating over a linear combination of local test statistics from individual secondary users. This combats the destructive channel effects between the target and the secondary nodes. The study concludes that the optimization of pdf would approximate the maximum of the probability of detection for a fixed probability of false alarm.

However, cooperation among users facing more or less independent fading, shadowing is likely to be correlated across space. This correlation can be dealt with by increasing the number of users up to certain sensitivity levels as mentioned in [8]. When correlation is distance-dependent, cooperation is desired among more distant users. Increasing the number of users in a distance-dependent correlated setting is asymptotically limited by the distance spread. Furthermore, a hard decision scheme performs as well as a soft decision, with small differences arising from finite number of samples. Even so, trust is critical for such a cooperative system to make this operation reliable.

In [9],hard decision rules like AND and OR and soft decision rules like Square Law Combination (SLC) and Maximum Ratio Combination (MRC) were introduced. The study proved that these rules can be combined to optimize the throughput performance. In this search, three decision rules, each consist of two decision stages (hard and soft) are proposed to improve the throughput of CR in cooperative scenario. The simulation results showed that the proposed rules enhance the throughput as compared with traditional ones. They demonstrated that the first proposed rule enhances the throughput by 106% and 58.9% at SNR equals -10 dB in Rayleigh fading channel over the classical OR-SLC and the AND-SLC rules, respectively. Under the same simulation conditions, the second proposed rule enhanced the throughput by 163% and 97.5%, while the third proposed method enhances throughput by 210% and 135%, respectively.

In [10], the spectrum sensing as an essential part of cognitive radio (CR) technology, and cooperative spectrum sensing (CSS) could efficiently improve the detection performance in environments with fading and shadowing effects, solving hidden terminal problems. Hard and Soft decision detection are usually employed at the fusion center (FC) to detect the presence or absence of the primary user (PU). However, soft decision detection achieves better sensing performance than hard decision detection at the expense of the local transmission band. In this Search, proposed a tradeoff scheme between the sensing performance and band cost. The sensing strategy is designed based on three modules. Firstly, a local detection module is used to detect the PU signal by energy detection (ED) and send decision results in terms of 1-bit or 2-bit information. Secondly, and most importantly, the FC estimates the received decision data through a data reconstruction module based on the statistical distribution such that the extra thresholds are not needed. Finally, a global decision module is in charge of fusing the estimated data and making a final decision. The results from a simulation show that the detection performance of the proposed scheme outperforms that of other algorithms. Moreover, savings on the transmission band cost can be made compared with soft decision detection.

The authors in [11]discussed the cognitive radio cycle which consists of spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility. They showed that the spectrum sensing is the most important one and has a significant impact on throughput because it directly concerns with PU detection. They explained how the successful spectrum sensing can ensure that there is no interference between the secondary user and primary user and how to aid the secondary user to recognize and utilize the spectrum holes. From the previous review, it is found that most studies are focusing on improving the throughput by controlling the sensing time and the number of cognitive users. Very few works concentrated on designing efficient decision rules used at fusion center as an approach to improve the throughput. Furthermore, even these few works have considered the use of simple structured decision mechanisms based on single stage without multi-verifications.

1.5 Aim and objective

The aimof this work is to improve throughput in cognitive radio network.Themain objectives of this work can be summarized in the following points:

1) To discuss the major challenges which occur in the environment of spectrum sensing, particularly, related to cooperative spectrum sensing models.
2) To simulate the throughput of existing cooperative spectrum sensing based on traditional fusion rules.
3) To analyze the tradeoff and the limitations of the existing spectrum sensing techniques.
4) To propose a novel fusion rules for enhancing the throughput and detection probability of cognitive radio users.
5) To evaluate the enhancement of the proposed decision rules for spectrum sensing as compared with traditional ones using MATLAB program.
6) Finally, considering the positive sides of the proposed work, some possible future directions will be addressed.

1.6 Study Contributions

The main contribution of this thesis is to study the performance of several energy detection based on cooperative spectrum sensing techniques. Different detection rules based on cooperative spectrum sensing are introduced, analyzed and compared. Furthermore, a new decision rule is proposed in this study which based on taking the statistical average of all sensing information measured by the individual cooperative users. The comparison between all these rules is done by evaluating the performance of each rule and its response to the detection probability and false alarm introduced by the energy detector. Channel throughput is adopted as a key performance for each rule.

Most of the works reported in this thesis can be found in pear reviewed research publication [12].

1.7 Thesis Outlines

After this brief introduction chapter, the rest of this thesis is organized as follows:

Chapter Two introduces the concept of the cognitive radio networks and spectrum sensing processes. Important terminologies, key benefits and definitions are given. Different spectrum detectors are explained and important formulas are presented. Some challenges facing this technology and their solutions are also listed.

Chapter Three covers the cooperative cognitive radio and decision-making rules. Various cooperative categories and basic decision-making schemes are introduced and formulated. One new decision rule is also proposed and evolved.

Chapter Four provides assessments of the rules described in Chapter three in means of selected system model and MATLAB simulation. Performance, evaluations and result discussion on each scheme are recorded.

Finally,**Chapter Five** concludes the obtained results and put forward some inspiration and guidance that may lead to further research topics.

CHAPTER TWO

Cognitive Radio Network and Spectrum Sensing

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Cognitive Radio Network and Spectrum Sensing

This chapter introduces a brief background to the definitions and concept of cognitive radio (CR), its terminologies, key benefits and various aspects of spectrum sensing. The classification of spectrum sensing schemes is discussed in detail. Cognitive's main functions and challenges facing this technology are outlined.

2.1 Definition of Cognitive Radio

A cognitive radio was first developed by Joseph Mitola in his 1999 paper who defined the cognitive radio as [13]: "A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains."

Later on, Simon Haykin defined a cognitive radio as [14]: "An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming Radio Frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- highly reliable communications whenever and wherever needed;
- efficient utilization of the radio spectrum".

Coming from a background where regulations focus on the operation of transmitters, the Federal Communications Commission (FCC) has defined a cognitive radio as [15]: "A radio that can change its transmitter parameters based on interaction with the environment in which it operates".

Also, the broader IEEE group has defined the cognitive radio as [16]: “A type of radio that can sense and autonomously reason about its environment and adapt accordingly. This radio could employ knowledge representation, automated reasoning and machine learning mechanisms in establishing, conducting, or terminatingcommunication or networking functions with other radios. Cognitive radios can be trained to dynamically and autonomously adjust its operating parameters”.

Another definition has given by the reference [16] which states: “An adaptive radio that is capable of the following:

- awareness of its environment and its own capabilities,
- goal driven autonomous operation,
- understanding or learning how its actions impact its goal,
- recalling and correlating past actions, environments, and performance”.

From the above different definitions of the cognitive radio technology, one can note that there is a harmonization of these definitions. The main common factors of these definitions are the ability of the cognitive radio to have

1. Observation: the radio is capable of acquiring information about its operating environment.
2. Adaptability: the radio is capable of changing its waveform, operating frequency, power, etc.
3. Intelligence: the radio is capable of applying information towards its goal.

2.2 Concept of Cognitive Radio

The fast evolution in wireless communication has led to the huge request of the frequency spectrum. Some frequency bands are congested and other frequency bands are underutilized. In this regard, cognitive radio has been developed as a new technology to avoid this problem. It enables the access to unoccupied spectrum holes. The cognitive radio shares the unused spectrum with the secondary unlicensed user (SU) without causing any interference to the primary user (PU) [17]. This is classified as Dynamic Spectrum Access (DSA) scheme and illustrated in Figure 2.1.

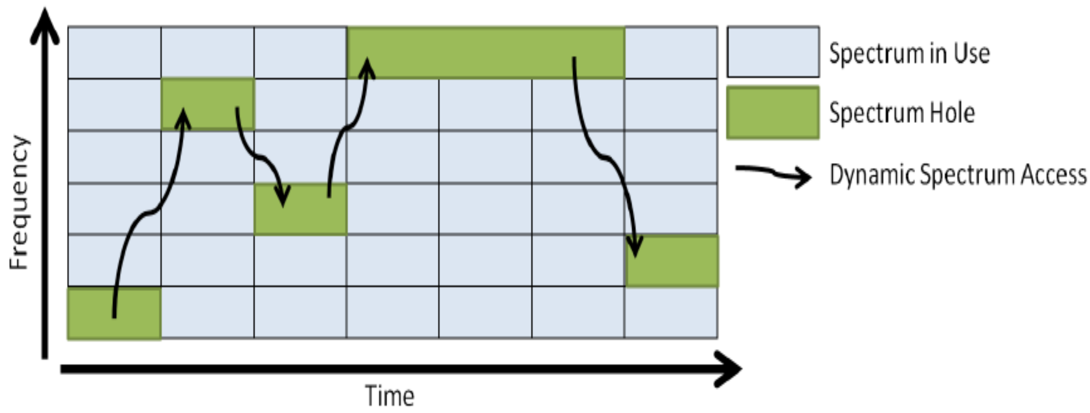

Figure 2.1 The concept of dynamic spectrum access [17].

Cognitive radio user dynamically and opportunistically accesses the spectrum hole (sometimes known as white space) avoiding an access to the licensed spectrum which is occupied by the primary user who should not affected by the operations of CR users.

So, each CR user has to detect the primary users (licensed users) if they are present or absent. This is usually achieved by sensing the spectrum bands and the process is called spectrum sensing [18, 19].

2.3 The Terminologies in Cognitive Radio

In the literature of CR, the commonly terminologies referring to the important elements of CR can be listed as follows [20]:

- Primary user (licensed user): A primary user is a user who has authorized right to access the licensed spectrum band.
- Secondary user (unlicensed user, CR user): A secondary user is a user who has no rights to utilize the licensed spectrum band. It senses the spectrum for unutilized portions of the radio spectrum and

uses this spectrum to transmit its signals without causing any interference to the primary user.

- White spaces (spectrum holes): White spaces are the unutilized part of the licensed spectrum band. The main task of CR is to search for white spaces.

2.4 Cognitive Radio Cycle

As illustrated in Figure 2.2, a cognitive radio system performs a 3-process cycle: sensing, analyzing, and deciding. The CR user needs to detect the radio environment once it needs to access the spectrum. In this phase, spectrum sensing captures the information and detects the spectrum holes. CR determines the characteristics of the transmission such as bandwidth, data rate and the transmission mode. Then once the CR user starts to operate in the captured white space, it should track of the changes in the radio environment, as this radio environment might change over the time and location. When the primary user relocated the spectrum, CR user should stop utilizing that channel immediately (or jump to another available spectrum hole) to avoid harmful to the primary use.

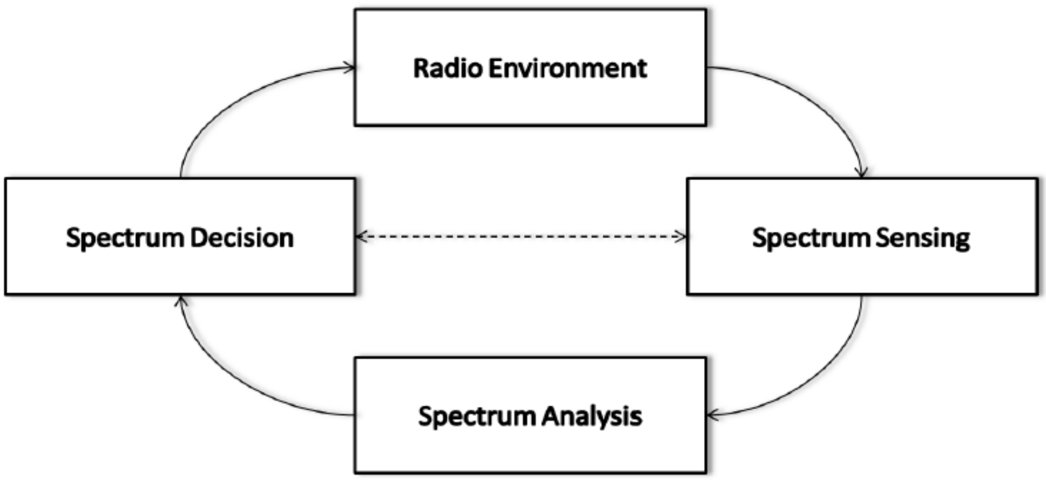

Figure 2.2 The cognitive radio cycle.

Basic cognitive cycle comprises ofthe following three basic tasks:

- Spectrum Sensing.
- Spectrum Analysis.

- Spectrum Decision.

2.4.1 Spectrum Sensing

Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, including availability of spectrum and transmit power, interference level and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions.

2.4.2 Spectrum Analysis

Spectrum analysis is based on spectrum sensing which is analyzing the situation of several factors in the external and internal radio environment (such as radio frequency spectrum use by neighboring devices, user behavior and network state) and finding the optimal communication protocol to use the channel.

2.4.3 Spectrum Decision

According to the results of spectrum sensing and spectrum analysis, the spectrum decision is made to select appropriate channels for data transmission. Different decision making will be studied in this thesis. For cooperative sensing, each SU makes a binary decision based on its local spectrum sensing and reports its one decision bit to a fusion center (FC). The decision bits from all SUs are fused together by a special logic to make the final decision. This algorithm is regarded as decision fusion or hard fusion.

2.5 Cognitive Radio's Key Benefits

Cognitive radio networks offer optimal diversity (in frequency, power, modulation, coding, space, time, polarization and so on) which leads to:

- **Spectrum efficiency:** this will allow future demand for spectrum to be available. This is the basic purpose of implementing CR.
- **Higher bandwidth services:** to support Multimedia Broadcast-Multicast Services (MBMS). This service is promised to be facilitated by the implementation of CR.

- **Graceful degradation of services:** when conditions are not ideal, a graceful degradation of service is provided, as opposed to the less desirable complete and sudden loss of service. This feature of CR is very important in providing services to the users especially when they are mobile and the base stations in contact are constantly changing.
- **Improved Quality of Service (QoS):** (latency, data rate, cost,…etc.), suitability, availability and reliability of wireless services will improve from the user’s perspective.
- **Benefits to the service provider:** more customers in the market and/or increased information transfer rates to existing customers. More players can come in the market.
- **Future-proofed product:** a CR is able to change protocols, modulation, spectrum band,… etc. without the need for a user and/or manufacturer to upgrade to a new device**.**
- **Common hardware platform**: manufacturers will gain from economies of scale because they no longer need to build numerous hardware variants, instead using a single common platform to run a wide range of software. This also assists in rapid service deployment.
- **Flexible regulation:** by using a form of policy database, regulation could be changed relatively quickly as and when required, easing the burden on regulators.
- **Emergency service communications:** joint operations during major incidents would benefit greatly as police, fire, ambulance and coastguard could be linked together in one radio with each radio user sensing the spectrum being used by the other parties and reconfiguring itself.
- **Benefits to the licensee:** CR can pave the way for spectrum trading, where licensees would be allowed to lease a portion of their spectrum rights to third parties on a temporal, spatial or other appropriate basis to recoup some of the expense of its 24hrs a day license and even make money [21].

2.6 Spectrum Sensing

The spectrum sensing is the first step in cognitive radio network operations which locates the presence or absence of the hole on a band [22]. The CR user monitors spectrum bands and search for the un-used portions of the bands. The goal of the spectrum sensing is to decide between the two hypotheses, namely [23]:

$$H_0: \quad r(n) = N(n) \text{PU absent} \tag{2.1}$$

$$H_1: \quad r(n) = h(n)s(n) + N(n) \qquad \text{PU present} \tag{2.2}$$

where $r(n)$ is the received signal at instant n, h is the channel gain, $s(n)$ is the transmitted signal of primary user and $N(n)$ is the sample of additive white Gaussian noise (AWGN). H_0 is a null hypothesis, which states that the licensed user is absent in a certain spectrum band and the existence of spectrum hole. H_1 is an alternative hypothesis which indicates that the primary user signal is present and there is no spectrum hole [24].

The parameters that affect the performance of spectrum sensing process is listed below:

i. **Probability of false alarm** P_{FA}: It is the probability of undetected spectrum holes. A large P_{FA} produces poor spectral efficiency in cognitive radio because of false decisions which lead to increasing the interference between the secondary user and primary user [25, 26].

ii. **Probability of detection** P_D: It is the probability of detected spectrum holes, larger P_D is preferred because it gives precise decisions [25, 26].

iii. Number of sensed spectrum samples N_s. A large number of sensed spectrum samples improves the probability of detection, so gives true decisions. But from another side, increasing the number of samples leads to increase the sensing time [27]. Therefore, the number of samples can be expressed as [25].

$$N_s = \tau f_s \tag{2.3}$$

where τ is the sensing time and f_s is the sampling frequency.

iv. **Threshold λ:** A predefined threshold is required to decide the absence or presence of the primary user signal. The threshold selection affects P_D and P_{FA}, where increasing the threshold will decrease P_D and P_{FA} [25, 26]. The common equation for setting the threshold assuming P_D is constant as in [28, 29]

$$\lambda_h = Q^{-1}\left(\frac{P_D\sqrt{1+2\,SNR}}{\sqrt{N_s}}\right) + 1 + SNR \qquad \text{For hard decision rule} \tag{2.4}$$

$$\lambda_s = Q^{-1}\left(\frac{P_{FA}}{\sqrt{N_s}}\right) + 1 \qquad \text{For soft decision rule} \tag{2.5}$$

where $Q^{-1}$is the inverse of complimentary error function $Q(\cdot)$. The threshold level selection Signal to Noise Ratio (SNR) is based on maximizing the difference between P_D and P_{FA}. This can be achieved by making P_D as high as possible and P_{FA} as low as possible.

2.7 Cognitive Radio Main Functions

The fundamental requirements for SUs are to control the interference to the potential PUs in their vicinity. To guarantee a high spectrum efficiency while avoiding any kind of harmful interference to the licensed users (PUs), some important functionalities should be provided by cognitive radio such as spectrum sensing, dynamic frequency selection and transmit power control [30]. These main functions can be summarized as following:

- Spectrum Sensing: detecting unused spectrum and sharing the spectrum without harmful interference with other users.
- Spectrum Management: capturing the best available spectrum to meet users' requirements (QoS, bit rate,… etc.)

- Spectrum mobility: maintaining seamless communication requirements during the transition to better spectrum.
- Spectrum sharing: providing the fair spectrum scheduling method among the co-existing (SUs).

In this thesis, the focus will be only on the spectrum sensing processes. The other three functions can be mentioned as future studies for researches who are interesting in this area.

2.8 Spectrum Sensing Analysis

CR noncooperative spectrum sensing occurs when only one secondary user performs the primary user detection process. According to this scenario, three different aspects for spectrum sensing schemes are discussed the proceeding subsections. Cooperative spectrum sensing is introduced in the next chapter.

2.8.1 Energy Detection

Energy detection has become a widely used technique to sense the primary user signal [30]. A block diagram of a conventional energy detector is illustrated in Figure 2.3. A band-pass filter (BPF) is first applied, and then its output is squared, integrated, and compared against a threshold to make a decision on the presence of a signal. The energy detection method is attractive because of its implementation simplicity compared to other sensing schemes, as well as fast detection of the primary signals. It has a good resistance against dynamic radio environment where none a prior knowledge about the PUs is available (non-coherent detector). However, the performance of the energy detector is easily affected by channel fading, shadowing, and interferences.

The signal statistics (the computed energy) are compared to a predetermined threshold. The average total energy detected E, using N_s samples, is defined as

$$E = \frac{1}{N_s}\sum_{i=1}^{N_s} |r(in)|^2 \qquad (2.6)$$

If E is more than or equal to λ this indicates that the spectrum is in use (hypothesis H_1) and if E is smaller than λ, this means there is a hole in spectrum (hypothesis H_0). The block diagram of energy detection spectrum sensing technique is shown in Figure 2.3.

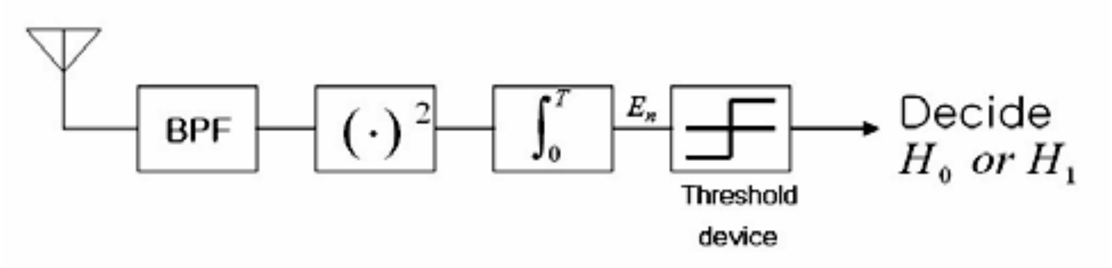

Figure 2.3 Block diagram of a conventional energy detector.

Specifically, the energy of the received signal is collected in a fixed bandwidth W and a time slot duration T and then compared with a pre-designed threshold λ, if $E \geq \lambda$, then the cognitive radio assumes that the primary system is in operation, i.e., H_1. Otherwise, it assumes H_0.The average probability of detection, false alarm, and missing of energy detection (The miss detection occurs when the primary user is in operation but the cognitive radio fails to sense it) over noisy and fading channels can be given by, respectively, [31]:

$$P_D = E[P_\lambda\{H_1|H_1\}]_\eta = e^{-\frac{\lambda}{2}} \sum_{n=0}^{\alpha-2} \frac{1}{n!}\left(\frac{\lambda}{2}\right)^2 + \left(\frac{1+\bar{\eta}}{\bar{\eta}}\right)^{\alpha-1} \times \left(e^{-\frac{\lambda}{2(1+\bar{\eta})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{\alpha-2} \frac{1}{n!}\left(\frac{\lambda\bar{\eta}}{2(1+\bar{\eta})}\right)^n\right) \tag{2.7}$$

$$P_{FA} = E[P_r\{H_1|H_0\}] = \frac{\Gamma(m, \frac{\lambda}{2})}{\Gamma(m)} \tag{2.8}$$

$$P_m = E[P_r\{H_0|H_1\}] = 1 - P_D \tag{2.9}$$

where $\bar{\eta}$ denotes the average SNR at the cognitive radio. α is a certain margin of protection which is a measure of how much interference above the noise floor the primary user can tolerate (typical value is 5dB). $E[\cdot]_\eta$ represents the expectation over the random variable η (the instantaneous SNR) which is modeled as exponential distributed. $P_r\{\cdot\}$ is the probability of the event. $\Gamma(\cdot)$ is the *gamma function,* and $\Gamma(\cdot,\cdot)$ is the *incomplete gamma function*, given by

$$\Gamma(x) = \int_0^\infty t^{(x-1)} e^{-t}\, dt, \qquad \text{for } x \text{ integer, } \Gamma(n-1) = n! \tag{2.10}$$

$$\Gamma(x,a) = \frac{\int_0^x t^{(a-1)} e^{-t}\, dt}{\Gamma(a)} \tag{2.11}$$

Gamma function and incomplete gamma function have inbuilt functions in MATLAB Library as ***gamma***(a) and ***gammainc***(x,a), respectively.

Finally, m in Equation (2.8) is Time *Bandwidth product* $m = TW$ with $m = 5$ is chosen throughout this study which is typical value.

2.8.2 Matched Filter

The matched filter detection is a linear filter and is used when a secondary user has a prior knowledge of the PU signal properties. This prior information includes carrier frequency, modulation type and pulse shape. This condition makes the matched filter detection impractical. A matched filter maximizes the signal-to-noise ratio (SNR) of the received signal so it is the optimal signal detection. Its performance degrades when there is a reduction of channel knowledge due to rapid changes in the channel state conditions.

A matched-filtering process is equivalent to a correlation scheme; wherein a signal is convolved with a filter whose impulse response is a mirror and time shifted version of the reference signal. The matched filter $h(t)$convolves the received signal $r(t)$ with a time-revered version of the known signal as;

$$r(t) \otimes h(t) = r(t) \otimes s(T - t - \tau) \tag{2.12}$$

where T refers to a symbol time duration and τ is a shift in the known signal $s(t)$, and $\otimes$ refers to the convolution operator.

The details of this technique can be found in [32] and [33].

2.8.3 Cyclostationary Detection

A signal is said to be cyclostationary if its autocorrelation is a periodic function of time with some period. Cyclostationary feature detection exploits the periodicity of the received signal to identify the presence or absence of primary users. The periodicity is commonly embedded in sinusoidal carriers, spreading code and cyclic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation. The complex system depicting this method of detection is also presented in [33, 34].

A signal $s(t)$ is said to be cyclostationary, if its mean and autocorrelation function $E[s(t)], R_s(t,\tau)$ are periodic, i.e., for any integer$k$:

$$E[s(t)] = E[s(t + kT_0)] \quad \text{and} \quad R_s(t,\tau) = R_s(t + kT_0, \tau)] \tag{2.13}$$

The details of using cyclostationary analysis as a technique to accomplish signal detection is described in [35].

Compared to energy detection, cyclostationary feature detection has a better performance when SNR is low. However, it has the same disadvantage as matched filter detection in the sense that it needs prior knowledge of the secondary user. Also, it requires a long detection time which makes it less popular than energy detection.

Because energy detection is the most popular and simplest sensing method, it has been selected for spectrum sensing in this thesis. So, the two disadvantages mentioned above are overcome.

2.9 Challenges of Spectrum Sensing

The main challenges facing spectrum sensing come from the following aspects :

- Hardware requirements;
- Hidden primary user problem;
- Sensing duration;
- Decision fusion in cooperative sensing; and
- Security.

In this study, neither challenges from the hardware nor from security are considered. The focus will be on solving the following three problems: firstly,the Hidden Primary User Problem, secondly, Sensing Duration and finally, Decision Fusion in Cooperative Sensing.

2.9.1 Hidden PU Problem

This problem is caused by many factors such as path-loss and shadow fading. These factors depend on the relative location between PU and SU. Because of these factors, sometimes, SU (as a cognitive device) is blind to an active PU. This is a common problem which occurs in spectrum sensing with a single SU. In this case, SU causes interference to PU because of miss detections. In order to prevent this issue, cooperative scenario with multiple SUs performing sensing process can deal with the hidden PU problem.

2.9.2 Selection of Sensing Duration

It is an important problem in current spectrum sensing algorithms. A long sensing duration guarantees a good probability of detection but causes low spectrum utilization. A short sensing duration has a high spectrum utilization but its detection performance is low. Is not guaranteed to be able to detect an active PU quickly, which causes interference to PU, while a fast sensing causes a low spectrum utilization. Thus, the selection of sensing duration represents a trade-off between spectrum utilization and detection performance [36].

2.9.3 Decision Fusion in Cooperative Sensing

It is a key problemfor cooperative spectrum sensing in cognitive radio networks. Traditional methods such as the AND rule or the OR rule do not provide an elegant compromise between the probability of detection and the probability of false alarm. Therefore, it is necessary to propose a better decision-making method. Instead of fusing data and making decisions based on a simple threshold. More modern methods which deal with the decision-making problem in a novel way using machine learning algorithm [37]. In which a decision-making engine has been constructed by letting it learn from a prior knowledge database and from its own experience to make decision automatically.

In next chapter, cooperative spectrum sensing is discussed based on energy detection.

Different decision-making rules will be presented and a new rule based on statistical average of the cooperative users is also proposed and formulated.

CHAPTER THREE

Cooperative Cognitive Radio and Decision-Making Rules

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Cooperative Cognitive Radio and Decision-Making Rules

Cooperation has always benefits. Using cooperative communications can greatly improve the data transmission and reduce the transmission errors. It is defined as the willingness of users in the same network to share information, power and computation with neighboring nodes and this can lead to savings of overall network resources. In this chapter, cooperation among cognitive users is considered. This eases to reduce the uncertainty of information recorded by single user detection. Different decision-making rules to collect and combine this information and network throughput calculation are also presented in this chapter.

3.1 Cooperative Scenario in Sensing Process

A number of sensing techniques have been proposed in the literature. These techniques are classified into two main categories: cooperative sensing and noncooperative sensing . There are many schemes for spectrum sensing depending on the CR network operation scenarios. Figure 3.1 shows the classification of spectrum sensing schemes. The right branch of the figure was discussed in Chapter 2 .

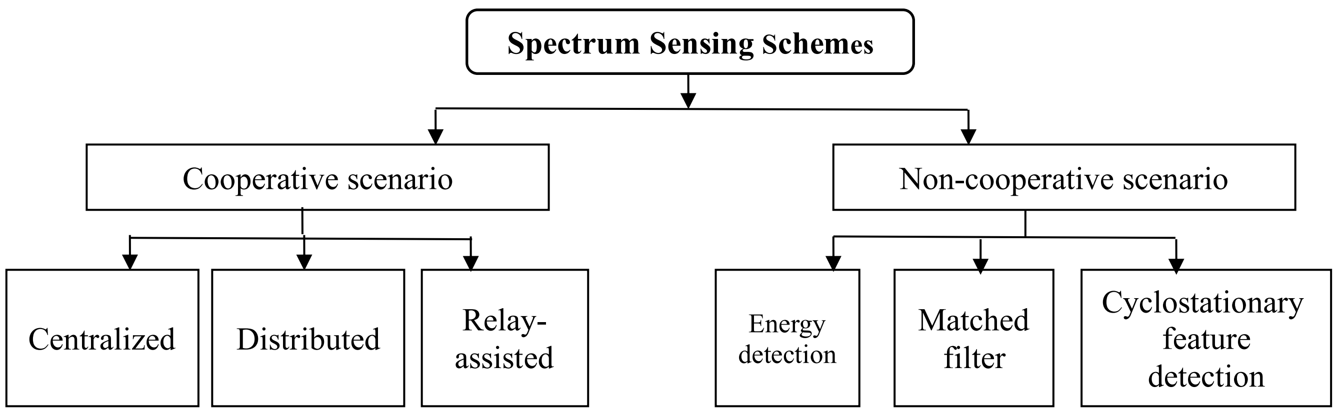

Figure 3.1 Classification of spectrum sensing schemes [38].

The natural property of the wireless propagation of signals can experience deep fade and not be able to detect the primary user. Hidden terminal problem occurs in conventional energy detection. Furthermore, there is still a chance when the CR user has a line-of-sight to the primary user but cannot detect the PU's existence due to shadowing uncertainty. When CR user experiences hidden terminal problem or shadowing uncertainty, the transmitter detection cannot detect the PU's presence. As a result, cooperation among CR users can reduce an uncertainty caused by the single user's detection. Using multiple sensing nodes, cooperative sensing can exploit spatial diversity and mitigate multipath fading and shadowing effects, which are the main factors that deteriorate performance of single user's detection.

Cooperative spectrum sensing occurs when a group or network of CR users contribute to sense the information they gain for PU detection as shown in Figure 3.2. The cooperative detection can provide more accurate performance. However, it requires additional operations and overhead traffic to communicate among CR users. As a result, there can be an effect on the performance of resource-constrained networks.

3.2 Cooperative Sensing Categories

There are different cooperative sensing categories based on how CRs share data in the network. These categories are shown in Figure3.3 and briefly explained in the subsequent subsections.

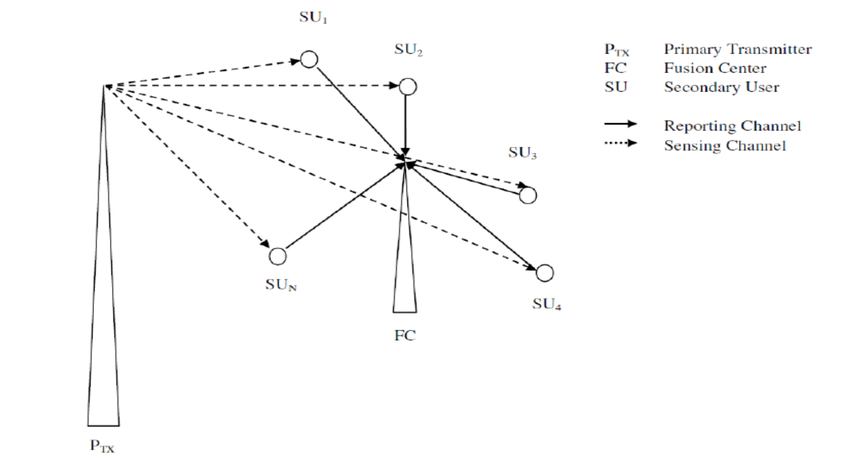

Figure 3.2 System model of cooperative sensing [26].

3.2.1 Centralized Cooperative Detection

In this approach, there is a central node called fusion center (FC) within the network that collects the sensing information from all the CR users. All CR users are sending the sensing results via a control channel, where a link between each cooperating CR and FC is called a reporting channel [39].

3.2.2 Distributed Cooperative Detection

Unlike centralized approach, distributed cooperative sensing does not use the FC for making the decision. None of the CR users take control. Each CR user sends its sensing information to other CR users, merges its information with the received sensing information, and decides whether the PU is present or not [39].

3.2.3 Relay-assisted Cooperative Detection

This category is based on CR users observing weak sensing and reporting channels in one part as well as strong sensing and reporting channel in another and trying to complement and cooperate with each other to improve the performance of Cooperative Spectrum Sensing (CSS).

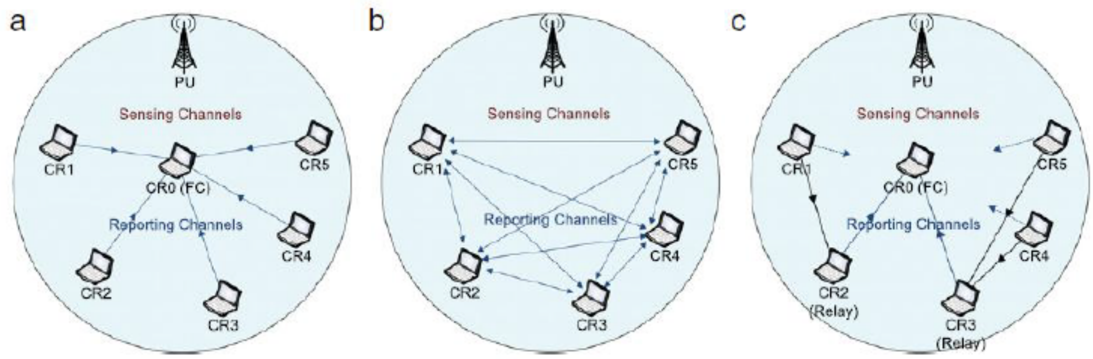

Figure 3.3: Cooperative sensing schemes [40]

(a) Centralized, (b) Distributed (de-centralized), (c) Relay assisted.

As seen in Figure 3.3(c), the relay-assisted CSS can exist in both distributed and centralized structures based on the demands on sensing and reporting at any given time. This category can also be operated as a multi-hop CSS category. It should be noted that the relay for CSS has a distinctly different purpose from the relays in cooperative communications [41].

3.3 Fusion Rules

The cooperative spectrum sensing shares the information among cognitive radios and combine their results which lead to enhance the detection of cognitive radio networks. The shared information can be in a form of hard and soft decisions [42,43].

3.3.1 Hard Decision Combining Rules

In HDC rules based cooperative spectrum sensing, CR users forward its local decision to the fusion center to make a final decision. Assuming that the energy observations at each CR user is independent and identically distributed (i.i.d.). All decisions from the cognitive radio users are then sent to the fusion center, where the global decision is made. The probability of detection P_D and the probability of false alarm P_{FA} at the fusion center are given by [44, 45]:

$$\mathrm{P}_D = \sum_{i=K}^{N_c} \binom{N_c}{i} (P_{D,i})^k (1 - P_{D,i})^{N_c - i} \tag{3.1}$$

$$\mathrm{P}_{FA} = \sum_{i=K}^{N_c} \binom{N_c}{i} (P_{FA,i})^k (1 - P_{FA,i})^{N_c - i} \tag{3.2}$$

where N_c is the number of secondary users sensing the spectrum and $P_{FA,i}$ is the probability of false alarm of the i^{th} cognitive user, k is set according to the used rule, and $\binom{\mathrm{Nc}}{k}$ is binomial coefficient.

Here below, different decision combining rules are described.

3.3.1.1 OR Rule Decision

In this rule, if any one of the local decisions sent to the decision maker is a logical one, the final decision made by the decision maker is digit "1". The OR rule decides that a hole is present if any of the users detect a hole [46, 47], therefore k is set to 1 in Equation (3.1) and Equation (3.2). The probability of detection and probability of false alarm of the final decision of this rule are, respectively [48]:

$$\mathrm{P}_{D,OR} = 1 - (1 - P_D)^{N_c} \tag{3.3}$$

$$\mathrm{P}_{FA,OR} = 1 - (1 - P_{FA,})^{N_c} \tag{3.4}$$

where N_c is the number of cooperative CR users.

3.3.1.2 AND Rule Decision

In this rule, if all of the local decisions sent to the decision maker are one, the final decision made by the decision maker is digit "1". The fusion center's decision is calculated by logic AND of the received hard decision statistics. The AND rule decides that a hole is present if all users detect a hole [45, 46] therefore k is set to N_c in Equation (3.1) and Equation (3.2). The probability of detection and probability of false alarm of the final decision of this rule are, respectively [48]:

$$\mathrm{P}_{D,AND} = (P_D)^{N_c} \tag{3.5}$$

$$\mathrm{P}_{FA,AND} = (P_{FA})^{N_c} \tag{3.6}$$

3.3.1.3 MAJORITY Rule Decision

In this rule, if half or more of the local decisions sent to the decision maker are the final decision made by the decision maker is one, the MAJORITY rule decides that a hole is present if half or more of users detect a hole [46, 47] therefore k is set to $N_c/2$ in Equation (3.1) and Equation (3.2). The probability of detection and probability of false alarm of the final decision are, respectively [48]:

$$\mathrm{P}_{D,MAJORITY} = \begin{cases} \sum_{i=Nc/2}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ \ is\ even \\ \sum_{i=ceil(\frac{Nc}{2})}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ \ is\ odd \end{cases} \tag{3.7}$$

$$\mathrm{P}_{FA\ MAJORITY} = \begin{cases} \sum_{i=Nc/2}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ \ is\ even \\ \sum_{i=ceil(\frac{Nc}{2})}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ \ is\ odd \end{cases} \tag{3.8}$$

where $ceil(\frac{Nc}{2})$ rounds the elements of $Nc/2$ to the nearest integers greater than or equal to $Nc/2$.

3.3.1.4 Middle Plus One (MPO) Decision

Middle Plus One (MPO) is first proposed rule and it is a type of hard decision rules. The mechanism of its operation is as follows: the fusion center makes a final decision of "0" when half plus one or more of the local decisions sent to the fusion center are "0" (indicating the existence of hole) therefore k is set to $(\frac{Nc}{2} + 1)$ in Equation (3.1) and Equation (3.2) and the fusion center indicates that the hole is present. This rule will increase the throughput since it increases the number of secondary users that give the same decisions which decrease the probability of false alarm. The probability of detection and the probability of false alarm of MPO rule is given in the following equations:

$$\mathrm{P}_{D,MPO} = \begin{cases} \displaystyle\sum_{i=\frac{Nc}{2}+1}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1-P_{D,i})^{N_c-i}, & N_c \ \ is\ even \\ \displaystyle\sum_{i=ceil\left(\frac{Nc}{2}\right)+1}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1-P_{D,i})^{N_c-i}, & N_c \ \ is\ odd \end{cases} \tag{3.9}$$

$$\mathrm{P}_{FA,MPO} = \begin{cases} \displaystyle\sum_{i=\frac{Nc}{2}+1}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1-P_{FA,i})^{N_c-i}, & N_c \ \ is\ even \\ \displaystyle\sum_{i=ceil\left(\frac{Nc}{2}\right)+1}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1-P_{FA,i})^{N_c-i}, & N_c \ \ is\ odd \end{cases} \tag{3.10}$$

3.3.1.5 k-out-of- n Rule Decision

In k-out-of-n -rule based hard decision rule, the final decision of H_1 is made only at least k CR users report H_1local decision. The probability of detection and probability of false alarm of the final decision are [49].

$$\mathrm{P}_{D,k-out\,n} = \sum_{i=k}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1-P_{D,i})^{N_c-i} \tag{3.11}$$

$$\mathrm{P}_{FA,k-out\,n} = \sum_{i=k}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1-P_{FA,i})^{N_c-i} \tag{3.12}$$

3.3.1.6 Average Rule Decision

In this rule, the final decision of H_1 is made only when the average of all CR reports lies above a certain predefined threshold. This threshold represents the long-term observations of the average of probabilities of detection of the primary user presence. Monte Carlo (MC) method, which is a stochastic technique based on the use of random numbers can form the basis of calculating this threshold. The higher the number of Monte Carlo samples, the greater the confidence of this threshold. Therefore k in Equation (3.1) and Equation (3.2) is set a value where the count of CR users performing spectrum sensing exceed the predefined threshold. The threshold of the probability of detection and false alarm probability can be expressed as

$$\mathrm{P}_{D,a} = average\left(P_{D,i} \colon \forall\, i = 1 \ldots\ N_c\right)|_{MC} \tag{3.13}$$

$$\mathrm{P}_{FA,a} = average\left(P_{FA,i} \colon \forall\, i = 1 \ldots\ N_c\right)|_{MC} \tag{3.14}$$

where $average(\cdot)$ is the statistical average function.

Then the value of k will be the minimum value of users those satisfy the following criteria

$$\mathrm{k} = \min \begin{cases} count(P_{D,i} \colon P_{D,i} \ \geq \quad P_{D,a} \forall\, i = 1 \ldots\ N_c) \\ count(P_{FA,i} \colon P_{FA,i} \ \geq \ P_{FA,a} \forall\, i = 1 \ldots\ N_c) \end{cases} \tag{3.15}$$

where $min(\cdot)$ is the known minimum function, and $count(\cdot)$ is a function that counts its arguments.

Now, this value of k can be plugged in Equation (3.1) and Equation (3.2) to find the probability of detection and probability of false alarm of the final decision.

$$\mathrm{P}_D = \sum_{i=1}^{k} \binom{k}{i} (P_{D,i})^i (1 - P_{D,i})^{K-i} \tag{3.16}$$

$$\mathrm{P}_{FA} = \sum_{i=1}^{k} \binom{K}{i} (P_{FA,i})^i (1 - P_{FA,i})^{K-i} \tag{3.17}$$

3.3.2 Soft Fusion Rules (Data Fusion)

In a soft fusion scheme, cognitive radio users send their sensing information to the fusion center without making local decisions. The fusion center then combines the forwarded observations and compares the aggregated energy value to the fusion threshold. The decision is made at the fusion center by using one of the combining rules [46, 50]. The major combining rules in this detection scheme are Square Law Combination (SLC) and Maximum Ratio Combination (MRC).

3.3.2.1 Square Law Combination (SLC)

In this combination rule, the energy at each node is sent to the fusion center. At fusion center these energies are added to each other and the result is compared with a predefined threshold to decide the presence or absence of the spectrum hole. The test statistics for this rule is [51]:

$$\mathrm{E}_{SLC} = \sum_{i=1}^{N_c} E_i \tag{3.18}$$

where E_i is the statistics of the i^{th}CR user energy.

3.3.2.2 Maximum Ratio Combination (MRC)

The difference between SLC and this rule is that in MRC the received energy from each i^{th} CR user is multiplied with certain normalized weight w_i, then added to each other whereas in SLC the received energies are directly added.

The test statistics for this rule is:

$$\mathrm{E}_{MRC} = \sum_{i=1}^{N_c} w_i E_i \tag{3.19}$$

MRC soft combination scheme defines weight coefficients as [52]

$$w_i = \sum_{i=1}^{N_c} \frac{E_i}{\sqrt{\sum_{i=1}^{N_c} E_i^2}} w_i \tag{3.20}$$

3.4 Throughput of Cognitive Radio

The throughput in cognitive radio is defined as the ratio of the total transmission time to the total frame time after successful final decision is taken [53]. The frame structure in cognitive radios consists of sensing time and data transmission time, as shown in Figure 3.4. According to the frame structure: first, the cognitive user senses the spectrum band for a specific time duration τ. Then, in the case of hole presence, the user starts data transmission over remaining frame time duration $(T - \tau)$.

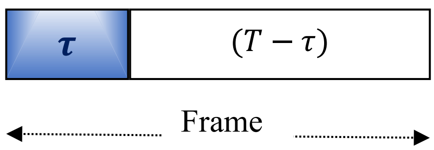

Figure 3.4 Frame structure for cognitive radio network, (τ: sensing slot duration; $(T - \tau)$: data transmission slot duration).

The normalized achieved throughput can be expressed as [27]

$$\mathrm{R} = \frac{(T - \tau)}{T}(1 - P_{FA}) \tag{3.21}$$

3.5 Throughput Improvement in Cognitive Radio

According to Equation (3.21) and what previously discussed in this chapter, by controlling some parameters, the throughput of cognitive radio can be improved. Some of these parameters act directly and others indirectly to the throughput improvement. These parameters can be listed as below:

1. **Sensing time τ:** a higher sensing time results in precise spectrum sensing, and avoiding interference with the licensed user. However, an increase in sensing time results a decrease in transmission time,

leading to low throughput [54], and shorter sensing time degrades the sensing process [55], so the optimal sensing time can maximize the SU's throughput [56].

2. **Frame duration T:** For a given sensing time, the larger frame duration, the longer the data transmission time $(T - \tau)$ and maximum throughput value. Also, the longer the frame duration, the more chances that the PU becomes active, thus more interference between PU and SU, which degrades the throughput. Thus, there exists an optimum frame duration for which interference is minimum and throughput of the CR is maximum [57].
3. **Signal to noise ratio SNR for secondary user:** The throughput of the system increases with increasing SNR value until maximum throughput is reached [58], so throughput has a direct relationship with SNR.
4. **The number of secondary user N_c:** using the cooperative spectrum sensing is preferable because the SUs can better use the channel which leads to increase the throughput. The throughput increases with increasing the number of cooperative SUs [59].
5. **Fusion rules:** throughput is affected by fusion rules that make the global decisions. However, using appropriate fusion rule in cooperative spectrum sensing scheme causing improve the throughput in cognitive radio.

In this thesis, the efforts are devoted to improve the throughput through the use of efficient fusion rules.

In next chapter, analysis and evaluation for these decision rules will be presented through numerical examples. Simulation comparison between different scenarios of sensing process is executed using MATLAB program.

CHAPTER FOUR

Simulation Results

CHAPTER FOUR

Simulation Results

In this chapter, the simulation of Four decision rules to enhance throughput in CR are presented. The traditionaldecision rules: OR rule, MAJORITY rule and Middle Plus One (MPO) rule are simulated. Then the proposed decision rule named as AVERAGE rule is also simulated. These rules are evaluated for the purpose of comparing the throughput with each other. The scenario consists of sensing stage (local decision), transmission stage (reporting) and decision stage (global decision).

4.1 Simulation Setting and Parameters

In this simulation, the system model is set up as illustrated inFigure 4.1. Energy detection technique is adopted to detect whether primary user is transmitting or not. It is assumed that number of cognitive radio users are random uniformly distributed around the area where the primary user is in operating. The sensing procedure is that the CR users locally sense the PU. Then, theycollaboratively forward either its decision or observation to the fusion center. The reporting channel of error-free is assumed such that the fusion centerreceivesexactly the same information as sent. The fusion center makes finaldecision and inform all CR users.

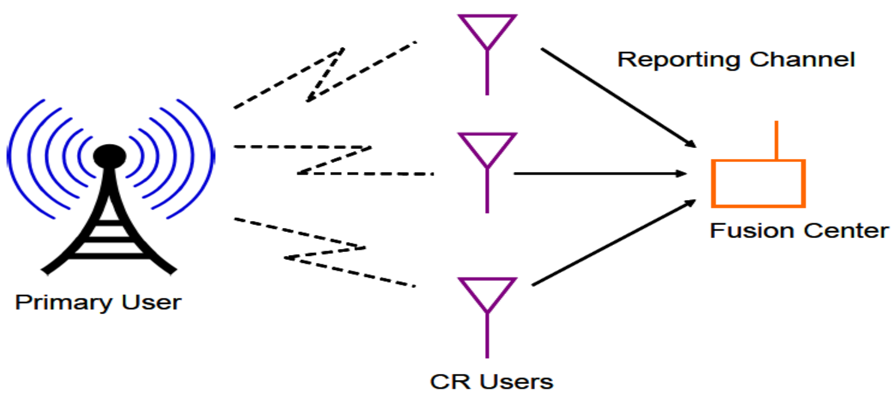

Figure 4.1 The system model.

The simulation parameters used in this analysis are given in Table 4.1. The total frame duration is 0.1 sec, including the sensing and transmission time. The primary user signal is assumed to be random data using QPSK modulation. Cooperative sensing with variable number of users is used in all the decision rules. The proposed rules are simulated over AWGN transmission channel. MATLAB R2013a version is used for simulation.

Table 4.1: Simulation parameters.

Parameter	Value
PU carrier frequency	1 MHz
PU modulation type	QPSK
Sampling frequency	6 MHz
Bits per symbol	2
Total frame length	0.1 sec
Number of cooperative users	2-10
Spectrum sensing method	Energy detection

4.2 System Model

A centralized cooperative spectrum sensing scheme is used, where a number of secondary users sensing for the primary user. The primary user data are generated randomly and QPSK modulated. The sensing stage is performed using the energy detection method, in which each secondary user computes the energy of the sensed spectrum. This requires to transform the primary signal to frequency domain. The sensing process is performed in AWGN channel. After that either hard or soft decision schemes are used. An error free transmission is assumed at the reporting channel where the throughput is calculated. Figure 4.2 shows the flowchart of the sensing scheme model.

4.3 Hard Decision Rules

Four hard decision rules are adopted for simulation, these are: OR rule, MAJORITY rule, Middle Plus One (MPO) rule, and AVERAGE. The flow chart of these rules is presented in Figure 4.3. First the initial parameters are defined and a primary user signal is QPSK generated. Since the computation of throughput depends on false alarm probability Equation 3.21, the statistics are repeated "TEST" times for each N_c secondary users. At that point the flowchart is divided into two paths. Each path simulates a certain hypothesis H_0 or H_1. In H_1 path, the generated primary signal is added to the noise and fading collected from channel.

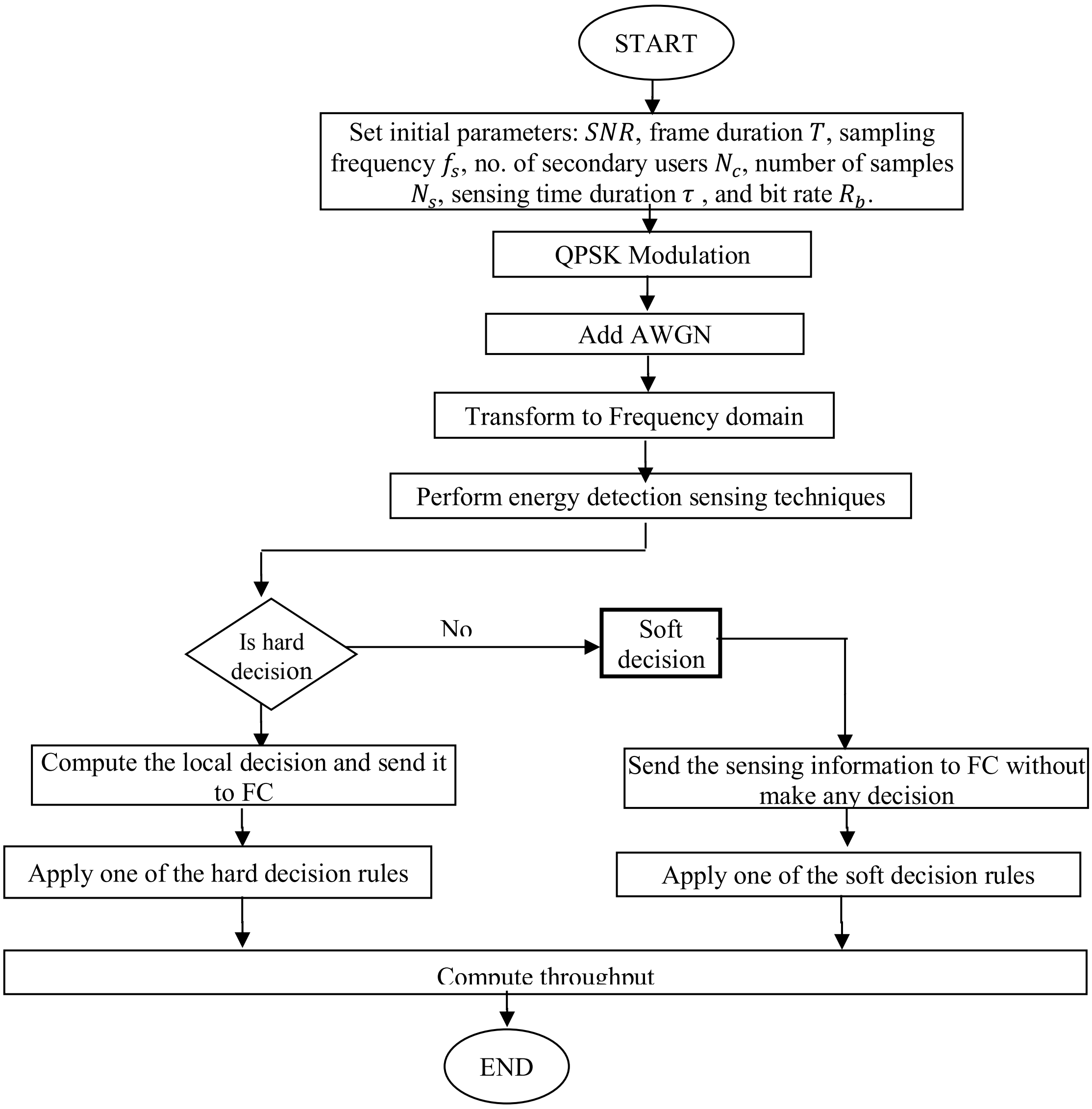

Figure 4.2 Flowchart of the sensing model.

If the accumulated energy along the tested spectrum does not cross the threshold value λ, which points out a false alarm, the false counter *CountFA* is increased by one. Otherwise, no increment is done to the counter.

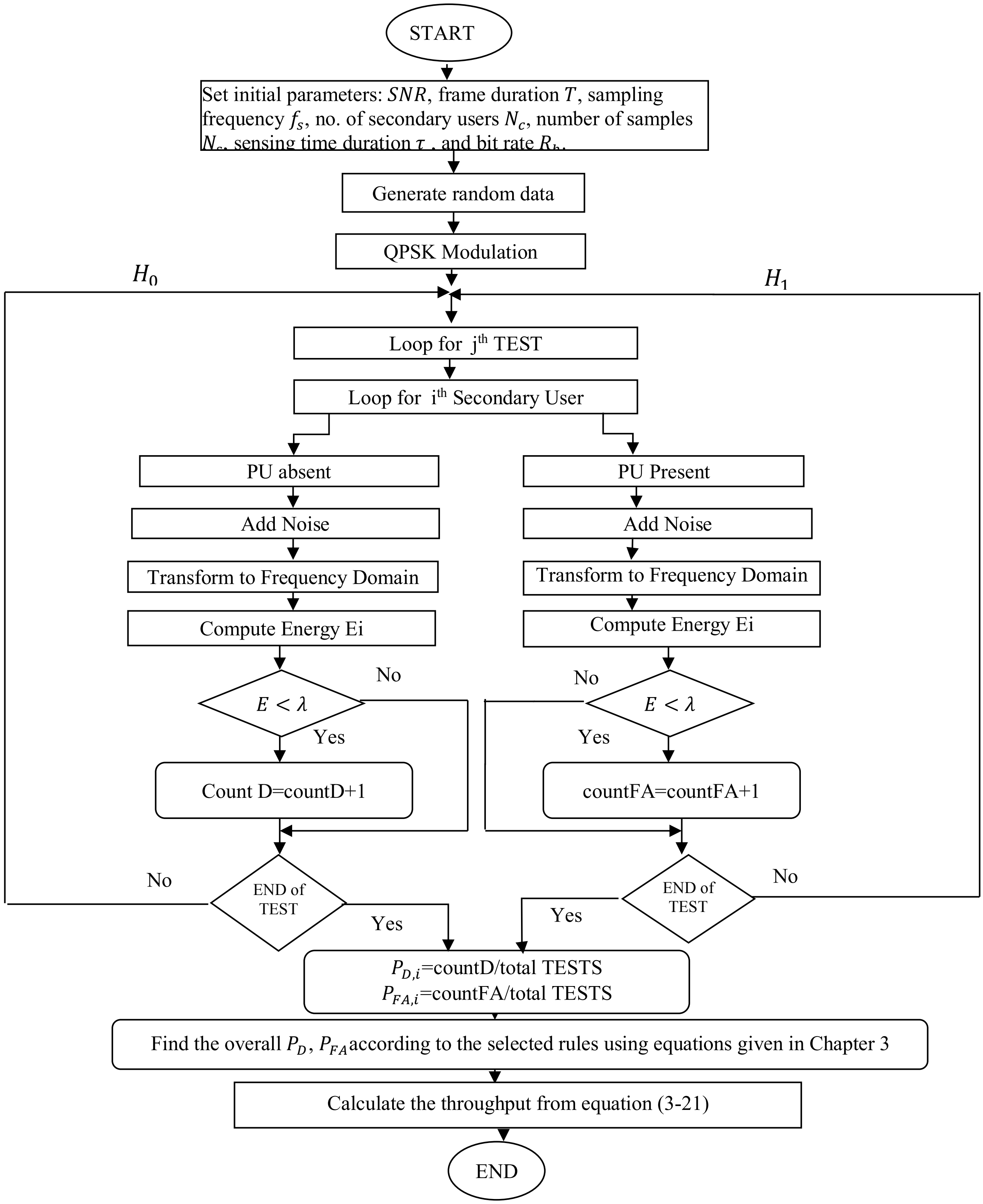

Figure4.3 Flowchart of hard decision rules.

This counter value for each cognitive user after Test iterations is stored to compute false alarm probability of i^{th} cognitive user $P_{FA,i}$ by dividing the number of times the threshold crossed to the total number of tests. Then the global false alarm probability is computed using the equations corresponding to the used decision rulethese equation are given in Chapter 3 from Equation (3.3) to Equation (3.17).

In H_0 path the same procedure is performed but this time the primary signal is not added to noise plus fading signal and the calculated probability is detection probability $P_{D,i}$.Finally, the throughput R is calculated using Equation (3.21) as shown in the flowchart.

4.3.1 Simulation Results of OR Rule

Figure 4.4 shows a relation between the probabilityof detection as a function of number of users. It can be observed from the figure that as the number of users increases, the corresponding probability of detection increases as well. For example, when there are 3 users in the network, the probability of detection is 69%, and when the number of users is 6, the probability of detection is 98%. This is because, as the number of users increases in the cooperative network, then there are more chances to estimate the correct probability.

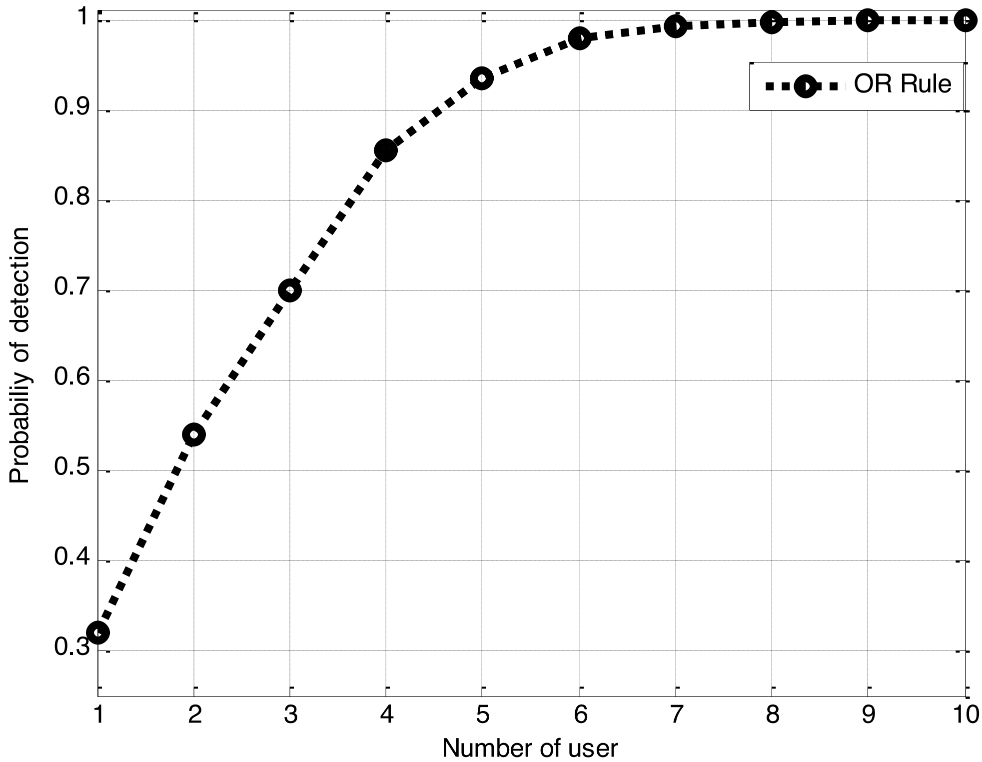

Figure 4.4 Probability of detection versus number of users (OR rule)**.**

Figure 4.5 reveals that as the number of users increases, the probability of false alarm decreases. For instance, when the number of users is 3 the probability of false alarm is 5.6% , similarly, when the number of users increases to 7 users the probability of false alarm drops to 3.8% .This trend is due to the reason that, with the increase of the number of users in a cooperative network, the probability of making false detection decreases..

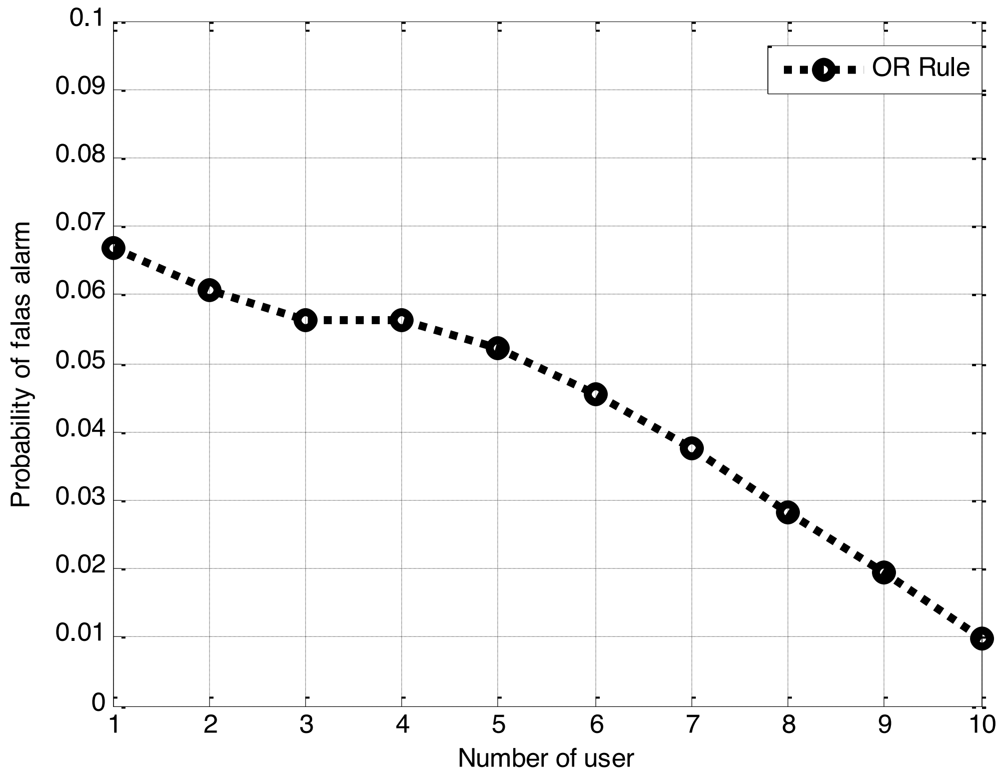

Figure 4.5 Probability of false alarm versus number of users(OR rule).

Figure 4.6 depicts that, with the increase in the number of users, network throughput increases. For instance, when the number of users is 3, the normalized throughput ratio is 90%, while as the number of users increases to 7, the throughput ratio reaches 92%. The increasing trend of throughput with the number of users is because when there are more active users in the network then there would be more resultant channel capacity, therefore, throughput increases with the increase of users.

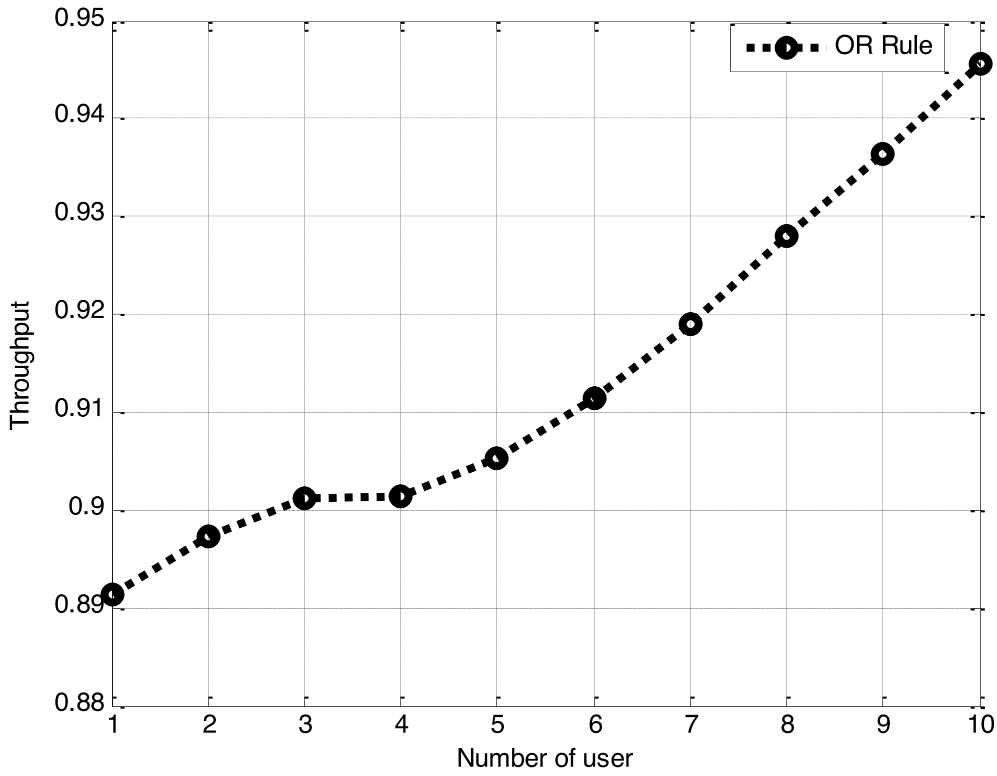

Figure 4.6 Throughput versus number of users (OR rule).

4.3.2 Simulation Results of the MAJORITYRule

In Figure 4.7, it can be noticed that when the number of users increases to 3, the probability of detection is 63%. Similarly, when the number of users increases to 7, the probability of detection is 86%. This result is generated using Equation (3.7) and Equation (4.8).

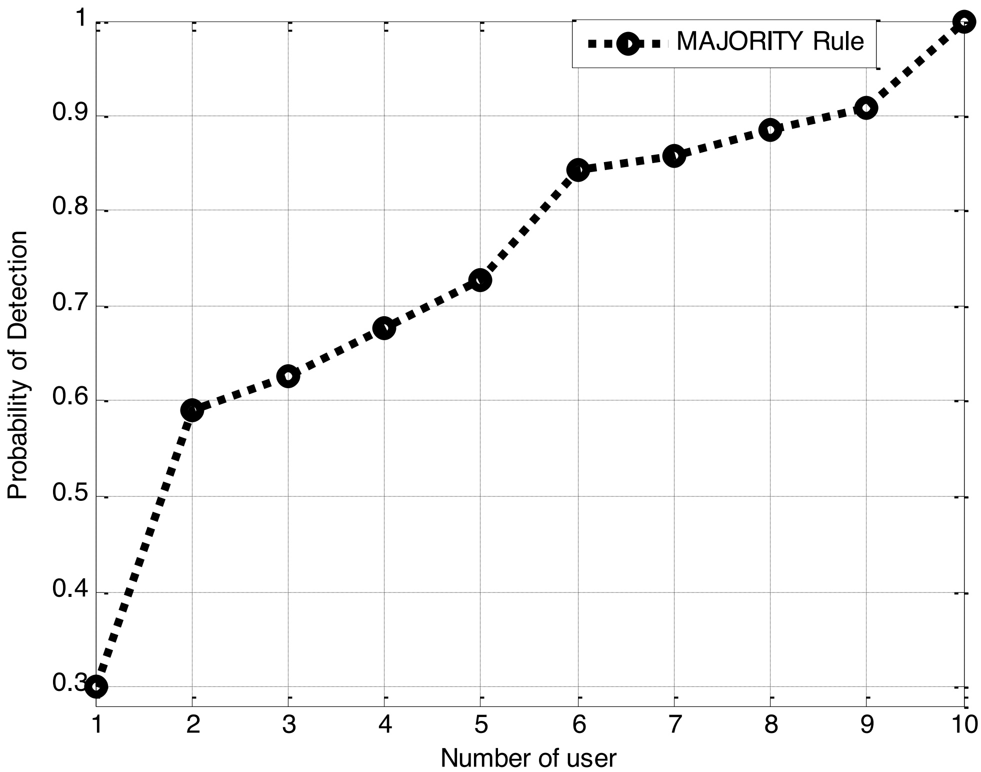

Figure 4.7 Probability of detection versus number of users(MAJORITY rule)**.**

Figure 4.8 unveils that with the increase of user density, the probability of false alarm decreases. For example, when the number of users increases to 3, the probability of false alarm reaches 11%. Similarly, when the number of users increases to 7, the probability of false alarm falls to 3.2%.

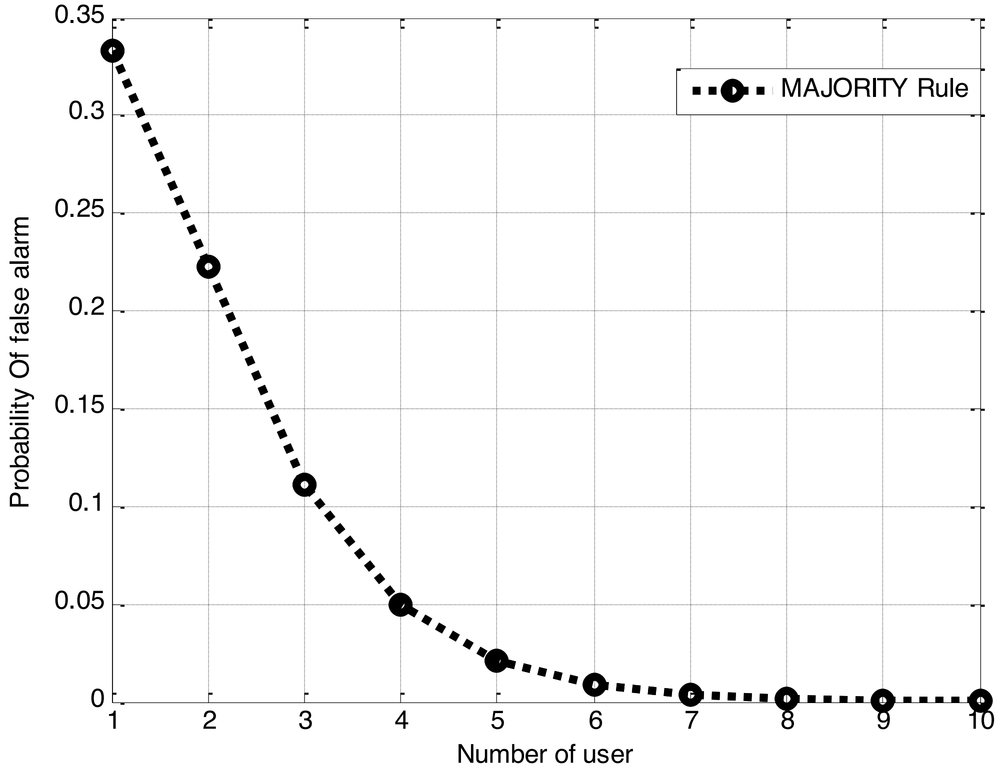

Figure 4.8 Probability of false alarm vs number of users(MAJORITY rule)**.**

Finally, in Figure 4.9, the throughput ratio reaches 85% when the number of users is 3. More than 6 user, the throughput reaches to saturated value of about 96%.Increasing the number of cooperative users upon this value, the increasing of network throughput is modest.

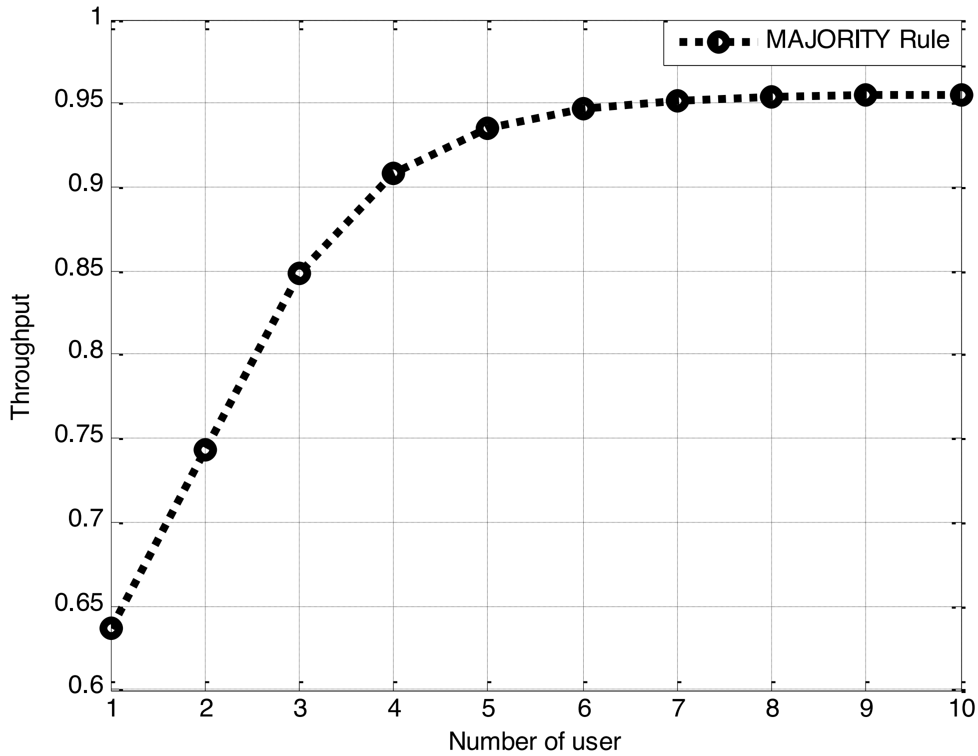

Figure 4.9 Throughput versus number of users(MAJORITY rule)**.**

4.3.3 Simulation Results of Middle Plus One Rule

In Figure 4.10, when the number of users is 3, the probability of detection ratio is 72%, while the probability of detection increases to 98% when the number of users increases to 7. Thus, detection probability increases with the increase in user density.

Figure 4.11 shows that, when the number of users is 3, the probability of false alarm reaches 4%. Correspondingly, when the number of users increases to 7, the probability of false alarm reaches 0.04%.

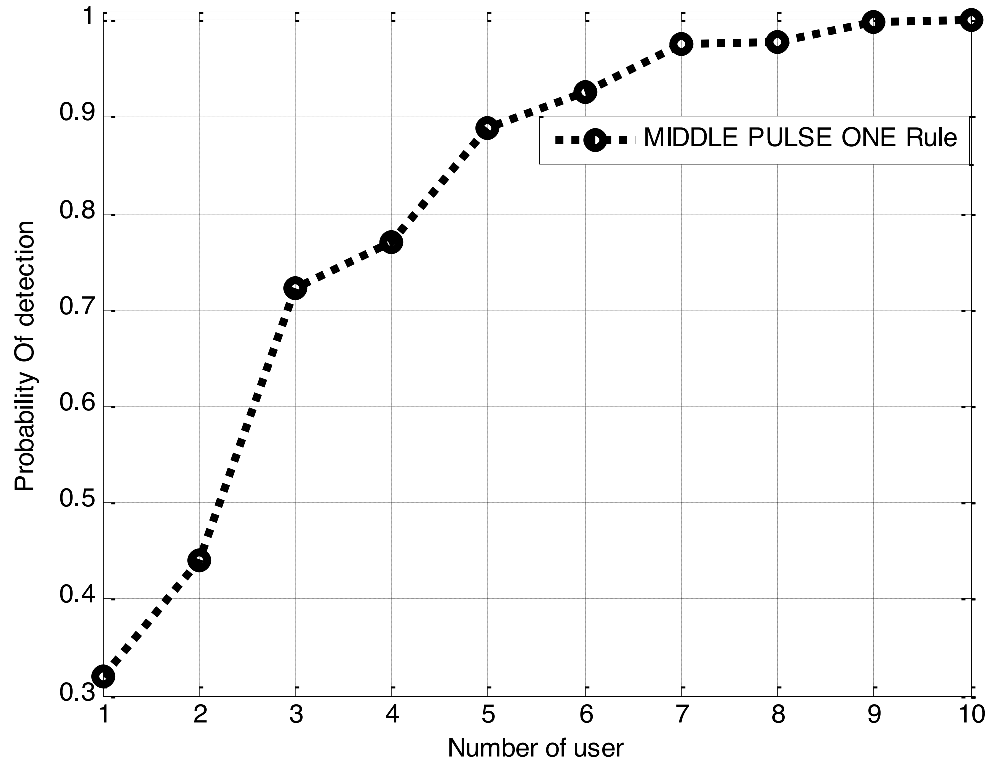

Figure 4.10 Probability of detection versus number of users (MPO rule).

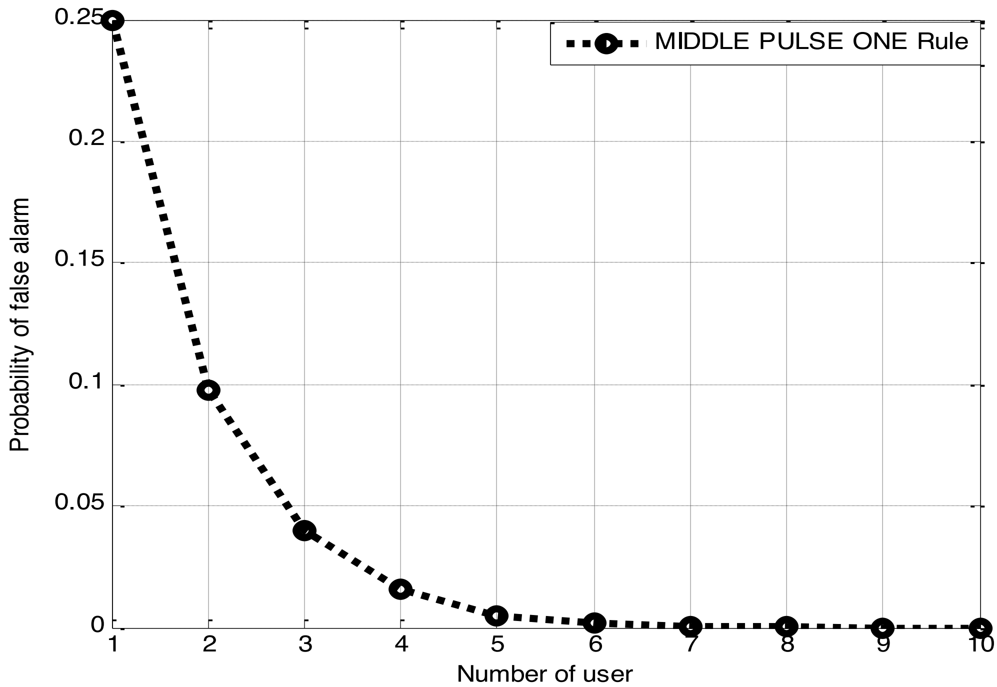

Figure 4.11 Probability of false alarm versus number of users (MPO rule).

The throughput for MAJORITY rule as a function of cooperative users is illustrated in Figure 4.12.The throughput increases with number of users increases. More than five users do not contribute any further throughputs.

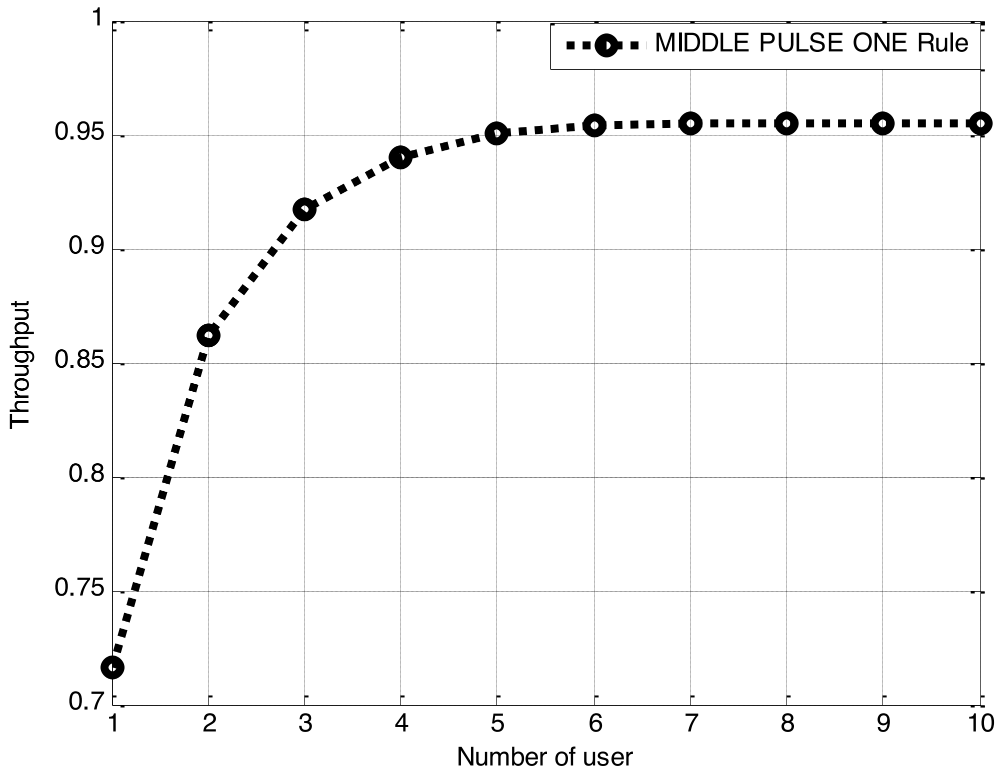

Figure 4.12 Throughput versus number of users (MPO rule).

4.3.4 Simulation Results of AVERAGE Rule

In Figure 4.13, when the number of users in the network increases, then the probability of detection increases as well. For example, when there are 3 users in the network, the probability of detection is 56%, and when the number of users is 7, theProbability of detection increases to 80%.

Figure 4.14 shows that, when the number of users is 3, the probability of false alarm decreases to 0.03. Similarly, when the number of users increases to 7, the probability of false alarm falls to 0. In conclusion, a higher number of user's density results in zero percent of false alarm probability which is the good side of an average rule.

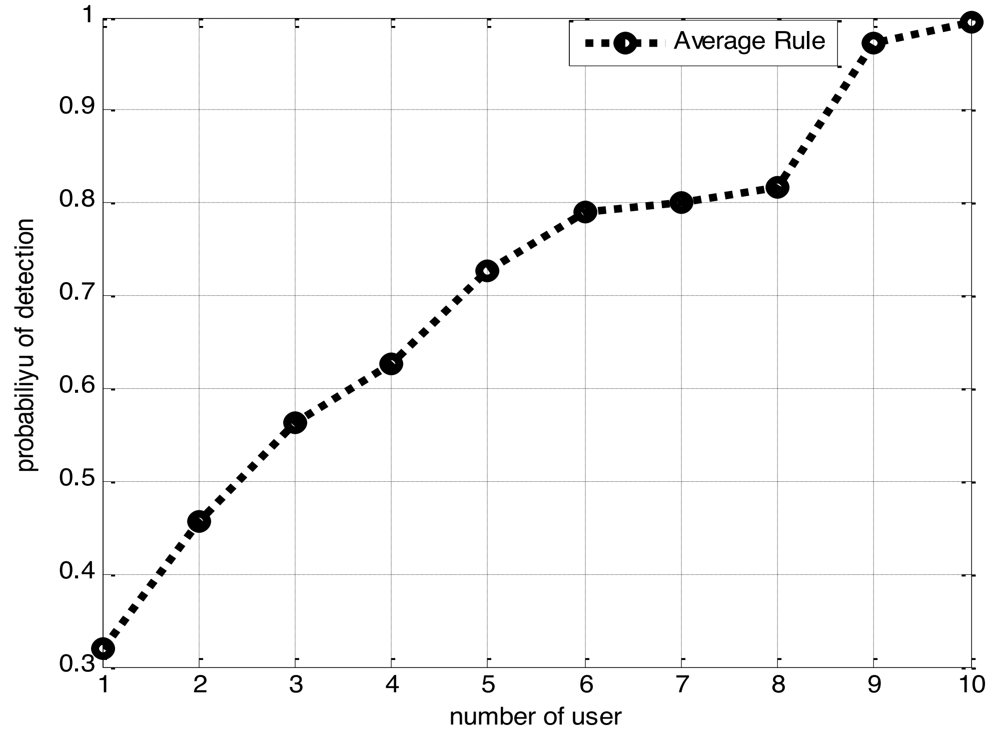

Figure 4.13 Probability of detection versus number of users (AVERAGE rule).

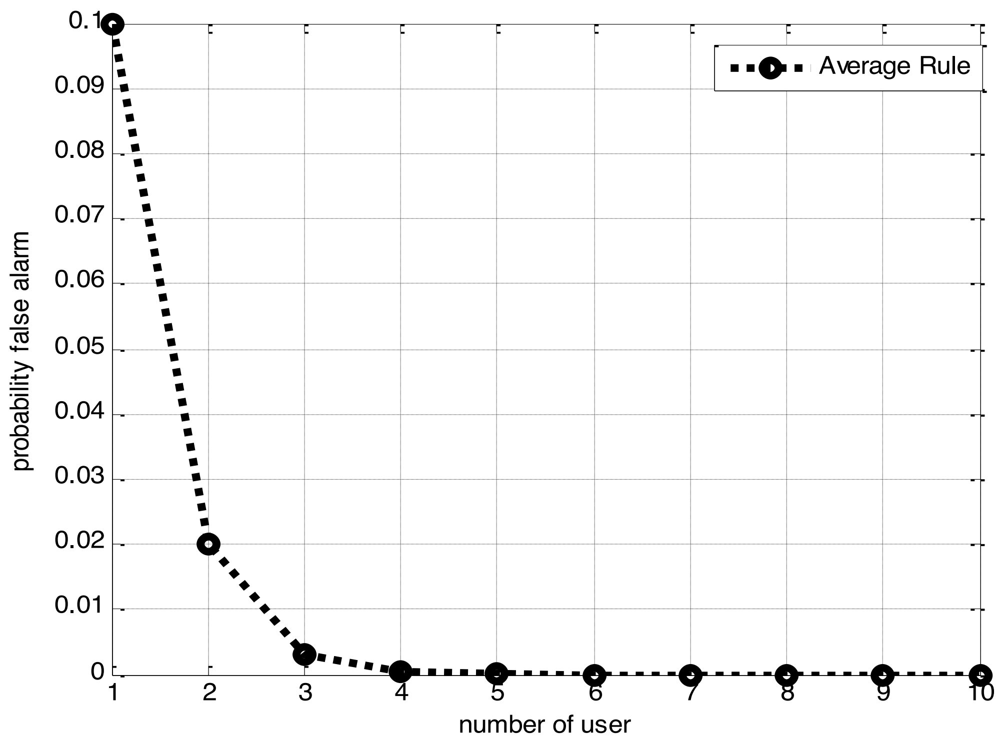

Figure 4.14 Probability of false alarm vs number of users (AVERAGE rule).

Figure 4.15 uncovers that, when the number of users in the network is 3, the throughput ratio is 95%, similarly, the throughput ratio increases to 96% when the number of users is 7. In summary, increasing the number of users' density significantly improves the throughput of the overall network. Higher the value of throughput, the higher will be the data rate. Hence, a user will experience good coverage with the best data rate.

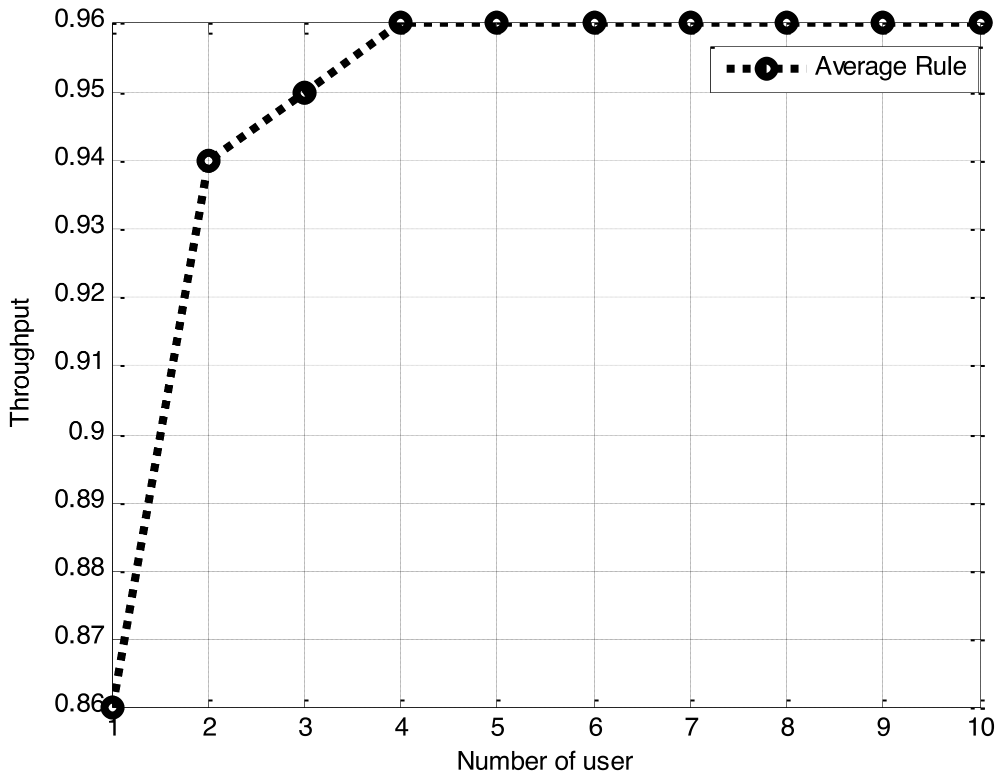

Figure 4.15 Throughput versus number of users (AVERAGE rule).

4.3.5 Comparison Between Decision Rules

In this subsection, the performance of different rules is repotted on the same graphs, this is to make comparison simpler and to illustrate the performance of the different rules. Figure 4.16 reveals that the probability of detection increases with the increase of the number of users, for all schemes. This is because that when there are number of devices (or number of users) are involved in the cooperative communication model, there is a high probability of correct decision making expected. When there is a high density of cooperative mobile users, then there would be high probability to make a correct decision. For example, in a cognitive radio network, when there are number of users are present then fusion center (FC) would be receiving a large amount of channel information from different nodes, which improves the reliability of the network. However, the performance of different schemes for making the correct detection is different from each other. It can also be observed from Figure 4.16 that the probability of detection of 'OR Rule' better than the rest of the schemes. For instance, in the case of 7 users, the probability of detection of 'OR Rule' and the probability of detection of 'MPO Rule' is 98%, the probability of detection of 'MAJORITY Rule' is 86% however, AVERAGE Rule is only 80%. It is important to note that the performance of all the schemes matches when there are high number of mobile users performing spectrum sensing. In summary, for a lower number of users, 'OR Rule' outperforms than rest of the schemes.

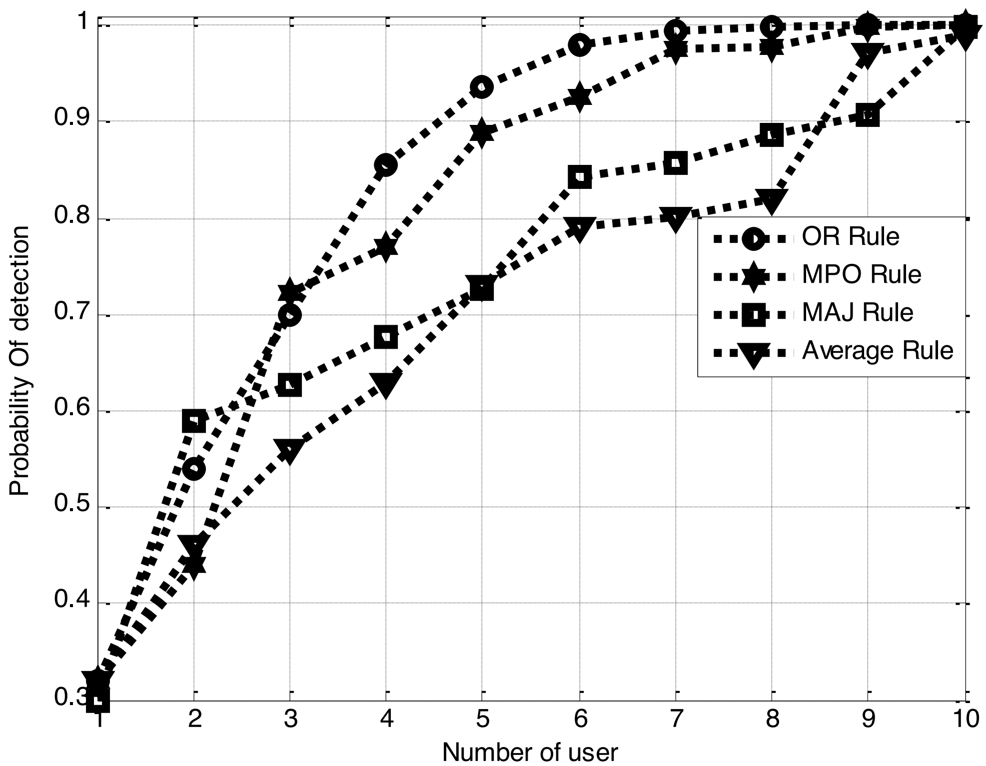

Figure 4.16 Probability of detection versus number of users (for all rules).

Figure 4.17 collects the probability of false alarm as a function of number of cooperative users for the four rules. The probability of false alarm has a higher value for a lower number of users. This is because, when lower number of users are present in the network, there is a high probability that the fusion center will make wrong decisions of existing a channel (false alarm). In the case of fewer users, the fusion center does not have enough statistics information to make the correct decision about the presence of the primary user signal.

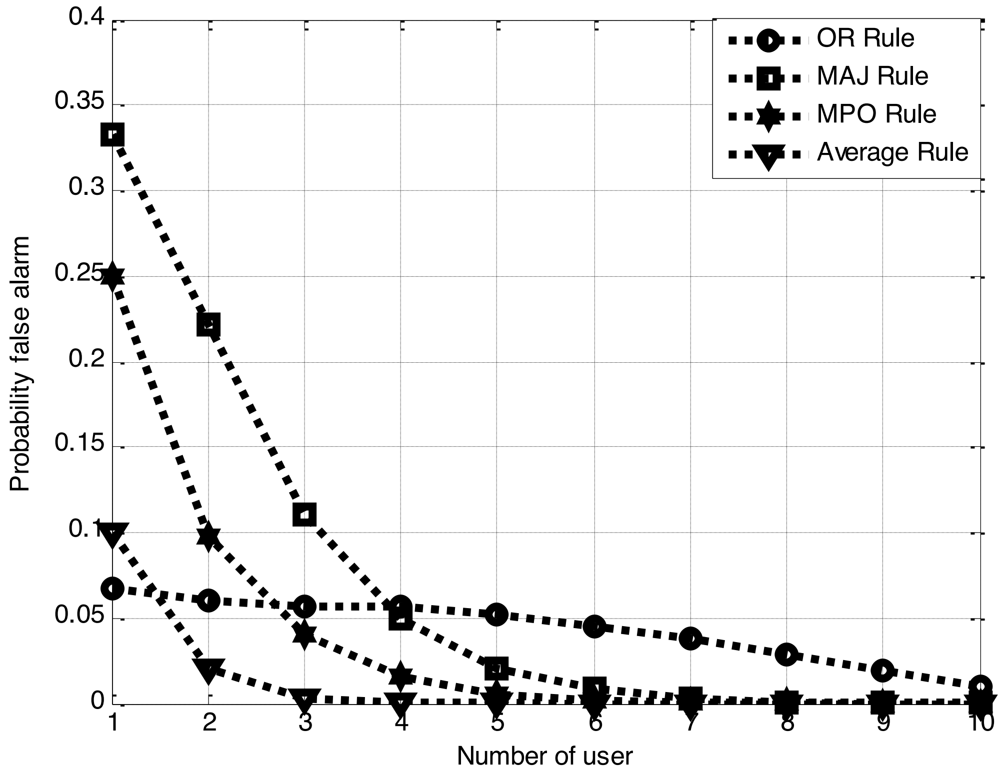

Figure 4.17 Probability of false alarm versus number of users (for all rules).

Figure 4.18 compares the performance of all the studied schemes in terms of achieved throughput versus the number of users present in the network. It is obvious that for a higher number of users in the network, there would be higher throughput It can be depicted from Figure 4.18 that for a higher number of users, throughput is high as well. However, 'AVERAGE Rule' gives better throughput compared to the other traditional schemes. In conclusion, 'AVERAGE Rule' is the best option when throughput maximization is the key requirement of the network.

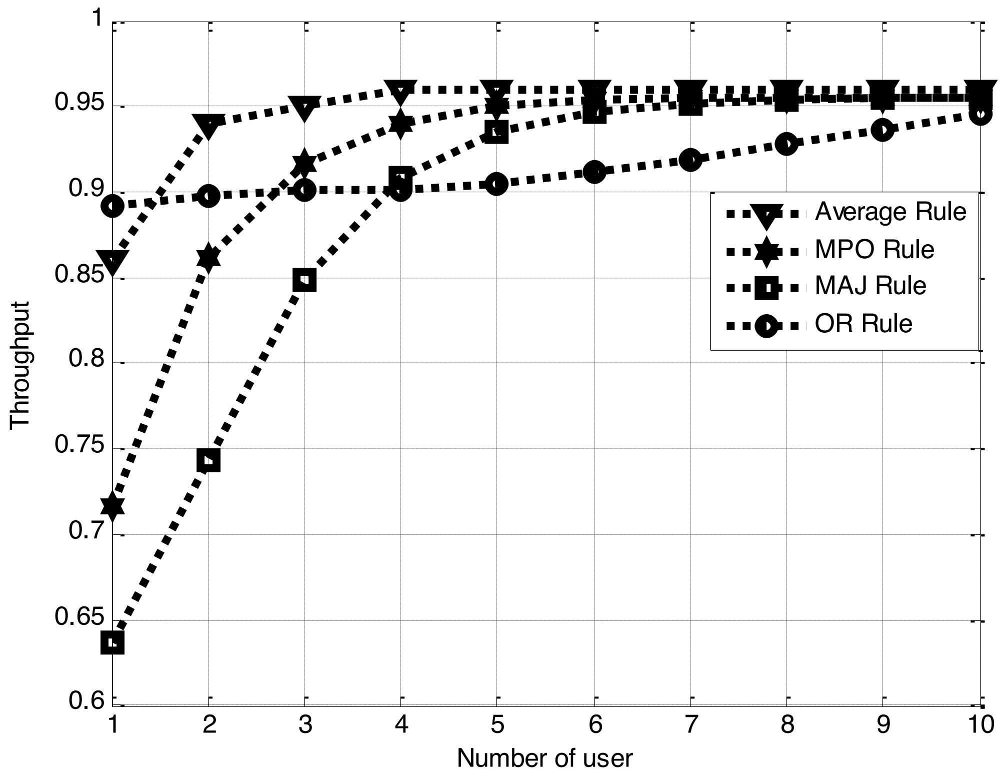

Figure 4.18 Throughput versus number of users (for all rules).

4.4 Soft Decision Rules

Two soft decision rules are simulated, these are: Square Law Combination(SLC) and Maximum Ratio Combination (MRC). The flow charts for the designed soft decision rules are shown in Figures (4.19) and (4.20), respectively. The procedure of soft decision rules is the same as the hard decision rules(where it is also based on statistical calculation of P_{FA} and P_D and then calculating the throughput) but with following differences:

1. In SLC, instead of comparing the energy of each cognitive user E_i with local threshold λ_i, the energies are added to each other producing a total energy $E_T$which is then compared to global threshold λ_{SLC} at fusion center.
2. In MRC, instead of comparing the energy of each cognitive user E_i with local threshold λ_i, the energies are added to each other after multiplying each energy with a corresponding weight w_i, then the total energy E_T is compared to global threshold λ_{MRC} at fusion center.

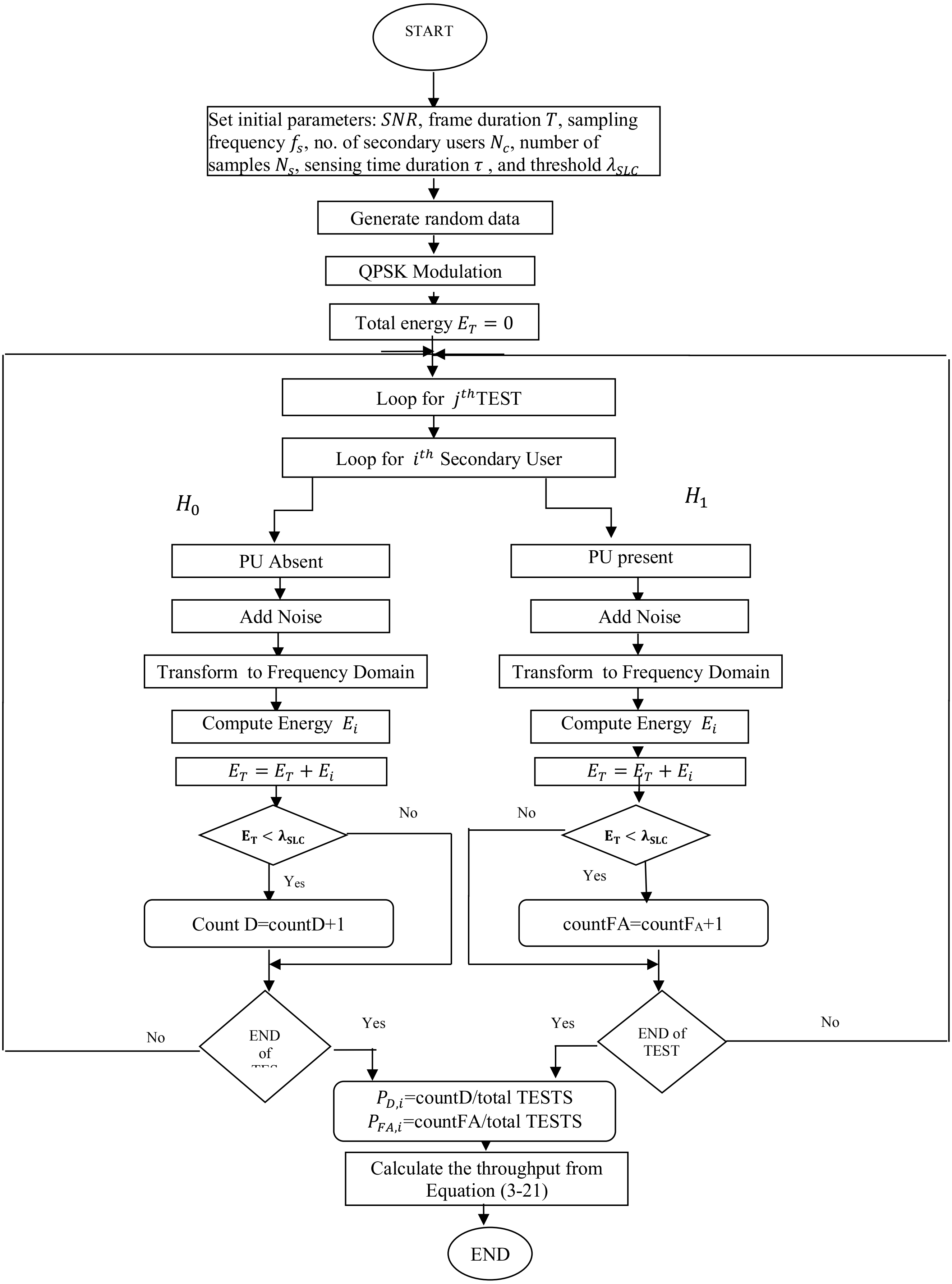

Figure4.19 Flowchart of Square Law Combining (SLC) rule.

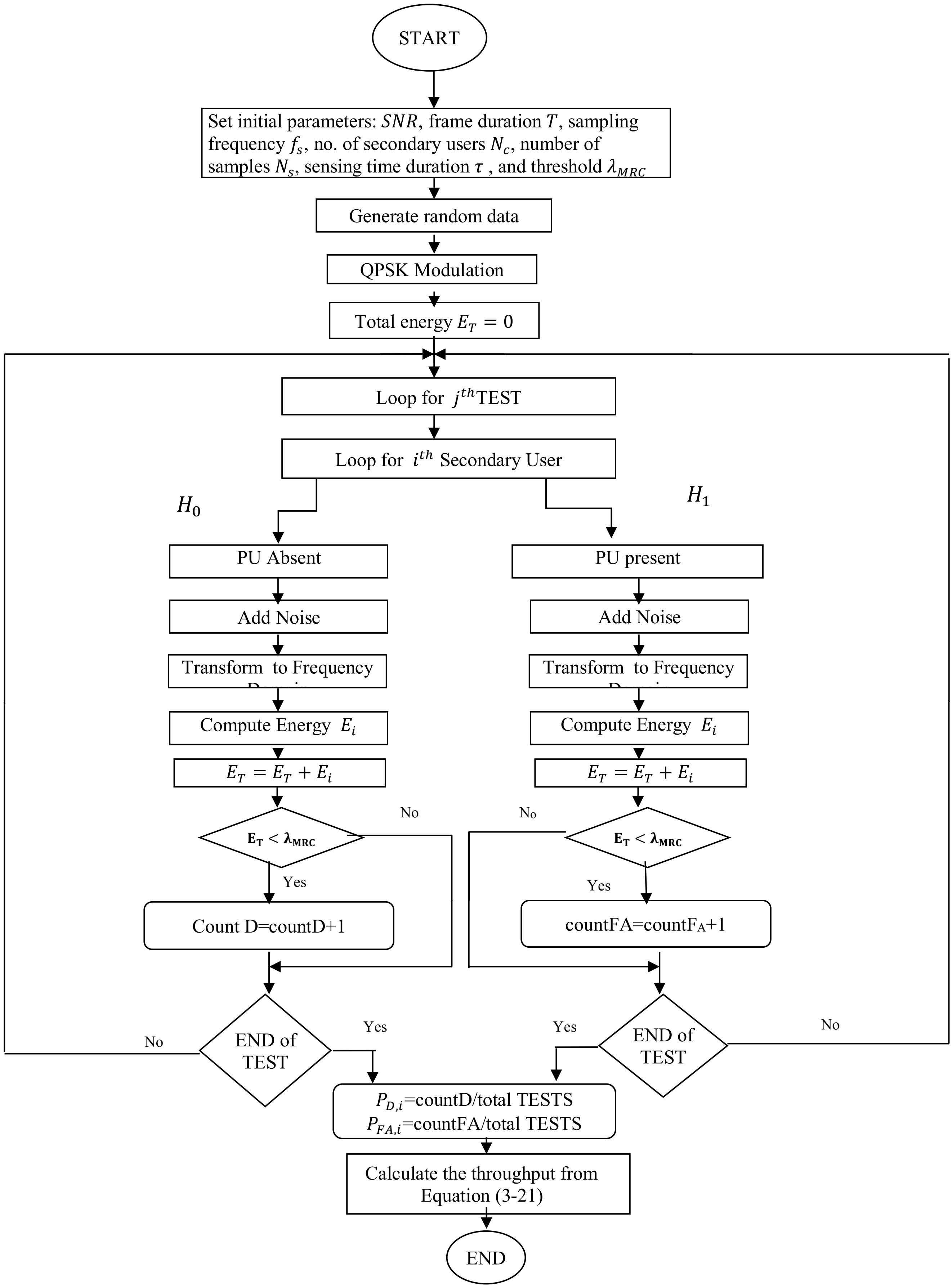

Figure4.20 Flowchart of Maximum Ratio Combining (MRC) rule.

4.4.1 Simulation Resultsfor SLC and MRC Rules

Figure 4.21 depicts the performance of probability of detection with increasing the number of users in both the algorithms; SLC and MRC. However, MRC performs better as compared to SLC. For example, having 3 users in the network results in 0.97 in the case of SLC, whereas MRC reaches to 0.99. It can also be observed that, when number of users reaches 5 the performance of both the algorithms behave the same. The cost paid to get this improvement is the complexity of MRC rule.

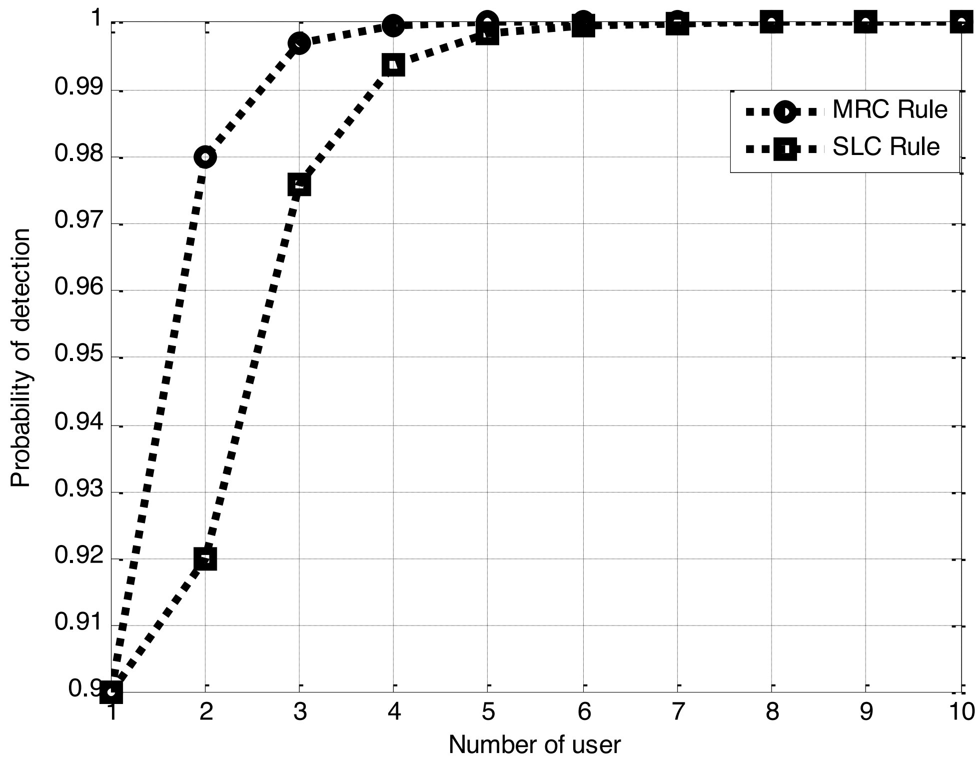

Figure 4.21 Probability of detection for soft decision rules vs number of users.

Similarly, Figure 4.22results in lowering the probability of false alarm when the number of users increases. However, false alarm probability is less in case of MRC. For instance, 2 users results 8% false alarm probability in case of SLC, whereas MRC has just 2% false alarm probability. Again, the simplicity of SLC implementation yields to this performance degradation.

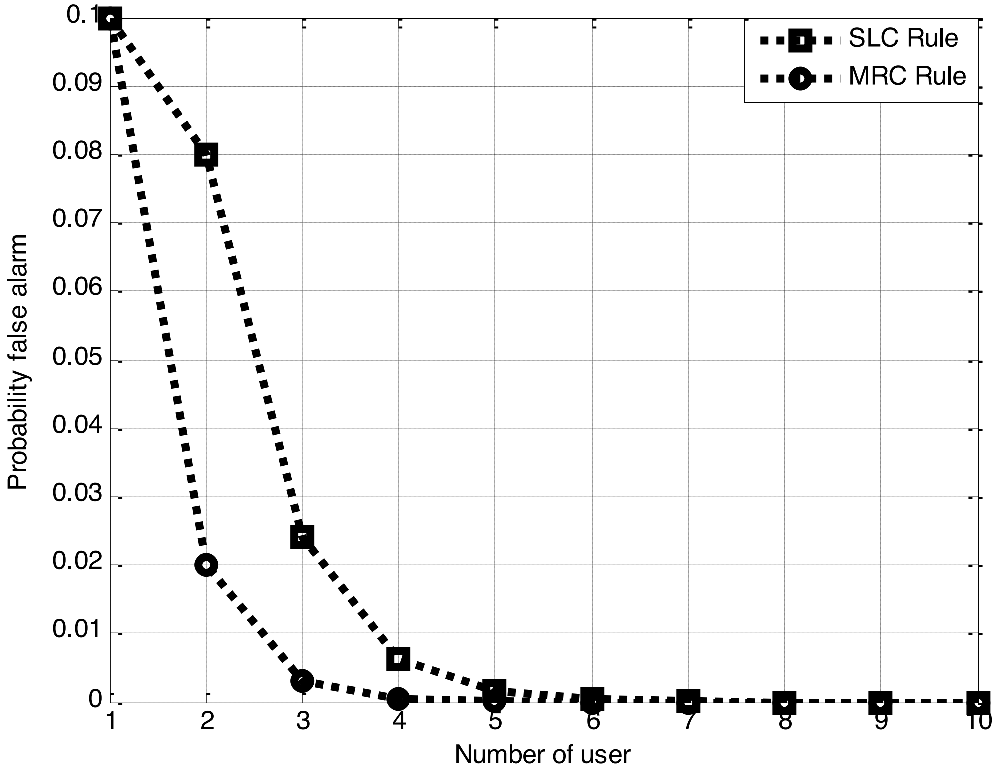

Figure 4.22 Probability of false alarm for soft decision vs number of users.

Finally, Figure 4.23 shows the comparison of SLC and MRC in terms of throughput. when number of users are increased from 1 to 10. It can be observed that MRC outperforms as compared to SLC. For instance, when there are 4 users, then MRC provides a throughput of 0.95, whereas SLC gives a throughput of 0.91. On the other side, it can also be noticed that increasing the number of users more than 5 does not improve the performance in both algorithms. Both algorithms provide a constant throughput of 0.95 (MRC) and 0.92 (SLC).

In a nutshell, it can be concluded that MRC detection criteria is better than SLC.

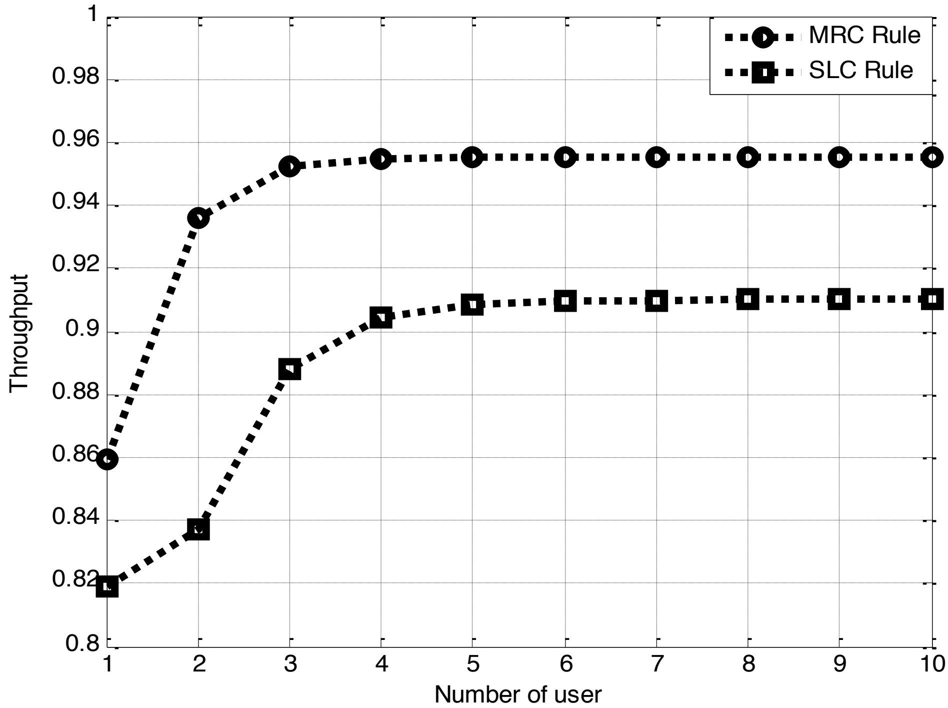

Figure 4.23 Throughput for soft decision rules versus number of users**.**

CHAPTER FIVE

Conclusions and Future Work

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Conclusions and Future Work

5.1 Conclusions

Static spectrum assignment policy causes low spectrum utilization while the demand for spectrum continues to increase. To solve this issue, Cognitive Radio has been introduced. It is a paradigm which can potentially improve the utilization of spectrum scarcity by admitting unlicensed users access to the licensed bands for data transmission when the primary users of these bands are inactive. In order to implement such dynamic spectrum access (DSA), techniques including spectrum sensing, spectrum analysis and spectrum decision must be implemented. This thesis focuses on investigating spectrum sensing techniques by applying energy detection which has proved to be less complex, most feasible and has to be considered as sub-optimal detector.

According to the results of spectrum sensing and spectrum analysis, the spectrumdecision is made to select appropriate channels for data transmission.

The conventional spectrum sensing is implemented by authorizing a single secondary user to perform sensing process. This approach of spectrum sensing cannot cope with the natural properties of wireless propagation channels. Fading phenomena, hidden terminal problem and shadowing are examples of troubles of wireless transmission which mostly yield to uncertain sensing results.

On the other hand, cooperation among CR users can reduce the uncertainty caused by the single user's detection. Employing multiple sensing nodescooperatively can enhance the performance of detection and overcome the negative attributes of the wireless channel. However, this requires additional operations and overhead traffic to communicate among CR users. As a result, there can be an effect on the performance of resource-constrained networks.

This thesis focuses on the collaboration approach, each user may independently perform local spectrum sensing and then report a decision to FC. The FC then makes a decision on the presence or absence of the PU signal in order to reduce the probability of detection errors. The commonly hard decision fusion rules are AND, OR, and Majority rules. This study deals with the performance of energy detection based on cooperative spectrum sensing techniques. Different detection rules based on cooperative spectrum sensing are introduced, analyzed and compared. A new rule is also proposed in this study which based on taking the statistical average of all sensing information measured by the individual cooperative users. Monte Carlo algorithm is used to simulate the statistical average for the similar channel environment. This value is used as a threshold value to compare with the measured results.

The comparison between all these rules is done by evaluating the performance of each rule and its response to the detection probability and false alarm measured by the energy detector. For the sake of brevity, AND and $\boldsymbol{k}$-out-of-$\boldsymbol{n}$ rules are omitted in this study because they give the worst performance compared to the introduced decision rules. Soft decision rules are also studied in this thesis Square Law Combination and Maximum Ratio Combination are chosen for comparison sake.Channel throughput is adopted as a key performance for each rule.

The performance of all the studied schemes in terms of achieved throughput versus the number of users present in the network are presented. It is observed that morenumber of users in the network, higher throughput is achieved. However, the 'AVERAGE Rule' gives better throughput compared to the other traditional schemes. In conclusion, 'AVERAGE Rule' offers the best option when throughput maximization is the key requirement of the network.

For soft combining techniques, MRC provides the better performance than SLC. One of its major drawbacks is its significant hardware requirements. The soft combining schemes exhibit much better performance than the conventional hard combination schemes.

5.2 Future Works

In this section, asset of suggested future works is shortly listed in the following possible areas:

1. The system was evaluated over Rayleigh multipath fading channel. The evaluation can be extended to include frequency selective fading channels of Rayleigh.
2. The energy detection spectrum sensing method is used in this study. Other sensing schemes such as matched filter, cyclostationary, can be used in future works.
3. This work assumes that the transmission channel (reporting channel) is free of errors (these problems were assumed in sensing channel only). The effect of transmission channel problems on throughput improvement can be investigated.
4. Sensing time is very important parameter. The sensing time period has to be optimized to minimize energy consumption in cooperative users and maximize the network throughput. Future study might deal with this optimization problem.
5. Other interesting topics in cognitive radio technology such spectrum management, spectrum sharing and spectrum mobility are good scholar fields for analysis and evaluation.

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