- To enhance the spectrum sensing algorithm for better Qos in Cognitive radio networks
- To apply this method to cognitive radio network and validate the results by applying enhanced spectrum sensing on spectrum analyzer
- To calculate the route sustenance time and connection sustenance time which are very important parameters for improving the Qos of a Cognitive radio network
- To further enhance the Qos of cognitive network architecture by using combination of enhanced spectrum sensing and hybrid spectrum sensing for joint interweave and overlay model.
- To apply the proposed algorithms and enhancing them for cognitive radio enabled IoT (Internet of Things) network.

1.7 Thesis Organization

The thesis is organized as follows. Chapter 2 discusses about spectrum sensing algorithms and enhancing the conventional spectrum sensing method. For the purpose of validation the proposed algorithm is applied on spectrum analyser and results are presented. In the third chapter analysis about route sustenance time and connection sustenance time are done, which are very important parameters in improving Qos of cognitive radio networks. These two parameters are tested on vehicular and pedestrian traffics and results are presented. In chapter 4 a joint interweave underlay mode is presented with the help of proposed Enhanced spectrum sensing and Hybrid spectrum sharing. In this chapter the focus is on power optimization based on the PU sensing result. In chapter 5 proposed algorithms are applied on cognitive radio enabled IoT network. In this chapter spectrum quality and spectrum availability are estimated based on two parameters called global information about spectrum usage and instant spectrum status information. Chapter 6 gives conclusions and directions for future work.

CHAPTER 2: ENHANCED SPECTRUM SENSING

In the previous chapter, we have discussed about cognitive radio, cognitive radio networks, QoS in CRNs and Essential components of CRNs from QoS perspective. If closely observed, in order to have an efficient network which maintains good throughput, secondary users (SUs) must sense true unused primary user (PU) channels. It is to say that spectrum sensing unit at the cognitive radio should perform well without any probability of false alarms and probability of missed detections. In this chapter the focus is on spectrum sensing part and improvising one of the frequently used sensing methods. Later in the chapter, the proposed enhanced sensing algorithm is applied on hardware for validation of the proposed algorithm.

2.1 Spectrum Sensing (SS)

Most of the spectrum which is licensed is unused both in frequency and time. Wireless networks tend to have burst traffic and therefore, at a very fine time scale the efficient exploiting of unused licenced spectrum will lead opportunity for secondary users who are in need (Unlicensed Users). Thus spectrum sensing plays a pivotal role in CRNs. The SU duty is to sense the spectrum, quickly transfer its data and vacate the bands when the primary user comes back without causing any interference to the primary user network. There are several methods proposed in literature for the identification of the unused spectral bands. In the following sub sections, we describe few of them briefly

2.1.1 Energy Detection Based Spectrum Sensing

Energy detection method is most commonly used SS algorithm because of its ease of implementation and low computational load [22-25]. Added to this, compared to other sensing methods, this is simpler as receivers do not require apriori knowledge of PU signal. Signal detection is done by comparing the output from the energy detector with a predefined threshold. The bottlenecks associated with energy detection algorithm include threshold detection for PUs, performance degradation under low signal to noise ratio (SNR) values. Let us consider that the received signal is of the form

$$y(n) = x(n) + w(n) \tag{2.1}$$

Where *x(n)* is the input signal and *w(n)* is the additive white Gaussian noise (AWGN) and n is the index for number of samples. Then the energy detector output is given as

$$M = \sum_{n=0}^{N} | y(n) |^2 \tag{2.2}$$

Where, *N* is the number of samples which are to be observed. When there is no transmission from PU the received signal *x(n)* = 0. The decision metric *M* is compared with a fixed threshold *λ* to decide whether PU is present or not. This can be given as binary hypothesis problem:

$$H_0 : y(n) = w(n) \tag{2.3}$$

$$H_1 : y(n) = x(n) + w(n) \tag{2.4}$$

The performance evaluation of energy detection algorithm is made on two probabilities: probability of detection P_D and probability of false alarm P_F. P_D is the probability of detection of a signal when it is present in the observed frequency band. P_D is given as

$$P_D=P_r(M>\lambda \mid H_1) \tag{2.5}$$

False alarm is the one when energy detector gives a decision that primary user is present when it is not, and the probability of false alarm, P_F is given as

$$P_F=P_r(M>\lambda \mid H_0) \tag{2.6}$$

It is obvious that, large probability of detection is desired. P_F has to be maintained as low as possible so as not to interfere with the PU. To achieve this, λ_E must be selected properly to have a balance between P_D and P_F for which a priori knowledge of detected signal powers and noise are required. It is quite easy to estimate noise power but not the signal power as it changes depending on distance between CR and PU and characteristics of PU transmissions. However, to achieve a specific false alarm rate noise variance is enough for a threshold selection.

White noise can be described as a zero mean Gaussian random variable with variance $\sigma^2{}_w$, i.e., $w(n)=N(0,\sigma_w^2)$. For better analysis signal term is also defined as zero mean Gaussian variable, i.e. $x(n)=N(0,\sigma_x^2)$. As per the assumptions made the decision metric Eq. (2.2) will follow chi square distribution and hence, it can be given as

$$M=\frac{\sigma_w^2}{2}\chi_2^2 N \qquad\qquad H_0$$

(2.7)

$$\frac{\sigma_w^2 + \sigma_x^2}{2}\chi_2^2 N \qquad H_1$$

Where $\chi^2{}_2N$ is a chi square distribution with $2N$ degrees of freedom.

In energy detection algorithm threshold depends on the noise variance. Therefore, there will be performance loss for even a small noise power estimation error [26]. Many solutions are derived for this problem; by using MUSIC (Multiple signal classification) algorithm [27] dynamic estimation of noise level is done by separating signal and noise subspaces. When an autocorrelation is performed on incoming signals, the smallest eigen value is termed as noise variance. Then for satisfying a certain false alarm rate the noise variance obtained or the smallest eigen value is chosen as threshold. In [28] to satisfy a certain probability of false alarm an algorithm is stated to get the decision threshold. For unknown noise power cases forward methods are proposed in [29] which are based on energy measurements. Hence this method is more suitable for practical scenarios where there is no prior knowledge about noise variance.

Energy detector is applied on wireless local area network (WLAN) channels to know busy and idle periods and analysis of measurement results are done in [30], [31], [32]. Energy detector is also applied on slots of global system for mobile communications (GSM) [33] to exploit idle slots. But in GSM scenario CR network should be in synchronous to PU network and also sensing time is limited to each slot. For opportunistic usage of unused cellular bands same kind of approach is used in [34]. Fast fourier transform(FFT) is applied on incoming signals of TV channels [35] to get the power level and is compared with the threshold to know which TV channels are used. In

[36][37] energy detection algorithm performance is tested by applying on various fading channels.

2.1.2 Waveform- based sensing

For the purpose of synchronisation in wireless systems known patterns such as preambles, Midambles, spreading sequences etc. are shared. Sensing can be performed effectively at the receiver if known patterns are readily available [38], [39], [40]. Waveform based sensing is applied only when the transmitting patterns are known and it is also termed as coherent sensing. In [38] it is shown that the convergence time and reliability is more in waveform based sensing when compared with energy detection. It is also mentioned that as the length of known pattern increases sensing performance also increases.

From [38], the metric of waveform based sensing is given as

$$M = \mathrm{Re}[\sum_{n=1}^{N} y(n)x^*(n)] \tag{2.8}$$

Where * indicates conjugate operation. When PU is not present the metric is given as

$$M = \mathrm{Re}[\sum_{n=1}^{N} w(n)x^*(n)] \tag{2.9}$$

The sensing metric when PU is present is given as

$$M = \sum_{n=1}^{N} |x(n)|^2 + \mathrm{Re}[\sum_{n=1}^{N} w(n)x^*(n)] \tag{2.10}$$

By comparing the decision metric M with a fixed threshold λ, decision can be made on whether PU is present or absent.

In [41] it is evident that for waveform based sensing that the measurement time is very short but it is susceptible to synchronisation errors. In [31], [32] and IEEE 802. 11b [42] packet preamble signals are considered for experimenting the WLAN channel usage characteristics. In summary if known patterns of the waveform is known then this method is advantageous otherwise this method is not used for spectrum sensing. This sensing method is susceptible to synchronisation errors which eventually increases false alarms.

2.1.3 Cyclostationarity- based Sensing

In this method cyclostationary features of received signals are determined for detecting the presence of PU's [43], [44], [45], [46]. The periodicity in mean and autocorrelation [47] or signal itself is the features of cyclostationarity- based sensing method. Sometimes these features are induced intentionally for spectrum sensing purpose [48-51]. The prime benefit of cyclostationarity based sensing is it can differentiate noise signals and original signal easily. Cyclostationarity is also used for distinguishing between different types of primary users and transmissions [52].

From [48] the cyclic spectral density (CSD) of a required signal is given as

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau) e^{-j2\pi f\tau} \tag{2.11}$$

Where $R_y^{\alpha}(\tau) = E[y(\eta+\tau)y^*(\eta-\tau)e^{j2\pi\alpha n}]$ is the cyclic autocorrelation function (CAF) and α is the cyclic frequency. Cyclic frequencies are extracted or assumed to be known [53] for identifying the features of transmitted signals.

In [49-51] specific cycle frequencies at certain frequencies are generated and altered before transmission in the orthogonal frequency division multiplexing (OFDM) waveform. These cycle frequencies are then used for efficient classification of signals. To increase the robustness against multi path fading in [51] cyclic features obtained in the signal are increased but at the rate of increased bandwidth and overhead. In [54] hardware implementation of cyclostationarity based sensing is presented. In summary if the cyclic features of the primary signal is not known then it is difficult to do spectrum sensing.

2.1.4 Radio- Identification based sensing

By identifying the kind of transmission technologies used by PU's gives a clear picture about spectrum characteristics. With the knowledge of identifying which transmission technology is used by PU enables CR to have higher accuracy and higher dimensional knowledge. For instance, CR identifies that PU's technology is Bluetooth, CR will use this information for extracting important information in spatial domain. In certain applications CR wants to communicate with the identified transmission technology. Radio identification can be done by techniques like feature extraction and classification [55]. The objective is to find out the presence of any known transmission technology and if nothing is present, the communication happens through them. The two important tasks to achieve radio identification based sensing are initial mode identification [IMI] and alternative mode monitoring [AMM]. Possible transmission mode for cognitive device is done in IMI and AMM monitors other modes when CR communicates in different mode.

Several features are identified in this method from the received signal and those features will help in selecting the most optimal PU technology by applying various classification methods. Features acquired like how much energy is detected and how much it is distributed among the spectrum are from energy detection algorithm are used for classification in [56], [57]. In [58] the reference features selected are channel bandwidth and its shape. The prime discriminating feature among others is channel bandwidth. Radial basis function (RBF) neural network is used for classification. With the help of energy detector the received signals centre frequency and operation bandwidth are extracted in [59]. For identifying spectrum opportunities these features are given to Bayesian classifier to determine any active PU is present or not. In [60], [61] neural networks and standard deviation of instantaneous frequency and its duration are extracted for identifying active transmissions using these features. For detection and signal classification, cycle frequencies of incoming signals are used in [60]. Identification of signals are performed using hidden Markov model (HMM). In [62], [63] features like spectral coherence function and spectral correlation density are identified for detection and classification. Again in this method also if primary user signals features are not known then it is difficult to know which channel is free and can be used by secondary user.

2.1.5 Matched Filtering

One of the optimal methods for PU detection is matched filtering when apriori information about PU signal is known [64]. Comparing to other detection algorithms the benefit of matched filtering is it takes less time to achieve a specific probability of missed detection or probability of false alarm [65]. At low SNR's for a target probability of false alarms the number of samples increases for matched filtering. But, matched filtering requires perfect knowledge about PU's and features such as frame format, pulse shaping, modulation type and order, operating frequency and bandwidth are required for demodulating received signals [66]. Though it is very efficient method when compared to all the above spectrum sensing methods, an apriori information about primary user must be known which is not true in practical scenarios.

2.1.6 Other sensing methods

Other spectrum sensing methods are time- frequency analysis, wavelet transform based estimation, multi taper spectral estimation and Hough transform. In [67] to detect edges in power spectral density of a wideband channel, wavelets are introduced once the edges of an occupied and empty bands and their transmissions are detected, estimation of powers between two bands are done. Using this information decision about PU, spectrum is characterised as occupied or not occupied. By assuming sparse signal spectrum and by using sub nyquist sampling the method proposed in [67] is modified in [68]. To obtain coarse spectrum knowledge efficiently sub nyquist sampling is used. In [69], [70] analog implementation of wavelet transform is used for coarse sensing. Analog implementation is better because of its low power consumption and real time analysis.

In [71] multi taper spectrum estimation is proposed which is an approximation to maximum likelihood power spectral density estimator. This method is optimal for wide band signals and it is less complex when compared to maximum likelihood estimator. But also this requires more number of computations. In [72] for IEEE 802.11 systems random Hough transform of received signals are used to identify the presence of rador pulses. This method is used where periodic pattern is known beforehand. In [73] statistical covariance of noise and signal are used to develop algorithm for detecting the PU signal presence.

Among all the above discussed sensing methods Energy detection method is frequently used because of its simplicity in design, apriori information about PU is not required. But conventional energy detection method has the problem of false alarms and missed detections. In this work the focus was to improvise the energy detection method for better probability of detection.

2.2 Enhanced Spectrum Sensing

The spectrum sensing problem can be formulated as a binary hypothesis testing problem with the following two hypotheses:

$$H0 \ : y[n] = w[n] \qquad n = 1, 2,\dots\dots\dots,N \tag{2.12}$$

$$H1 \ : y[n] = x[n] + w[n] \quad n = 1,2,\dots\dots\dots,N \tag{2.13}$$

where H0 is a null hypothesis stating that the received signal samples y[n] correspond to noise samples w[n] and therefore there is no primary signal in the sensed spectrum band, and hypothesis H1 indicates that some licensed user signal x[n] is present. N denotes the number of samples collected during the signal observation interval (i.e., the sensing period), emphasizing that the decision is made based on a limited number of signal samples. The ideal spectrum sensor would select hypothesis H1 whenever a primary signal is present and hypothesis H0 otherwise. Unfortunately, spectrum sensing algorithms may fall into mistakes in practice, which can be classified into missed detections and false alarms. A missed detection occurs when a primary signal is present in the sensed band and the spectrum sensing algorithm selects hypothesis H0, which may result in harmful interference to primary users. On the other hand, a false alarm occurs when the sensed spectrum band is idle and the spectrum sensing algorithm selects hypothesis H1, which results in missed transmission opportunities and therefore in a lower spectrum utilization. Based on these definitions, the performance of any spectrum sensing algorithm can be summarized by means of two probabilities: the probability of missed detection Pmd = (H0/H1), or its complementary probability of detection Pd = P(H1/H1) = 1- Pmd, and the probability of false alarm Pfa = P(H1/H0). Large Pd and low Pfa values would be desirable. Nevertheless, there exists a trade-off between Pd and

Pfa, meaning that improving one of these performance metrics in general implies degrading the other one and vice versa.

Energy detection measures the energy received on a primary band during an observation interval and declares the current channel state Si as busy (hypothesis H1) if the measured energy is greater than a properly set predefined threshold, or idle (hypothesis H0) otherwise[74]

$$T_i(Y_i) = \sum_{n=1}^{N}[Y_i\,[n]]^2 \gtrless \lambda \tag{2.14}$$

Where $T_i(Y_i)$ is the test statistic computed at the i[th] sensing event over a signal vector $Y_i = (Y_i\,[1], Y_i[2]............Y_i[N])$ and λ is a decision threshold to distinguish between the two hypothesis in (2.12) and (2.13). The procedure employed to select the algorithm's decision threshold is an important aspect since it represents the parameter configured by the system designer to control the spectrum sensing performance. The decision threshold could be chosen for an optimum trade-off between Pd and Pfa. However, this would require knowledge of noise and detected signal powers. While the noise power can be estimated, the signal power is difficult to estimate since it depends on many varying factors such as transmission and propagation characteristics. In practice, the threshold is normally chosen to satisfy a certain Pfa, which only requires the noise power to be known. The decision threshold required for a target probability of false alarm is [74]

$$\lambda = (\,Q^{-1}\,(\,P_{fa,target}^{CED}\,)\sqrt{2N} + N\,)\sigma_\omega{}^2 \tag{2.15}$$

The problem which encounters in conventional energy detector (CED) is misdetections and false alarms occurring due to instantaneous signal energy variations. In order to avoid this, as cognitive user will any how sense the spectrum continuously, all the test statistics related to past will be present. With the help of past test statistics if there is any instantaneous variation in the signal energy also the misdetections and false alarms can be minimized. Therefore, in enhanced spectrum sensing instead of just comparing the present test statistic with the threshold we compare average of all past test statistics and just before test statistic with the threshold to make a decision about primary users presence or absence. The simulation results shows the improvement in the probability of detection.

In the thresholding stage, moving average method is used to compute the threshold required to find the vacant spectrum. In moving average method, a subset of frequencies are considered and an average is computed with Equation 2.16.

$$\bar{T}_k = \frac{1}{M}\sum_{i=0}^{m-1} T_{k-i} \qquad \text{Where } k = M, M+1, ... \tag{2.16}$$

By shifting this subset forward, an average is computed again. This process is repeated till the average of the whole spectrum is computed. The minimum of these averages is multiplied by a certain scaling factor to decide the threshold. This threshold helps in detecting the vacant spectrum. The same process is repeated for three test statistics considered as shown in Figure 2.2, Figure 2.3 and Figure 2.4. In the second stage, the opportunistic user senses the licensed spectrum of the primary user in order to detect the availability and use it. This current sensed spectrum is compared with the last or recent test statistic in order to obtain a reliable common vacant spectrum as shown in Figure 2.5. This leads to a reduction in the probability of false alarm. In the third stage, the average of all the test statistics is computed and is compared with the sensed spectrum in order to obtain the reliable common vacant spectrum as shown in Figure 2.7. This final stage ensures further reduction in the probability of false alarms thus, increasing the reliability in communication. This detection of reliable vacant spectrum helps the opportunistic user to shift to other free channels effectively whenever the licensed user wants to access his channel. The following algorithm gives the clear information about the enhanced spectrum sensing:

Algorithm:

$S_i \in \{H_0 , H_1\}$

for each sensing event i do

$T_i (Y_i) \leftarrow$ Energy of N samples

$T_i^{avg} (T_i) \leftarrow$ Mean of $\{T_{i-L+1} (Y_{i-L+1}), T_{i-L+2} (Y_{i-L+2}),\ldots\ldots T_{i-1} (Y_{i-1}), T_i (Y_i)\}$

if $T_i (Y_i) > \lambda$ then

    $S_i \leftarrow H_1$

else

if $T_i^{avg} (T_i) > \lambda$ then

    if $T_{i-1} (Y_{i-1}) > \lambda$

        $S_i \leftarrow H_1$

else

        $S_i \leftarrow H_0$

    end if

else

  $S_i \leftarrow H_0$

 end if

 end if

end for

2.3 Simulation Results

In order to avoid instantaneous energy drops, false alarms and signal misdetections the proposed enhanced energy detector exploits the past spectrum sensing history. The energy drops, false alarms and missed detections is due to primary transmission power pattern and the radio channel fading properties. If the sensing events are close in time then finding the current status of channel based on past spectrum sensing results is reasonable. This means performance of proposed algorithm can be achieved when the target channel is sensed with enough periodicity. But when the sensing frequency is increased with sensing interval N constant, the time allocated for data transmission will be decreased which results in secondary user throughput degradation. To maintain the average throughput, N should be decreased along with the period between two consecutive sensing events. If N is decreased too small, the test statistic may follow the instantaneous variations of the received signal energy. This can lead to missed detections. The aim of this chapter is to reduce probability of false alarms. Hence the enhanced spectrum sensing can be improved with short sensing intervals and high sensing frequencies. As threshold plays an important role the moving average method will help to find the proper threshold. Spectrum sensing is applied on the targeted frequency band and a test statistic is calculated which is compared with calculated threshold. There is a database of test statistics available from which the reference signal is built. Once the sensed test statistic is computed it is compared with the reference database and Pus presence or absence is decided. If in the reference signal at the sensed band, if PU is present but recent test statistics decision is PU absent then a false alarm occurs. There is another case of false alarm where PU is absent but recent test statistic says PU is present then a missed detection happens but it doesn't disturbs the definition of CR where PU communication shouldn't get affected by SU communications. Hence this is not considered in our Probability of false alarm calculations. This is repeated for N number of iterations and the probability of false alarms are plotted. A number of test statistics are obtained and recorded using Matlab. 60K samples are considered to evaluate the test statistics and to calculate threshold a moving average method with window size of 1024 is chosen.

Figure 2.1, Figure 2.2, Figure 2.3 represent the three statistics recorded. With the help of the moving average method and enhanced energy detection proposed, vacant spectrum is detected as represented by the indicators in Figure 2.1. The average of the whole spectrum in each statistic obtained by applying moving average method is indicated by a red line in Figure 2.1 (ii), Figure 2.2 (ii), Figure 2.3 (ii).

The sensed spectrum by an opportunistic user is shown in Figure 2.4. This is compared with the recent test statistic. It is observed that the secondary user can use the vacant channels as shown in Figure 2.5.

Figure 2.6 represents the average of all the test statistics computed. It is compared with current statistic to comment on the availability of vacant spectrum. It is observed that the secondary user can use the vacant channels indicated in Figure 2.7.

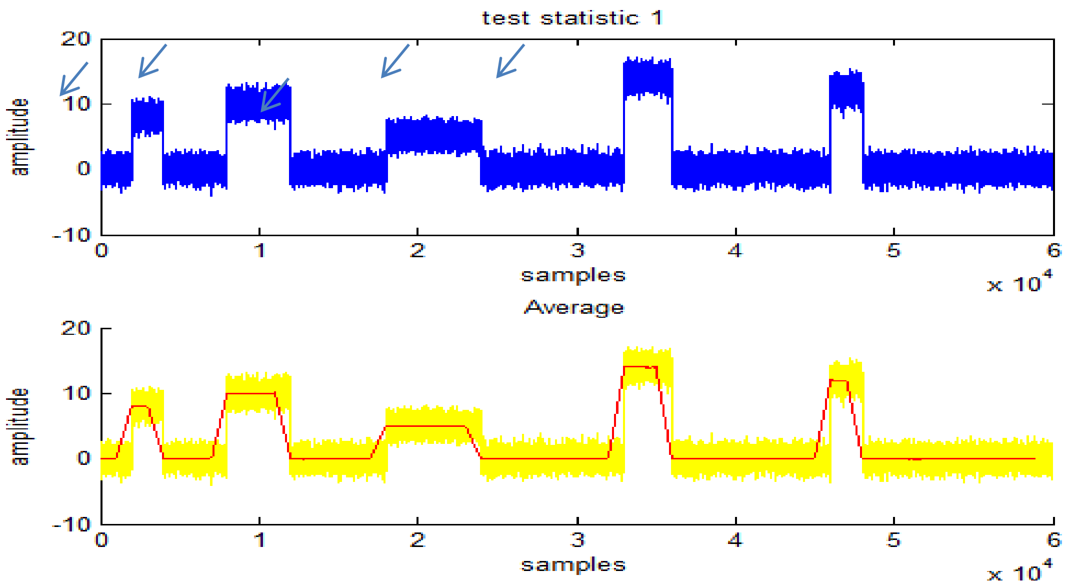

Figure 2-1: Test statistic 1-Detection of free spectrum by moving average method

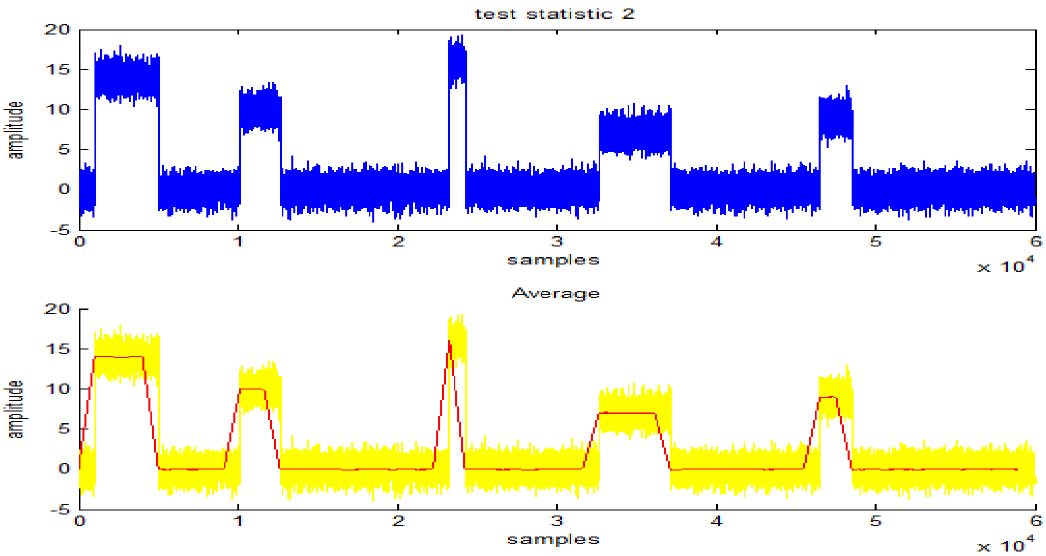

Figure 2-2: Test statistic 2-Detection of free spectrum by moving average method

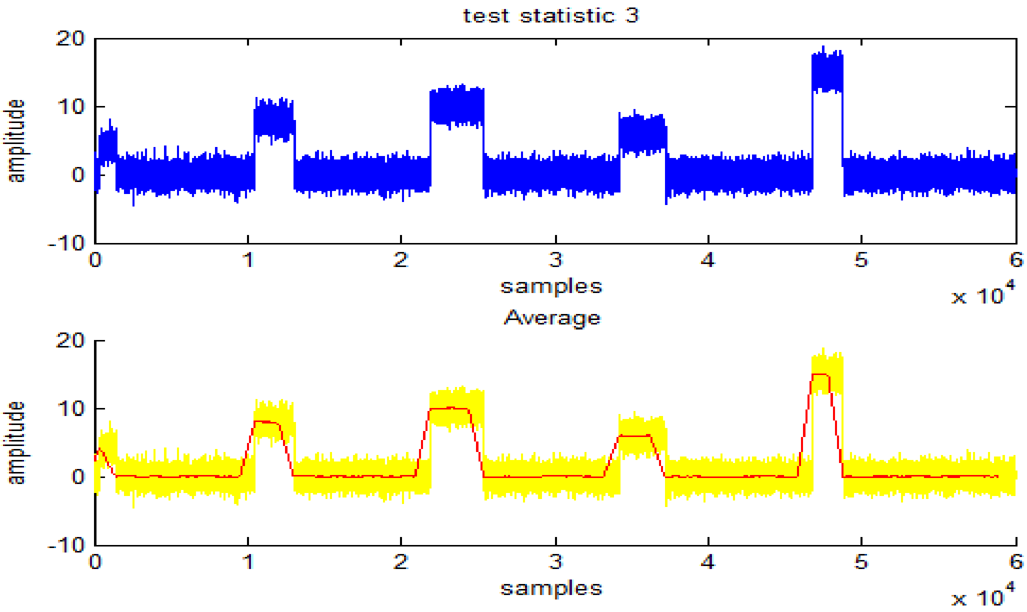

Figure 2-3: Test statistic 3-Detection of free spectrum by moving average method

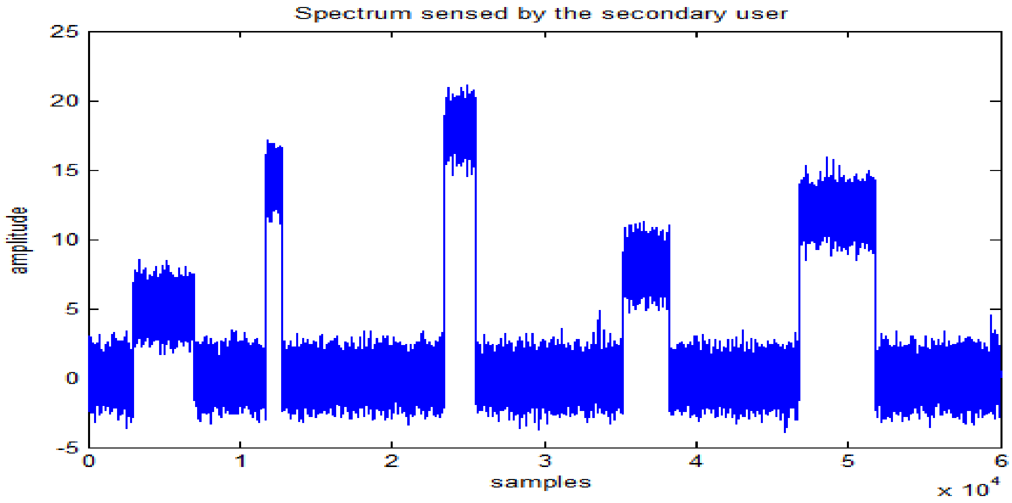

Figure 2-4: Current Sensed spectrum

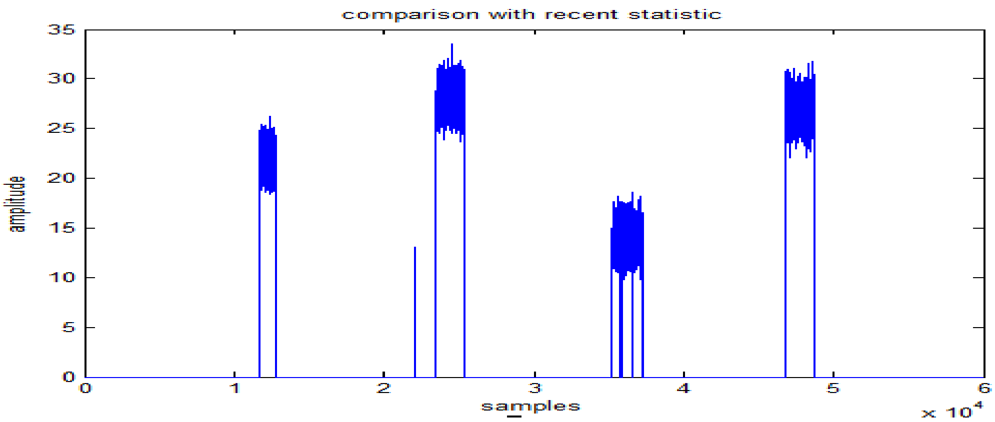

Figure 2-5: Comparison of the current spectrum with the past recent statistic

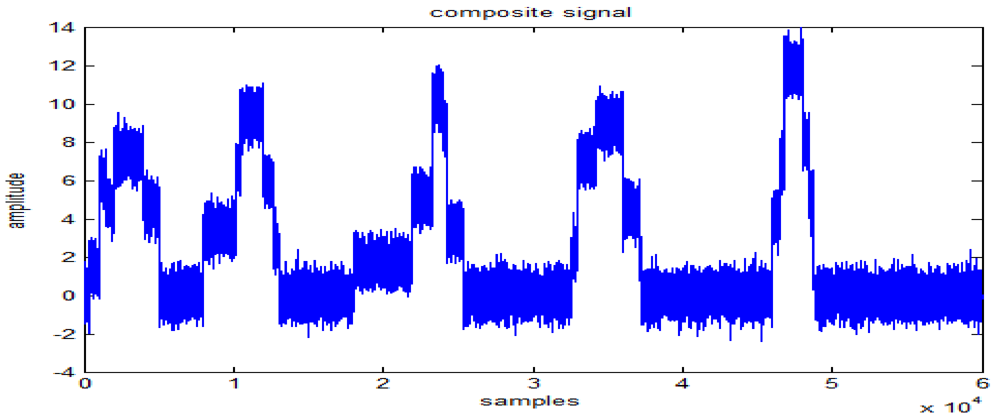

Figure 2-6: Average of all the test statistics

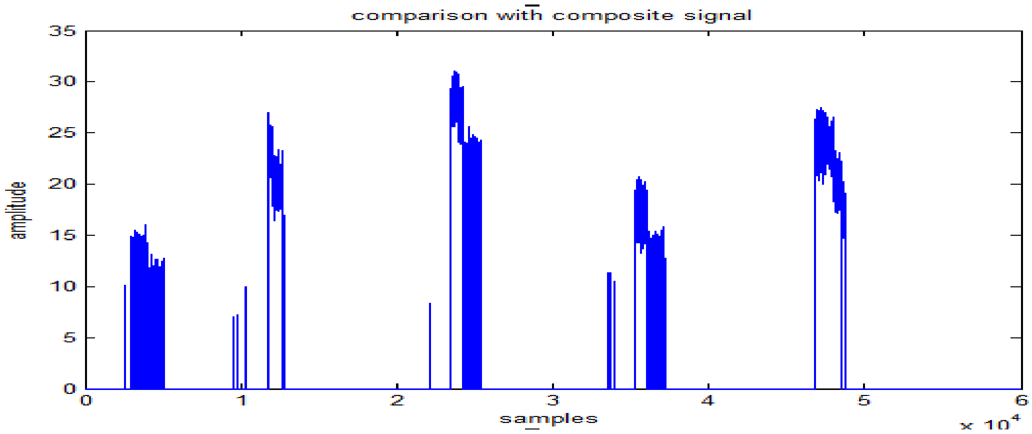

Figure 2-7 Comparison of current sensed spectrum with the average of all the past statistics

Figure 2.8 shows the comparison of probability of false alarm for the three stages mentioned in this work. Equation 16 from [74] is taken as reference to calculate probability of false alarm. First stage represents thresholding stage, second one obtained after the comparison of current sensed spectrum with the recent test statistic, and the third shows the false alarm probability after comparison of the spectrum with the average of all the test statistics obtained. It can be deduced from Figure 2.7 that the probability of false alarms have reduced by the enhanced energy detection method proposed in this work.

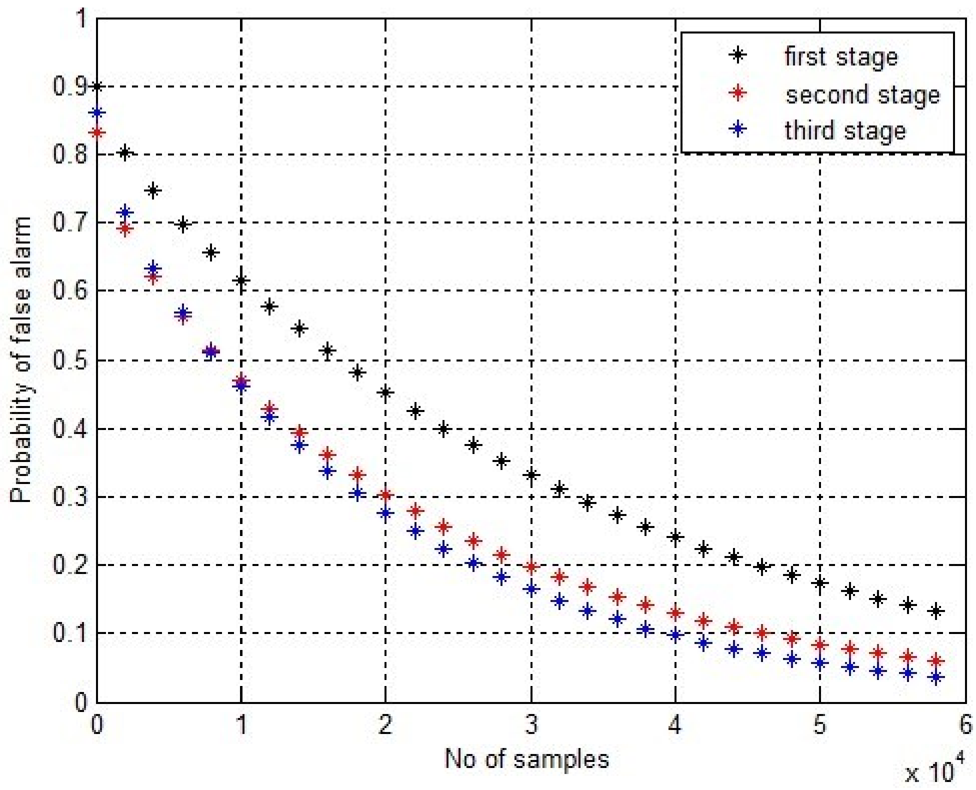

Figure 2-8 Probability of false alarms comparison

It is clearly observed that with the help of enhanced spectrum sensing the probability of false alarms are decreased when compared to conventional energy detector. To validate our proposed algorithm tests are conducted on spectrum analyzer readings.

The performance of spectrum sensing is characterized by both accuracy and efficiency, and more importantly the time taken to make a decision and also the complexity involved in doing so. In this work a simple detection technique is proposed based on a peak excursion threshold. To go around developing this method, a reference spectrum is formulated which is void of missed detections, by using an improved energy detection method which was discussed earlier in this chapter, and use it to compare decisions made by the proposed model. The model is modelled for false alarms making certain assumptions about missed detections. Later, the equations developed are verified for accuracy and efficiency over large data sets.

2.4 Application of Enhanced Spectrum Sensing on Spectrum Analyser (Agilent N9320B)

The Agilent N9320B spectrum analyser (an off the shelf spectrum analyser, that is used in this work) measures the power ratio of a signal against the frequency. It operates within the frequency range of 9 KHz to 3 GHz. Its primary use is to measure the power of the spectrum of known and unknown signals. The input signal a spectrum analyser measures is electrical, however, spectral compositions of other signals, such as acoustic pressure waves and optical light waves, can be considered through the use of an appropriate transducer.

Power ratio of the signal measured is in decibels per milliwatt (dBm), which can be converted to milliwatts by

$$P_{(\mathrm{mW})} = 1\mathrm{mW} \cdot 10^{(P(\mathrm{dBm}) / 10)} \tag{2.20}$$

- Peak excursion (R_{ex}): Peak excursion is used as a measure to judge whether maxima in a spectrum can actually be considered a “peak”, in cognitive radio terms, band underutilization by primary user. It is defined as the minimum amplitude variation (rise and fall) required for a signal to be identified as peak [76]. If the difference (peak excursion) is greater than a certain preset threshold value, then the former is considered a peak. It is measured in decibels per unit of power (generally dBm).
- Sweep time (T_{sw}): The time duration for which a signal or set of signals (within a range of frequencies) is analyzed. The primary motive usually is detecting peaks and spectrum holes. The longer the sweep time, the better is the accuracy in sensing the spectrum.

2.5 Detection based on Peak Excursion

In the proposed detection based on peak excursion, sets of consecutive samples are taken and the sample with the highest amplitude (power ratio) is tested to exceed the nearby samples with the least amplitude (power ratio) by an amount of R'_{ex} (threshold).

$$R_{ex}[n] = Y[n] \sim \{Y[n_{-1}], Y[n_{+1}]\} \gtrless R'_{ex} \tag{2.21}$$

where, $Y[n_{-1}]$ and $Y[n_{+1}]$ represent the local minima adjacent (to the left and right respectively) to the sample being tested as a peak. $R_{ex}[n]$ is the difference between the nth sample and its nearby local minima.

The presence of a primary user is indicated, if

$$R_{ex}[n] \geq R'_{ex} \tag{2.22}$$

And the null hypothesis indicated by,

$$R_{ex}[n] < R'_{ex} \tag{2.23}$$

The comparison mentioned is very elementary. The choosing of the threshold (R'_{ex}) is very important, as the decision is singly dependent on the threshold.

2.6 Selection of the threshold R'_{ex}

To make the process of choosing the threshold simple, a simplistic equation is developed. The assumption is that there are no missed detections in the process of choosing the threshold. To ensure this, all records used to model the equation are tested against the reference signal and records showing any sign of missed detection are not considered.

Further, an equation is derived for calculating the number of false alarms in terms of the threshold. This would enable to calculate the threshold based on a requirement of false alarms.

2.7 Results and Discussions

The frequency range of 90 MHz to 100 MHz is considered as the spectrum under study. Radio channels consistently transmit signals within this band, and hence, can be used for study as the signals are consistent over a long period of time. Here, a radio station transmitting is analogous to a primary user's presence and the converse, absence.

Figure 2.9., shows the raw spectrum as recorded by the analyser. Multiple instances of the same are recorded, are averaged, and passed through the enhanced spectrum sensing to yield Figure 2.10. The signal as shown (in Figure 2.10) is the reference signal

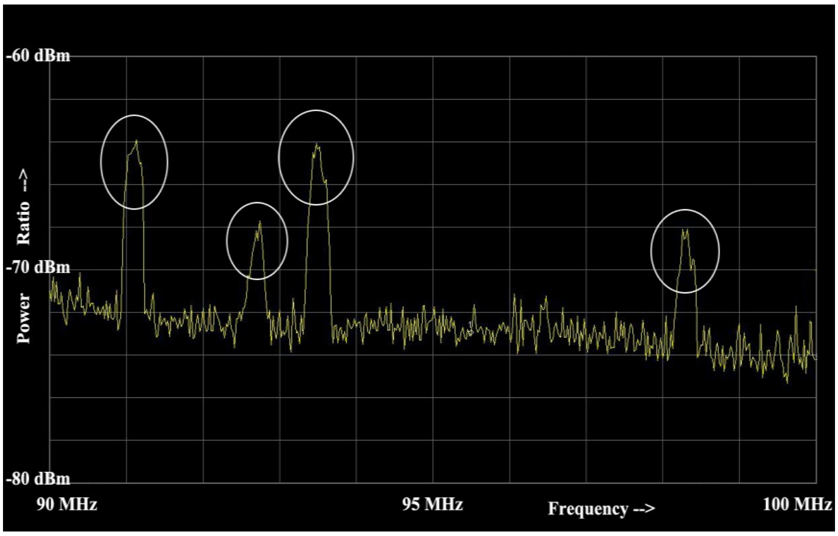

Figure 2-9 Spectrum as sensed by the spectrum analyser

The depicted spectrum indicates the presence of signals at the bursts recorded at the bands of 91.1 MHz, 92.7 MHz, 93.5 MHz and 98.3 MHz. Hence, ideally the enhanced energy method should indicate the presence of a primary signal corresponding to the bands utilized by the radio channels (i.e., H_1) and the null hypothesis (H_0) elsewhere.

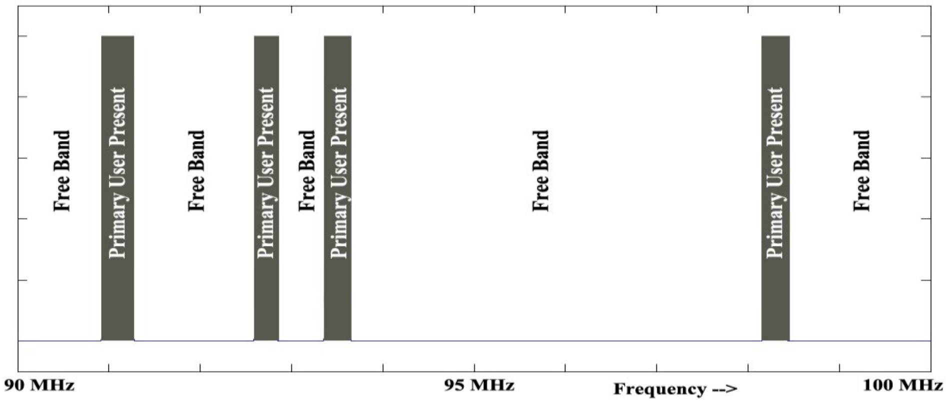

Figure 2-10 The formulated reference signal after passing through the enhanced spectrum sensing

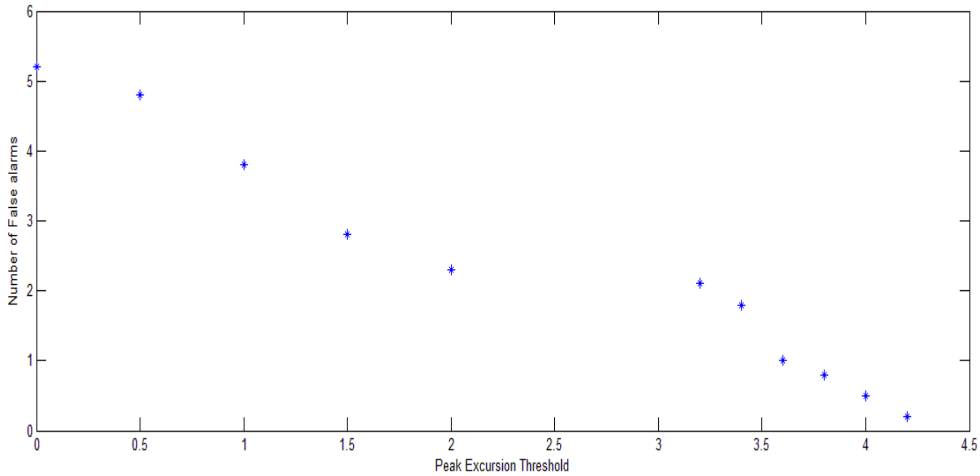

Figure 2-11 Peak Excursion Threshold Vs. Number of False alarms

In Figure 2.11., we have conducted an experiment on the recorded data by varying different peak excursion thresholds and it is observed that the false alarms are decreasing with the proper selection of threshold.

Repeated experimentation was carried out to find out a relationship between the peak excursion and false alarms arising out of it. It was found that the square of the difference of average signal strength and noise strength, multiplied by the peak excursion to have an exponential relationship as,

$$N_{fa} \propto e^{-R'_{ex} \times (\Delta R)^2} \quad (2.24)$$

where, ΔR is given by

$$\Delta R = \overline{R}_s \sim \overline{R}_n \tag{2.25}$$

and $\overline{R}_s$, $\overline{R}_n$ are given by [76]

$$\overline{R}_s = \sqrt{\frac{\sum_{n=1}^{N}(y_n)^2}{N}} \quad ; \quad y_n \in H_1 \tag{2.26}$$

$$\overline{R}_n = \sqrt{\frac{\sum_{n=1}^{N}(y_n)^2}{N}} \quad ; \quad y_n \in H_0 \tag{2.27}$$

Here, $\overline{R}_s$ is the average signal power ratio of the bands under use by the primary user. $\overline{R}_n$ is the average noise power ratio of the bands (not under use by the primary user). N is the number of samples of the spectrum. y_n is the n^{th} sample in the spectrum. Rex, Rs and Rn are threshold, signal and noise spectral values respectively.

But, just a dependency on a thresholding parameter would be insufficient and hence, the dependency of false alarms was tested with the sweep time (or simply the sensing time). It was found that they were related as,

$$N_{fa} \propto e^{-T_{sw}{}^2} \tag{2.28}$$

The relations obtained above in equations (2.24) and (2.28), put together would results in the following equation,

$$N_{fa} = ae^{-(b \times R'_{ex} \times (\Delta R)^2 + c \times T_{sw}^2)} \tag{2.29}$$

where, 'a' ($3.296x10^6$) is a scaling factor, 'b' ($4.629x10^{-2}$) and 'c' ($5.267x10^2$) are weight constants of the power ratio component and time respectively. The values indicated are those that have been practically calculated.

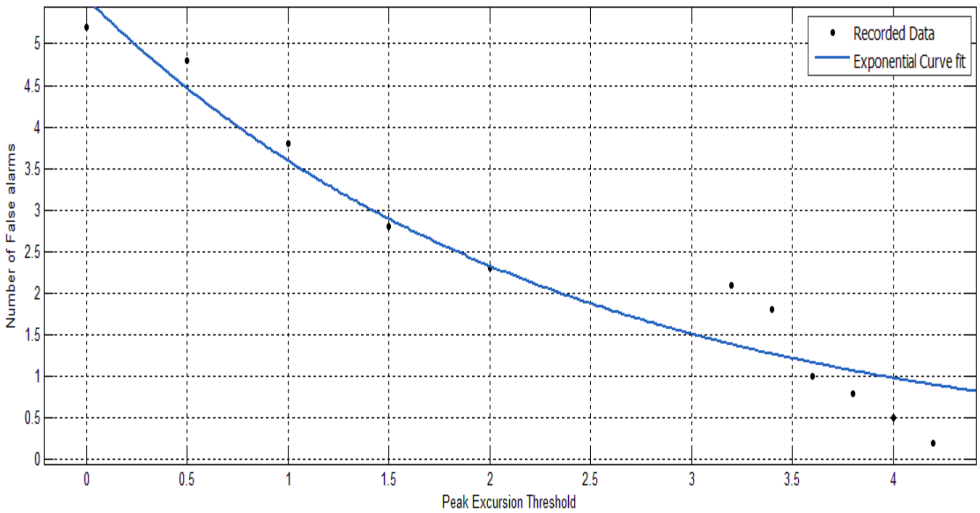

Figure 2-12 Exponential curve fitted for the recorded data from spectrum analyser

We wanted to observe whether Figure 2.11 follows any trend so that we can provide reference for False alarms. With the help of Matlab curve fitting tool box, exponential curve fitting is applied on Figure 2.11 and it is observed from Figure 2.12 that the variance between the Curve fitting and the practical data (in Figure 2.11.) is 0.0826 and standard deviation of 0.2873. A variance consistently less than 0.1 is obtained pointing out the accuracy of the model proposed. The same is tabulated below in Table I, along with a few more values.

TABLE I: Tabulated values of ranges of $\overline{R_s}$ and $\overline{R_n}$ (in dBm) and corresponding averages of variance and standard deviation

S.No	$\overline{R_s}$(dBm)	$\overline{R_n}$(dBm)	Variance	Standard Deviation
1	-60 to -65	-65 to -70	0.08776	0.2962
		-70 to -75	0.04987	0.2233

2	-65 to -70	-70 to -75	0.10712	0.3273
		-75 to -80	0.05488	0.2343
3	-70 to -75	-75 to -80	0.12019	0.3467

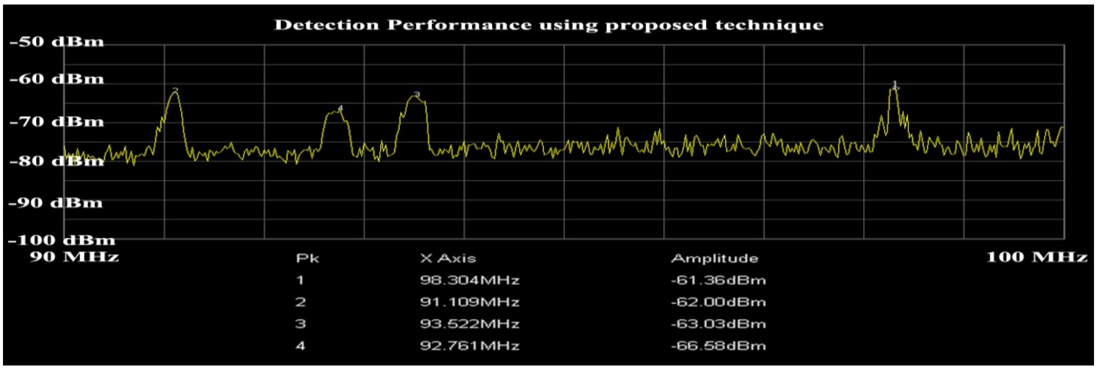

Figure 2-13 Peaks detected by using parameters (R'_{ex} = 6.7dBm and T_{sw} = 100ms) from derived model

Figure 2.13. Shows a sweep of spectrum under observation, with the parameters of peak excursion and sweep time obtained from the model described in (2.29), with number of false alarm of 0.1, or in terms of probability, 2.51×10^{-4}, calculated through the expression,

$$P_{fa} = \frac{N_{fa}}{N-(n \in H_1)} = \frac{N_{fa}}{(n \in H_0)} \tag{2.30}$$

where, P_{fa} denotes the probability of false alarms and N refers to the number of samples in the recorded signals. $n \in H_1$ and $n \in H_0$ refer to the number of samples that satisfy the respective statements in the binary hypothesis.

This method produces a near real time decision about spectrum occupancy. In the example shown in figure 2.13, the sweep time is 100ms, and so for each of the detections, the time required would be,

$$T_{decision} = \frac{n_x \times T_{sw}}{N} \tag{2.31}$$

where, n_x is the number of samples required for the decision (from the local minima to the left of the peak to the minima to the right), T_{sw} is the sweep time and N is the number of samples in the spectrum under observation. In the case discussed in figure 2.13, the times required vary from 3.19 milliseconds to 5.32 milliseconds.

2.8 Conclusions

In this chapter enhanced spectrum sensing is developed for improving the QoS by decreasing the probability of false alarms.

Later in this chapter, a simple model based on peak excursion is discussed, which optimizes the time taken to make a decision about the spectrum utilization. Also, the complexity involved in doing so is very minimal, and so hardware modelling of the same would be very cheap. This can also be done using easily accessible off the shelf spectrum analysers, which also outputs the peak frequency in each band under use by the primary user. The false alarm and missed detection values obtained too are pretty minimal.

Though we have enhanced the spectrum sensing method the secondary user has to vacate the band when the primary user wants the licensed spectrum. Eventually secondary user has to sense for another free band and continue its communication. If we really want to enhance the throughput of the CRN we need to seek answers for the following:

a) The probability that there is atleast one relay, which is feasible for a user who is not in the coverage area.

b) How long (on average) will a mobile relay remain feasible?

c) Assuming rerouting, with the help of relay handover, how long a connection will sustain? (Connection sustaining time).

In the next chapter, the above said parameters are tested and discussed.