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Performance Evaluation of Real Time Spectrum Sensing in Cognitive Radio Networks

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ABSTRACT: Spectrum scarcity and congestion has motivated new communication paradigm to exploit the existing wireless spectrum opportunistically. An emerging technology based on Cognitive Radio (CR), has the potential to maximize spectrum usage efficiently. A key feature of cognitive radio technology is spectrum sensing, which is the detection of unused or vacant frequency bands *i.e.* spectrum holes. The paper presents an energy detection technique through Power Spectral Density (PSD) estimation for real time sensing of occupied and vacant spectrum bands. The Neyman-Pearson hypothesis is considered for detecting the presence and absence of user signal, over a bandwidth of 5MHz, with probability of detection and probability of false alarm as metrics. The real time implementation of algorithm has been done on Wireless open Access Research Platform (WARP) board with FPGA Virtex 6. The received Welch PSD estimates from the proposed technique is then used in energy detection process for identifying spectrum holes that can be used by CR systems to access opportunistically. The performance of various modulation schemes *viz* BPSK, QPSK and QAM are presented and discussed for improved signal quality.

Keywords: Cognitive Radio, Spectrum Sensing, Energy Detection, Power Spectral Density estimates, WARP.

Abbreviations: CR, cognitive radio; CRN, cognitive radio network; ED, energy detection; BPSK, binary phase shift keying; QPSK, quadrature phase shift keying; QAM, quadrature amplitude modulation; AWGN, additive white gaussian noise; 5G, fifth generation; FFT, fast fourier transform; FPGA, field programmable gate array; PU, primary user; SU, secondary user; PSD, power spectral density; WARP, wireless open access research platform.

I. INTRODUCTION

Wireless communication technology has made a remarkable transition from first transatlantic radio transmission by G. Marconi in 1897 to cellular mobile communications in late 1970s with the advent of solid-state radio frequency hardware. Thereafter, almost every ten years a new generation of cellular system has emerged. First generation (1G) communication system is of early 1980s. The 2G communication system were deployed in 1992, while 3G in early 2000, followed by 4G communication systems in 2010. Technological development during 1G to 4G has witnessed a transition from analog voice only services to GPRS (General Packet Radio Service) to LTE (Long Term Evolution), with speed of transmission from 11 Mbps in year 2000 to 300 Mbps in year 2010 [1]. The fifth generation (5G) standards are being introduced now in early 2020s, with an aim to incorporate the existing wireless and wired communication technologies into all IP (Internet Protocol) networks. Now under 5G communication systems, the new wireless architecture is being created to enable human-centric communications at data rates as high as 1Tbps; technological solutions for huge system capacity of 10-100 Mbps/m^2; an end-to-end latency of less than 1ms; ubiquitous connectivity and increased energy efficiency to cater the upcoming requirements of ever increasing number of data-based applications, wireless and IoT (internet of things) based devices [2]. The number of wireless devices at global level are expected to increase from ~7 billion in 2015 to ~100 billion by 2025, out of which ~208 million new subscribers will get connected in India itself [3]. Hence, demand for wireless spectrum has increased exponentially. The limited available spectrum and the inefficient spectrum usage have brought in a new communication paradigm based on cognitive radio to exploit the existing wireless spectrum efficiently.

Cognitive Radio (CR), a recent innovative extension of SDR (software defined radio) was introduced to the wireless radio community by Mitola & Maguire in 1999. He described, “CR is a goal driven framework in which the radio autonomously observes the radio environment, infers context, assesses alternatives, generates plans, supervises multimedia services, and learns from its mistakes [4]. Accordingly, cognitive radio networks (CRNs) have opened immense possibilities for utilization of congested radio frequency spectrum by sensing and monitoring the idle portions of spectrum in time, space and frequency domain referred as 'spectrum holes'. These are the unused frequency bands of the licensed primary users (PUs) can be allowed to be used by the unlicensed-cognitive or secondary users (SUs), without causing any harmful interference to the PUs. The channel reuse may cause interferences, degrade the SNR of received signal and consequently decrease overall capacity of the system [5]. CR systems help in overcoming these issues by spectrum management strategies implemented through cognitive cycle.

CR systems works in coordination with the receiver and transmitter channel in a Cognitive Cycle comprising of four steps: *first step* is spectrum sensing and analysis at the receiver end to detect the unused frequency bands. The channel identification on the receiver side for coherent detection of the message signal and planning possible action strategies is the *second step.* Deciding the optimal operative strategy to allow spectrum sharing after learning from provided information is the *third step* of cognitive cycle. *Last step,* is spectrum mobility for providing uninterrupted communication to SUs while switching to alternate spectral band if PU resumes the networks. Reliable spectrum sensing is one of the key technologies for enabling spectrum coexistence and efficient utilization of available spectrum.

II. RELATED WORK

In CR systems, spectrum sensing is the major task for detection and monitoring of spectrum holes. Energy detection, matched filtering detection, and cyclostationary (or feature detection) are classical spectrum sensing techniques where sensing algorithms are based on the users' transmitted signal. Such algorithms are less complex and technologically mature. Among different methods for spectrum sensing, energy detection (ED) is simple to realize hence most popular signal detection method in practical implementation. Moreover, any prior information about the PU *i.e.* transmitted signal properties, channel information, or even the type of modulation is not required for ED algorithm. Although, ED technique suffers from poor performance at low SNR, however literature reveals various algorithms and variations of ED to get best out of this simple technique towards optimizing the spectrum usage [6]. Although energy detection can be implemented in time as well as in frequency domain, however the approach is more flexible in frequency domain. Urkowitz (1967) proposed a model for the general analysis of energy detector in time domain in Additive White Gaussian Noise (AWGN) channel [7]. Lee and Akyildiz (2008) proposed maximum a posteriori probability (MAP) based sensing framework on the energy detection and primary user activities based decision criterion to address the interference and the spectrum efficiency issues [8]. Moghimi *et al.*, (2011) proposed a novel hybrid ED scheme for spectrum sensing which turned out to be of low–complexity with locally optimal decision metric [9]. Dhope *et al.,* (2011) described a hybrid detection method which exploited the advantages of energy detection and covariance absolute value for different types of input [10]. Various aspects of hybrid detection based on ED and cyclostationary techniques are reviewed [11]. Chen (2010) proposed a modified ED algorithm, wherein the squaring operation of the signal amplitude is replaced with an arbitrary positive power operation [12]. Periodogram and Welch's periodogram has been quite a popular method for ED simulation studies [13-17]. To improve the performance and detection sensitivity, double threshold and dynamic threshold [18-20] based energy detection algorithm have been proposed. Koley *et al.*, (2015) applied gradient-based ED for wide band in GSM and CDMA bands [21]. Digham *et al.,* (2007) focused on multiple antenna processing based energy detection under different fading channels and quantify the improvement in the probability of detection [22]. Pandharipande and Linnartz (2007) compared multiple antenna CR processing *vis-a-vis* a single antenna based ED scheme under Rayleigh fading channel [23]. Ciftci and Torlak (2008) compared ED models in AWGN and Rayleigh channels [24]. ED technique has been used for narrow band sensing and wideband sensing by employing an array of energy detectors as multiband joint detection (MJD) [25, 26].

For CR based communication system, experimental implementation is an important step to demonstrate its working over-the-air. CR testbed/CR platform can significantly speed up the simulation and experimental evaluation in real time [27, 28]. Although, literature survey revealed versatility of energy detection technique under varied communication system, only few have demonstrated the experimental implementation using BEE2 Memec, USRP and WARP platform [13-15, 20, 29, 30].

In this paper, spectrum sensing based on energy detection technique through power spectral density (PSD) estimation is studied in frequency selective AWGN environment for signals under various modulation schemes. The implementation of proposed simplistic CRN simulation was performed on WARP (Wireless open-Access Research Platform) for real time sensing of occupied and vacant frequency bands.

III. METHODOLOGY AND EXPERIMENTAL SETUP

A. Energy detection based spectrum sensing

Spectrum sensing provides the required awareness about spectrum availability to the CR environment and is formulated as a binary hypothesis:

$H_0 : x_n = w_n$

$H_1 : x_n = s_n + w_n, \quad n = 1, 2, \ldots, N-1$

where, x_n is the n^{th} sample of the received by a SU, s_n is the primary transmitted signal by the PU and w_n is the additive white gaussian noise(AWGN) with mean zero and variance σ^2. The variable, N denotes number of signal samples.

H_0 and H_1 represent the null hypothesis and true hypothesis respectively. The Neyman-Pearson criteria is used to compare the test statistics, T with predefined threshold λ, for the energy detection method which is expressed as [6]:

$$T(x) = \sum_{n=0}^{N-1} x_n^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \qquad (1)$$

The sensing is based on test statistic values of signal samples received; if the threshold value exceeds the value of test statistics, it is inferred that H_1 is true (*i.e.* PU present, channel is occupied and busy), otherwise H_0 (*i.e.* PU absent, channel is vacant or unused).

For detection of the signal energy, the received signal is first passed through a Band Pass Filter (BPF), sampled by ADC (analog-to-digital converter) and then it is converted to frequency domain by taking its Fast Fourier Transformation (FFT) followed by squaring its magnitude and then taking average over the selected band. Average power is finally compared with the threshold, λ for identification of the idle slot in the chosen bandwidth of spectrum. This property is used for simulations and implementation on wireless platform.

The Probability of detection (P_D), is the probability of finding a channel occupied actually by the PU. This occurs when the value of received test statistics, T is greater than the value of threshold, indicating the hypothesis H_1 and is given as [13]:

$$P_D = P(T > \lambda / H_1) = \mathrm{Q}\left(\frac{\lambda - N\sigma_x^2}{\sqrt{2N\sigma_x^4}}\right) \quad (2)$$

where, Q represents standard Gaussian complementary cumulative distribution function, σ_x^2 is the variance of transmitted signal and N is the number of samples.

The probability of finding channel occupied when it is actually vacant is the probability of False Alarm (P_{FA}). It is indicated by the hypothesis H_0 and is given as [13]:

$$P_{FA} = P(T < \lambda / H_o) = \mathrm{Q}\left(\frac{\lambda - N\sigma_x^2}{\sqrt{2N\sigma_x^4}}\right) \quad (3)$$

Probability of missed detection (P_M) is given as,

$$P_M = 1 - P_D \quad (4)$$

While a missed detection reduces the spectral efficiency, a false alarm causes interference with the PU detection, therefore optimum detection performance is achieved when detection probability is maximized subject to the constraint of the probability of false alarm. As per IEEE 802.22 standard, the false-alarm probabilities and detection probability are assumed to be $P_{FA} \leq 0.1$ and $P_D \geq 0.9$.

B. Power Spectral Density Estimation by Periodogram and Welch Method

In frequency domain, power spectral density (PSD) estimation is considered to obtain the energy measurement, which is used to decide presence or absence of user signal.

To optimize the performance of the detection method, it is important to accurately estimate the energy or its equivalent, the power of bandwidth of interest. The periodogram is the simplest non-parametric method of PSD estimation [16]. It can be obtained by first estimating the autocorrelation sequence from the observed samples x[0], x[1], ... x[N-1] and applying the FFT to transforms a signal from a time domain to a frequency domain. Periodogram makes use of the power of each frequency of the signal for PSD estimation. This property is used in the simulations and for real-time implementation. However, due to high variance periodogram are inconsistent. By applying Welch's approach, data are divided into several overlapping segments. Then a window function is applied on each segment, followed by computing of periodogram for each segment. Lastly, the averaged periodogram of each segment is known as Welch Periodogram [17]. They are consistent and can be used to achieve better resolution of the signal.

C. Hardware and Software setup

All simulated operations between transmitter and receiver *i.e.* modulation, energy detection by PSD estimation and allocation were done using MATLAB-2018b and Xilinx iMPACT.

The flow diagram depicting energy detection simulation is shown in Fig. 1. After initialization of carrier and sampling frequency bands, user data is modulated over frequency bands using different modulation techniques *viz*. Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM).

The modulated signal is passed through an AWGN channel to the energy detector. The received PSD output recorded as Periodogram and Welch's periodogram is used to assess the cognitive spectral environment about the occupied and vacant spectrum slots status based on the Neyman-Pearson criteria. On detecting a vacant slot, SU is allotted to that slot. In Matlab, Periodogram function, P_{xx}= Periodogram(s) is used and average power in the signal over that particular frequency band is H_{PSD} = dspdata.psd(P_{xx}).

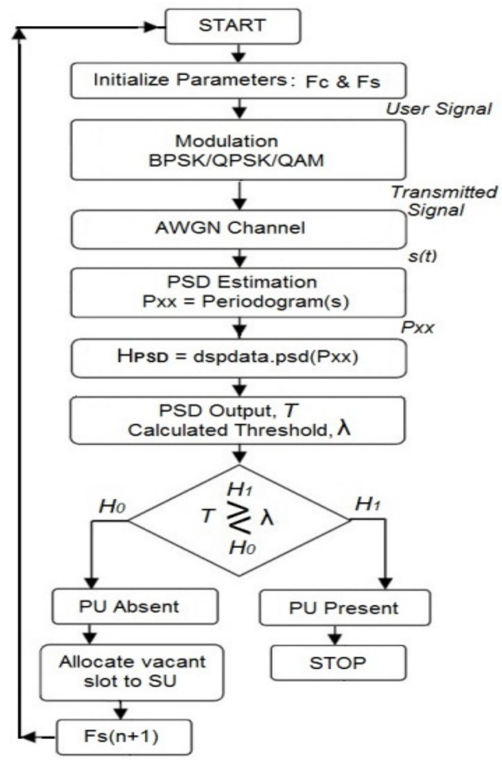

Fig. 1. Flow chart for PSD based energy detection.

WARP is used for validating the performance of energy detector. WARP has a reconfigurable field programmable gate array (FPGA) for performing signal processing applications which supports different radio boards at the front end. For present study two WARP boards with Xilinx Virtex-6 LX240T FPGA (Mango Communications, USA) each with one antenna 2.4/5GHz were used. The primary user signals are generated in transmitter WARP board whereas other WARP board is configured as a receiver board for secondary user. Transmission and reception of the signal are performed wirelessly. A common Ethernet Switch (1Gbps) connects the transmitting WARP nodes, receiving WARP nodes and host PC equipped with WARPLAB7 and Simulation Software to establish the communication link. The hardware setup for experimental implementation of spectrum sensing is shown in Fig. 2. The chosen frequency band (1 MHz - 5MHz) is the input signal for FPGA implementation. The received signal is sampled by A/D Converter with frequency of 12 MHz.

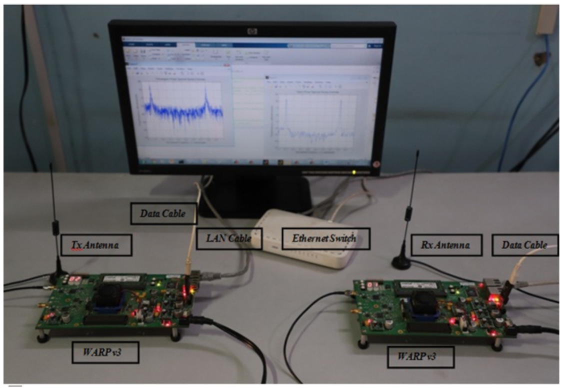

Fig. 2. Experimental Setup.

Following parameters were considered for present work.
Number of samples: 1000
Carrier frequencies, F_C : 1, 2, 3, 4, 5 MHz
Sampling frequency, F_S : 12 MHz
Signal to Noise Ratio, SNR: – 30 db to 10 db
Probability of false alarm, P_{FA} : 0.001, 0.01, 0.1
Threshold value at P_{FA} = 0.01 : 1.0735

IV. RESULTS AND DISCUSSION

A simplistic CR environment with multiple users is simulated for monitoring the spectrum holes. Probability of detection, P_D of primary user signal over 5 MHz is computed using test statistic (T),

A. Performance evaluation of Energy detection

The performance of Energy Detector is measured by its ability to achieve maximum detection probability at an optimum false alarm probability for a given SNR. The receiver operating characteristic (ROC) curves, as plot of P_D *vs* P_{FA} are the performance metrics for evaluating the performance of sensing technique.

Fig. 3 shows ROC plots for BPSK signal at SNR value of 10 dB. Simulated results are found to be in close proximity to the theoretical model.

B. Effect of SNR on Probability of Detection

From the PSD based data about PU's activity, SUs sense the channel and translate the values of SNR to P_D using Neyman-Pearson detection strategy at a constant P_{FA}. Fig. 4 shows the variation of P_D with SNR for different P_{FA} values, from where probability of false alarm as 0.01 was considered as optimum value for further studies on estimating P_D values for different models under study.

Probability of detection and probability of missed detection at different SNR values ranging from –30 dB to +10 dB at constant P_{FA} as 0.01 were computed using Eqn. (2) and (4), values are included in Table 1. With increasing SNR, the detection probability increases and probability of missed detection decreases; at SNR value ≥ –5 dB, P_D reaches unity whereas P_M reduces to zero for BPSK and QPSK modulated signal.

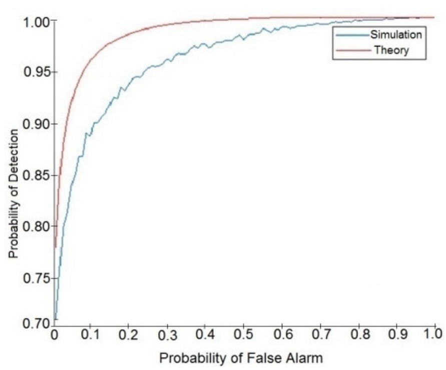

Fig. 3. ROC plots for the energy detector at SNR 10dB.

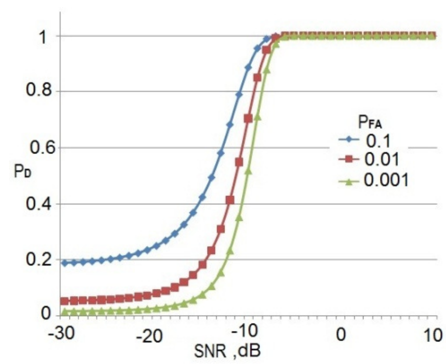

Fig. 4. Probability of detection *vs* SNR at different P_{FA}.

Table 1: SNR based Performance of spectrum sensing by energy detection for BPSK and QAM modulated signal at P_{FA} = 0.01.

SNR (dB)	BPSK		QPSK		QAM	
	P_D	P_M	P_D	P_M	P_D	P_M
-30	0.2836	0.7164	0.1806	0.8194	0.0022	0.9978
-25	0.3006	0.6994	0.2012	0.7988	0.0087	0.9913
-20	0.3565	0.6435	0.2525	0.7475	0.0125	0.8750
-15	0.5433	0.4567	0.2633	0.7367	0.0260	0.9740
-10	0.9321	0.0679	0.8021	0.1979	0.8140	0.1860
-9	0.9757	0.0243	0.8757	0.1243	0.9671	0.0329
-8	0.9945	0.0055	0.9545	0.0455	0.9970	0.0030
-7	0.9994	0.0006	0.9784	0.0216	1	0
-6	0.9994	0.0006	0.9964	0.0036	1	0
-5	1	0	1	0	1	0
0	1	0	1	0	1	0
10	1	0	1	0	1	0

For QAM signals the P_D reached unity and P_M reduces to zero at SNR value ≥ -7 dB.

Fig. 5 includes representative periodogram at SNR -10 db and +10 db, which gives a comparative view on the effect of noise on transmitted signal. In general, high disturbances (noisy channel) were observed in channel at lower SNR, which might leads to high probability of error in the received signal.

On comparing the simulation results, it was clear that signal resolution for slot status identification (occupied or vacant) could be achieved at much lower SNR for received signal modulated under QAM as compared to the BPSK and QPSK signals. These observations are in concordance with earlier sensing studies based on energy detection [29].

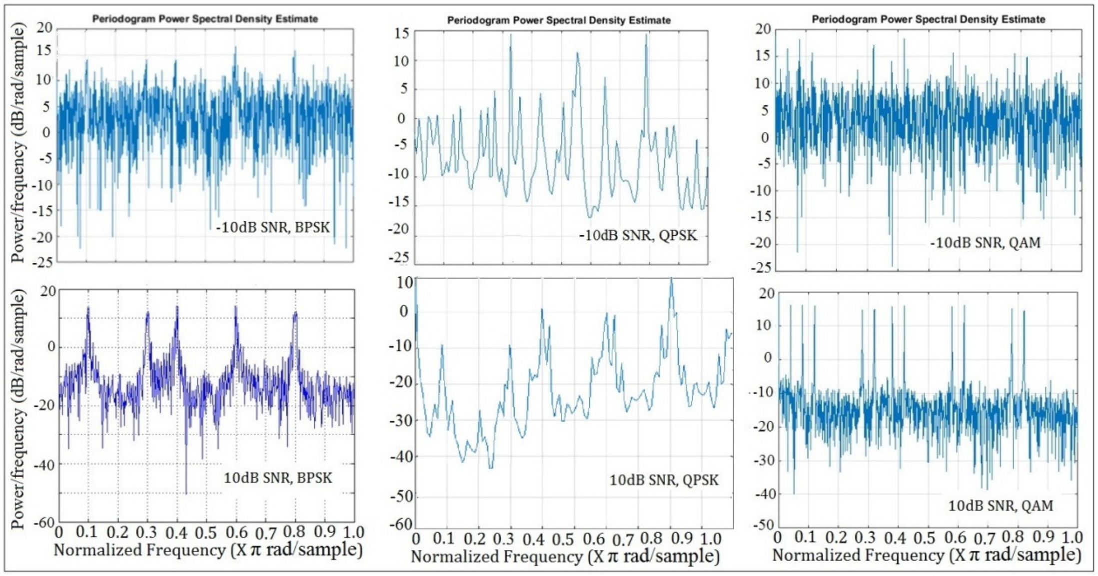

Fig. 5. Energy detector output as periodogram psd estimates at SNR -10 db (upper row) and +10 db (lower row) for BPSK, QPSK and QAM signals.

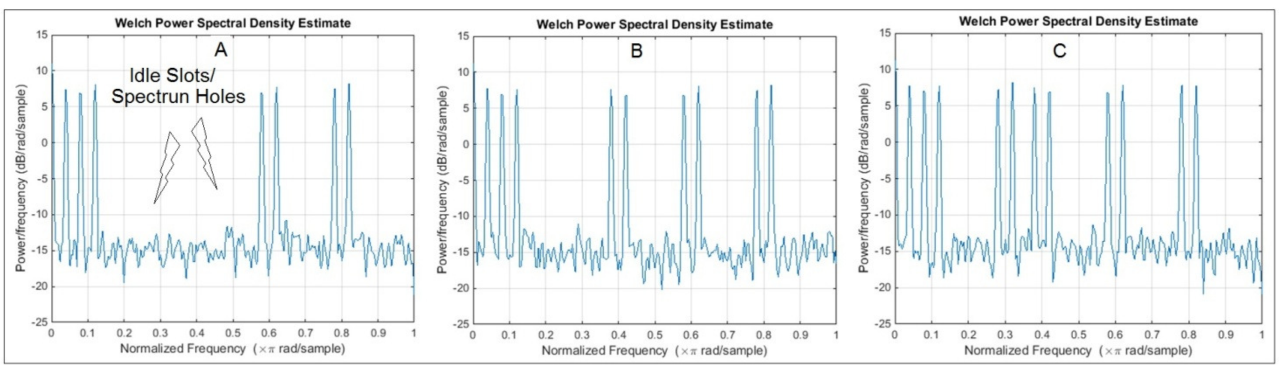

Fig. 6. Welch curves showing channel allocation to SUs for QAM signal in AWGN channel for multiple slots. A: 3 PU, 0SU; B: 3PU, 1 SU; C: 3PU, 2SU.

C. Monitoring Spectrum Holes by Welch method

For allocation of idle spectrum bands to SUs, the CR system continuously monitors for spectrum hole through energy detection. Frequency signal peaks in periodogram higher than that of the threshold value are marked as occupied channel. The lower frequency peaks are indicative of vacant /free channel, designated as spectrum holes. Welch method revealed PSD estimates with high contrast and resolution to differentiate the busy an idle band and are therefore considered better for monitoring the spectrum holes as shown in Fig. 6 for QAM signal. Fig. 6-A depicts a stage where three primary users: PU_1, PU_2 and PU_3 are present at 1st, 4th and 5th slots respectively and 2nd and 3rd slots are identified as spectrum holes where no activity of PU is recorded, confirming that PU is absent. Looking at the available vacant slot, now the CR system will automatically assign it to the SUs. Among the available frequency slots, SU_1 access the channel as per local allocation policy. Presently SU_1 is shown to occupy channel 4 as evident from increased power of 4th slot (Fig. 6-B). Now the system will again search for the next spectrum hole and automatically assign available 3rd slot to SU_2 as shown in Fig. 6-C.

V. CONCLUSION

Spectrum sensing using energy detection based on PSD estimates for CRNs has been performed successfully in a multiple user environment. Simulations were carried out for BPSK modulated, QPSK modulated and QAM signals and discussed. On varying the values of SNR, it was observed that for lower SNR values, performance of detections was reduced. For QAM signals, detection occurred at SNR value -7dB, thus it can sense more channels at a given time as compared to BPSK and QPSK signals. Performance of energy detection was evaluated using ROC curves. WARP boards were used for the implementation of the algorithm in real time. PSD estimates in the form of Welch Periodogram of the received signal were used to identify the available vacant bands, which could be allocated to SUs to improve the overall throughput of system.

VI. FUTURE SCOPE

It is envisaged to implement the spectrum sensing model for a complex real time scenario of heterogeneous cognitive environment involving femtocells.

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