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ENERGY BASED SPECTRUM SENSING, POWER SPECTRUM ESTIMATION AND PAPR ANALYSIS FOR COGNITIVE RADIO NETWORKS

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ABSTRACT

An electro magnetic spectrum is the source for all wireless communication. However, communication in this medium is often interrupted by complications such as hidden terminal problem. noise uncertainty and channel uncertainty. In order to provide an efficient solution, in this paper, we propose an energy based spectrum sensing, power spectrum estimation and analysis for cognitive radio networks. In this technique, two hypothesis are used to identify the presence and absence of primary users in the channel. When the channel is not used by primary users the slots are allocated for secondary users. Further, power spectrum is estimated by means of five different methods. Finally, PAPR analysis is performed using the complementary cumulative distribution function (CCDF). The proposed technique is simulated in MATLAB.

Keywords: *Electro Magnetic Spectrum, CCDF, PAPR, Wireless Communication, Power Spectrum*

1. INTRODUCTION

1.1 Cognitive Radio Networks (CRN)

One of the valuable natural licensed resources with limited physical extent is termed as the electromagnetic radio spectrum. To assure security and reliability of wireless communication, spectrum is administered by governments. An innovative way of observing wireless communication is through Cognitive Radio (CR). It has the capacity to rectify the problem of spectrum underutilization. Run of the mill wireless applications are increasing without numbering. This expansion of applications brings in challenging state of affairs in wireless communications. Allocating spectrum statistically leads to the problem of under utilization [1] [2] [3].

The cognitive radio is described as a auspicious technology to get better efficiency in spectrum utilization as it allocates unused frequency bands to other looked for applications [4]. Cognitive radios are radio systems that help for utilization of spectrum. cognitive radios are continuous spectrum sensing, recognizing unused spectrum and allocating spectrum holes when primary (licensed) systems are in idle state [5].

Customer’s growing needs such as wireless, reduced size, intelligent and flexibility put forward greater demand for wireless communication systems. Smart phones, tablets, netbooks and personal digital assistant (PDA’s) are some of the case in point of latest wireless practical devices. [6]

1.2 Spectrum Sensing

The process of monitoring spectrum for the presence and absence of primary users and allocating slots to secondary users when primary users are in idle state and then reallocating slots back to primary users when they enter into active state. The entire process is termed as spectrum sensing. Hidden node problem and interference to primary users are the main disputes of spectrum sensing [2].

In cognitive radio networks, spectrum sensing is termed as the significant utility function. Weak primary radio signals are identified by spectrum sensing usually of unidentified signal types. It also observes the network for deallocating the spectrum holes once primary users entered into active state. [5] A lot of spectrum sensing techniques have been proposed among that matched filtering, energy

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detection and cyclostationary feature detection are the well-known spectrum sensing techniques. [2]

- **Energy Detection technique**

This technique can be exploited when cognitive radio lacks any information about primary user. It gives details of presence and absence of primary user by calculating received signal in the band of interest and it compares the calculated energy with a predefined threshold and decides the result.

- **Matched filtering**

When the sensing technique obtains adequate information about primary user, this method can be used as spectrum sensing technique.

- **Cyclostationary feature detection**

For recognizing the spectrum occupancy this technique makes use of hidden periodicities in the signal of primary user.

1.2.1 Challenges in Spectrum Sensing

Hidden terminal problem is the challenging task in spectrum sensing. Owing to this problem, secondary user accesses the communication medium unaware of primary user (licensed) and introduces interference to the primary user. Some of the causes of hidden terminal problem are cruel multipath fading and high penetration loss. [7]

Other than hidden terminal problem there are a lot of disputes associated with spectrum sensing are uncertainty in channel, aggregation interface and noise, interface limit. [2]

1.2.2 Spectrum Mobility Issues

- To switch over frequency bands when required, a cognitive radio ought to store the available bandwidths.
- It is possible that spectrum handoff, modification and adaptation to other components may put forward high latency in the protocol stack.
- During spectrum handoff performed by secondary users, two essential criteria's have to be considered. First, channel must be free of primary user and secondly, notification has to be forwarded to the receiver of secondary link. [2]

1.3 Problem Identification

From a pool of research work in this area, we have presented some spectrum sensing works in section-2. As of it we could observe that some works didn't contain any practical scenario for implementation of cognitive radio network. Though there are many methods exist to find the power spectral estimation, only few methods are implemented. There is no work which addresses spectrum sensing and analysis both combined. OFDM shows lower performances in existing works.

Objectives

The following are the objectives of the proposed solution.

- To propose an energy based spectrum sensing technique.
- Power spectrum estimation using Periodogram, Correlogram, Blackman tukey Barlett and Welch techniques and comparison
- To perform PAPR analysis using OFDM and Wavelet Packet Modulation (WPM)

The paper is structured as follows,

Section-2 Literature review
Section-3 Proposed solution
Section-4 Simulation results
Section-5 Conclusion

2. LITERATURE REVIEW

In paper [4], F. L. Liu et al. have presented a new wideband spectrum sensing algorithm. Their algorithm is based on compressed sensing theory. Their method gives an effective sparse signal representation method for the wideband spectrum sensing problem. It is also analyzed that the presented method can effectively detect all spectral holes by finding the sparse coefficients. At the same time, the signal sampling rate and acquisition costs can be substantially reduced by using the compressive sampling technique.

Zhi Quan et al. [5] have proposed an optimal linear cooperation framework for spectrum sensing to precisely detect the weak primary signal. Within this framework, spectrum sensing is based on the linear combination of local statistics from individual cognitive radios. The main objective of their technique is to minimize the interference to the primary radio while meeting the requirement of opportunistic spectrum utilization.

Wael Guibene et al. [6] have presented a spectrum sensing algorithm for wideband cognitive radio. Their algorithm makes use of sensed spectrum discontinuity properties. They have examined an algebraic framework so as to design spectrum discontinuities. The information derived

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at the level of these irregularities will be used in order to derive a spectrum sensing algorithm.

Muthumeenakshi K et al. [7] have presented a realistic cognitive radio network. Their architecture has considered both the sensing and reporting channels to be affected by noise uncertainties. The channel uncertainties considered are Additive White Gaussian Noise (AWGN) and Rayleigh fading. Energy Detection is used at the individual secondary nodes for spectrum sensing. To diminish the effects rooted in a noisy environment, they have used two detectors namely Minimum Mean Square Error (MMSE) detector and Maximum Likelihood (ML) detector at the receiving end of the imperfect reporting channels.

D.D.Ariananda et al. [8] have formed the possibility of employing wavelet packet decomposition as a basis for new spectrum sensing approach is investigated. They have utilized three types of sources, namely partial band, single tone and swept tone to examine the performance of their wavelet based approach. The advantage of this process is the wavelet based approach is quite promising for spectral estimation and can be a suitable technology for CR applications.

Tuan T. Do et al. [9] have introduced a distributed approach for spectrum sensing, which uses the multiuser diversity among secondary users to improve sensing capability in cognitive radio networks. They have adopted a cooperative sensing framework to overcome low SNR and shadowing. As they have used the detection probability as the only performance metric, fairness and delay issues can be ignored in spectrum sensing scenarios.

Juan Andrés Bazerque et al. [10] have introduced a cooperative approach to the sensing task of wireless cognitive radio (CR) networks. Their approach is based on a basis expansion model of the power spectral density (PSD) map in space and frequency. Joint estimation of the model parameters enables identification of the unused frequency bands at arbitrary locations. This method consequently facilitates spatial frequency reuse. Their novel scheme capitalizes on two forms of scarcity: the first one introduced by the narrow-band nature of transmit-PSDs, which is relative to the broad swaths of usable spectrum; and the second one emerging from sparsely located active radios in the operational space. Further, they have designed an estimator of the model coefficients based on the Lasso algorithm to use these forms of scarcity and reveal the unknown positions of transmitting CRs.

3. PROPOSED SOLUTION

3.1 Overview

In this paper, we propose an energy based spectrum sensing, power spectrum estimation and analysis for cognitive radio networks. In this technique cognitive radio (CR) constantly monitors the spectrum for white spaces (idle state of primary users). This is achieved through an energy based spectrum sensing technique. Here, the hypothesis H_0 denotes the absence of primary user and H_1 represents the presence of primary user. When the hypothesis H_0 is identified by CR, it allocates the slots to secondary users. This is continued until primary user enters into the active state. Further, power spectrum value of each node is calculated using five methods namely Periodogram spectral estimate, Bartlett's spectral estimate, Welch spectral estimate, Blackman Tukey spectral estimate and Correlogram spectral estimate. Finally, PAPR analysis is performed.

3.2 Energy based Spectrum Sensing Technique

In general, there are various spectrum sensing techniques exists for cognitive radio networks. In our technique, we utilize energy detector based spectrum sensing technique because this technique can be adapted to all cases with ease of use. It endures low computational and implementation complexities. Further, this approach is typically used when the network lacks primary user signal or inability of the receiver to collect adequate information about primary user signal.

Energy detection mechanism is termed as signal detection, which detects the presence or absence of signal in the band through an energy detector. This scheme can be put into operation in both time and frequency domains. Based on the knowledge of power of noise value in the band to be sensed, threshold value of energy detection can be regulated.

Let us consider H_0 and H_1 as the two hypotheses namely null hypothesis and alternative hypothesis respectively to detect the primary user signals. Here, null hypothesis H_0 represents the absence of primary user signal on the primary spectrum channel and H_1 denotes the presence of primary user signal. In our energy detection method, the hypothesis either H_0 or H_1 is decided based on the computation of energy. [14]

Consider Pr_S as the probability of successful detection and Pr_F as the probability of false

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detection. When an energy detector detects the hypothesis falsely, then a false alarm event take place. The probability of false event is termed as Pr_F. The probability of successful detection by an energy detector is known as Pr_S. The throughput of secondary user is increased when the Pr_F is lessened.

Consider $R_i(s)$ as the received signal sensed at node i, where (i=1, 2…n), P(s) as the general primary signal that we intend to detect. We take into account that P(s) is transmitted on the fading channel with the gain $G_i(s)$ and noise $N_i(s)$. The above assumptions are made under a given degree-of-freedom, which is achieved from' n' nodes and L_s samples sensing durations, then the energy detection problem can be described as follows,

$$H_0 : R_i(s) = N_i(s) \tag{1}$$

$$H_1 : R_i(s) = G_i(s)P(s) + N_i(s) \tag{2}$$

Assume RP be the received signal power, then the primary signal P(s) is modulated in phase-shift keying (PSK) scheme with RP. Now, the $G_i(s)$ is described by an independent and identically distributed (i.i.d) Rayleigh fading channel and $N_i(s)$ is described through an independent and identically distributed (i.i.d) zero-mean, complex-valued additive white Gaussian noise (AWGN), then $G_i(s)$ and $N_i(s)$ can be given as follows,

$$G_i(s) \sim CN(0, \sigma_G^2) \tag{3}$$

$$N_i(s) \sim CN(0, \sigma_N^2) \tag{4}$$

An energy detector brings together measured energy, which is computed in sensing duration with sensing nodes. We presume that each node and each sample is independent of each other and the estimated energy is incorporated with equal gain. Thus, the decision rule can be given as follows,

$$D_R = \sum_{i=1}^{n} \sum_{j=1}^{n} |R_i(s)|^2 \underset{H_0}{\overset{H_1}{\lessgtr}} \delta \tag{5}$$

Where, δ is the threshold value and D_R is the test statistic for the binary hypothesis test.

With the intention of finding probability of success and probability of false detection, the probabilistic characteristic of test statistic is developed for both hypotheses namely H_0 and H_1 using the probability density function (PDF). Consider the test statistic D_R as the summation of the squared Gaussian random variables and it trails a Chi-squared distribution with the degree of freedom (2ij). The Central Limit Theorem (CLT) ways and means the Chi- squared distribution and the Gaussian distribution. Therefore, we can rewrite both hypotheses on the word of CLT as follows,

$$H_0 : D_R \sim N(ij\sigma_N^2, ij\sigma_N^4) \tag{6}$$

$$H_1 : D_R \sim N(ij(P\sigma_G^2 + \sigma_N^2), ij(P\sigma_G^2 + \sigma_N^2)^2) \tag{7}$$

By means of probabilistic model, probability of successful detection (Pr_S) and probability of false detection (Pr_F) can be derived as follows,

$$Pr_S(n_i) = Q(\frac{1}{1+}(Q^{-1}(Pr_F) - \sqrt{ij})) \tag{8}$$

$$Pr_F(n_i) = Q(\sqrt{ij} + (1+)Q^{-1}(Pr_S)) \tag{9}$$

As per Gaussian distribution, Q (●) is the tail probability and $= \frac{P\sigma_G^2}{\sigma_N^2}$ denotes the signal to noise ratio (SNR) of primary user, where measured at the secondary sensing node.

Thus, based on hypothesis H_0 and H_1 absence and presence of primary users are identified respectively.

3.3 Power Spectrum Estimation

We can measure the ideal power spectrum of a signal (s(i)) by computing the ideal autocorrelation ($A_P(p)$),

$$A_p(\beta) = E[s(i)s(i+\beta)] = \lim_{X\to\infty} \frac{1}{2X+1} \sum_{i=-X}^{X} s(i)s(i+\beta) \tag{10}$$

$A_P(p)$ is an average value, which is measured at the interval $(-\infty, \infty)$. In our technique, the computed power spectrum is compared against various spectrum estimation techniques such as, [11]

1) Periodogram spectral estimate
2) Bartlett's spectral estimate
3) Welch spectral estimate
4) Blackman Tukey spectral estimate
5) Correlogram spectral estimate

3.3.1 Comparison of Power Spectrum Estimation

(i) Periodogram spectral estimate

Periodogram is the simple method to evaluate the auto correlation of final length of a signal. In this method, they are suppressing that the observed signal ($s_X(i)$) is the condensed form of actual signal s(i). This can be symbolized as follows,

$$s_X(i) = s(i)Y_X(i) \tag{11}$$

$$0 \le i < X$$

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Here, $Y_X(i) = \begin{cases} 1, \\ 0, & \text{Otherwise} \end{cases}$

The calculation of autocorrelation is measured at the finite interval as,

$$\hat{A}_{perio}(\beta) = \frac{1}{X}\sum_{i=0}^{X-\beta-1} s(i)s(i+\beta) \quad (12)$$

The corresponding mathematical form of equation (12) is,

$$\hat{A}_{perio}(\beta) = \frac{1}{X}\sum_{i=-\infty}^{\infty} s_X(i)s_X(i+\beta) = \frac{1}{X}s_X(\beta) * s_X(-\beta) \quad (13)$$

Thus, the estimated power spectrum in Periodogram method through Discrete Time Fourier Transform (DTFT) as,

$$\hat{PS}(e^{k\mu}) = \frac{1}{X}|R_X(e^{k\mu})|^2 \quad (14)$$

Here, as per DTFT $R_X(e^{k\mu})$ denotes the observed signal $s_X(i)$

(ii) Bartlett's spectral estimate

The Bartlett's spectral estimate method partitions the length (X) of signal into D segregations such that each segregation with the length of L_e = X/D. Upon the partitioned segments the Periodogram method is operated. The cumulative value of this method is considered as the Bartlett's power spectrum value. This value can be estimated as,

$$\hat{PS}_{Bartl}(e^{k\mu}) = \frac{1}{D}\sum_{n=0}^{D-1}\frac{1}{L_e}\left|\sum_{i=0}^{Le-1} s(i+nL_e)e^{-ki\mu}\right|^2 \quad (15)$$

Here, $\frac{1}{L_e}\left|\sum_{i=0}^{Le-1} s(i+nL_e)e^{-ki\mu}\right|$ symbolizes the periodogram value of segregation n. The above equation can be rewritten as,

$$\hat{PS}_{Bartl}(e^{k\mu}) = \frac{1}{X}\sum_{n=0}^{D-1}\left|\sum_{i=0}^{Le-1} s(i+1L_e)e^{-ki\mu}\right|^2 \quad (16)$$

By averaging the value of n segregations, the Bartlett's method imposes zero variance.

(iii) Welch's spectral estimate

The keynote of Welch's method is it permits the overlapping of segregations and thereby it eradicates the adjustment between spectral resolution and variance. With varying truncation window, an enhanced Periodogram method is operated on each overlapping segregation. Thus, the power spectral value computed using Welch's method is given as,

$$\hat{PS}_{Welch}(e^{k\mu}) = \frac{1}{DL_eV}\sum_{n=0}^{D-1}\left|\sum_{i=0}^{Le-1} W(i)s(i+nO)e^{-ki\mu}\right|^2 \quad (17)$$

Where,

$D \rightarrow$ *Number of segregations*,

$L_e \rightarrow$ *Length of each segregation*,

$V \rightarrow \frac{1}{L_e}\sum_{i=0}^{Le-1}|W(i)|^2$

$W(i) \rightarrow$ *Truncation window of signal*

$s(i), W(i) = \begin{cases} 1, \\ 0, \end{cases} \rightarrow O$

Offset between two successive segregations

(iv) Blackman-Tukey Spectral Estimate

Consider the equation given in (equation-12), in that when the value of β is larger then the estimation mechanism goes comes to be worst as β is designed for smallest number of terms. To prevail over this downside of spectral estimation mechanism, the Blackman-Tukey spectral estimate mechanism puts on $W_{BL-T}(\beta)$ to $\hat{A}_{perio}(\beta)$ before the operation of DTFT. This method uses $W_{BL-T}(\beta)$ to assign smaller weights to β.

Hence, the value $\hat{PS}_{BL-T}(e^{k\mu})$ can be put across the support interval $[-Q, Q]$ of window $W_{BL-T}(\beta)$ as,

$$\hat{PS}_{BL-T}(e^{k\mu}) = \sum_{y=-Q}^{Q} W_{BL-T}(\beta)\,\hat{A}_p(\beta)e^{-ky\mu} \quad (18)$$

(v) Correlogram Spectral Estimate

The correlogram method calculates power spectrum by taking advantage of DTFT of auto correlation function. It can be given as, [15]

$$\hat{PS}_{COR}(e^{k\mu T}) = \sum_{D=-L}^{L} R_X[D]\, e^{-ky\mu T} \quad \text{where, } L < X \quad (19)$$

L = X-1 can be taken as the maximum correlation lag, then the above equation can be rewritten as,

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$$\hat{PS}_{COR}(e^{k\mu T}) = \sum_{D=-(X-1)}^{X-1} R_X[D]\, e^{-ky\mu T} \qquad (20)$$

3.4 Integration of Spectrum Sensing and PAPR Analysis

3.4.1 Peak-to-Average-Power-Ratio (PAPR) Analysis

In multicarrier scheme, assume C as the total number of channels and s(i) as the modulated signal that comes out as a result of linear combination of the pulse shaping functions such as $\{\psi_{p,q}(i), q \in Z, p = 0,...C-1\}$ valued with the transmitted symbols $w_p[q]$, [13]

$$s(i) = \sum_{q=-\infty}^{+\infty} \sum_{p=0}^{C-1} w_p[q]\psi_{p,q}(i) \qquad (21)$$

A rectangular pulse shaping of interval t_S is used by OFDM modulation and from a carrier spacing $1/t_S$, orthogonality is attained. Then the rectangular function can be given as,

$$\psi_{p,q}(i) = e^{-k2\pi \frac{p}{ts} t \Pi_0^{ts}(t-qt_S)} \qquad (22)$$

Where, $\Pi_0^{t_S}(i) = \begin{cases} 1 & \text{if } 0 \le t < t_S \\ 0 & \text{else} \end{cases}$

The OFDM spectrum passes through an ideal bandlimited rectangular spectrum when there is no power amplifier is used (linear case). This case defines that OFDM signal, which is included in a block, will present itself as Gaussian and it shows high difference in consecutive blocks. Thus, the variation (difference) in transmitted signal can be measured in terms of PAPR.

$$\text{PAPR} = \frac{\max |s(i)|^2}{S_E} \qquad (23)$$

Where $S_E = E\{|s(i)|^2\}$, here E {□} is the statistical average operator.

When a channel makes use of modulated pulse shaping $\psi(i)$, the PAPR of the transmitted signal is upper bound by,

$$\text{PAPR} \le C \max_{0 \le i \le t_S} |\psi(i)|^2 \qquad (24)$$

When OFDM modulation uses $\psi(i)$ as a rectangular pulse shaping then PAPR ≤ C

In this technique, PAPR is calculated in terms of maximum peak power as per equation (24). Apart from the calculation of maximum power evaluation, calculation of the power distribution is more significant for the hardware implementation. [12]

In OFDM, the signal s(i) is traversed into the channel as a total of random symbols modulating orthogonal basis functions. The multicarrier signal can be designed as a zero-mean Gaussian distributed random variable with variance σ_l^2 for a large value of channels C as per the central limit theorem.

Let $a = |l|^2$ be the general variable and we can attain the central chi-square distribution as,

$$P_a(a) = \frac{1}{\sqrt{2\pi a \sigma_l}} e^{\frac{-a}{2\sigma_l^2}} \qquad (25)$$

Now we can describe the PAPR using the complementary cumulative distribution function (CCDF) as follows,

$$CCDF(PAPR_0) = \Pr ob[PAPR > PAPR_0] \qquad (26)$$

By making the most of equation (25) in (26), we can amend the PAPR analysis as,

$$CCDF(PAPR_0) = 1 - (1 - e^{-PAPR_0})^X$$

An empirical approximation attained through computer simulations for every higher value C can be symbolized as,

$$CCDF(PAPR_0) = 1 - (1 - e^{-PAPR_0})^{\delta X}$$

Here, δ is set to 2.8 during computer simulation

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3.5 Power Spectrum Estimation and Analysis for Cognitive Radio Networks

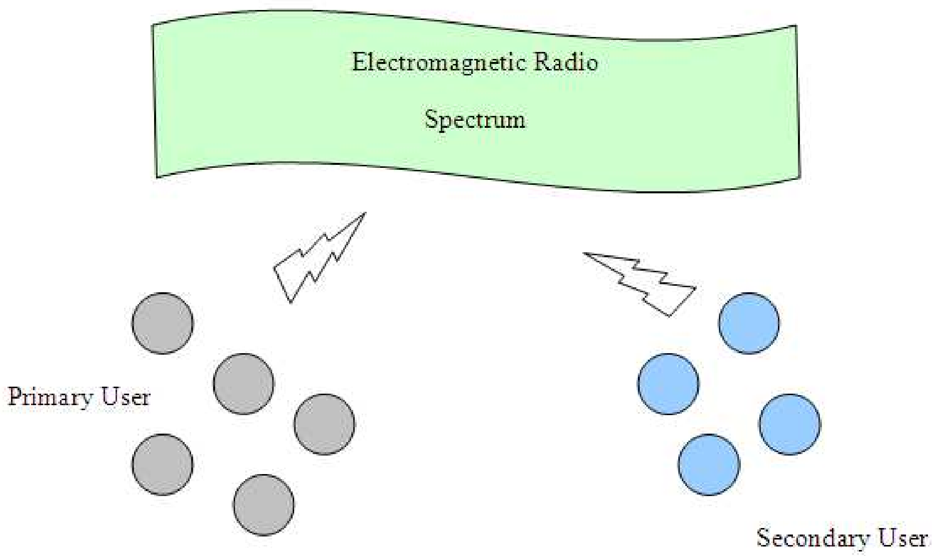

Figure-1 Architecture Diagram

Consider the cognitive radio network with 4 primary users and a number of secondary users. The cognitive radio (CR_i) uninterruptedly monitors the network to discover the spectrum hole. Spectrum hole denotes the absence of primary user. This is accomplished using energy based spectrum sensing technique described in section 3-2. The H_0 denotes the absence of primary user and H_1 represents the presence of primary user. When the hypothesis shows H_0, then cognitive radio decides that the corresponding primary user is in idle state and spectrum hole occurs. Instantaneously, CR_i allocates the slots to the secondary users. In this, secondary user can makes use of allocated slots until primary user is in idle state. When primary user is changed to active state, then the slots allocated to secondary users are again reallocated back to primary users.

Further, power spectrum of a node is estimated using five different methods namely Periodogram spectral estimate, Bartlett's spectral estimate, Welch spectral estimate, Blackman Tukey spectral estimate and Correlogram spectral estimate as given at length in section 3.3. After the estimation of power spectrum, PAPR analysis is performed using the complementary cumulative distribution function (CCDF) (section-3.4).

The algorithm for power spectrum estimation and analysis for cognitive radio networks is described below in algorithm-1,

Algorithm-1

1. Let P_i be a set of primary users and S_i be a set of secondary users
2. Let CR_i be the cognitive radio in the network
3. CR_i monitors the electro magnetic spectrum network
3.1 Invokes energy based spectrum sensing technique
3.2 If (Hypothesis = H_1) then
3.2.1 It shows the presence of primary user
3.2.2 Network is allocated only for primary users
3.3 Else if (Hypothesis = H_0) then
3.3.1 It shows the absence of primary user
3.3.2 CR_i allocates the slots to secondary users
3.4 Until (State of primary user = Active)
3.5 End if
4. Power Spectrum of nodes are estimated
5. PAPR analysis is performed using complementary cumulative distribution function (CCDF)

4. SIMULATION RESULTS

In our work we are taking the two phases like Spectrum sensing and power spectrum estimation and PAPR analysis.

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The work is focused on the practical implementation of a cognitive radio network. It is first assumed that there are 4 primary users in the spectrum. The cognitive radio network continuously looks for the spectrum hole where primary user is not present which is determined by the energy detection method. As soon as it finds out the spectrum hole, it allots it immediately to the secondary user and whenever primary user wants to occupy the slot, secondary user immediately vacates it. The Power Spectrum Density of signal is calculated and it is compared with the threshold value to determine the presence of primary signal [1].

The primary user1, primary user2 and primary user4 are present as shown in figure-2 and if the secondary user wants to transmit the data, then sensing of spectrum occurs in which it finds the primary user 3 is not using the band and that particular band is allocated to that secondary user as shown in figure-3.

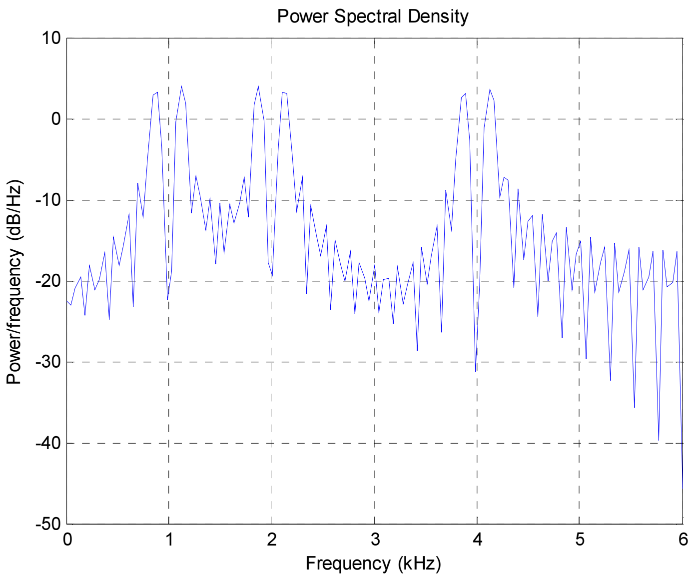

Figure.2 Power/frequency Vs Frequency for primary user1,primary user2 and primary user4.

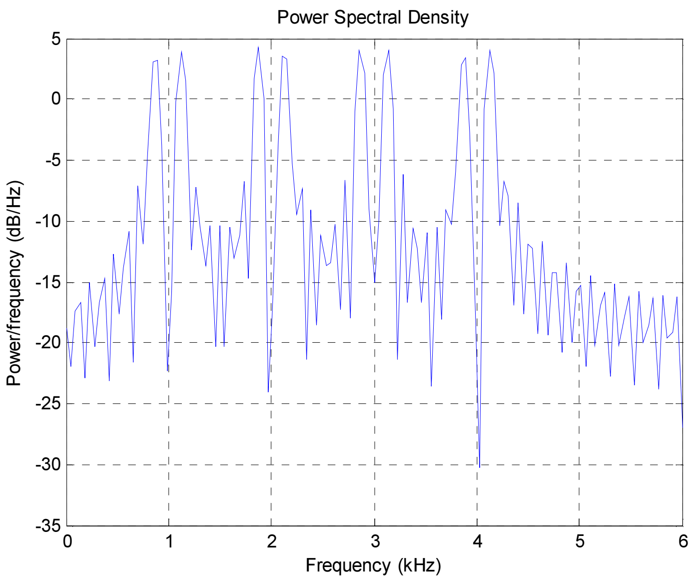

Figure.3 Power/Frequency Vs Frequency For Primary User1,Primary User2 Primary User4 And Secondary User In The 3rd Unoccupied Band.

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After the energy detection we are estimating the power spectrum by various methods like Periodogram spectral estimate, Correlogram spectral estimate, Blackman tukey spectral estimate, Barlett spectral estimate and Welch spectral estimate [2].

The Periodogram based spectral estimation is done and the corresponding graph is shown below in figure-4. Likewise Correlogram spectral estimation, Blackman tukey spectral estimation, Barlett spectral estimation and Welch spectral estimation are shown in figure-5, figure-6, figure-7 and figure-8, respectively.

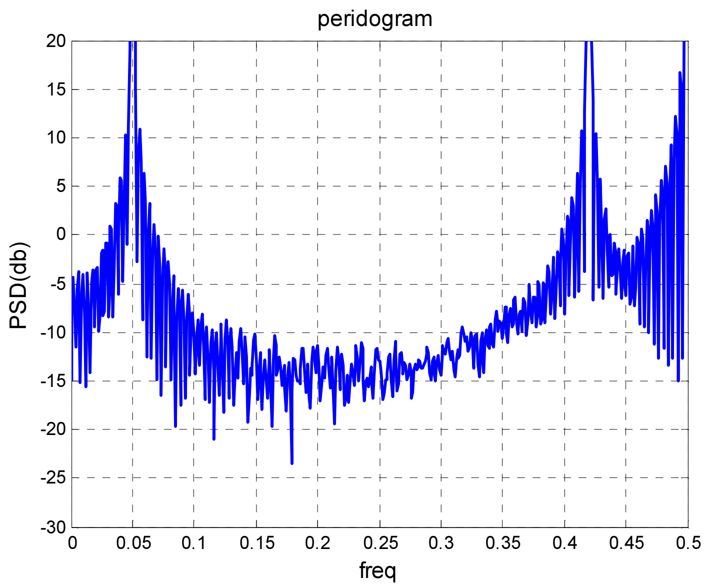

Figure.4 Psd Vs Frequency

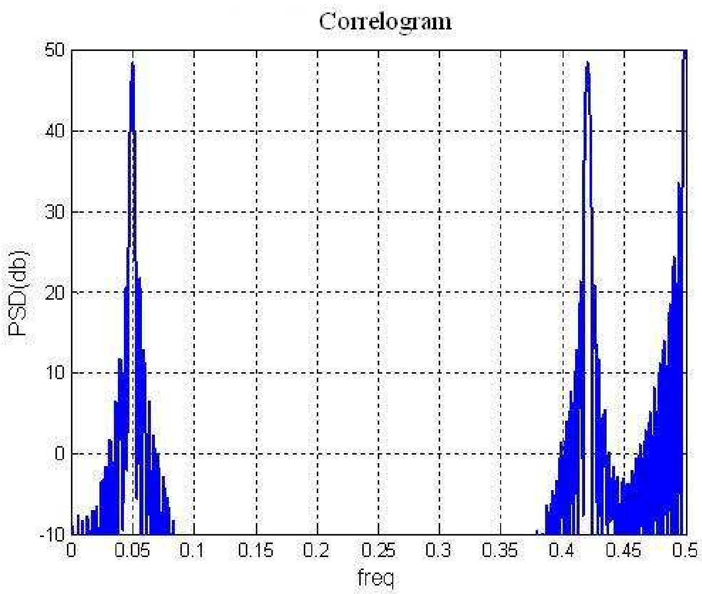

Figure.5 Psd Vs Frequency

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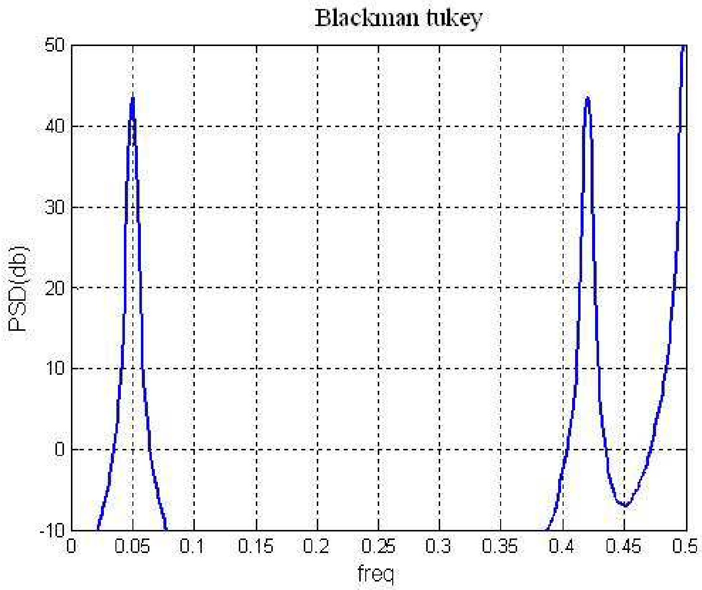

Figure.6 Psd Vs Frequency

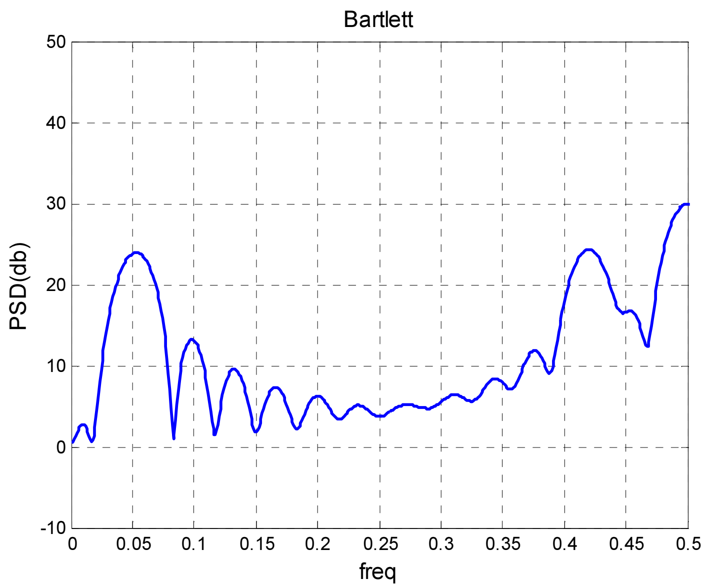

Figure.7 Psd Vs Frequency

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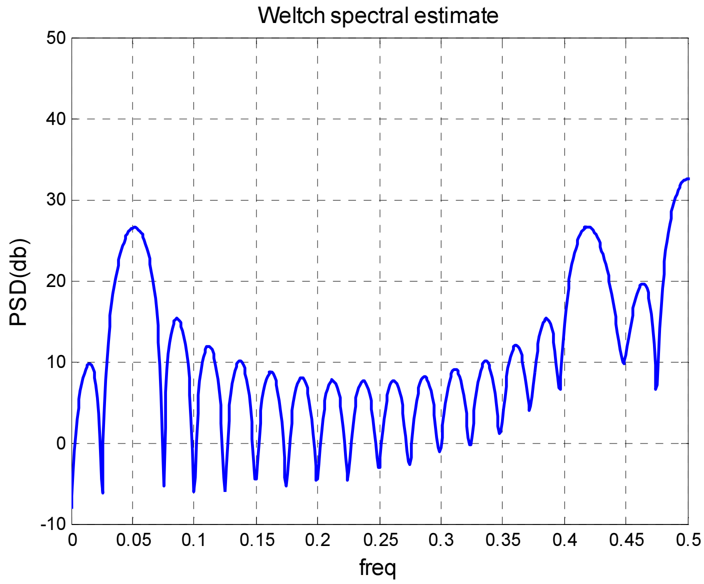

Figure.8 Psd Vs Frequency

In PAPR analysis, we are studying the transmission and reception of signals in cognitive radio using the Orthogonal Frequency Division Multiplexing (OFDM) modulation and Wavelet Packet Modulation (WPM). Those modulations are designed separately and the sensitivity of different WPM schemes versus OFDM schemes to sampling phase error has to be implemented. The figure-9 shows the graph for the peak to average power ratio for the wavelet packet modulation and orthogonal frequency modulation. Our WPM based modulation reduces the PAPR value at 10^-1 whereas for the OFDM the PAPR reduces at 10^-2.

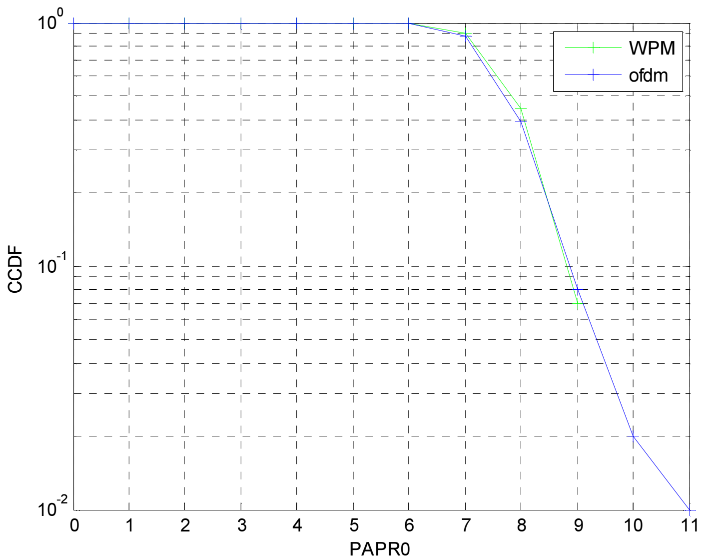

Figure.9 CCDF vs. PAPR for the WPM and OFDM

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5. CONCLUSION

In this paper, we have proposed an energy based spectrum sensing, power spectrum estimation and analysis for cognitive radio networks. In this technique, two hypotheses are used to identify the presence and absence of primary users in the channel. Here, the hypothesis H_0 denotes the absence of primary user and H_1 represents the presence of primary user. When the channel is not used by primary users the slots are allocated for secondary users. Further, power spectrum is estimated by means of five different methods namely Periodogram spectral estimate, Bartlett's spectral estimate, Welch spectral estimate, Blackman Tukey spectral estimate and Correlogram spectral estimate. Finally, PAPR analysis is performed using the complementary cumulative distribution function (CCDF). The proposed technique is simulated in MATLAB.

However the proposed work assumes the existence of previous power spectral estimation and PAPR analysis techniques. Hence the future work will be designing efficient new technique for power spectral estimation and PAPR analysis.

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