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Spectrum sensing using 16-QAM and 32-QAM modulation techniques at different signal-to-noise ratio: a performance analysis

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ABSTRACT

Spectrum sensing techniques are implemented for effective use of spectrum resources in the cognitive-radio. In this research work attempt has been made for the performance of energy detector with cooperative spectrum sensing using double dynamic threshold on the MATLAB software. Additive white gaussian noise is used and the frequency range between 54 MHz to 862 MHz is considered with wideband. Findings in receiver operative curve have been observed to analyze probability-of-detection (P_d) under different values of probability-of-false alarm (P_f) condition and diverse ranges of signal to noise ratio with different number of samples of input signal. Presence and absence of primary user has been marked by using a hypothetical model based on Neyman pearson approach. From the results, it has been observed that more the number of sample values, better is the probability-of-detection (P_d) value as achieved for 32-QAM signal as compared to 16-QAM signal. Also, better results have been witnessed at -9db signal to noise ratio value as compared to -15db and -20db. This work provides almost 10% of enhancement in the probability of detection at -9db signal to noise ratio for 16-QAM modulated signal as compared to the existing model where the implementation of energy detector spectrum sensing technique through simulink model.

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1. INTRODUCTION

From the literature review it has been revealed that, there is no proper utilization of radio spectrum. Here detailed explanation of various techniques of spectrum sensing techniques has been provided. Depending upon the type of application, sensing technique can be selected. Cognitive radio is the best suitable technique for detection of spectrum holes and better utilization of unused or partial frequency bands in the spectrum. Cognitive radio performs four basic functions i.e., sensing, sharing, mobility and management. Depending upon the range of frequencies, sensing process has to be decided and according to their utilization sharing and mobility process will be performed. Further, management process will be considered for better usage of spectrum [1], [2]. Among four basic functions of cognitive radio, more emphasis is placed on sensing process which includes the detection of unused bands and then used by the secondary users. Various spectrum sensing techniques are available based upon the transmitter method i.e., energy detector or blind detection method [3],

[4]. Cyclostationary spectrum sensing method includes cyclic features and correlation approach used in the matched filter spectrum sensing technique.

Cyclostationary approach is more complex as compared to the other two methods. Matched filter is better technique as compared to energy detector but in this technique prior knowledge of primary user signal is required. Many more techniques, such as eigen values, wavelength based and covariance methods are available [5], [6]. Among all the techniques, energy detector is most preferred technique because it has low complexity and also no prior knowledge of signal is required. In cooperative sensing method, each cognitive radio user provides the information of primary user to the fusion center (FC). The other important criteria in the sensing method is the bandwidth, either it is considered as narrow or wideband. In narrowband sensing the value of bandwidth must be less than the value of coherence bandwidth whereas in wideband sensing method wide range of band is considered which follows the Nyquist and sub-Nyquist criteria [7], [8]. To sense the spectrum simultaneously, energy and hardware are the constraints [9]. For better transmission various cognitive radio must establish sensing synchronization. Better spectrum utilization can be achieved if information of spectral leads to effective acknowledgement of spectrum holes.

Three models i.e., Interwave, underlay and overlay are used in the cognitive radio network based upon the accessibility of bands. Occupied bands are not accessed by the un-licensed user in case of interwave type. Sharing mechanism is used by the users in underlay model and transmission process followed by the users in overlay model [10]. By considering the various dimensions like frequency, geographical space and time, the concept of spectrum sensing can be re-evaluated [11]. With the help of probability-of-detection and false-alarm-probability, energy detector sensing can be summarized. Performance of various spectrum sensing techniques at different level of threshold, can be achieved by receiver operating characteristic (ROC). Farrow structure (based on different bandwidth and filter values) is one of the solution to reduce the hardware complexity and sensing time issue [12]. By adding filters at the transmitter and receiver section better bandwidth utilization can be obtained for orthogonal frequency division multiplexing (OFDM) [13]. Maximum eigen-value to minimum eigen -value ratio and ratio of average to minimum eigen values are the two algorithms proposed solution of noise uncertainty [14]. Improvement in detection of signal rate at different values of frequency can be obtained by incorporating different techniques of power spectral density [15]. Dempster-Shafer theory was introduced for cooperative spectrum sensing technique to calculate degree of trustworthiness.

Number of approaches based upon IEEE802.22 standard were also introduced for cooperative spectrum sensing. Performance of cooperative spectrum sensing was analyzed and evaluated by incorporating perception learning model and two performance metrices i.e., probability-of-detection and false-alarm-probability [16]. Trustful factor is one of the technique to achieve the robustness detection [17]. Joint optimal model is the solution to minimize the overhead problem during the sensing. For improvement in the throughput of the system polyblock algorithm has been introduced [18].

The problem of interference can be overcome with the benefit of cognitive radio which results better practice of radio spectrum. Majorly three important tasks have been introduced via the cognitive radio. First task under this availability of spectrum holes can be find out with radio-scene analysis. Identification of channel is the second task of cognitive radio which provides the availability of channel's capacity at the transmitter section. Transmission of power control and spectrum management is the third task that can be performed by the cognitive radio.

Techniques based upon digital-signal-processing can be used for the improvement in radio sensitivity and the detection of primary or licensed users. Fading and shadowing are the obstacles for the detection of licensed user in individual sensing process. The cooperative decision is one of the solutions to minimize the probability of interference. Fading is one of the factors to affect the phase and amplitude of the signal. Spectrum sensing techniques can be analyzed by using different fading models i.e for Rayleigh, Nakagani-n, Rice and lognormal. One of the factors is coordination that play important role for accurate sensing better outcome of energy detector spectrum sensing technique has been obtained for various variations of signal-to-noise ratio (SNR) [19].

2. MATERIALS AND METHOD

In sensing process, identification of primary user is based upon the amount of energy content present in specific band. Noise is the significant factor to calculate the value of the threshold. Noise is embedded with modulated signal at the receiver section. Noise present in the secondary users can detect the position of primary users. Only noise-oriented signal indicates the vacant band with absence of user whereas presence of signals along with the noise declares the presence of primary user [20]. Neyman pearson is binary hypothesis which is used for the identification of primary user. probability-of-detection (P_d) represents real existence of the primary user over the given samples and probability-of-false alarm (P_f) represents the falsy existence of primary user over the sample, are the two types of parameters which are present in the Neyman pearson. Probability-of-detection is computed in (1). Additive white gaussian noise (AWGN) is used in this research, this is the type of random noise and it has widespread range of frequency over the channel.

$$P_d = \mathrm{Q}\left(\frac{\lambda - N(\sigma noise^2 + \sigma signal^2)}{\sqrt{2N(\sigma noise^2 + \sigma signal^2)^2}}\right) \tag{1}$$

$$\lambda = \sigma_{noise}{}^{2}\,(\mathrm{Q}^{-1}(P_f)\sqrt{2N} + \mathrm{N})) \tag{2}$$

Here, gaussian distribution is denoted by Q, N denotes the number of samples, λ represents the value of threshold which can be calculated by (2). Noise and signal power represented by σ_{noise} and σ_{signal} the respectively. Here, P_f is false alarm probability and during the simulations ,the value of P_f is set as constant i.e., (0.01 to 1) and Q^{-1} represents the inverse of the gaussian distribution. Modulation type consideration is important, in this work better detection is obtained from 32-QAM (quadrature amplitude modulation) as compared to 16-QAM because of the high data rate property of the 32-QAM. If the energy present in the received signal is greater than the value of threshold, then it signifies the present of vacant band.

In a spectrum band, if the value of P_f is not considered appropriate then correct detection of primary user can't be achieved. That is why, fixed value of probability-of-false-alarm (P_f) is considered for better detection of primary user [21], [22]. Figure 1 depicts the block diagram for identification of primary user using 16-QAM in Figure 2(a) and 32-QAM in Figure 2(b) (where signal is modulated by using 16-QAM and 32-QAM) and incorporated with double dynamic threshold. Further, 16 QAM and 32 QAM techniques are used at different value of SNR i.e -9db, -15db and -20db. In QAM two components i.e. (quadrature and in phase) are present which are different with respect to each other in terms of phase and amplitude [23]. In 16-QAM, simultaneously set of four bits are transmitted in different phases (in-phase and quadrature phase), whereas in 32 QAM, set of 5 bits are transmitted in simultaneous manner (in-phase and quadrature phase) as Figures 2(a) and 2(b). Also, cooperative spectrum sensing with double dynamic threshold is adopted for analyzing the performance [24].

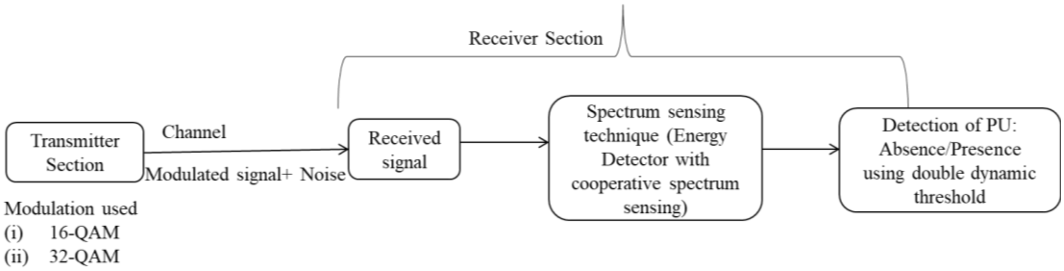
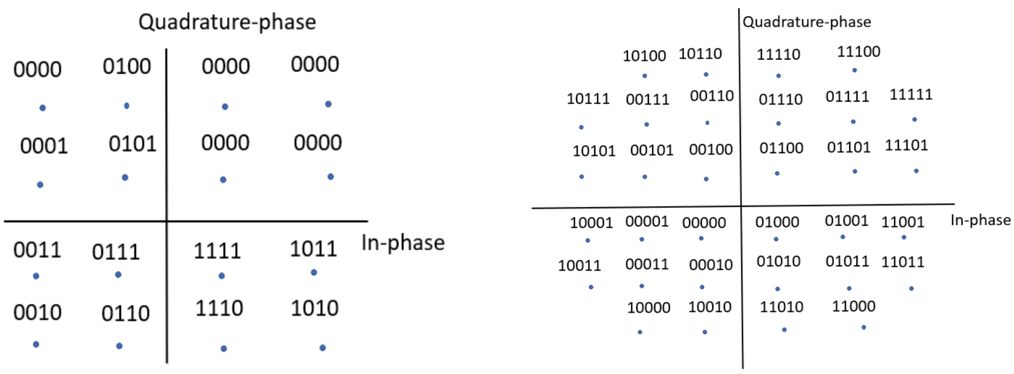


Figure 1. Block diagram for identification of primary user using 16-QAM and 32-QAM



(a) (b)

Figure 2. Comparing probability of detection for spectrum sensing technique using modulation technique in (a) 16-QAM and (b) 32-QAM

3. SIMULATION RESULTS AND ANALYSIS

In this section, performance of primary user detection has been analyzed for 16-QAM and 32-QAM modulated signals under different SNR i.e. -9db, -15db and -20db. All the simulations are obtained through MATLAB software and the wideband is used during the simulations. AWGN is used and the frequency range between 54 MHz to 862 MHz is considered. Trade-offs between probability-of-detection and probability-of-false-alarm can be employed using ROC curve. Findings in ROC has been observed to analyze P_d under different values of P_f conditions and different ranges of SNR with different number of samples. Figures 3 and 4 displays P_d vs P_f curve for 16-QAM and 32-QAM signal for 500 and 1,000 number of samples at -9db SNR.

When the number of samples are 500 and probability-of-false-alarm (P_f) is considered as 0.1, then probability-of-detection (P_d) is found to be 0.7 for 16-QAM and for 32-QAM signal, it is observed as 0.9. When the number of samples are 1,000 and P_f is considered as 0.1, then P_d is found to be 0.97 for 16-QAM and for 32-QAM signal it is observed as 1. When the number of samples are 500 and P_f is considered as 0.3, then P_d is found to be 0.99 for 16-QAM and for 32-QAM signal it is observed as 1. When the number of samples are 1,000 and P_f is considered as 0.3, then P_d is found to be 1 for 16-QAM and for 32-QAM signal. When the number of samples are 500 and P_f is considered as 0.5, the value of P_d is found to be 1 for 16-QAM and for 32-QAM signal it is also observed as 1. When the number of samples are 1,000 and value of P_f is taken as 0.5 then P_d is found to be 1 for 16-QAM and for 32-QAM. These results indicates that the probability of detection is better for 32-QAM. Further, it has been observed from the results as tabulated in Table 1, as more the number of samples, better would be the primary user detection. Also lower the value of P_f, better is the detection.

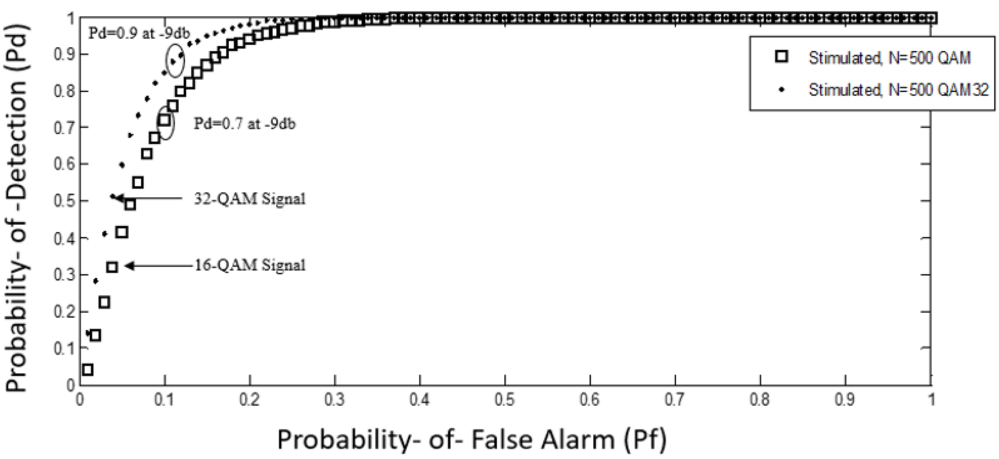


Figure 3. P_d vs P_f curve for 16-QAM and 32-QAM at 500 samples at -9db

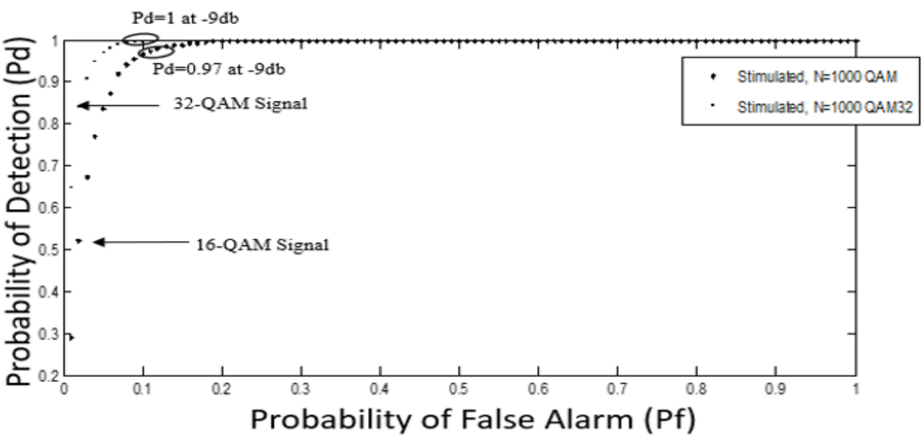


Figure 4. P_d vs P_f curve for 16-QAM and 32-QAM at 1,000 samples -9db

Table 1. Performance results of 16-QAM and 32-QAM

Number of samples (N)	Modulation type	Probability of false alarm (Pf)	Simulated (Pd) at -9db	Simulated (Pd) at -15db	Simulated (Pd) at -20db
N=500	16-QAM	0.1	0.7	0	0
N=500	32-QAM	0.1	0.9	0	0
N=1,000	16-QAM	0.1	0.97	0	0
N=1,000	32-QAM	0.1	1	0	0
N=500	16-QAM	0.3	0.99	0.27	0.01
N=500	32-QAM	0.3	1	0.38	0.02
N=1,000	16-QAM	0.3	1	0.5	0.01
N=1,000	32-QAM	0.3	1	0.62	0.03
N=500	16-QAM	0.5	1	0.96	0.82
N=500	32-QAM	0.5	1	0.98	0.84
N=1,000	16-QAM	0.5	1	0.99	0.91
N=1,000	32-QAM	0.5	1	1	0.94

Figures 5 and 6 displays P_d vs P_f curve for 16-QAM and 32-QAM signal for 500 and 1,000 number of samples at -15 db SNR. When the number of samples are 500 and 1,000 and the value of P_f is taken as 0.1, then the value of P_d is found to be negligible for 16-QAM and for 32-QAM signal. When the number of samples are 500 and P_f is considered as 0.3, P_d is found to be 0.27 for 16-QAM and for 32-QAM signal, it is observed as 0.38. When the number of samples are 1,000 and P_f is considered as 0.3 then P_d is found to be 0.5 for 16-QAM and for 32-QAM signal, it is observed as 0.62. When the number of samples are 500 and P_f is considered as 0.5 then the value of P_d is found to be 0.96 for 16-QAM and for 32-QAM signal, it is observed as 0.98. When the number of samples are 1,000 and P_f is considered as 0.5, then the value of P_d is found to be 0.99 for 16-QAM and for 32-QAM signal, it is observed as 1. It is observed from the analysis that the detection of probability is better for 32-QAM as compared to 16-QAM.

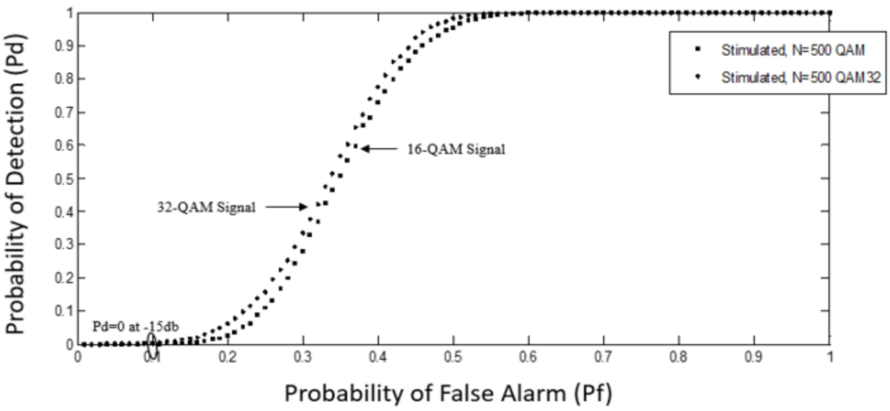


Figure 5. P_d vs P_f curve for 16-QAM and 32-QAM at 500 samples -15db

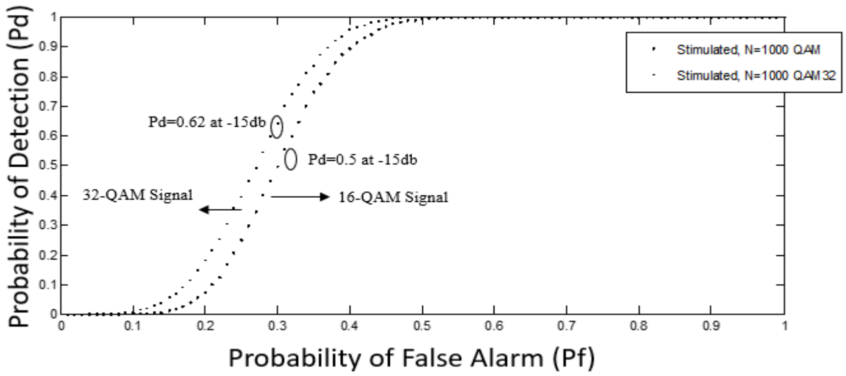


Figure 6. P_d vs P_f curve for 16-QAM and 32-QAM at 1,000 samples -15db

Figures 7 and 8 displays P_d vs P_f curve for 16-QAM and 32-QAM signal for 500 and 1,000 number of samples at -20db SNR. When the number of samples are 500 and 1,000 and P_f is set as 0.1 then P_d is found to be negligible for 16-QAM and for 32-QAM signal. When the number of samples are 500 and P_f is taken as 0.3 then P_d is found to be 0.01 for 16-QAM and for 32-QAM signal, it is observed as 0.02. When the number of samples are 1,000 and P_f is considered as 0.3 then P_d is found to be 0.01 for 16-QAM and for 32-QAM signal, it is observed as 0.03. When the number of samples are 500 and P_f is considered as 0.5 then the value of P_d is found to be 0.82 for 16-QAM and for 32-QAM signal, it is found as 0.84. When the number of samples are 1,000 and P_f is considered as 0.5 then the value of P_d is found to be 0.91 for 16-QAM and for 32-QAM signal, it is 0.94. Results indicates that the P_d is better for 32-QAM as compared to 16-QAM and also more the number of samples, better would be the detection.

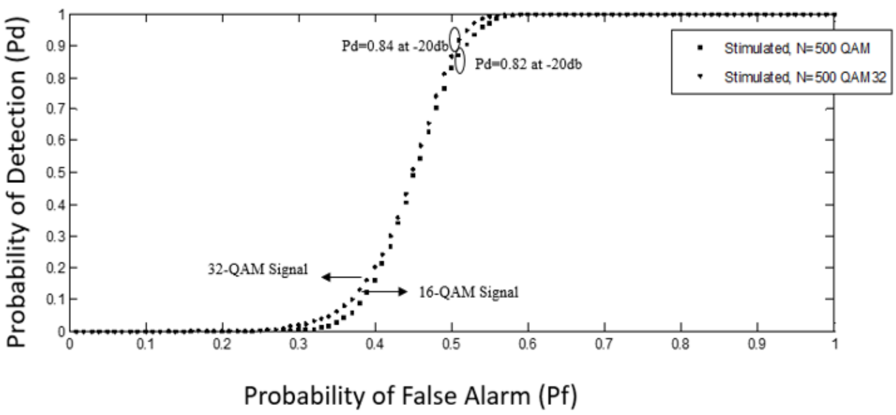


Figure 7. P_d vs P_f curve for 16-QAM and 32-QAM at 500 samples -20db

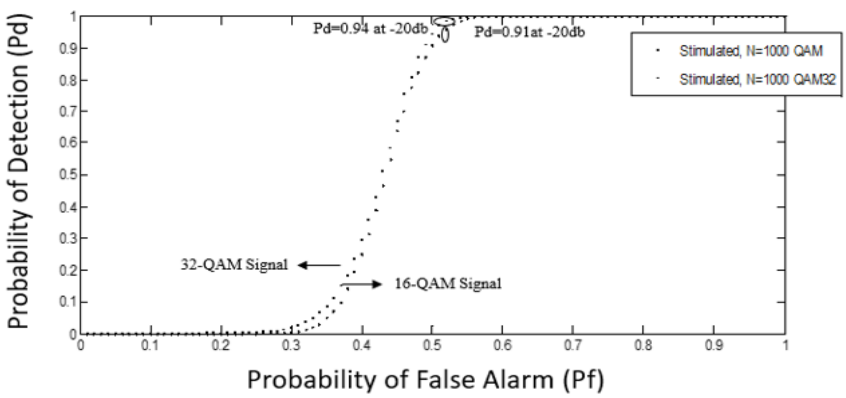


Figure 8. P_d vs P_f curve for 16-QAM and 32-QAM at 1,000 samples -20db

It has been reported that for 500 samples and if the value of P_f is set as 0.1 then the value of P_d is found to be 0.7 for 16-QAM signal at -9db SNR and P_d is found to be 0.9 for 32-QAM signal at -9db SNR, whereas P_d is found to be negligible at -15db and -20db for 500 number of samples and for both the 16-QAM and 32-QAM. For 1,000 number of samples and P_f is taken as 0.1, the value of P_d is found to be 0.97 for 16-QAM signal at -9db SNR and P_d is found to be 1 for 32-QAM signal at -9db SNR, whereas P_d is found to be negligible at -15db and -20db for 1,000 number of samples and both for 16-QAM and 32-QAM. At -9db SNR P_d is found to be 0.99 for 16-QAM signal and P_d is found to be 1 for 32-QAM. Whereas at -15db SNR, P_d is 0.27 and at -20 db SNR P_d is 0.01 for 16-QAM. For 32-QAM and 500 number of samples, P_d is 1 at -9db SNR, 0.38 at -15 db SNR and 0.02 at -20db SNR and P_f is 0.3.

For 1,000 number of samples and 16-QAM modulated signal, P_d is 1 at -9db SNR, 0.5 at -15db SNR and 0.01 at -20db SNR at P_f is 0.3, whereas for 32-QAM P_d is 1 at -9db SNR, 0.62 at -15db SNR and 0.03 at -20db SNR and P_f is considered as 0.3. For 16-QAM signal where P_f is 0.5, number of samples are 500 and

P_d is 1 at -9db SNR, 0.96 at -15db and 0.82 at -20db SNR, whereas for 32-QAM modulated signal, P_d is 1 at -9db, 0.98 at -15db and 0.84 at -20db SNR. Where P_f is 0.5 and 1,000 are the samples then P_d is 1 at -9db, 0.99 at -15db and 0.91 at -20db SNR, whereas for 32-QAM P_d is 1 at -9db, 1 at -15db and 0.94 at -20db SNR. From the graphs it is observed that P_d is better for 32-QAM as compared to 16-QAM also at low SNR, better P_d had achieved. This work provides almost 10% of enhancement in the P_d at -9db signal to noise ratio for 16-QAM modulated signal as compared to the existing model where the implementation of energy detector spectrum sensing technique through simulink model [25]. In this paper, cooperative spectrum sensing with double dynamic threshold has been introduced also instead of 16-QAM ,32-QAM comparison is also introduced.

4. CONCLUSION

In this research, the performance of energy detector with cooperative spectrum sensing technique has been analyzed using double dynamic threshold. ROC have been plotted while considering P_d and P_f parameters as obtained under different SNR values. Here, different samples of signals modulated using 16-QAM and 32-QAM were used with P_f 0.1, 0.3 and 0.5. Along with the value of SNR as -9db, -15db and -20db. It has been observed that spectrum sensing is better with 32-QAM as compared to 16-QAM. As the value of SNR decreases, P_d also decreases. Also, from the results it is found that the P_d is better for -9db SNR as compared to other SNR. By incorporating this method, enhancement in primary user detection can be achieved. In future, improvement in spectrum sensing technique shall be obtained by hybrid spectrum sensing technique.

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