ISSN: 2229-6948(ONLINE)
DOI: 10.21917/ijct.2021.0347

CASE STUDIES OF ENERGY-BASED RADIO FREQUENCY SPECTRUM SENSING TECHNIQUE FOR COGNITIVE RADIO NETWORKS

K.S. Shilpa, P. Trinatha Rao and Sunita Panda
Department of Electronics and Communication Engineering, GITAM School of Technology, India

Abstract

The trend to overcome wireless interference emerged in techniques like frequency agility, hopping, dual band technologies etc. However, these techniques suppress inter-operability of wireless technologies operating at the same frequency like Wi-Fi, ZigBee, Bluetooth, Z-Wave, etc. As a result, in the unlicensed wireless public infrastructures bandwidth available for usage is becoming short of hand and utilizing only licensed band increases cost of ownership which cannot be sustained by public infrastructures and developing countries. Thus, new digital era requires a technology which can help overcome the foresaid challenges that can utilize both licensed and unlicensed spectrums through adaptive methodologies that ensures very high wireless communication availability in circumstances of bandwidth non-availability due to overcrowding or wireless interference at lower affordable cost. Thus, a group of radio that forms a network designed for this purpose is called Cognitive Radio Network (CRN). In the proposed paper an effort is made to provide simulated performance analysis insight of novel energy-based channel sensing mechanism which is the crucial aspect of spectrum management in cognitive radios. In simulation the mechanism is analysed for different cases in which combination of both real and complex information and noise signals are used. Through proper results and graphs different factors for consideration are presented. Sensing in co-operative cognitive networks is also discussed, addressing different issues like bandwidth, quantisation techniques, detection accuracy etc. that may help fellow researcher to continue the further developments with less time and efforts.

Keywords:

Cognitive Radio Networks, Energy Based Sensing, Null Hypothesis, Low SNR, Complex Gaussian Noise

1. INTRODUCTION

Cognitive Radio (CR) is a new intelligent concept for wireless communication which is an extension of Software Defined Radio (SDR) that senses and monitors its external environment and internal state making decisions about their radio operating behavior based on sensed information and predefined objective. It dynamically selects the frequency of operation and also dynamically adjusts its transmitter parameters such as transmission power, operating frequency, type of modulation, frame format etc. The core potential advantages introduced by cognitive radio are improved spectrum utilization, network reconfigurability and increased communication quality. A wireless network with the capabilities of radio environment awareness, autonomous decision making, adaptive reconfiguration and intelligent learning from experience of a continuously varying environment called as cognitive radio network (CRN) is proposed which is an interconnection of several cognitive radios to solve the challenges of efficient radio resource utilization and heterogeneous network convergence with the aim of improving the end-to-end performance of wireless communication networks.

Spectrum sensing in spectrum management process is the important and challenging technology for both low and high signal to noise ratios of transmitted primary signal for a broad class of cognitive radio communications involving spectrum alertness by detecting spectrum holes by secondary users (SUs) without causing intervention to the primary users (PUs). Co-operative type of behaviour in sensing the spectrum helps in obtaining good sensing results which involves multiple secondary users and a single decision making node. In order to support this there are choices of decision making rules that help in achieving the acceptable good sensing performance.

The paper is organized as follows. Brief discussion on basics of cognitive radio networks (CRNs) is covered in section 2. Section 3 deals with a flow chart that clearly explains the process of spectrum management in cognitive radio networks. Categorization, issues and performance measurement parameters of spectrum sensing are provided in section 4. Statistical analysis incorporated in the energy-based sensing mechanism under study is provided in section 5. Brief discussion on co-operative spectrum sensing methodology is carried out in section 6. Details of simulation environment, parameters and simulation results are presented in section 7 and conclusion is provided in section 8.

2. COGNITIVE RADIO TECHNOLOGY

Unlike software defined radios having only traditional radio and software functionality support, the technology that provides extended functionalities such as intelligent assessment capability and reconfigurability along with traditional radio and software functionality is the cognitive radio [1].

Cognitive radio network is a multiuser, multifaceted wireless communication system with users embedded with intelligent cognitive radio in them designed to offer most resourceful utilization of underutilized free and licensed radio frequency spectrums [1]. Secondary networks, Dynamic spectrum access wireless systems or unlicensed networks are the other possible ways of calling CRNs.

Classification of CRNs includes Infrastructure based CRNs (Centralized architecture) e.g. CRAHNs and Infrastructure-less CRNs (Distributed architecture) e.g. CRCNs and CR-WRANs.

The architecture of the cognitive radio network [2] includes four components of CRNs include Primary user (PU), Secondary user (SU), PU base station and CR/SU base station. The primary users also called licensed users use their respective licensed bandwidth for transmission of data. The secondary user's also known as unlicensed users have permission to use the unlicensed bands of frequency as well as available licensed band of primary users.

The SUs request for the channel when in need for its communication to CR base station. Then CR base station looks for the free band by performing sensing operation and allots free frequency bands to the SUs.

Depending on the type of operation the respective channels showed in the figure are utilized. PUs transmits data over licensed channels only. The SUs utilize unlicensed channel and available licensed channels by detecting PU activity over this channel. Furthermore, if PUs are found within the licensed spectrum at any time then they have to leave the channel as soon as possible and shift to other available channel. In the presence of multiple SUs, they have to contend among themselves to access the licensed portion of the spectrum.

3. SPECTRUM MANAGEMENT IN CRNS

The Fig.1 displays the steps in the form of flow chart that gives clear understanding of management of spectrum bandwidth in cognitive radio networks by cognitive radios.

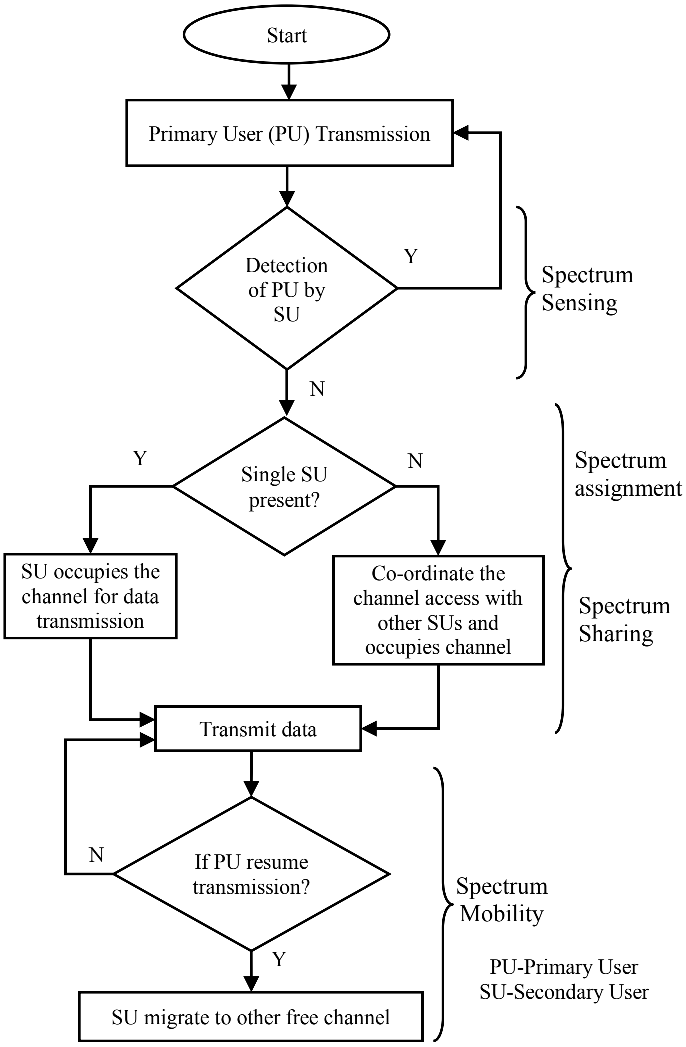

Fig.1. Process of Spectrum Management by Cognitive Radios

It Involves Spectrum sensing, Spectrum assignment, Spectrum sharing and Spectrum mobility.

- ***Spectrum Sensing***: It is the initial and important step in the cognitive wireless systems' spectrum management process involving spectrum agility through finding free frequency bands without disturbing PU activity.
- ***Spectrum Assignment***: Utilization of the spectrum holes (free bands) in cognitive networks requires dynamic bandwidth allocation for correct and effective use of the resources reducing the interference between secondary and primary users. The spectrum allocation in CR networks face many design problems such as interference, connectivity, stability, throughput and fault tolerance.
- ***Spectrum Sharing***: When a secondary user is utilizing the licensed band of primary user for its data transmission and if the other SUs in the network prefer to transfer the data at the same time over the same licensed bandwidth, then multiple SUs are supposed to share and utilize the spectrum by coordinating among themselves which is known as spectrum sharing to prevent collisions and any intervention to the possible extent [3]. This appreciably improves the spectrum efficiency in CRNs. The three techniques used to facilitate spectrum sharing process are underlay, overlay, and interweave [4].
- ***Spectrum Mobility***: In rapidly changing surroundings, the secondary users' communications are disturbed often when the primary user reappears. Since the PU has higher priority than SU, it is required to give up the occupied channel by SU and switch to some other available channel enabling continuous data transmission termed as spectrum mobility.

4. SPECTRUM SENSING

In CRNs, each radio must sense the surrounding spectral environment to learn about incumbents or interferers, from which it determines the availability and non-availability of spectrum bands for its communication and physical layer radio parameters to be used. This is known as spectrum sensing by cognitive radio in a network. The detection behaviour in spectrum sensing can be classified into two types: non-cooperative behaviour and co-operative behaviour. The comparison of these detection behaviour is given in Table.1.

Table.1. Comparison of detection behaviour

Parameter	Spectrum detection behaviour	
	Non co-operative	Co-operative
Agility	Average	Good
Performance accuracy	Less	More
Overhead traffic	Less	More
Total energy consumption	Average	Poor
Fairness of energy consumption	Good	Average
Robust against SNR	Poor	Average

4.1 CATEGORIZATION OF SPECTRUM SENSING METHODS [1]

4.1.1 On the Type of Estimation:

Direct method, in which judgement of channel occupancy is obtained directly from the signal using the frequency domain approach. Another method in which the judgement is available from the autocorrelation of signal using the time domain approach indirectly.

4.1.2 On the Need for Spectrum Sensing:

There are 3 categories under this section. They are discussed below.

- ***Primary Transmitter detection***: In this transmitted PU signal is detected by the local interpretations from the SUs in a particular band at any given instant of time. There are three different sensing techniques under this category.
- ***Energy Detector***: This technique of sensing PU is the basic and well accepted among research community that need not have any prior information regarding primary user. Finding the appropriate detection threshold to finalize the existence or nonexistence of PUs is a challenging task since it depends on the noise variance. Study of detection theory and hypothesis testing need to be understood thoroughly for this purpose. It also depends on type of noise and type of PU signals considered. Further after deciding the correct known threshold value the received signal's energy is compared with that for knowing the presence or lack of signal. Double threshold energy detectors, Improved energy detectors, adaptive double thresholds detectors are also been implemented by various researchers.
- ***Matched Filter Detector***: This is an optimum technique of PU sensing and detection because matched filter tries to maximize the signal to noise ratio even in the presence of large amount of noise. But this method requires some information regarding PU signal beforehand like kind of digital/analog modulation techniques being applied on the signal, shape of the pulse etc. Hence CRs need to be equipped with timing and carrier recovery circuits and other devices that raise the application complexity.
- ***Cyclostationary Feature Detection***: Since many of the signals transmitted exhibit periodical or regular features existing in modulation techniques, carrier signals, cyclic prefix method to avoid ISI and few other characteristics and in contrast noise do not have any kind of periodicity nature in it. This helps the technique to distinguish and identify the PU signals more efficiently.

Comparison of primary transmitter detection sensing techniques is given in Table.2. Receiver uncertainty and shadowing problems are the main drawbacks of transmitter detection techniques.

- ***Primary Receiver Detection***: In order to address or mitigate receiver's uncertainty, other techniques for spectrum sensing were initiated where few amount of information regarding receiver is known from its self-structure. They are: Local oscillator leakage and Sensor nodes for receiver detection methods.
- ***Interference Temperature Management***: It is an interference management technique. The concept being used in this technique is setting a certain upper bound interference boundary in a given frequency band of operation for a particular environmental area and taken care that secondary CR nodes should not produce any sort of interference to primary users while using the same bandwidth in the same region [1].

4.1.3 On Sensing Frequency Range:

Wideband and Narrowband spectrum sensing techniques come under this category.

Table.2. Comparison of transmitter detection sensing techniques

Parameter	Spectrum Sensing Technique		
	Energy detector sensing technique	**Matched filter sensing technique**	**Cyclostationary feature Detection**
Implementation	Simple	Optimal	High computational complexity
SNR	Less efficient only under hypothesis 1 in low SNR regimes	Maximize SNR even in the presence of noise	Robust in low SNR
Detection time	High	Less	High
Detection performance	Better	Good	Optimal
Accuracy	Less	Highest	Less

4.2 ISSUES AND CHALLENGES

Large numbers of uncertainties are to be considered to provide solution for the various issues of spectrum sensing in CRNs. Those include channel uncertainty due to channel fading and shadowing, noise and aggregate interference uncertainty where user level co-operation among different CRs and system level cooperation among different CRNs need to be considered and sensing interference limit [5] [6].

4.3 OPTIMISATION ALGORITHMS IN CRNS FOR SPECTRUM SENSING

Variety of modern heuristic algorithms is designed to provide solution for numeric optimization problems, such as: population based algorithms, stochastic algorithms and iterative based algorithms. Population based algorithms can be sub-divided into 2 groups such as evolutionary algorithms & swarm intelligence based algorithms.

4.4 PERFORMANCE MEASUREMENT OF SPECTRUM SENSING

There are three probabilities which are important to measure or consider when performing spectrum sensing in cognitive radio networks. First, the probability of detection (P_D) defined during the presence of primary user transmission, which is stated as the probability of rightly declaring the presence of PU activity. Secondly probability of false alarm (P_{FA}), that is defined when PU activity is absent, as the probability of wrongly declaring the presence of PU signal. Third, probability of missed detection (P_M), which is defined as probability of not detecting the PU signal even though it is present in the respective sensing bandwidth. Good detection prefers more detection probability and lesser values of false alarm and missed detection probabilities [7].

In this paper it is concentrated and discussed on energy-based signal detection sensing mechanism which is one of the primary transmitter detection mechanisms that comes under the category of sensing need. Concentrated on simulating and troubleshooting the mechanism under different scenarios considered and study on how to improve the effectiveness of the mechanism using different advanced concepts and ideas.

5. STATISTICAL ANALYSIS USED IN THE DETECTION MECHANISM

The modern detection theory is the basis for decision making and information extraction. The approach towards the design of energy detection based spectrum sensing to find the occurrence or absence of signal is the theory of hypothesis testing. There exist two types of testing like multiple and binary hypothesis testing. The main objective is to decide whether the information signal from primary user is present which is usually associated with noise or only noise signal is present, hence binary hypothesis testing is employed. The classic approach in solving the problem of detection in a best possible way is a Neymann Pearson approach [8].

Thus if $S(n)$ indicates signal sample transmitted by primary user and $u(n)$ is noise sample added, $Z(n)$ is the signal sample received by secondary user then,

Hypothesis 1, the case when information signal is received by end user along with noise is given by,

$$Z(n)=S(n)+u(n). \tag{1}$$

Hypothesis 0 or null hypothesis, the case when no signal i.e. only noise is received is given by,

$$Z(n)=u(n) \tag{2}$$

The equation for the probability of detection P_D for selected threshold ε is given by,

$$P_D = Q\left(\left(\frac{\varepsilon}{\sigma^2} - SNR_r - 1\right)\sqrt{\frac{N}{2SNR_r + 1}}\right) \tag{3}$$

where, σ^2 is the variance of noise signal, $Q(\cdot)$ is the Q function and SNR_r is the received signal-to-noise ratio of PU signal at the SU receiver and N denotes the total number of samples considered for processing and N is the maximum integer value which is not greater than τf_s where, f_s is the sampling frequency of the information signal, τ is the sensing time and for simplicity we choose $N=\tau f_s$.

Therefore the threshold for the particular probability of false alarm can be calculated by,

$$\varepsilon = \frac{Q^{-1}\left(P_{FA}\right)\cdot\sigma^2}{\sqrt{N}} + 1 \tag{4}$$

Also for a given probability of false alarm P_{FA}, the probability of detection is expressed as,

$$P_D = Q\left(\left(Q^{-1}\left(P_{FA}\right) - SNR_r\sqrt{N}\right)\sqrt{\frac{1}{2SNR_r + 1}}\right) \tag{5}$$

6. CO-OPERATIVE SPECTRUM SENSING

In this, the information from multiple secondary CR users is combined to detect the PUs. This has emerged as a possible efficient sensing behaviour when there are densely populated nodes and nodes suffer strength degradation due to various factors such as shadowing problem, multipath fading, hidden node problem etc. which will improve its usability [2]. This behaviour along with energy-based determination of primary signals provides more accurate sensing performance than non-cooperative mechanism but at the cost of extra overheads and functions which will further increase the bandwidth usage and complexity respectively. Group based co-operative spectrum sensing methodology has been proposed by researchers to reduce reporting overhead or bandwidth [9]. Also incorporating group based CSS along with machine learning techniques for decision fusing improve the detection performance to a greater extent along with significant reduction in bandwidth [9]. Many other approaches are being studied and implemented at different levels of communication system such as quantization techniques like multibit and single bit group based CSS[10], type of modulation techniques used at physical layer etc. to reduce the overheads to minimize the bandwidth usage.

There is other type of spectrum sensing behaviour called as Non co-operative sensing. In this secondary CR users are self-sufficient in sensing and identifying PU transmitter signal from its individual study and surveillance irrespective of the presence of other secondary users.

There are 2 ways for the implementation of co-operative detection behaviour, (i) Centralised cooperative detection mechanism in which a master node aggregates the data or decisions from all the SUs and apply various fusion rules on the data such as soft decision rules, hard decision rules, machine learning algorithms etc. to accurately know the activity of transmitted primary user signal. (ii) Distributed cooperative detection mechanism [11].

6.1 FUSION RULES IN CSS

These are the protocols that are followed or executed by the master node called fusion center or decision center to ultimately decide the activity of the PU. The Fig.2 shows the classification of fusion rules that are used at the master node.

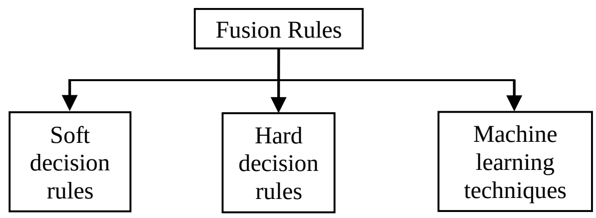

Fig.2. Classification of Fusion rules

- ***Soft Decision Rules (Data fusion rules)***: Process the measurements from all the secondary users together and then make final decision based on the calculated statistics.
- ***Hard Decision Rules (Decision Fusion Rules)***: The final decision is made by fusing the individual decisions made by secondary users.

- ***Machine Learning Classification Algorithms***: The pattern classification algorithms are used wherein the received sample energy at the secondary user are treated as features and given to classifier to detect the availability or non-availability of primary user signal. Each occurrence of PU activity is categorized into separate classes by obtaining a best hyperplane between the classes [12].

The Table.3 shows the comparison of the above said fusion rules.

Table.3. Comparison of Fusion Rules

Parameter	Fusion rules		
	Soft decision rules	**Hard decision rules**	**Machine learning techniques**
Nature of operation	Traditional	Traditional	Smart and intelligent method for co-operation among SUs
Bandwidth	More bandwidth at reporting channel	Less bandwidth at reporting channel	More bandwidth at reporting channel
Detection performance	Better	Less	Good
Energy consumption	More	Less	More
Reporting errors	Co-operation with soft scheme is more sensitive to reporting errors	Co-operation with hard scheme is less sensitive to reporting errors	Fewer errors
Computation complexity	Complex	Simple	Less Complex
Performance stability	Better	Degraded than soft decision rule	More

7. RESULTS AND DISCUSSIONS

Simulation is carried out in Matlab 2018a. The topology considered for simulation includes a single primary user and a single secondary user. The nature of noise considered is both real and complex Gaussian and different type of signals are taken into account such as real valued random signal, complex valued signal and Binary phase shift keyed modulated carrier signal. Throughout the experimentation the relative variance of the noise with respect to signal is considered and the design model considered is Monte Carlo simulations to calculate practical values of probability of detection.

- **Scenario 1**: Real valued random PU signal and real valued random white Gaussian noise with mean zero and relative power.

In this case false alarm probability is kept constant to 0.2, number of samples considered for detection is 800 and number of Monte Carlo simulations considered are 10000.The primary user signal's SNR values are varied from -30 dB to +30dB.

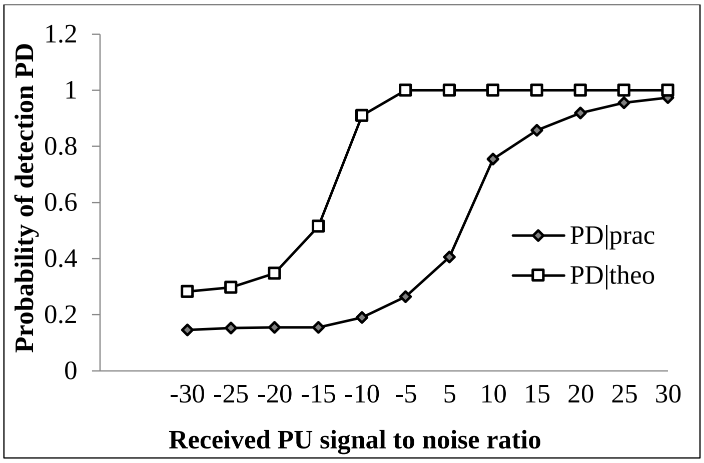

Fig.3. p_d vs. SNR

From the Fig.3, it can be inferred that as primary user signal's signal to noise value increases the detection probability is increased.

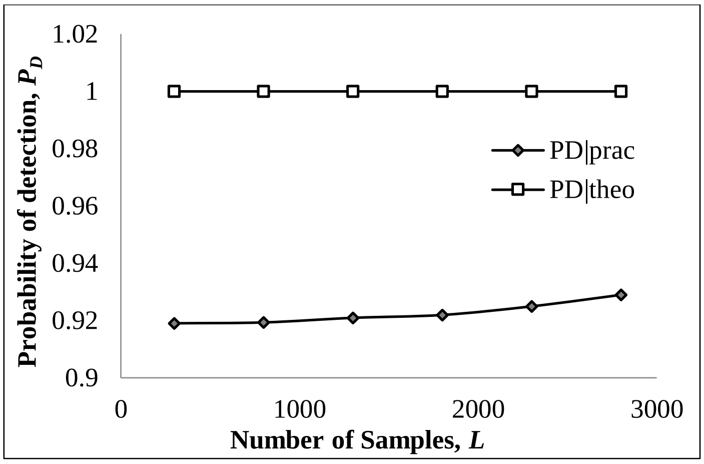

Fig.4. P_D vs. L for fixed high SNR

From the Fig.4, it is observed that for the fixed higher SNR values, when the number of samples (L) considered for detection process increases then we can get better probability of detection. Here the parameters considered are fixed false alarm probability as 0.2, primary user SNR as +20dB. Calculated practical and theoretical probability of detections and plotted the observations.

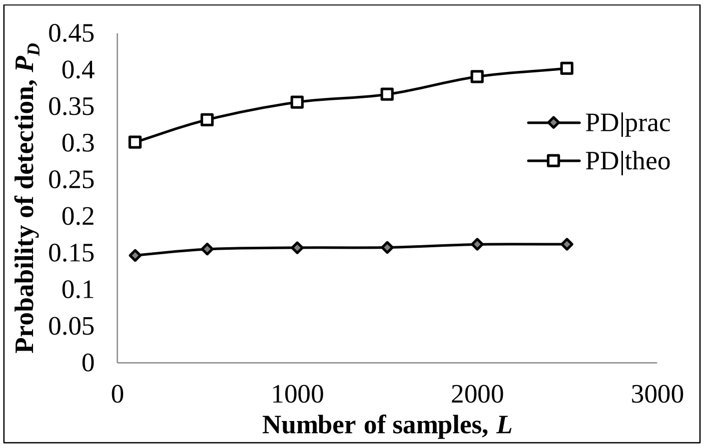

Fig.5. P_D vs. L for fixed low SNRs

The Fig.5 shows the plot for variance of probability of detection with the different values of L (No. of samples). It is clear from simulation results that for the interested fixed lower value of primary signal SNR, if we increase the number of samples under consideration then the probability of detection also increases.

Table.4. Scenario 1 PU activity status representation

Region of SNR	Transmitted signal by PU	PU signal status by SU	
		Present	Absent
High	signal +noise	Yes	-
	noise	-	Yes
Low	signal +noise	-	Yes
	noise	-	Yes

The Table.4 shows the status of PU activity obtained in case of scenario 1.It is observed that at high signal to noise ratio values, under the hypothesis 1 when both signal and noise are transmitted by primary user and under null hypothesis where only signal is transmitted, PU signal is detected correctly. At low signal to noise ratio region, under hypothesis 0 detection is correct but under hypothesis 1 when signal is transmitted along with noise, the detection is wrong i.e. problem of missed detection is noticed.

- **Scenario 2**: Deterministic Binary phase shift modulated PU signal and real random valued White Gaussian noise with mean as zero and appropriate variance depending on signal power are considered.

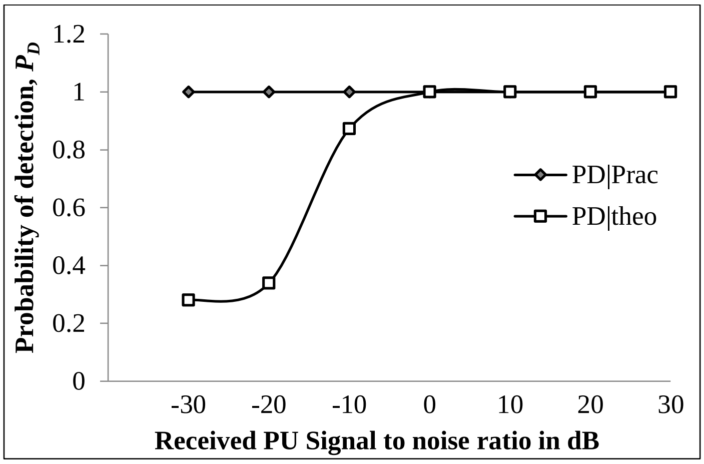

Fig.6. Probability of Detection (P_D) vs. SNR of PU user

The Fig.6 shows that as the signal to noise ratio value of the primary user signal increases the detection probability also increases. In this case the parameters considered are fixed false alarm probability as 0.2, number of Monte Carlo simulations considered are 10000 and number of samples considered are 800.

The Table.5 below shows the PU activity status for the scenario 2. Accordingly it is observed from the experiments that in this combination of signal and noise types, at both high and low SNR regimes, under hypothesis 1 and 0 the detection is correct and energy detector is working fine.

Table.5. Scenario 2 PU activity status representation

Region of SNR	Transmitted signal by PU	PU signal status by SU	
		Present	Absent
High	signal +noise	Yes	-
	noise	-	Yes
Low	signal +noise	Yes	-
	noise	-	Yes

- **Scenario 3**: Binary phase shift modulated PU signal which is deterministic and known deterministic real valued white Gaussian noise with mean value zero and appropriate variance depending on signal power is considered for analysis.

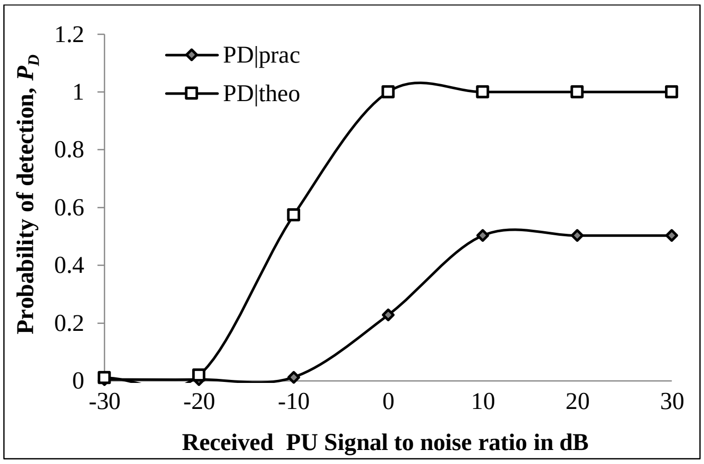

Fig.7. P_D vs. SNR

The Fig.7 above shows that for a varying range of low and high PU signal SNRs, the detection probability increases with the increase in the SNR values. The parameters considered in this scenario are fixed false alarm probability as 0.2 and number of samples considered is 800.

The Table.6 shows the primary user signal status for the scenario 3 considered. Results show that at high value of PU signal SNRs, under both the hypotheses detection is correct. But at the low SNR values, under hypothesis 1 missed detection is noticed i.e. even though the PU signal is being transmitted detector is unable to detect.

Table.6. Scenario 3 PU activity status representation

Region of SNR	Transmitted signal by PU	PU signal status by SU	
		Present	Absent
High	signal + noise	Yes	-
	noise	-	Yes
Low	signal + noise	-	Yes
	noise	-	Yes

- **Scenario 4**: PU signal is deterministic PSK modulated signal and noise is known deterministic circularly symmetric complex Gaussian (CSCG) noise for the purpose of analysis.

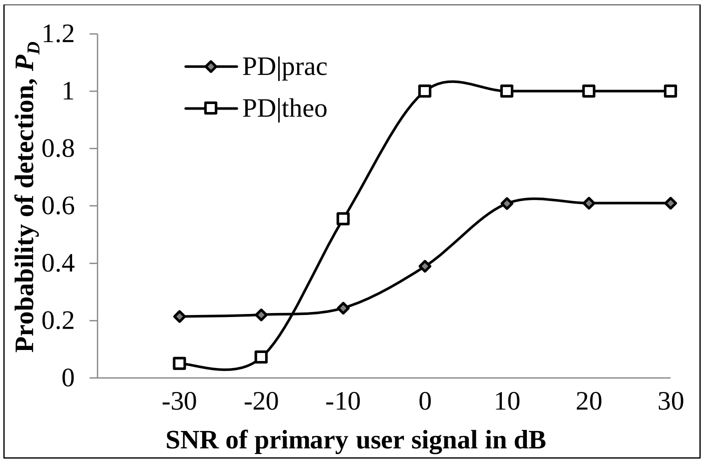

Fig.8. Probability of Detection (P_D) vs. SNR of PU user

The Fig.8 shows that the detection probability (P_D) increases as the SNR value of PU signal increases. The parameters set in this scenario are fixed false alarm probability of 0.2 and number of samples considered are 800.

The PU signal availability status under this case is obtained as given in the Table.7. In this case it is found that energy detector is working correctly for high SNR regime under both the hypotheses and for low SNR regime under hypothesis 0. But having a missed detection issue only at low SNR regime under hypothesis 1.

Table.7. Scenario 4 PU activity status representation

Region of SNR	Transmitted signal by PU	PU signal status by SU	
		Present	Absent
High	signal +noise	Yes	-
	Noise	-	Yes
Low	signal +noise	-	Yes
	Noise	-	Yes

8. CONCLUSION

In this paper, a simulation based case study analysis of energy based spectrum sensing is carried out for different combination of signal and noise types. The performance metrics considered is the variation of probability of detection with respect to primary user's SNR and no. of samples. The parameter of interest was improving this type of sensing even under lower signal to noise ratio regions for correct signal detection. It is found from the analysis that in the case of scenario 2 the energy detector sensing is working fine under both the SNR regimes and at both the hypotheses and for all the remaining scenarios considered energy detector is detecting the primary signal properly at high SNRs under both hypotheses and at low SNRs, under hypothesis 0.The problem of missed detection is observed only under hypothesis 1 at low SNR regimes. This can be due to multipath fading, shadowing effect or hidden node problem in real time applications. Hence from the later study followed by simulation results in the paper the possible solution to this missed detection issue at lower SNRs under hypothesis 1 can be overcome by employing virtual co-operation among multiple secondary users which is called co-operative spectrum sensing that has to be supported with various advanced decision fusion rules. Advanced and improved CSS schemes can also provide best detection performance.

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