CHAPTER 2
REVIEW OF LITERATURE

2.1 History of Cognitive Radio

The need for a flexible and robust wireless communication is becoming more evident in recent era. The future of wireless networks is thought of as a union of mobile communication systems and internet technologies to offer a wide variety of services to the users. Conventionally, the policy of spectrum licensing and its utilization lead to static and inefficient usage. The requirement of different technologies and market demand leads to spectrum scarcity and unbalanced utilization of frequencies. It has become essential to introduce new licensing policies and co-ordination infrastructure to enable dynamic and open way of utilizing the available spectrum efficiently.

One promising solution to such problems is the Cognitive Radio. It has an intelligent layer that performs the learning of environment parameters in order to achieve optimal performance under dynamic and unknown situations. It enables a smooth and interactive way of using the spectrum and communication resources between technologies, market and regulations.

The following steps highlights genesis of the cognitive radio to its evolution till the date [15]:

- In 1999, Joseph Mitola coined the term ‘Cognitive Radio’ for the first time in his doctoral thesis [1].
- In 2002, the Defense Advanced Research Projects Agency (DARPA) funded the NeXt Generation (DARPA-XG) program. The purpose was to define a policy based spectrum management framework so the radios can make use of the spectrum holes existing in time and space.
- This depicts the attention of the Federal Communications Commission which then confirmed the underutilization of the bands based on the research conducted by it. Later the commission issued a notice for proposed rule making [2] whose main aim was to explore the cognitive radio technology to utilize spectrum efficiently.
• In 2004, the Institute of Electrical and Electronic Engineers (IEEE) formed the IEEE 802.22 working group for defining the Wireless Regional Area Network (WRAN) Physical and Medium Access Control (MAC) layer specifications.

• By end 2005, IEEE launched the Project 1900 standard task group for next generation radio and spectrum management. It was related to giving standard terms and formal definitions for spectrum management, interference and co-existence analysis and policy architecture, dynamic spectrum access radio systems.

• In 2006, IEEE organized the first conference on cognitive radio (CROWNCOM) so as to bring together new ideas regarding the cognitive radio from a diverse set of researchers around the world.

• It was followed by FCC, TV band unlicensed service project launch with cognitive radio technology.

• By 2008 end, the FCC established rules to allow cognitive devices to operate in TV White Spaces on a secondary basis.

• In 2010, FCC released a Memorandum Opinion and Order that determined the final rules for the use of white space by unlicensed wireless users [17].

• In July, 2011, the IEEE published IEEE 802.22 (WRAN) as an official standard [18].

• Currently, IEEE is working on the standard for recommended practice for installation and deployment of 802.22 systems.

2.2 SPECTRUM Sensing for Cognitive Radio

Spectrum sensing is the most important task among others for the effective process of cognitive radio networks. Spectrum sensing enables the capability of a cognitive radio to measure, learn, and be aware of the radios in operating environment, such as the spectrum availability and interference status. Availability of radio spectrum varies depending on time, frequency and location resulting in spectrum access opportunities. Secondary users can use the available idle spectrum in an opportunistic manner. Spectrum sensing helps secondary users to achieve this objective by identifying the
available spectrum reliably and rapidly. Spectrum sensing also helps secondary users to detect the presence of primary signals to protect the primary users' transmission. It also helps in quickly determining if the primary users have become active in the bands used by secondary users so that those bands can be vacated immediately. This is important for ensuring that the interference caused to the primary users’ transmissions remains below a permitted level. Moreover, detection of other secondary users may be necessary as well for co-existence with other secondary networks [16].

Recent surveys on spectrum sensing and related issues can be found widely in the literatures [19 - 21]. The spectrum sensing problem is traditionally formulated as a binary hypothesis testing problem and is described in section 2.3. To identify the idle spectrum and protect the primary users' transmissions, different local spectrum sensing techniques have been proposed for individual secondary users based on hypothesis testing. Some of the most common spectrum sensing techniques for the detection of primary users' transmission for cognitive radio networks is discussed in section 2.4.

2.3 Hypothesis Testing

A key task in spectrum sensing is to decide whether the spectrum is idle or busy. The spectrum sensing problem is traditionally formulated as a binary hypothesis test [22]. The null hypothesis denoted by $H_0$ corresponds to the absence of the primary user's transmission, i.e., the received signal being only noise. On the other hand, the alternative hypothesis denoted by $H_1$ indicates that the primary user's transmission is present, i.e., the received signal contains the primary signal along with noise. In case the hypotheses have no unknown parameters, the hypotheses are called simple. If there are unknown or unspecified parameters, then the hypotheses is called composite. As an example, a binary hypothesis test for detecting the primary user's transmission in an additive white Gaussian noise (AWGN) channel is given by

$$x_i(n) = \begin{cases} w(n) & H_0 \\ h(n)s(n) + w(n) & H_1 \end{cases}$$  \hspace{1cm} (2.1)

where $x(n)$ is the received signal at the $n^{th}$ time instant, $h(n)$ is the channel gain at the $n^{th}$ time instant. The primary user's transmitted signal is denoted by $s(n)$ and $w(n)$ is
the AWGN noise. In most practical cases, a test statistic \( Y \) is computed from the observation vector \( x = [x(1); x(2); \ldots; x(N)] \) containing \( N \) observation samples, and detection is based on comparing the test statistic \( Y \) to the threshold \( \gamma \). If the test statistic is greater than the threshold, i.e., \( Y > \gamma \) then \( H_1 \) is declared true. Otherwise, \( H_0 \) is declared true.

Two main performance metrics that are crucial in the design of spectrum sensing techniques are the probability of miss-detection, \( P_m \), and the probability of false alarm, \( P_f \). The probability of miss-detection is defined as the probability that the detector declares the absence of primary user transmission (decide \( H_0 \)), when PU transmission is actually present (\( H_1 \) is true). The probability of false alarm is defined as the probability that the detector declares the presence of PU transmission (decide \( H_1 \)), when PU transmission is actually absent (\( H_0 \) is true).

The trade-off between the probability of false alarm and miss-detection is depicted in Fig 2.1. In the figure, the likelihood distributions for the absence and presence of the primary user's signal are both assumed to be normally distributed with respective means \( \mu_1 \) and \( \mu_2 \) and the variances of the distributions are taken to be equal.

![Fig 2.1: Trade-off between probability of false alarm and probability of miss-detection](image)

It is clear from the above discussion that the probability of detection, \( P_d = 1 - P_m \), need to be high as it indicates the level of protection of the primary users' transmissions.
from the interfering secondary users' transmissions. On the other hand, low probabilities of false alarm are necessary in order to maintain high opportunistic secondary throughput, since a false alarm would prevent the unused bands from being accessed by secondary users leading to inefficient spectrum usage.

There are two basic hypothesis testing methods in spectrum sensing: the Neyman-Pearson (NP) test [23, 24] and the Bayes test [25, 26]. In an NP test, the objective is to maximize the detection probability, $P_d$, given the constraint on the probability of false alarm $P_f$. Based on the signal detection problem in (2.1), it can be shown that the NP test is equivalent to the likelihood ratio test (LRT) [19]. The LRT test statistics is given by

$$Y_{lrt} = \prod_{n=1}^{N} \frac{P(x(n)|H_1)}{P(x(n)|H_0)} = \gamma_{lrt}$$  \hspace{1cm} (2.2)

In a Bayes test, the objective is to minimize the expected cost called the Bayes Risk (BR) given by

$$BR = \sum_{i=0}^{1} \sum_{j=0}^{1} C_{ij} P(H_i|H_j) P(H_j)$$  \hspace{1cm} (2.3)

where $C_{ij}$ and $P(H_i|H_j)$ are, respectively, the cost and the probability of declaring $H_i$ when $H_j$ is true, and $P(H_j)$ is the prior probability of hypothesis $H_j$, $i, j \in \{0, 1\}$. In other words, the Bayes risk to be minimized is the sum of all possible costs weighted by the probabilities of two incorrect detection cases (false alarm $P(H_1|H_0)$ and misdetection $P(H_0|H_1)$) and two correct detection cases. With the knowledge of the prior probabilities $P(H_1)$ and $P(H_0)$, the LRT of a Bayes test can be represented as

$$Y_{br} = \prod_{n=1}^{N} \frac{P(x(n)|H_1)}{P(x(n)|H_0)} = \gamma_{br}$$  \hspace{1cm} (2.4)

For the particular case of the binary loss function, $C_{ii} = 0$ and $C_{ij} = 1$ for $i \neq j$, the Bayes risk, BR, is equal to the probability of error (PE). Therefore,

$$P_E = P(H_1|H_0) P(H_0) + P(H_0|H_1) P(H_1)$$

$$= P_f P(H_0) + P(1 - P_d) P(H_1)$$  \hspace{1cm} (2.5)
As mentioned earlier, if the distributions of the received signal under the two hypotheses depend on unknown parameters, then the detection problem becomes a composite hypothesis testing problem. One of the approaches to composite hypothesis testing that do not require prior knowledge of the unknown parameters is the generalized likelihood ratio test (GLRT) [20, 26]. In GLRT, the unknown parameters are determined by the maximum likelihood estimates. Although GLRT is not an optimal test, it is robust and easy to implement. The GLRT is given by

\[
Y_{glrt} = \prod_{n=1}^{N} \frac{\max_{\theta_1} P(x(n)|\theta_1, H_1)}{\max_{\theta_0} P(x(n)|\theta_0, H_0)} = \gamma_{glrt}^{H_1}
\]

where \(\theta_1\) and \(\theta_0\) are the unknown random parameters.

### 2.4 Sensing Techniques

In this section, we will discuss some of the most common spectrum sensing techniques for the detection of the primary transmitter in the cognitive radio literature. From the perspective of signal detection, sensing techniques can be classified into two broad categories: coherent and non-coherent detection. In coherent detection, the primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with prior knowledge of primary signals. In non-coherent detection, no prior knowledge of the primary signal is required for detection. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest, that is, narrowband and wideband.

The classification of sensing techniques is shown in Fig 2.2. Next, we introduce primary transmitter detection, energy detection, matched filter detection, cyclostationary detection and briefly discuss some other spectrum sensing techniques. A more complete review on various spectrum sensing techniques and design challenges can be found in [27, 28].
Fig 2.2: Classification of spectrum sensing techniques.

2.4.1 Primary Transmitter Detection

An efficient approach to identify spectral opportunities with low infrastructure requirement is to detect the primary receiver within operative range of a secondary user. Practically however, this is not feasible as the SU cannot locate a receiver since it is not intelligent enough. Hence, spectrum sensing methods rely on detecting the primary transmitter. With this, a primary user transmitter is detected on the basis of the received signal at the secondary user end.

The primary transmitter detection model represents analysis of the received signal at the secondary user. In its simple form, the idea is to find primary transmitters operating at a given time by using local measurements and observations. With these techniques, the SU examines the signal strength generated from the PU to exploit the free space (whitespace) within the channel. Analytically, when the decision on the availability of a primary user is to be made, it is reduced to an identification problem [29]. This is formalized as hypothesis test as:

![Hypothesis Test Diagram]

Fig 2.3: Hypothesis test with possible outcomes and their corresponding probabilities.
where $x(n)$ is the received signal at the $n^{th}$ time instant, $h(n)$ is the channel gain at the $n^{th}$ time instant. The primary user's transmitted signal is denoted by $s(n)$ and $w(n)$ is noise (of variance $\sigma^2$) in the channel. $H_0$ is the null hypothesis; representing a sensed state with an absence of the licensed user signal. $H_1$ denotes the existence of a licensed user signal within the spectrum under consideration. From Figure 2.3, four possible cases can be defined for the detected signal:

- case 1. declaring $H_0$ when $H_0$ is true ($H_0 \mid H_0$);
- case 2. declaring $H_1$ when $H_1$ is true ($H_1 \mid H_1$);
- case 3. declaring $H_0$ when $H_1$ is true ($H_0 \mid H_1$);
- case 4. declaring $H_1$ when $H_0$ is true ($H_1 \mid H_0$).

Case 2 is known as a correct detection, whereas cases 3 and 4 are termed a missed detection and false alarm respectively. The goal of the signal detector is to achieve correct detection all the time. However, this cannot be accomplished absolutely in practice because of the statistical nature of the problem. Therefore, signal detectors are designed to function within minimum error levels.

A prominent issue for spectrum sensing is missed detection; as it implies interfering with the primary system. Also, the false alarm rate has to be kept as low as possible, to enable the system exploit possible transmission opportunities. The performance of the spectrum sensing technique is influenced by the probability of false alarm, $P_f = P(H_1 \mid H_0)$, an important metric for spectrum sensing.

Equation (2.7) shows that a reliable method to differentiate a signal from noise is required. Transmitter detection methods under study include the following: energy detection, matched filter and cyclostationary detection [30].

2.4.2 Energy Detection

An appropriate option to ascertain the availability of an active communication link when the transmitted signal structure is unknown consists of using an energy detector (ED) [34]. This method is based on the premise that the energy of a signal to be
detected is always higher than the energy of the noise. This classic method, referred to as radiometry is founded on two assumptions:

1.) The noise power is known a priori; and 2.) The test statistics can be accurately modeled as independent and identically distributed (iid) gaussian random variables [36].

In practice, the energy detection is suitable when the SU cannot gather sufficient information about the PU signal [35]. This method is more generic (as compared to other methods described later in this section), as receivers do not need prior knowledge of the primary user's signal; by which case it is non-coherent. The ED method is also by far the most versatile means of spectrum sensing because of its low computational and implementation complexities [32]. Originally, this approach was outlined in the classic work by Urkowitz [38], were it is assumed that the signals are deterministic in nature, existing over a flat band-limited Gaussian noise channel and exact noise variance is known a priori.

By applying the sampling theorem to estimate the received signal energy and from the Chi-square statistics of the resulting sum of the squared Gaussian random variables, signal detection is reduced to a simple identification problem; formalized as a hypothesis test. Based on this assumption, a proposed model for detection of energy in deterministic signals under AWGN in the time domain was presented [36]; consisting of passing the received signal \( y(t) \) through an ideal band pass filter (BPF) with a center frequency \( f_o \) and bandwidth \( W \), with transfer function:

\[
H(f) = \begin{cases} 
\frac{2}{N_o}, & |f - f_o| \leq W \\
0, & |f - f_o| > W 
\end{cases}
\]  

(2.8)

where \( N_o \) is the one-sided noise power spectral density which normalizes if found convenient to compute the false-alarm and detection probabilities using the related transfer function. From these, the signal is then squared and integrated over an interval \( T \), to produce a test statistic, \( V \), compared to a threshold, \( k \). The receiver makes a decision on the target signal, based on the condition that the threshold is exceeded.

The received signal \( s(k) \), of the SU is represented by the binary hypotheses, as represented in Equation (2.1). Where \( x(k) \) is the transmitted unknown deterministic
signal, and $n(k)$ is assumed to be AWGN with zero mean and the variance is known beforehand. $H_0$ and $H_1$ correspond to the absence and presence of the primary user respectively. Though the archetype energy detector proposed in [37] addresses detection of unknown deterministic signals buried in Gaussian noise, the analysis carried out therein however concerns the time domain, which makes it difficult to estimate the spectral component. Since then however, ED analysis has been considered with several modifications in literature.

In Shehata [39], the authors propose an adaptive scheme to explore ED based spectrum sensing. This method comprises a side detector applied to monitor the spectrum to improve the detection probability. The system model consists of a PU transmitting a Quaternary phase shift keying modulated signal within a 200 KHz bandwidth. The sampling frequency is set 8 times the bandwidth and a 1024-point Fast Fourier Transform (FFT) is used to compute the received signal energy. Results presented indicate improved execution of spectrum sensing during reemergence of the PU in the wake of the sensing time. Nonetheless, from the choice of bandwidth under consideration, this study is restricted to only frequency modulated (FM) signals. Numerical analysis of the ED method over fading channels is presented by Reisiet al. in [40]. In this work, deviating from exact solutions since there are computationally complex, the authors derive approximate closed form expressions for the probability of detection ($P_d$) for Nakagami fading channels and also obtain a rule of thumb expression relating the number of samples (sensing time) to the Signal-to-Noise ratio (SNR) for a given probability of detection and probability of false alarm regarding Nakagami fading models.

In [26, 29-33] however, detecting unknown deterministic signals is developed as a binary hypothesis test problem. With this, the detection statistics is based on the Neyman-Pearson criterion, wherein the performance of the system is expressed in terms of false alarm and detection probability. These articles for the most part, deal with the sophistication, while leaving out the reliability and accuracy of these techniques. The focus in [37] is shifted towards the sensing latency. The possibility of quickest detection, founded on a statistical test to detect the change of distribution in observations as responsively as possible is applied to reduce the transient time between the two states, while ensuring certain false alarm probability.
These methods apply well-known algorithms like the generalized likelihood ratio test, parallel cumulative sum test, windowed GRLT etc., In retrospect, the methods of energy detection described in the above studies have no resolution component. Likewise, the sensitivity is critically impeded by the practical restriction from the sampling rate of the analog-to-digital converter (ADC) [14]. With the aim of improving the overall sensing performance while scanning wide frequency bands, [43] proposes another form of this method using rows of filters (filter banks).

With this, a collection of $N$ sub-filters is used to divide whole frequency bands of interest into $N$ sub-bands. The $i^{th}$ sub-filter of the bank is used to extract spectral information from the $i^{th}$ sub band of interest with a normalized center frequency. It is noteworthy that filters of this nature are not very reliable in implementation since the frequency response of the filter influences the quality of estimated power in the sub-band [33]. In [35], an experimental study of ED based spectrum sensing is realized using software defined radio test bed. Since the choice of the theoretical threshold relies largely on acquisition of a perfect knowledge of noise power (which is challenging in a real environment), the authors apply a histogram based method to determine an appropriate threshold.

The offered method eliminates the need to model the test statistics in energy detection by collecting a sufficiently large number of samples to obtain two histograms of the test statistics under hypothesis $H_0$ and $H_1$. Based on these histograms, a threshold is chosen to meet design criteria of the false-alarm and miss-detection probabilities. The construction of the histogram method however, requires large number of samples to ascertain a wide range of noise power in the signal; making selection of this threshold requires a considerable amount of time. Added to this, the proposed model functions more like an off-line process; which should be done before energy detection.

Recent studies on detection of signals operating in a band of frequencies are executed by splitting spectrum into multiple channels using a theory of quickest detection. Quickest detection refers to real-time detection of changes as quickly; after they occur. In [41], the authors study a case where single narrowband energy detector node is to sense multiple channels. This detector operates with a predetermined belief factor - based on past primary user action to ascertain which channel to sense in the future. This approach proved to reduce sensing time; ensuring a certain false alarm
rate is met. In [42], the authors extend this to a case involving multiple narrowband detectors employed to sense wide band channels, with an assumption that the numbers of channels are more than the number of detectors. Similar analysis in [41] assumes a belief factor, adopted to show more spectrum holes can be harvested, as opposed to concentrating each detector on a particular narrowband at all times. An underlying premise from these studies so far is the dynamic range of detector spanning entire bandwidths, while sensing a narrowband per time. Moreover, these assumptions will involve fast changes in the frequency of the local oscillator which imposes its own limitation to the viability of this approach. More so, the analysis so far relies heavily on accurate knowledge of the distribution of primary user activities to reach an optimum detection. Several techniques have been propounded in literature for detecting the availability of a signal using a single node, it is apparent that not much work has been done in assessing the performance of the energy detection scheme as a standard of spectrum sensing employed for opportunistic access.

In the year 2007, Chunhua Sun [43] proposed a technique for cooperative spectrum sensing in cognitive radio under bandwidth constraints. His proposal is on energy detection of primary user presence using binary hypothesis by accumulating the energy of the sensed signal and comparing with a predefined threshold. If it is greater than the threshold then local decision is declared as presence otherwise absent. Such decisions along with detected energy are collected from a group of secondary users and the combined decision is taken centrally. This method requires higher overheads and long sensing time which results in low efficient system which in turn limits the utilization factor.

Later in 2009, Wei Zhang [44] proposed another technique in which multiple cognitive radios collaboratively detect the spectrum holes (white space) through energy detection and investigate the optimality of cooperative spectrum sensing with an aim to optimize the detection performance. He derived the optimal voting rule for energy detector which can apply to cooperative spectrum sensing. Further detection threshold is optimized for the same energy detection. This sensing algorithm requires few cognitive radios rather than total number of cognitive radios in cooperative spectrum sensing with in the error bound.
Sina Maleki and Sundeep Prabhakar [45] in the year 2011 came out with energy and throughput strategies for cooperative spectrum sensing in cognitive radios. An efficient cooperative spectrum sensing based cognitive radio network utilizes convinced number of secondary users to sense the spectrum while satisfying a constraint on the detection performance. He derived the optimal number of cognitive radios under two scenarios: energy efficient and a throughput optimization setup. In the energy efficient setup, the number of cooperating cognitive radios is minimized for a k-out of-N fusion rule with a constraint on the probability of detection and false alarm while in the throughput optimization setup, the throughput is maximized in the cognitive radio network by deriving the optimal reporting time in a sensing time frame which is proportional to the number of cognitive users, subject to a constraint on the probability of detection. Both problems are simplified to line search problem. The performance is evaluated for different fusion rules and the conclusion is made that OR and Majority rules are the best choice of detection performance.

2.4.3 Matched Filter Detection

Unlike energy detection, a Matched Filter (MF) is a linear filter designed to maximize the output signal-to-noise ratio for a given input signal [50]. With this scheme, secondary users require complete knowledge of the PU transmitted signal. These information includes modulation format, carrier frequency, order, pulse shape, and packet format, are to be known to the secondary user ahead of time [47]. These features are used to detect and implement a MF when primary users have pilots, preambles, synchronization words or spreading codes, leading to coherent detection. 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 [48]. In operation, a MF convolves the received signal \( r(t) \) with a time-reversed version of the known signal as:

\[
M(t) = r(t) \otimes s(T - t + \tau)
\]

where, \( T \) refers to a symbol time duration and \( \tau \) is a shift in the known signal. The output of a MF, \( M \) is compared with a threshold factor \( k \), to decide the presence or absence of a PU. [46]. Typically, an MF is implemented digitally, and its realization is illustrated in Fig 2.4.
An advantage of the MF is that it requires less time to achieve detection; however, false detection occurs when incorrect information concerning the transmitted signal is available at the SU end. A significant drawback of this technique is that an SU would require dedicated receivers for every primary user class.

Another demerit of this scheme is the large amount of power consumed as several receiver algorithms relating to the various technology schemes are executed for detection [49, 53]. So far, research work involved with this method is based to a large extent on tackling the disadvantages posed by the conventional design of an MF. In [52] a reconfigurable matched-filter based spectrum is proposed to tackle the error associated with the traditional MF design. The generic filter method is the option adopted. In this set up, the coefficient set of the generic filter is changed periodically to scan spectrum of the wireless channel associated with each standard.

The effectiveness of this technique relies on reconfiguring the filter to implement the numerous communication standards available. In contrast, weighing the variability of the filtering requirements for different standards, the generic filter will have to be designed for the worst case to accommodate all standards. Aside this, the features of generic designs are slow and large with some degree of power consumption, making a generic implementation of the filtering block less attractive. The second option implemented is a design of optimized individual filters for each wireless standard; termed “space-multiplexing”. However, this would increase the size of the circuitry, not scalable with a number of standards; while power consumed is not featured in the final analysis. The authors in [51] apply MF spectrum sensing approach to sense the presence of a digital television (DTV) signal. First, the pilot tone is detected by passing the DTV signal through a delay-and-multiply circuit. A decision is reached if the squared magnitude of the output signal is larger than a threshold; by which case presence of a DTV signal is established. But in the generalized SS scenario however, use of a MF can be severely limited since complete information of the transmitted PU
signal is hardly available. In [52], a MF is adapted to sense unused spectrum in a WLAN (IEEE802.11a) by exploring the signals presence in minimum time. This is executed by incorporating an optimal threshold selection that increases sensing accuracy and interference reduction produced by the secondary network. From the foregoing, it is apparent that [53] this method is only applicable to systems with known signal patterns, such as wireless metropolitan area network (WMAN) signals, thus this method is often referred to as a waveform-based type of sensing; since it works on the signals characteristics. A challenge for this type of detector occurs often when it does not have information about the PU signal, making it suboptimal for efficient spectrum sensing for opportunistic access.

2.4.4 Cyclostationary Feature Detection

When signals exhibit statistical attributes like mean, autocorrelation etc., that change periodically with time, these are termed as Cyclostationary Features (CF) are associated with these. Usually, wireless transmissions present cyclostationary features depending on their data rate, modulation type, and carrier frequency. Most communication signals can be modeled as cyclostationary, since there exhibit underlying periodicities in their signal structures. Cyclostationary feature detection (CFD) is a method that applies cyclostationary features to detect a signal. The identification of a unique set of characteristics particular to a radio signal for a wireless access system can be used to detect the system based on its cyclostationarity features. These features have periodic statistics and spectral correlation not obtained with interference signals or stationary noise. Thus exploiting this periodicity in the received primary signal to identify the presence of primary users makes this method possess a high noise immunity compared to other spectrum sensing methods [54]. This theory conceptualizes the fact that man-made signals possess hidden periodicities such as the carrier frequency, symbol rate or chip rate, which can be regenerated by a sine-wave extraction operation, thus producing features at frequencies that depend on the built-in periodicities [55]. A basic analysis of this theory will be adequate to help understand its application.

A signal \( x(t) \) is said to be cyclostationary, if its mean and autocorrelation function \( E_x(t), R_x(t, \tau) \) are periodic [20, 48], expressed respectively by:
\[ E(x) = \mu(t + mT_0) \]

and

\[ R_x(t, \tau) = \Pi(t + mT_0, \tau) \quad (2.10) \]

where, \( t \) is the time index, \( \tau \) is the lag associated with the autocorrelation function and \( m \) is an integer. The periodic autocorrelation function is expanded by Fourier series, as,

\[ R_x(t, \tau) = \sum_{\alpha=-\infty}^{\infty} R_x^{\alpha}(\tau) \exp(2\pi j \alpha t) \quad (2.11) \]

where

\[ R_x^{\alpha}(\tau) = \lim_{T_0 \to 0} \frac{1}{T_0} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t - \frac{\tau}{2}) x(t + \frac{\tau}{2}) \exp(-2\pi j \alpha t) \quad (2.12) \]

The term in Equation 2.12 is the cycle autocorrelation, and for a cyclostationary process with period \( T_0 \), the function \( R_x^{\alpha}(\tau) \) possesses a component at \( \alpha = 1/T_0 \). But, for a stationary process such as noise, (2.6) will be zero-valued. Employing the Wiener relationship (i.e., taking the Fourier series representation with respect to \( \tau \)), results in the cyclostationary spectrum density (CSD), or the spectral correlation function (SCF), which when evaluated leads to,

\[ S^\alpha_x(f) = \lim_{T_0 \to \infty} \int_{-\tau}^{\tau} R_x^{\alpha}(\tau) \exp(-j2\pi f \tau) d\tau \quad (2.13) \]

The SCF in (2.7) is a function of frequency, \( f \), and the cycle frequency \( \alpha \), which makes it possible for cyclostationarity feature to be detected in the cycle frequency domain. Since different types of signals have different non-zero cyclic frequencies, they can be identified from their signature. To ease computing of the SCF, (2.7) is expressed alternatively as,

\[ S^\alpha_x(\tau) = \lim_{T_0 \to 0} \lim_{T \to \infty} \frac{1}{TT_0} \int_{-\frac{\tau}{2}}^{\frac{\tau}{2}} X_{T_0}(t, f + \frac{1}{\alpha}) X^1_{T_0}(t, f - \frac{1}{\alpha}) dt \quad (2.14) \]

The term \( X_{T_0}(t, f) \) represents the short time Fourier transform of \( x(t) \) with bandwidth \( 1/T \), where \( X^1_{T_0}(t, f) \) is the complex conjugate of \( X_{T_0}(t, f) \) given by

\[ X_{T_0}(t, u) = \int_{t-T_0/2}^{t+T_0/2} x(v) \exp(-j2\pi fv) dv \quad (2.15) \]
The expression (2.14) is known also as the time smoothed SCF which theoretically achieves true SCF for $T >> T_0$. The CSD is a two dimensional transform that consists of two variables: the cyclic frequency and the spectral frequency, $f$, [54]. It is clear from the foregoing that the cyclic spectral correlation function is the parameter employed for detecting primary user signals with this method. When SCF is plotted, the occupancy status of the spectrum can be determined. If a primary user signal is present in the operating frequency range, the SCF presents a peak at the center. The peak will be absent in a case where there is no primary user signal present in the frequency range of interest. Also, the SCF can be used to ascertain the type of modulation scheme applied to the primary user signal. This is accomplished by considering the number of secondary peaks at the double frequencies. If the modulation scheme employed is BPSK, there will be single secondary peaks when the operating frequency is doubled. Unlike the matched filtering approach that involves close synchronization with the signal of interest, cyclostationary analysis does not require frequency or phase synchronization, making it an attractive approach to detection of signals whose carrier frequencies and symbol timing are unknown [54].

Comparatively, the strength of this method lies in its strong performance under low SNR, since noise is totally random and does not present a form of periodic behavior [56]. Using cyclostationary analysis as a technique to accomplish signal detection was described in [55]. In [56], the authors study spectrum detection in a low SNR environment applying the noise rejection property of the cyclostationary spectrum. This is computed by measuring the cyclic spectrum of the received signal. Statistics concerning the spectrum of the stationary white Gaussian process were fully analyzed. An application to the IEEE 802.22 WRAN1, alongside analytic derivation of the probability of false alarm is also presented. Since the stationary Gaussian process has a zero-valued spectral correlation density function (SCD) at nonzero frequencies, the desired signal is detected by computing the SCD provided; the signal is cyclostationary such that its cyclic spectrum is not identically zero at some nonzero cyclic frequency. The authors in [57] present a theoretic and hardware implementation of this method, which involves spectral estimation of the cyclostationary spectrum density. This is executed by selecting an appropriate size of the FFT; since from (2.8), the number of correlations is largely determined by the size of the FFT. In this work, CSD estimation is performed along the axis of zero cyclic frequencies and the axis of
zero spectral frequency i.e. Equation (2.8) is evaluated at a set of discrete frequency pairs \((\alpha_k, f_j)\). Since practical estimation can only be performed within limited time duration, CSD is estimated by performing a sliding N point FFT, and correlating the appropriate spectral components.

With this type of analysis however, a tradeoff exists between the size of FFT and hardware cost. Usually, an FFT with a large data size provides more accuracy, more averaging time for CSD estimation, but with an increase in cost of hardware. It is also noteworthy that CSD estimation is a two dimensional transform, making it computationally complex.

Sutton et al. in [58] propose an alternative approach to feature detection using signatures embedded in a signal to solve a number of challenges associated with dynamic spectrum access applications; especially receiver complexity. Using a flexible cognitive radio platform, implementation of a full Orthogonal Frequency Division Multiplexing (OFDM) based transceiver using cyclostationary signatures is presented and the system performance is examined from experimental results. Although, methods presented therein are OFDM specific, similar techniques can be developed for any type of signal. A hardware implementation of the CFD technique is presented [55]. A detector for OFDM signals based on cyclostationary features is presented [56]; this exploits the inherent correlation of OFDM signals obtained by data repetition in the cyclic prefix; i.e. using knowledge of the length of the cyclic prefix and length of the OFDM symbol. The authors demonstrate that detection performance improves by 5 dB in applicable cases. The problem existent in many systems, where for particular applications, statistical features may not be the same for two adjacent periods which may change smoothly is considered. The periodicity that appears in the aforementioned process does not necessarily extend to a pure cyclostationary process, but leads to an almost cyclostationarity which presents a limitation using cyclostationary feature detection approach.

The authors propose a novel estimator for almost cyclostationary signals. Even as the CFD has advantages that include reduced sensitivity to noise and interfering signals, as well as the ability to extract key signal parameters - including carrier frequencies and symbol rates; on the flip side, an analysis of cyclostationarity is computationally intensive, requires significantly longer observation time and processing resources of
the SU may be limited for the needed signal processing tasks. Added to this, when an insufficient number of samples are utilized, the detection performance will degrade due to the poor estimate of the cyclic spectral density. From the review of the transmitter detection methods so far presented, it is apparent that though the energy detection method is “crude” [33]; but based on the evaluation criteria mentioned earlier (i.e. latency, complexity etc.), it possesses an edge over the more complex methods like cyclostationary feature and matched filter detectors, that require absolute knowledge of the PU transmitted signal. Also, from a practical implementation perspective [32], both matched-filter and cyclostationary feature detection techniques are primarily for narrowband sensing, whereas energy detection can be applied to wideband sensing.

Kyouwoong Kim [58] in the year 2009, proposed detection and classification of very low SNR signals with relaxed information on the signal parameters being detected is significant for proper CR functionality as it enables the CR to react and adapt to the changes in its radio environment. In this work, the cycle frequency domain profile or cyclic domain profile is used for signal detection and pre-processing for signal classification. Signal features are extracted from CDP using a threshold-test method. For classification, a Hidden Markov Model (HMM) has been used to process extracted signal features due to its robust pattern-matching capability. They also investigate the effects of varied observation length on signal detection and classification. It is found that the CDP-based detector and the HMM-based classifier can detect and classify incoming signals at low SNRs.

2.4.5 Interference Based Detection

This theoretical method employs an interference temperature model; which is a measure of how well a radio operating within a particular modulation scheme and protocol can tolerate interference in its spectrum space [61]. This follows the fact that signal power received at a primary receiver reduces exponentially with distance; continuously till it reaches a level of the noise floor [60]. Though a primary transmitter still operates at this point, the receiver handles this process as noise and not transmission. This makes it possible for a secondary user to utilize the channel, since no interference is introduced to the primary users' communication (as the primary receiver is not in receiving mode).
Above the maximum noise level, an interference cap is introduced, beneath this threshold; the primary receiver will treat this transmission as noise. An illustration of the interference temperature model is shown in Fig 2.5. The SU may exploit the channel if the detected primary signal level is below the interference temperature limit. More so, if the power of transmission of an SU stays below the interference gap, it may utilize any frequency parameter of its choice.

Fig 2.5: Interference temperature model

With this approach, it is hypothesized that the SUs will be allowed to transmit concurrently with the PUs under stringent interference avoidance constraints; wherein it is categorized as a spectrum underlay scheme. It is noteworthy nonetheless, that this method is far more challenging; since the prime problem faced with an implementation of this technique will be in determining specific receiver interference temperature levels for the various communication standards. Recently however, in [33], this approach to spectrum sensing was reportedly analyzed and declared to be non-implementable, thus no further survey on this method will be conducted in this work.

2.5 Cooperative Detection

In cooperative detection, multiple SUs collaborate in a centralized or decentralized manner to ascertain spectrum holes for opportunistic access. Each cooperating node within this context employs locally, any of the sensing methods previously described, while sharing the raw or refined sensing information with other node(s); dependent on a selected cooperation strategy [33]. This concept of collaboration is considered since effects of shadowing, multipath fading and receiver uncertainty pose severe
challenges to single user transmitter detection approach in spectrum sensing [32]. A depiction of this phenomenon is depicted in Fig 2.6.

![Fig 2.6: Multipath/shadowing and receiver uncertainty](image)

From the Fig 2.6, Cognitive radios CR1 and CR2 are within range of the primary transmitter (PU Tx) while CR3 is not. As a result of the obstruction from the house and due to multiple copies of the attenuated signal being sent, CR2 suffers multipath and shadowing problems, such that signals from the PU Tx may not be detected correctly. CR3 on the other hand is unaware of the transmission from PU Tx and the existence of primary receiver (PU Rx), consequently, transmission from CR3 may interfere with reception at the PU Rx; this phenomenon is known as the receiver uncertainty problem.

However, owing to spatial diversity, it is unlikely that all SUs spread in space within a network will simultaneously experience receiver uncertainty or fading problems. Since, secondary users that observe a strong signal from the PU Tx, like CR1 in the Fig 2.6, can sense and communicate sensed result to other users. This collaborative paradigm should tackle flaws in observation at the other users considerably. By this technique of cooperation amongst users, robustness is achieved without severe demands on individual radios; thus enhancing effective primary detection [62]. For CSS, SUs require two channels for local sensing to arrive at a decision. Initially, SUs establish a link with the primary transmitter to carryout local sensing; this link between primary transmitter and the various cooperating SUs is known as the sensing
channel. To share local spectrum sensing data with each other or the fusion center requires a control or reporting channel. So far, a medium access protocol coordinates the shift between these two channels [33]. Considering the mode of collaboration between sensing nodes in a detection scheme, cooperative spectrum sensing is broadly categorized as; centralized, distributed and relay assisted; based on how collaborating SUs convey sensing data within the network [32]. These three cases of cooperative sensing are depicted in Fig. 2.6. Essentially CSS consists of a series of actions requiring local sensing, reporting and information fusion [59]. The following subsections highlight the distinguishing features of the various collaborative strategies.

2.5.1 Centralized Cooperative Detection

In a centralized structure, a central unit, designated the fusion centre or base station (BS), determines eventual availability of spectrum holes after collating local SS information from cooperating SUs. This opportunity is either broadcast to all SUs or the FC itself controls traffic by managing detected spectrum usage opportunity in an optimum fashion. The central node/FC could be an access point (AP) in a wireless local area network (WLAN) or a base station in a cellular network; while in adhoc networks, any node once identified can act as a master to coordinate CSS. In operation, the FC selects a control channel for the transmitter and tasks the various SUs to send their local sensing results via a reporting channel. It is envisaged, cooperating SUs would send collected data to the FC, allowing it perform a data fusion to decide the presence of a primary signal; or they could each send individual decisions and the FC conducts decision fusion to assume a decision. For the scenario where the SU sends complete local sensing data, the fusion process is termed soft combining shown in Fig. 2.7 (a). When the SU quantizes the local sensing information before sending to the FC, this fusion process is termed quantized soft combining. For hard combining fusion, an SU makes decision after sensing and sends one bit as its decision to the FC.

In [51], employing CSS to reliably detect primary users is considered by exploiting multiuser diversity; with criteria of an SU possessing the highest SNR value being selected as the cluster head. Due to the varying distances from the PU, the value of the SNR changes among the SUs; this forms the underlying criteria adopted in this
scheme. The authors also present a two-layer model in implementing this technique so as to combat fading in the channels. Though results show a low bandwidth control channel for all spectrum sensing techniques, this method presents a challenge in practical implementation since the time involved in sensing will be prolonged, as it involves traversing two separate layers.

![Figure 2.7: Cooperative sensing techniques: (a) Centralized, (b) Distributed and (c) Relay assisted](image)

In [63], cyclostationary feature detection is proposed for CSS by applying the generalized likelihood ratio test (which is a complex hypothesis test involving the use of assumed parameters selected by the maximum likelihood estimates). This scheme enables detection of cyclostationary signals for multiple cyclic frequencies. A censoring technique employed for each cooperating user conveys locally sensed results to the FC. Empirical results presented indicate improved energy efficiency from this approach. In this work, the test statistic for data fusion at the FC is developed for cooperative sensing. Regrettably however, the consequence of cyclostationarity resurfaces; prior information of signals to be sensed is required, while the issue of complexity is unresolved. Cooperative processing trade-off is addressed in [64] for energy detectors, wherein, trade-off is formulated as an optimization problem to minimize the total sensing time, subject to constraints of false alarm and detection probabilities. Total sensing time to be minimized include integration time of an energy detector for local processing and reporting time; proportional to the number of cooperating SUs.

The results from this work show that, for higher detection sensitivity, a longer integration time is required. This is unlike the general notion of cooperation, wherein an increase in the number of cooperating nodes reduce the required sensing time to
achieve the same level of detection sensitivity. A general weakness of the centralized approach however, is that a FC becomes very critical; making its failure rue the whole concept of cooperation.

2.5.2 Distributed Cooperative Detection

In a distributed cooperation, SUs would not rely on an FC to make a cooperative decision; rather, it is conceived that the SUs communicate within nodes, then converge to a joint (global) decision on the presence or absence of PU in an iterative manner [33]. This is accomplished in three steps defined by a distributed algorithm as follows. First, each cooperating user sends its local sensing data to other users in its neighbourhood. Next, cooperating users combine data with the received sensing information from other users to decide on the presence or absence of a PU based on the local criterion. The shared spectrum observations are usually in the form of soft sensing results or quantized (binary/hard) version of local decisions about spectrum hole availability. In a case where the spectrum hole is not identified, SUs send combined sensing information to other users in the next iteration. This process continues until the scheme converges and a final unanimous decision on spectrum availability is achieved. In this manner, each SU in a distributed scheme partially plays the role of an FC. Figure 2.7(b) depicts cooperation in a distributed mode.

In [65] a distributed CSS scheme for wideband sensing in cognitive radio adhoc networks (CRAHNs) is proposed. With this scheme, each SU conducts compressed sensing locally, determines the local spectral estimates, and then conveys the spectrum state vectors to its one-hop neighbours. The authors propose a distributed average consensus method, wherein each SU iteratively updates its spectrum state with a weighted sum of the difference values between the SU and its neighbors. From this process, the spectrum state vectors converge to the average statistic at each SU for PU detection. In the same vein, the spectral estimates can be obtained cooperatively by consensus averaging.

The study in [65] is extended to include spectrum occupied by the SUs, termed spectral innovation; in addition to that of the PUs within wideband scenario. The accuracy of estimation is improved by utilizing a spectral orthogonality scheme between PUs and SUs. Based on the work in [60, 61] a distributed consensus
optimization scheme is proposed in [65] for sensing signals in a wideband. After sensed results are compressed, each SU determines an estimate of the instantaneous spectrum by performing an optimized consensus, resulting in enhanced results, which would be broadcast to the various one-hop neighbours. This process is repeated until convergence is reached. The average consensus technique incorporated in the above technique ensures fast convergence; though improvement in time resulting from this approach is however not considered in the final analysis.

Since sensing signals in multiple bands presents a challenge, [66] introduce an algorithm to tackle detection in a wideband via cooperative spectrum sensing. The proposed technique involves dividing a typical wideband of interest into various subbands, while a group of SUs are assigned the task of sensing particular narrow subbands. A base station (or FC) is employed in collating results and making final decisions over the full spectrum. Results indicate that the proposed algorithm minimizes time and amount of energy spent for wideband spectrum scanning and effectively detects primary user’s occupancy status in a wideband spectrum. The algorithmic program presented in this work is purely theoretic, hence ambiguous; since it does not specify a method for local sensing for the various subbands. The various methods proposed for the application of distributed detection consist of numerous iterations in accomplishing unanimous cooperative decisions, with substantial network information overhead and bandwidth consumption, while increasingly being too complex to implement, thus not aligning with the opportunistic access to spectrum bottom line.

2.5.3 Relay- Assisted Cooperative Detection

It is envisaged that under realistic conditions, the sensing and reporting channels in the schemes outlined previously may not function properly. For instance, a particular SU reporting channel may be weak, while its sensing channel strong arising from shadowing or multipath consequences; yet another SU may possess a strong reporting channel and a weak sensing channel [14, 32] as depicted in Fig. 2.7(c). The relay-assisted detection paradigm provides a scheme where an SU serves as a relay, forwarding sensed information. The centralized and distributed schemes are considered one-hop cooperation, while the relay-assisted approach is thought of as a multi-hop cooperative scheme.
In [66], a theoretic detection performance of an energy detector is considered for channels encountering both multipath fading and shadowing. An analytical framework using data and decision fusion is used to investigate performance; not considering SNR statistics of received primary signals. Under the analysis for data fusion, upper bounds of average detection probabilities were derived for four scenarios: 1) single relay; 2) multiple relays; 3) multiple relays with direct link; and 4) multi-hop relays. The analysis contained in this work is an analytical framework focused on the Rayleigh multipath fading and lognormal shadowing; leaving out other fading models. Although data and decision fusion models have been employed in earlier works to improve the performance and reliability of energy detection with distributed cooperative spectrum sensing, the analysis so far is still limited to a range of known bandwidth. This in itself presents a research gap to be explored.

2.6 Cooperation Overhead

The exploitation of spatial diversity in cooperative sensing results in a significant improvement in detection performance. However, cooperation among secondary users may also introduce a variety of overheads that limit or even compromise this improved detection performance. The overhead associated with all elements of cooperative sensing is called cooperation overhead. Cooperation overhead can refer to any transmission cost, extra sensing time, delay, energy and operations devoted to cooperative sensing and any performance degradation caused by cooperative sensing. Since the sensing time is proportional to the number of samples taken by each individual secondary user, the longer the sensing time is, the better the detection performance will be. However, when each secondary user is equipped with a single radio transceiver, it will be difficult for the secondary users to simultaneously perform sensing and transmission. Therefore, the more time is devoted to sensing, the less time is available for transmissions which reduces the secondary users’ throughput, also known as opportunistic throughput.

In addition, the cooperation overhead due to the extra sensing time will generally increase with the number of cooperating users due to the increased volume of data that needs to be reported to and be processed by the fusion center. This is known as the sensing efficiency problem or the sensing-throughput trade-off in spectrum sensing.
The cooperation overhead, in terms of the extra sensing time or reduced opportunistic throughput, will also increase as the delay in finding available channel increases. In [68], a sensing-period optimization mechanism and an optimal channel-sequencing algorithm were developed to maximize the discovery of spectrum access opportunities and minimize the delay in discovering an available channel when all secondary users participate in sensing an identical channel in each sensing period. Parallel cooperative sensing was proposed in [69, 70] where the cooperative secondary users are divided into multiple groups and each group senses one channel such that more than one channel is sensed in each sensing period. Since multiple channels are detected in one sensing period, the cooperation overhead associated with the delay in finding an available channel is significantly reduced.

In cooperative sensing, secondary users involve in activities such as local sensing and data reporting that consume additional energy. The energy consumption overhead can be significant if the number of cooperating secondary users or the amount of sensing results to be reported is large. One approach to address this issue is to use censoring to limit the amount of reported sensing data according to certain criteria or constraints. Since the censoring criteria are chosen to refrain cooperating secondary users from transmitting unnecessary or un-informative data, the energy efficiency can be improved in cooperative sensing. In [71], a simple censoring method was proposed to decrease the average number of sensing bits reported to the fusion center. In this method, the energy detector output of each secondary user is compared to two thresholds and the decision is sent to the fusion center if the energy detector output is between those two thresholds. Otherwise, no decision is made and this sensing output is censored from reporting. The results showed that even though the network probability of false alarm may degrade due to the possibility that the sensing outputs of all secondary users are censored, the amount of reported local decisions can be dramatically reduced. Therefore, the energy efficiency can be traded off with the network probability of false alarm.

Another approach to reduce the cooperation overhead in terms of energy consumption is to minimize the energy consumption with detection performance constraints. In [72], the energy efficiency problem was addressed by energy minimization under detection performance constraints. This method investigates the trade-off between the
two aspects of sensing time. On one hand, longer sensing time consumes more energy at each secondary user. On the other hand, longer sensing time can improve detection performance at each secondary user and reduce the number of cooperating users and the associated energy consumption overhead. Therefore, this method finds the optimal sensing time and the optimal number of cooperating users to balance the energy consumption in local sensing and the energy overhead due to cooperation for required detection performance.

2.7 Sensing Errors
A secondary user identifies spectrum access opportunities by detecting the presence of primary signals. Sensing errors, in terms of false alarms or miss-detections, occur due to noise and fading [10]. False alarms occur when idle channels are detected as busy, and miss-detections occur when busy channels are detected as idle. In the event of a false alarm, a spectrum access opportunity is overlooked by the secondary user, and eventually wasted if the access strategy trusts the sensing outcome. On the other hand, miss-detections may lead to collisions with primary users' transmissions. Therefore, in spectrum sensing, it is desired to minimize the probability of sensing error (i.e., sum of the probability of false alarm and the probability of miss-detection) which reduces the collision probability with primary users' transmissions and enhances the usage level of vacant spectrum. A well chosen detection threshold can minimize spectrum sensing errors, provide the primary users' transmissions with enough protection, and fully enhance spectrum utilization. In [53], the optimal threshold level for minimizing the probability of sensing error was determined without considering spectrum sensing constraints that may be violated. To alleviate this problem, an adaptive optimal spectrum sensing threshold level was derived to minimize the probability of sensing error while satisfying spectrum sensing constraints on the probabilities of false alarm and miss-detection. CSS using counting rule was studied in [73] and the sensing errors were minimized by choosing the optimal probability of false alarm to satisfy a given constraint and the optimal number of cooperating secondary users for both matched filtering and energy detection. CSS with correlated secondary users' local decisions was studied in [74].
The probability of sensing error was minimized by choosing the optimal assignments for the number of cooperating secondary users, $K$, in the $K$-out-of-$M$ fusion rule and the local threshold for a certain correlation index. It is usually assumed that the local observations and the combining decision are all made at the same time. In reality, this is not always valid and therefore, the CSS scheme should consider the case of asynchronous observations which results in time offsets between local sensing observations and the final decision at the fusion center. In [75], a probability-based combination scheme was proposed to combine asynchronous reports at the fusion centre.

The proposed combining scheme considers both detection errors and time offsets between local sensing observations and the final decision. Based on the knowledge of the primary user channel usage model and the Bayesian decision rule, the conditional probabilities of the local sensing decisions received at different times, conditioned on each hypothesis, and their combined likelihood ratio were calculated to make the final decision at the fusion centre.

Most of the studies on CSS analyze its performance based on the assumption of perfect knowledge of the average received SNR at the secondary user. However, in practice, this is not always the case. The effect of average SNR estimation errors on the performance of CSS was examined in [76]. In the noiseless-sample-based case, it was found that the probability of false alarm decreases as the average SNR estimation error decreases for both independent and correlated shadowing. In the noise-sample-based case, it was found that there exists a threshold for the noise level. Below this threshold, the probability of false alarm increases as the noise level increases, while above the threshold the probability of false alarm decreases as the noise level increases.

2.8 Conclusions

It is apparent that for transmitter based detection, energy detection method is the most viable approach to sensing spectrum for opportunistic access; since, not only does the pair of matched filter and cyclostationarity feature detection methods present some degree of complexity, both of this techniques require prior information on the signal type to be detected. In the same streak, for CSS, techniques available in literature
have not sufficiently assessed the capability of the traditional energy detector. Consequently, in this study, energy detector for detecting signals in a licensed band is described and its performance evaluated for both fading and non-fading environments. In the end, this method will prove to be an executable option for the detection of narrow and heterogeneous wideband signals traversing spectrum spread over multiple adjacent narrow bands. Also it is possible to extract the feature of primary signal in cyclostationary detection without prior knowledge of primary signal.