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Improving the Existing Spectrum Sensing Techniques for Cognitive Radio using Modulation Techniques

Manthan D. Rana[1], **Hina R. Patel**[2]

M.E Student, Electronics & Communication, Parul Institute of Technology, PO.Limda,Vadodara,Gujarat, India[1]

Assistant Professor, Electronics & Communication, Parul Institute of Technology, PO.Limda,Vadodara,Gujarat,India[2]

Abstract: Cognitive Radio plays an important role in wireless communication. With the ever increasing demand for wireless communications, the spectrum has become a scarce resource. It is becoming a major obstacle for the development of new wireless technologies and introduction of new applications and services. Cognitive Radio (CR) is one of the major technologies that is the solution to the spectrum scarcity problem. It allows the use of spectrum in an efficient manner. The spectrum sensing problem has gained new aspects with cognitive radio and opportunistic spectrum access concepts. It is one of the most challenging issues in cognitive radio systems. Although a lot of research has been done on techniques, but sensing of modulated signals hasn't been analysed. In this work, an analytical study and simulation result of spectrum sensing techniques for cognitive radio will be presented. Results of spectrum sensing techniques like, energy detection, cyclo-stationary feature detection and matched filter detection will be analyzed. All the analysis will be done for modulated signal communication, as modulated signals brings us to a more practical approach. Modulation Using BPSK has been done so other technique QPSK will be used.

Keywords: cognitive radio, spectrum sensing techniques, Digital Modulation Techniques.

I. INTRODUCTION

Cognitive Radio (CR) is a system or a model for wireless communication. It is built on software defined radio which is an emerging technology providing a platform for flexible radio systems, multiservice, multi-standard, multiband, reconfigurable and reprogrammable by software for Personal Communication Services (PCS). It uses the methodology of sensing and learning from the environment and adapting to statistical variations in real time. The network or wireless node changes its transmission or reception parameters to communicate efficiently anywhere and anytime avoiding interference with licensed or unlicensed users for efficient utilization of the radio spectrum. The definition adopted by Federal Communications Commission (FCC): "Cognitive radio: A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets." [11]. Hence, one main aspect of cognitive radio is related to autonomously exploiting locally unused spectrum to provide new paths to spectrum access.

The concept was first originated by Defense Advance Research Products Agency (DARPA) scientist, Dr. Joseph Mittola and the result of that concept is IEEE 802.22 , which is a standard aimed at using cognitive radio for Wireless Regional Area Network (WRAN) using white spaces in the TV frequency spectrum while assuring that no harmful interference is caused to the incumbent operation, i.e., digital TV and analog TV broadcasting, and low power licensed devices.

Spectrum hole or white space is spatially & temporally unused part of the radio spectrum, which is considered for use by Cognitive Radio. The most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users because most of the spectrum is already assigned which is shown in Fig.1. If this band is further used by a licensed user, the cognitive radio moves to another spectrum hole or stays in the same band, altering its transmission power level or modulation scheme to avoid interference as shown in Fig.1.

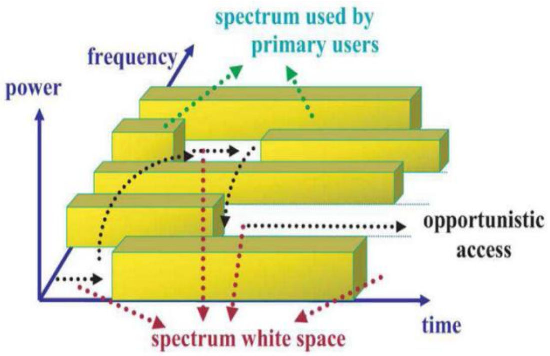

Fig.1 Spectrum White Space Concepts [8]

One main aspect of cognitive radio is related to autonomously exploiting locally unused spectrum to provide new paths to spectrum access. By detecting particular spectrum holes and exploiting them rapidly, the CR can improve the spectrum utilization significantly. To guarantee high spectrum efficiency while avoiding the interference to the licensed users, the CR should be able to adapt spectrum conditions flexibly.

Spectrum sensing by far is the key important component for introduce cognitive radio. Spectrum sensing is the task of obtaining awareness about the spectrum usage and existence of primary users in a geographical area. Spectrum sensing is understood as measuring several aspects like spectral content, or measuring the radio frequency energy over the spectrum when cognitive radio is considered, it is a more general term that involves obtaining the spectrum usage characteristics across multiple dimensions such as space, time, frequency, and code. It also involves occupancy of the types of the signals in the spectrum including the modulation, waveform, bandwidth, carrier frequency, etc.

II. COGNITIVE CYCLE

A basic cognitive cycle comprises of following three basic tasks:

- Spectrum Sensing
- Spectrum Analysis
- Spectrum Decision Making

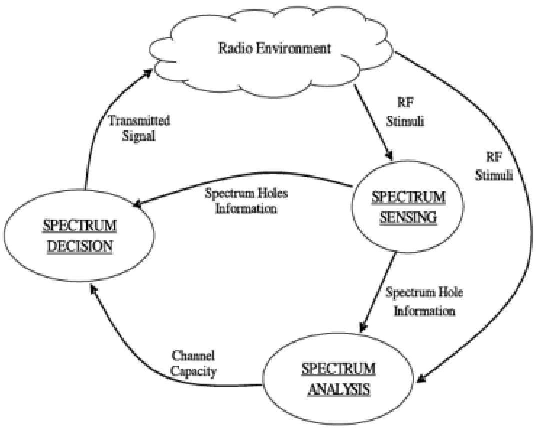

Fig. 2 Cognitive cycle [10]

Spectrum Sensing:

Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of spectrum and transmit power, interference and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across Frequency, Time, Geographical Space, Code and Phase.

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 and changing frequency or channel accordingly. It is also known as channel estimation.

Spectrum Decision Making:

Spectrum Decision Making calls for reconfiguration for the channel and protocol required for constantly adapting to mobile changing environments and adjustment of output power or even alteration of transmission parameters (such as modulation formats (e.g. low to high order QAM), variable symbol rates, different channel coding schemes) and characteristics by the Cognitive radio devices. CR should be able to use multiple antennas for interference nulling, capacity increase or range extension.

A. *Cognitive Radio's Key Benefits*

Cognitive Radio (CR) offers 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 met and is the basic purpose of implementing CR.
- Higher bandwidth services: Demand of MBMS is constantly on the rise which will be facilitated by the implementation of CR.
- Improved Quality of Service (QoS) (latency, data rate, cost etc) - Suitability, availability and reliability of wireless services will improve from the user's perspective.
- Commercial Exploitation: CR promotes spectrum liberalization (makes it much easier to trade spectrum between users). Indeed, a business case may exist for becoming a spectrum broker, whereby a third party manages the trade between supplier and demander and receives a commission.
- 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.

III. SPECTRUM SENSING

Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of spectrum and transmit power, interference and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across Frequency, Time, Geographical Space, Code and Phase.

A. *Spectrum Sensing Methods*

A number of different methods are proposed for identifying the presence of signal transmission all of which are in early development stage. They are:

- Energy Detection Based: The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. The disadvantage is inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values.
- Waveform Based: In this method known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc. Waveform-based sensing requires short measurement time.

- Cyclostationary Based: Cyclostationarity feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals.
- Matched filtering Based: Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known. It requires perfect knowledge of the primary users signaling features.

IV. PROPOSED METHOD

A. *Cooperative Sensing*

Cooperation is proposed in the literature as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. Cooperative sensing decreases the probabilities of misdetection and false alarm considerably. In addition, cooperation can solve hidden primary user problem and it can decrease sensing time. This can be done using control channel to share spectrum sensing result. Collaborative spectrum sensing is most effective when collaborating cognitive radios observe independent fading or shadowing [7].

Using Modulation techniques like FSK, PSK, BPSK, etc. along with spectrum sensing brings the cognitive radio systems generally talked about to more realistic approach and proposed system close to practical application here. Not only will this, using Modulation techniques make system more robust.

Thus, the goal is to use Cooperative Centralized Cognitive Sensing with Modulated Signal based communication in AWGN (zero mean and unity variance) and Rayleigh Fading Channel. Cooperation can be among cognitive radios or external sensors can be used to build a cooperative sensing network. Cooperation can be implemented in two ways: centralized or distributed. These two methods and external sensing are discussed in the following section.

(1) Centralized Sensing

In centralized sensing, a central unit collects sensing information from cognitive devices, identifies the available spectrum and broadcasts this information to other cognitive radios or directly controls the cognitive radio traffic. In the case of a large number of users, the bandwidth required for reporting becomes huge. In order to reduce the sharing bandwidth, local observations of cognitive radios are quantized to one bit (hard decisions). Furthermore, only the cognitive radios with reliable information are allowed to report their decisions to the central unit. Hence, some sensors are censored. Censoring can be implemented by simply using two threshold values instead of one. Analytical performance of this method is studied for both perfect and imperfect reporting channels.

(2) Distributed Sensing

In the case of distributed sensing, cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use. Distributed sensing is more advantageous than centralized sensing in the sense that there is no need for a backbone infrastructure and it has reduced cost.

(3) External Sensing

Another technique for obtaining spectrum information is external sensing. In external sensing, an external agent performs the sensing and broadcasts the channel occupancy information to cognitive radios. External sensing algorithms solve some problems associated with the internal sensing where sensing is performed by the cognitive transceivers internally. The main advantages of external sensing are overcoming hidden primary user problem and the uncertainty due to shadowing and fading. Furthermore, as the cognitive radios do not spend time for sensing, spectrum efficiency is increased. The sensing network does not need to be mobile and not necessarily powered by batteries. Hence, the power consumption problem of internal sensing can also be addressed.

V. SYSTEM MODEL

Suppose that we are interested in the frequency band with carrier frequency fc and bandwidth W and the received signal is sampled at sampling frequency fs. Consider the problem of detecting a signal in additive white Gaussian noise (AWGN), and then the goal of spectrum sensing is to decide between the following two hypotheses, When the primary user is active, the discrete received signal at the secondary user can be represented as

$$H1: Y[n]=S[n]+u[n] \quad \ldots\ldots.. \qquad \text{(I)}$$

This is the output under hypothesis H1. When the primary user is inactive, the received signal is given by

$$H0: Y[n]=u[n] \quad \ldots.. \qquad \text{(II)}$$

and this case is referred to as hypothesis H0.
Where Y[n] is received signal at the secondary user, S[n] is transmitted signal from the primary user with mean μx= 0 and variance σ2x, W[n] is AWGN with mean μw = 0 and variance σ2w.

The following assumptions should be considered:

a. The noise u(n) is a Gaussian, independent and identically distributed (iid) random process with mean zero and variance E[|u(n)|2]=σ2u;
b. The primary signal s(n)is an iid random process with mean zero and variance E[|s(n)|2]=σ2s;
c. The primary signal s(n) is independent of the noise u(n).

A. *Single Radio Sensing*

We first consider single radio spectrum sensing at individual secondary users. The test statistic using energy detection is given

$$T(Y) = \frac{1}{M}\sum_{n=1}^{M}|Y[n]|^2 \quad \ldots\ldots\ldots \qquad \text{(III)}$$

For M sufficiently large, we can approximate the test statistic in 3 as Gaussian by central limit theorem (CLT)

$$T|H_0 \sim N(\sigma_W^2\,, 2\sigma_W^4)$$
$$T|H_1 \sim N(\sigma_X^2 + \sigma_W^2\,, 2(\sigma_X^2 + \sigma_W^2)^2 \qquad \ldots\ldots\ldots\ldots \qquad \text{(IV)}$$

Where N(μ, σ) denotes Gaussian distribution with mean μ and variance σ. Then false alarm probability PFA and missed detection probability PMD can be evaluated as

$$P_{FA} = Q\left(\frac{\beta - \sigma_W^2}{\sqrt{2\sigma_W^4}}\right)$$
$$P_{MD} = 1 - Q\left(\frac{\beta - (\sigma_X^2 + \sigma_W^2)}{\sqrt{2(\sigma_X^2 + \sigma_W^2)^2}}\right)\ldots\ldots\ldots\ldots \qquad \text{(V)}$$

Where β denotes the threshold (normalized). Given PFA, β can be determined from (5.5) by

$$\beta = \sqrt{2\sigma_W^4}\,Q^{-1}(P_{FA}) + \sigma_W^2 \qquad \ldots\ldots\ldots\ldots \qquad \text{(VI)}$$

For a pair of target probabilities (PFA, PMD), the number of required samples to achieve the target pair is associated with SNR= / as follows:

$$M = 2\left[\frac{Q^{-1}(P_{FA}) - Q^{-1}(1 - P_{MD})(SNR + 1)}{SNR}\right]^2 \qquad \ldots\ldots. \qquad \text{(VII)}$$

B. *Cooperative Sensing for Multiple Radios*

For the cooperative sensing scenario, single radio sensing decisions from I secondary users are collected at a band of interest by a centralized control channel. From (3), the test statistic for cooperative sensing can be expressed by aggregate sum of I individual test statistics.

$$T_I(Y) = \frac{1}{M}\sum_{i=1}^{I}\sum_{n=1}^{M}|Y_i[n]|^2 \qquad \ldots\ldots \qquad \text{(VIII)}$$

If we assume that signal and noise variances are identical for all secondary users, respectively, i.e. σ2X,i = σ2X, σ2W,i = σ2W for all i, then we can resort to CLT as in the case of single radio sensing.

$$T_I|H_0 \sim N(I\sigma_W^2\,, 2I\sigma_W^4)$$
$$T_I|H_1 \sim N(I(\sigma_X^2 + \sigma_W^2)\,, 2I(\sigma_X^2 + \sigma_W^2)^2) \qquad \ldots\ldots \qquad \text{(IX)}$$

In a same way with (5), we can evaluate false alarm probability PFA,I and missed detection probability PMD,I of cooperative sensing as

$$P_{FA\,,I} = Q\left(\frac{\beta_I - I\sigma_W^2}{\sqrt{2I\sigma_W^4}}\right)$$
$$P_{MD\,,I} = 1 - Q\left(\frac{\beta_I - I(\sigma_X^2 + \sigma_W^2)}{\sqrt{2I(\sigma_X^2 + \sigma_W^2)^2}}\right)\ldots\ldots. \qquad \text{(X)}$$

Given PFA,I , threshold βI is determined by as follows:

$$\beta_I = \sqrt{2I\sigma_W^4}\,Q^{-1}(P_{FA\,,I}) + I\sigma_W^2 \qquad \ldots\ldots.. \qquad \text{(XI)}$$

In order to reach the desired pair (PFA,I , PMD,I), the number of minimum samples required is evaluated by

$$M_I = \frac{2}{I}\left[\frac{Q^{-1}(P_{FA\,,I}) - Q^{-1}(1 - P_{MD\,,I})(SNR + 1)}{SNR}\right]^2$$
$$\ldots.. \qquad \text{(XII)}$$

C. *Binary Hypothesis Testing:*

Example 1: In the case of Radar
H0: y = n.... (Null hypothesis: No target)
H1: y = a + n. (Target present)
Example 2: In the case of Communication
H0: y = −a + n.... (Transmitted symbol is 0.)
H1: y = a + n... (Transmitted symbol is 1.)

Where a is constant and n is noise.
So there are four possibilities for sensing:
Choose H0; H0 true.
Choose H1; H0 true. (False alarm)
Choose H1; H1 true. (Detection)
Choose H0; H1 true. (Miss Detection)

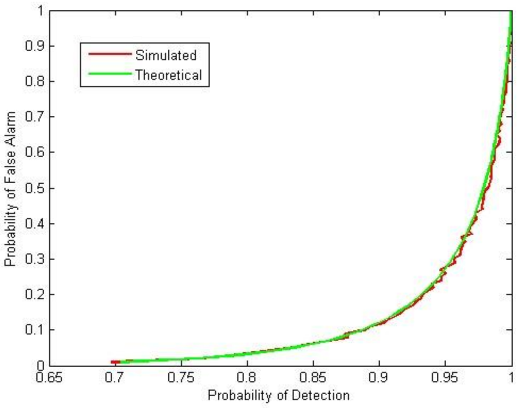

Fig. 3 Curve of Probability of False Alarm vs Probability of Detection for a Cognitive Radio

Fig. 3 shows that probability of false alarm increases when probability of detection increases for proposed algorithm compare to the theoretical value.

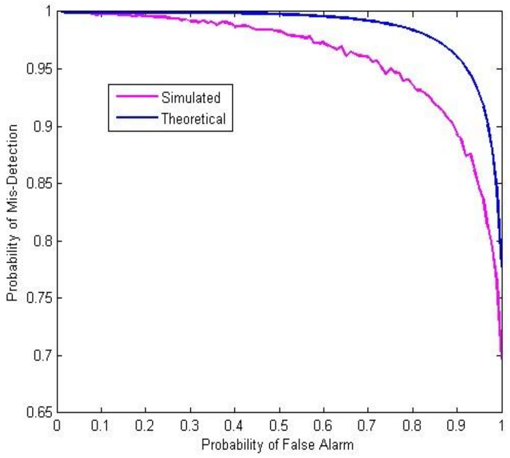

Fig. 4 Curve of Probability of False Alarm vs Probability of Missed Detection for a Cognitive Radio

Figure 4 shows that probability of Missed-detection decreases when the probability of flash alarm increases. So we need to choose an operating point where in the ratio of probability of Missed detection and the probability of false alarm becomes one.

VI. ENERGY DETECTION BASED SENSING

Energy detector based approach, also known periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities. In addition, it is more generic (as compared to methods given in this section) as receivers do not need any knowledge on the primary users signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor [7],[14]. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [7].

Let us assume that the received signal has the following simple form

$$y(n)=s(n)+w(n) \qquad \ldots\ldots\ldots\ldots \qquad \text{(XIII)}$$

Where s(n) is the signal to be detected, w(n) is the additive white Gaussian noise (AWGN) sample, and n is the sample index [7]. Note that s (n) =0 when there is no transmission by primary user. The decision metric for the energy detector can be written as

$$M = \sum_{n=0}^{N} |y(n)|^2 \qquad \ldots\ldots\ldots\ldots\ldots.. \qquad \text{(XIV)}$$

Where N is the size of the observation vector [7]. The decision on the occupancy of a band can be obtained by comparing the decision metric M against a fixed threshold λE. This is equivalent to distinguishing between the following two hypotheses:

$$H0{:}y(n)=w(n) \qquad \ldots\ldots\ldots\ldots\ldots\ldots. \qquad \text{(XV)}$$

$$H1{:}y(n)=s(n)+w(n) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots. \qquad \text{(XVI)}$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection PD and probability of false alarm PF. PD is the probability of detecting a signal on the considered frequency when it truly is present. Thus, a large detection probability is desired [7], [16]. It can be formulated as

$$PD=Pr(M>\lambda E|H1) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(XVII)}$$

PF is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$PF=Pr(M>\lambda E|H0) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(XVIII)}$$

PF should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λE can be selected for finding an optimum balance between PD and PF. However, this requires knowledge of noise and detected signal powers. The noise power can be estimated, but the signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and the distance between the cognitive radio and primary user. In practice, the threshold is chosen to obtain a certain false alarm rate. Hence, knowledge of noise variance is sufficient for selection of a threshold [7]. The white noise can be modeled as a zero-mean Gaussian random variable with variance $\sigma w2$, i.e. $w(n) = N(0,\sigma 2w)$. For a simplified analysis, let us model the signal term as a zero-mean Gaussian variable with variance $\sigma s2$,i.e. $s(n)= N(0,\sigma s2)$.

The threshold used in energy detector based sensing algorithms depends on the noise variance. Consequently, a small noise power estimation error causes significant performance loss. As a solution to this problem, noise level is estimated dynamically by separating the noise and signal subspaces using multiple signal classification (MUSIC) algorithm. Noise variance is obtained as the smallest Eigen value of the incoming signal's autocorrelation. Then, the estimated value is used to choose the threshold for satisfying a constant false alarm rate. An iterative algorithm is proposed to find the decision threshold [7]. The threshold is found iteratively to satisfy a given confidence level i.e. probability of false alarm. Forward methods based on energy measurements are studied for unknown noise power scenarios. The proposed method adaptively estimates the noise level. Therefore, it is suitable for practical cases where noise variance is not known [7], [14].

MATLAB Simulation for Energy Detection Based Sensing:

(1) One slot is free:.

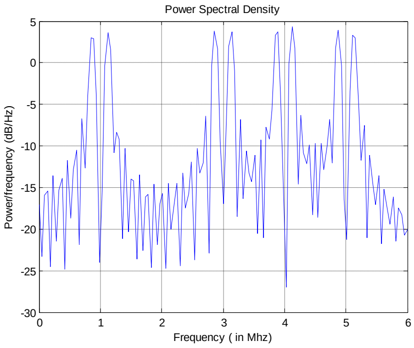

Fig. 5 Graph of Primary Users occupying 1, 3, 4 & 5 slots

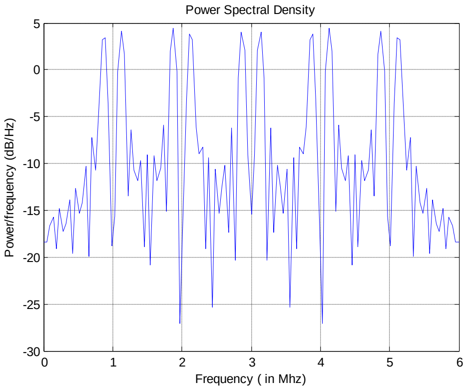

Fig. 6 Graph of Secondary User get 2nd unoccupied slot

(2) Two slots are free:

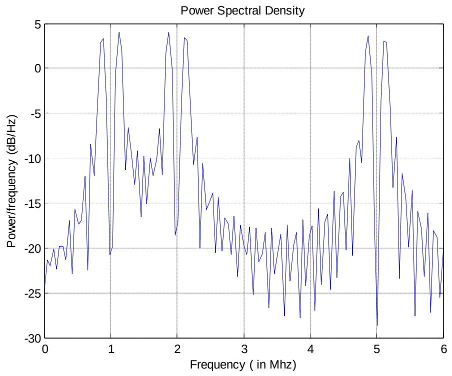

Fig. 7 Graph of primary users Occupying 1, 2 & 5 slots

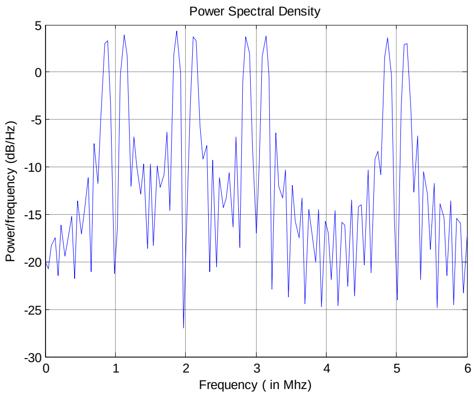

Fig. 8 Graph of secondary user get 3rd unoccupied slot.

VII. CYCLOSTATIONARY FEATURE DETECTION BASED SENSING

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals [7]. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [7].Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users.

The cyclic spectral density (CSD) function of a received signal (1) can be calculated as

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau) e^{-j2\pi f\tau} \ldots\ldots\ldots\ldots \qquad \text{(XIX)}$$

Where

$$R_y^{\alpha}(\tau) = E[y(n+\tau)y^{*}(n-\tau)e^{j2\pi\alpha n}] \quad \ldots. \qquad \text{(XX)}$$

It is the cyclic autocorrelation function (CAF) and α is the cyclic frequency [7]. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal x(n). Cyclic frequencies can be assumed to be known or they can be extracted and used as features for identifying transmitted signals.

The OFDM waveform is altered before transmission in order to generate system specific signatures or cycle-frequencies at certain frequencies. These signatures are then used to provide an effective signal classification mechanism. The number of features generated in the signal is increased in order to increase the robustness against multipath fading. However, this comes at the expense of increased overhead and bandwidth loss [7].

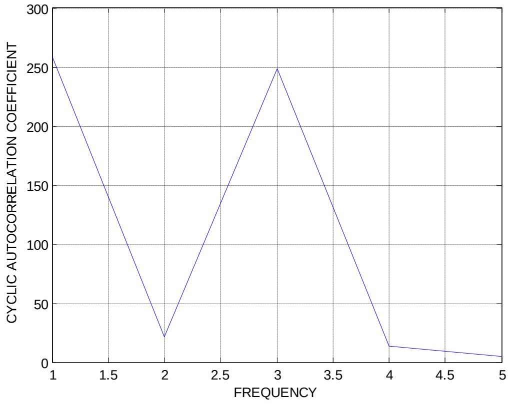

Fig. 9 Graph of cyclic autocorrelation coefficient vs. frequency for cyclostationary Feature Detection when 2nd slot is empty

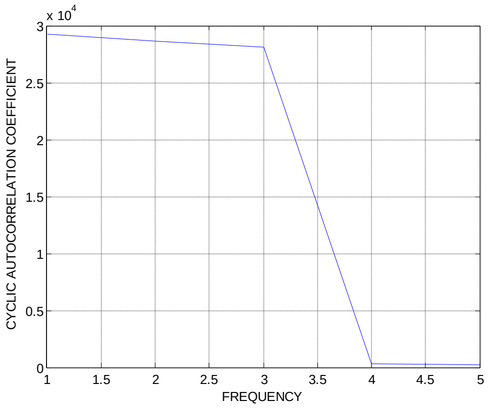

Fig. 10 Graph of cyclic autocorrelation coefficient vs. frequency for cyclostationary Feature Detection when 2nd slot is occupied

In order to compare the performances for different threshold values, receiver operating characteristic (ROC) curves can be used. ROC curves allow us to explore the relationship between the sensitivity (probability of detection) and specificity (false alarm rate) of a sensing method for a variety of different thresholds, thus allowing the determination of an optimal threshold [7].

One of the most challenging issues of spectrum sensing is the hidden terminal problem, which happens when the cognitive radio is shadowed or in deep fade. To address this issue, multiple cognitive radios can be coordinated to perform spectrum sensing. Several recent works have shown that cooperative spectrum sensing can greatly increase the probability of detection in fading channels. In general, cooperative spectrum sensing is performed as follows:

- Step 1: Every cognitive radio i performs local spectrum measurements independently and then makes a binary decision Di ∈ {0,1} for all i=1,•••,K;
- Step 2: All of the cognitive radios forward their binary decisions to a common receiver which is an AP in a wireless LAN or a BS in a cellular network;
- Step 3: The common receiver combines those binary decisions and makes a final decision H0 or H1 to infer the absence or presence of the PU in the observed frequency band.

In the above cooperative spectrum sensing algorithm, each cooperative partner makes a binary decision based on its local observation and then forwards one bit of the decision to the common receiver.

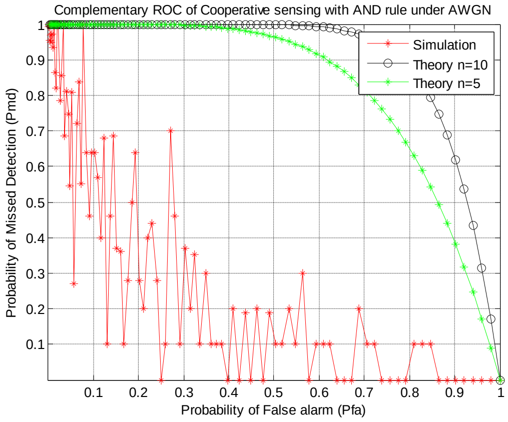

Fig. 11 Complementary ROC of Cooperative Sensing under AWGN Channel

Fig. 11 shows lists the performance results of cooperative spectrum sensing for different numbers of CRs over Rayleigh fading channels with an SNR n = 10 dB. It is seen that the probability of miss detection is greatly reduced when the number of cooperative CRs increases for a given probability of false alarm. Referring K as the sensing diversity order of cooperative spectrum sensing, since it characterizes the error exponent of Pm.

VIII. DIGITAL MODULATION TECHNIQUES

After the conversion of an Analog signal to digital by sampling different type of digital modulation schemes can be achieved by the variation of different parameter of the carrier signal for example the Amplitude variation gives BASK, Frequency variation gives BFSK and the phase variation gives BPSK. Also sometimes a combinational variation of this parameter is done to generate the hybrid modulation technique viz. a combinational variation of Amplitude and Phase Shift Keying (APSK). Many more digital modulation techniques are available and can also be designed depending upon the type of signal and the application Thus a better digital modulation technique is to be thought over by the designer which has an ability of exploiting the available transmitted power and the bandwidth to its full extent. In order to achieve a discrete signal it is essential to have the modulating signal of the form of a NRZ rectangular pulse thus yielding the modulated parameter as a discrete signal switching or keying between two discrete values. However, ASK, FSK, and PSK with Nyquiste pulse shaping at the base band form the basic technique of digital modulation, but other methods are also possible with hybridization of two or more basic digital modulation schemes with or without pulse shaping.

A. *Classification of Digital Modulation*

These digital modulation techniques can be classified basically either on the basis of their detection characteristics or in terms of their bandwidth compaction characteristics.

(1) Binary Amplitude Shift Keying [BASK]

The BASK is obtained by the alteration of the amplitude of the carrier wave. It is a coherent modulation technique hence the concept of the co-relation between the signal, number of basis functions, the I and Q components and the symbol shaping are not applicable here. It has very poor bandwidth efficiency. The basic merit of this technique is its simple implementations but is highly prone to noise and the performance is well established only in the linear region which does not make it a viable digital modulation technique for wireless or mobile application in the present scenario. The combination with PSK yields derivatives like QAM and Mary ASK, which have much important application with improved parameters.

(2) Binary Frequency Shift Keying [BFSK]

When two different frequencies are used to represent two different symbols, then the modulation technique is termed as BFSK.BFSK can be a wideband or a narrow band digital modulation technique depending upon the separation between the two carrier frequencies, though cost effective and provides simple implementations but is not a bandwidth efficient technique and is normally ruled out because of the receiver design complexities.

(3) Binary Phase Shift Keying [BPSK]

When the phase of the carrier wave is altered with reference of the modulating signal then the resultant modulation scheme is termed as Phase Shift Keying. The digital modulation technique can be said to be the simplest form of phase modulation and is known as binary because the carrier phase represents only two phase states. It is normally used for high speed data transfer application, provides a 3dB power advantage over the BASK modulation technique and is robust and simple in implementation but proves to be an inefficient user of the provided bandwidth and is normally termed as a non-linear modulation scheme. It provides small error rates than any other systems. The modulation techniques provide a number of derivatives.

(4) Differential Phase Shift Keying [DPSK]

For the perfect detection of a phase modulated signal, it become evident that the receiver needs a coherent reference signal but if differential encoding and phase shift keying are incorporated together at the transmitter then the digital modulation technique evolved is termed as Differential Phase Shift Keying. For the transmission of a symbol 1, the phase is unchanged whereas for transmission of symbol 0, the phase of the signal is advanced by 1800.The track of the phase change information which becomes essential in determining the relative phase change between the symbols transmitted. The whole process is based on the assumption that the change of phase is very slow to an extent that it can be considered to be almost constant over two bit intervals.

(5) Quadrature Phase Shift Keying (QPSK)

Another extension of the PSK digital modulation technique is the division of the phase of the carrier signal designed by allotting four equally spaced values for the phase angle [1-3] as π/4, 3π/4, 5π/4 and 7π/4,thus providing major advantage over BPSK by having the information capacity double to it, i.e. the QPSK has four message points in the constellation diagram and so it becomes a highly bandwidth efficient digital modulation technique. But the exact phase retrieval becomes a very important factor for the receiver design considerations, failing which can give rise to erroneous detection of the signal.

This factor increases the receiver design complexities. To compensate for these problems, normally the idea of pulse shaping the carrier modulated signal is employed with the Root Raised Cosine Pulse shaping for achieving better performances which in turn provides a demerits that the constant envelope property of the signal is lost but then there is a lost but there is a remarkable improvement in the ISI performance of this digital modulation technique.

(6) Minimum Shift Keying [MSK]

Minimum Shift Keying (MSK) is a modified form of continuous phase FSK. Here, in this case, the spacing between the two carrier frequencies is equal to half of the bit rate which is the minimum spacing that allows the two frequencies states to be orthogonal. An MSK signal can be said to be derived from either an Offset Quadrature Phase Shift Keying (OQPSK) signal by replacing a square pulse by ½ sinusoidal pulse or alternatively from an FSK signal. The information capacity of an MSK signal is equal to that of QPSK signal but due to the ½ cosine pulse shaping the bandwidth requirement is lesser than that required by QPSK.

It achieved smooth phase transitions thus providing a constant envelope. It has lower out of band power and can be said to be more spectrally efficient than the QPSK modulation technique. The major demerits which this digital modulation scheme suffer s is that it is in the class of linear modulation. The spectrum is not enough compact to realize data rate approximating RF channel bandwidth.

Comparing the MATLAB simulation of ROC of cooperative sensing with BPSK and ROC of cooperative sensing with QPSK:

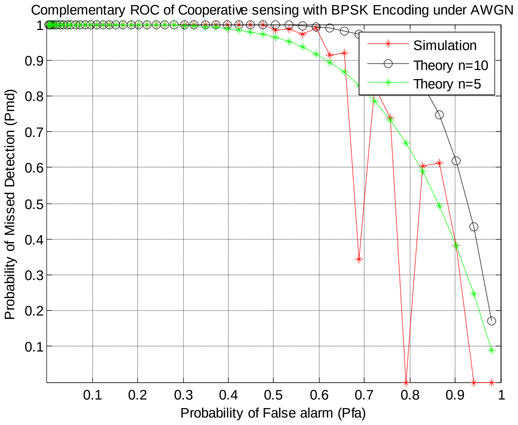

Fig. 12 Complimentary ROC of Cooperative Sensing with BPSK Encoding under AWGN Channel – Probability of Mis-Detection vs Probability of False Alarm

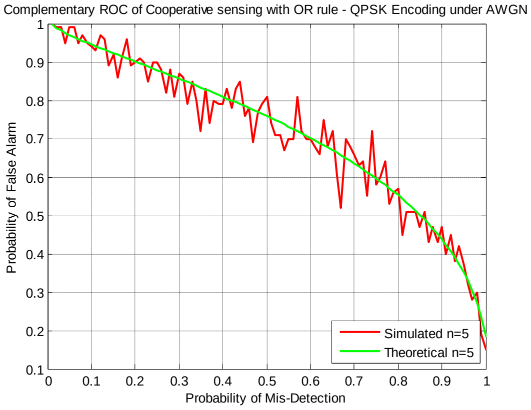

Fig. 13 Complimentary ROC of Cooperative Sensing with QPSK Encoding under AWGN Channel – Probability of Mis-Detection vs Probability of False Alarm

IX. CONCLUSION

With the increasing demand for radio spectrum on one hand and inefficient usage of the licensed bands on the other, a reform of the spectrum access policy seems inevitable. Opportunistic spectrum access is envisioned to resolve the spectrum scarcity by allowing unlicensed users to dynamically utilize white spaces across the licensed spectrum on a non-interfering basis. Cognitive radio networks offer a low-cost backward-compatible implementation of this novel paradigm thanks to their ability to autonomously identify white spaces and react to variations in spectrum usage and operation environment.
As discussed earlier, under fading or shadowing, a cognitive radio requires higher detection sensitivity in order to overcome the uncertainty introduced by channel randomness. The resultant sensitivity requirement may end up being too stringent as the cognitive radio has to maintain its sensing reliability even under worst case fading or shadowing. On the other hand, multipath fading effects vary significantly depending on the receiver's location, and users placed more than a few wavelengths apart are expected to experience independent fading. Therefore, the uncertainty due to fading may be mitigated by allowing different users to share their sensing results and cooperatively decide on the licensed spectrum

occupancy. The diversity gain achieved through such cooperative spectrum sensing improves the overall detection sensitivity without imposing higher sensitivity requirements on individual cognitive radios. Evidently, cooperative sensing enables users to employ less sensitive detectors. A less stringent sensitivity requirement is particularly appealing from the implementation point of view due to the reduced hardware cost and complexity. We note, however, that realizing such potential cost savings demands some flexibility in terms of access policies.

In particular, opportunistic spectrum access for a network of cooperating secondary users should be regulated based on their capabilities as a group rather than individual users. In that sense a group of cognitive radios should be permitted to cooperatively access a licensed band otherwise restricted to any of them individually.
Using remaining modulation techniques like PSK, MSK etc. more results can be compared.

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