Threshold Optimization For Energy Detection in Spectrum Sensing of Wireless Sensor Networks

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ABSTRACT

Efficient spectrum utilization is critical for the evolving landscape of wireless communication. This paper presents energy detectors (ED) as a fundamental technique for identifying spectrum holes by examining their performance under different noise levels from data derived from USRP in 2.4 GHz environment. A theoretical model is developed to analyse the influence of noise variance, threshold, signal-to-noise ratio (SNR), and the number of samples on detection performance. Using a noise floor reference of –65 dBm, a noise variance of 9.99×10^{-22} is derived, which resulted in 7.38% spectrum usage and 92.62% availability which resulted in significant opportunities for secondary user access. Further empirical evaluation using USRP data revealed that lowering the noise floor improved detection sensitivity and Pd, due to the lower noise variance, which raises the effective SNR, with Pd = 0.6820 with N = 8000 at Pfa = 0.01. The results obtained show detection performance is highly dependent on accurate noise floor estimation, threshold tuning, and sample size. Lower noise floors led to improved sensitivity for better detection of weak signals and thus improved spectrum utilization. These findings highlight the need for adaptive and noise-aware spectrum sensing strategies in hybrid detection systems for dynamic spectrum access.

Keywords: Energy Detector, Noise Variance, Spectrum Sensing, Threshold

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have become indispensable for various applications which enable real-time data collection and monitoring in scenarios where conventional wired systems are impractical or cost-prohibitive [1], [2]. With limited communication, processing, and storage capacity, WSNs are included of vast several independent sensors that are powered which detect surroundings signals. The swift expansion relating to wireless networks as well as information traffic has led to an excess of radio spectrum resources [3], [4]. Due to the growing number of wireless devices and applications, the electromagnetic radio spectrum is becoming more crowded [5].

The Federal Communications Commission (FCC) regulates the use of the radio frequency (RF) spectrum to ensure efficient and interference-free operation of wireless communications [6]. The RF spectrum is assigned to licensed users, primary users (PUs), only for specific services [7]. The static allocation of spectrum has led to underutilization of the allocated frequencies. Certain frequency bands are found to have usage for less than 15% of the total duration [8] or is even less than 5% according to Muzaffar et al. [9], [10]. When primary users fail to fully utilize their assigned spectrum, it leads to white spaces or spectrum holes as shown in Figure

1. These spectrum holes, which remain unused by primary users, contribute to inefficiency as secondary users are unable to access the spectrum.

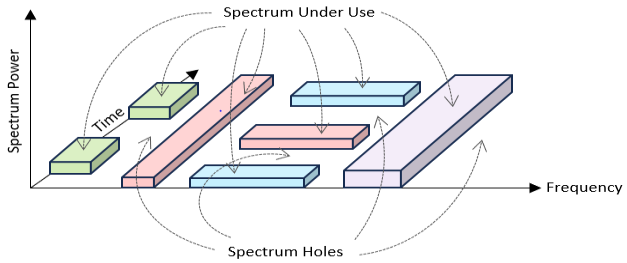


Figure 1. Spectrum under use and spectrum holes [11].

To address the issue of spectrum underutilization, Cognitive Radio (CR) technology provides an efficient solution. As described by Mitola, it is a technique designed to manage radio frequency scarcity by automatically detecting and adapting to changing conditions [7], [12], [13]. By enabling unlicensed users or known as secondary users (SUs) to independently access these spectrum holes, CR improves spectrum utilization, overall performance, and efficiency. The core functions of Cognitive Radio (CR) technology include spectrum sensing, decision-making, sharing, and mobility:

- **Spectrum Sensing –** The initial and vital step in CR where the system detects unused spectrum holes that can be accessed by SUs [14], [15].
- **Spectrum Mobility –** To maintain continuous communication, CR can switch from one frequency band to another when a PU reclaims its channel.
- **Spectrum Decision –** To select the most suitable channel for SUs based on the sensing results and communication needs.
- **Spectrum Sharing –** To manage how multiple SUs access available spectrum efficiently [16].

Spectrum sensing (SS) is one of the steps in cognitive radio systems which enables the identification and utilization of unused or underutilized spectrum bands while avoiding interference with primary users [3], [6], [17]. The main processes of spectrum sensing are depicted in Figure 2.

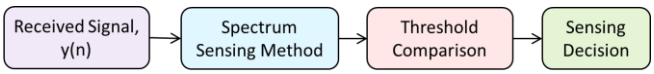


Figure 2. General model of Spectrum Sensing [18].

It is anticipated that the cognitive users, or SUs, are aware of the carrier frequency and modulation of the PU. By utilizing this data, the SU carries out spectrum sensing [5]. Every spectrum sensing method seeks to keep the false alarm probability under a specific threshold while maximizing the probability of detection, PD. Consequently, the optimization challenge in spectrum sensing involves maintaining the false alarm probability, Pfa below a certain level while achieving a desired detection probability.

Energy detection is by far the most prevalent technique for spectrum sensing [8], [19]. The method according to paper in [20] is a well-known spectrum sensing method, appreciated for its simplicity, ease of implementation, and low computational requirements. However, research of [21], [22], [23] have shown inherent limitations such as sensitivity to noise, challenges in selecting an appropriate threshold, and difficulty in distinguishing between signals. Despite its inherent limitations, studies in [19], [24] and [25] showed ED remains a viable and widely used method in modern wireless communication systems.

Godugu et al. [26] suggested that the energy detection method is highly efficient in evaluating the activity status of unknown primary users, whether they are active or idle where the technique compares the energy of the detected signal against a threshold to assess whether the spectrum is free for secondary users, thus indicating its occupancy. The threshold is a fundamental parameter that directly influences the accuracy and

efficiency of ED. In [27], the authors highlighted that adjusting the threshold improves detection accuracy. Arjoune et al. [28] showed that ED works well when the secondary user has no prior knowledge of the primary user's signal, though it is sensitive to noise and may cause false alarms. In [22], MATLAB simulations demonstrated that ED, using the Neyman-Pearson criterion, performs best at higher signal-to-noise ratios (SNRs) between -5 dB and 5 dB, with reduced performance at low SNRs. Baradkar and Akojwar [29] used ED to find unused spectrum by comparing signal energy to a threshold, showing that detection accuracy depends on the threshold and noise levels. If the threshold is set too low, the system may erroneously identify the presence of a signal which causes unnecessary interference and an elevated false alarm rate. Meanwhile, setting the threshold too high may result in failure to detect weak signals which can lead to missed opportunities for utilizing available spectrum and suboptimal resource allocation.

This paper presents the impact of threshold selection on the performance of ED to show how it affects detection reliability in different SNR conditions and noise levels. The best threshold for detection is determined in a 2.4 GHz environment using MATLAB software. The results presented demonstrate that careful threshold optimization is crucial for improving the performance of energy detection in cognitive radio networks. Consequently, determining the optimal threshold is crucial for achieving a balance between detection accuracy, minimizing false positives, and avoiding missed detections.

The rest of the paper is outlined as follows: Section 2.0 outlines the framework underlying the energy detector and threshold determination, while Section 3.0 presents the performance evaluation, providing insights into theoretical and empirical results. Finally, the paper concludes in Section 4.0, summarizing key findings and implications drawn from the study, as well as suggesting future research and development in related fields.

II. METHODOLOGY

The designed energy detector algorithm is simulated using the MATLAB R2024a software with a pre-dataset of USRP obtained by previous work of [30]. The USRP data consists of 80250 samples, N with a range amplitude value of -22 dBm to -113 dBm of -89 dBm average at 2.40 GHz to 2.48 GHz range. The USRP dataset is converted into linear scale for accurate signal computation and analysis of spectrum sensing. The characteristics of the dataset are summarized in Table 1.

Table 1. Summary of USRP data characteristics.

Parameters	Log-scale (dBm)	Linear scale
Average	-89.513	1.1168×10^{-12}
Sum	-7E+06	-
Max	-22.025	6.2736×10^{-6}
Min	-113.29	4.6838×10^{-15}

2.1 Energy Detector Algorithm

The energy detection algorithm determines the presence and absence of PU signals using the premade USRP dataset as input signal. The signal is fed into a bandpass filter to minimize noise and isolate the frequency range of interest. The output is squared and integrated over an interval time as shown in Figure 3.

The algorithm follows a structured process to determine whether a PU signal is present or absent. Thus, the energy detector formulates two hypotheses as follows [30], [31]:

$$H_0: Y(n) = W(n) \quad : PU\ Absent$$

$$H_1: Y(n) = S(n) + W(n) \quad : PU\ Present \quad (1)$$

where $S(n)$ and $W(n)$ represent the received PU signal and the additive white Gaussian noise (AWGN), respectively.

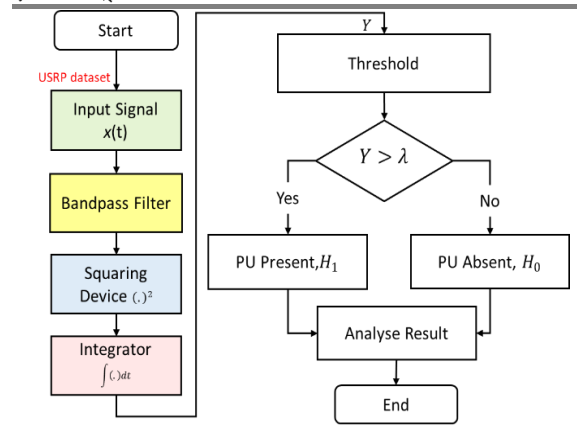


Figure 3. Flowchart of energy detection.

The signal consists of either noise, under the null hypothesis H_0, or the combination of a PU signal and noise under the alternative hypothesis H_1. The resultant signal is used to formulate test statistics, T, representing the received signal power. The total energy received over N samples is given by [32], [33]:

$$T = \sum_{n=0}^{N} |Y(n)|^2 \qquad (2)$$

where n = 0, 1, 2, …, N within a detection period. The test statistic T has a central Chi-Square distribution under hypothesis H_0 and a non-central Chi-square distribution under hypothesis H_1. For a large number of samples N, the distribution of T approaches a Gaussian distribution according to the central limit theorem, where the binary hypothesis is redefined as [31], [32], [34]:

$$H_0: T \sim Normal\,(N\,\sigma w^2, 2\,N\,\sigma w^4)$$

$$H_1: T \sim Normal\,(N(\sigma w^2 + \sigma s^2), 2\,N(\sigma w^2 + \sigma s^2)^2) \qquad (3)$$

where σw^2 and σs^2 are the noise variance and signal variance, respectively. The test statistic T is compared to a predetermined threshold, λ, to decide the presence or absence of the PU. The performance of the energy detector is characterized by three parameters under the binary hypothesis. The probability of detection, Pd, and the probability of false alarm, Pfa, of the general energy detector are defined as [32], [35]:

$$P_d = P(T > \lambda / H_1) = Q\left(\left(\frac{\lambda - (\sigma_s^2 + \sigma_w^2)}{\sqrt{2}(\sigma_s^2 + \sigma_w^2)}\right)\sqrt{N}\right) \qquad (4)$$

$$P_{fa} = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N}\sigma_w^2}\right) \qquad (5)$$

where SNR = σs^2 / σw^2. The value of Pd reflects how effectively the system can distinguish between the presence and absence of a signal amidst noise, while Pfa represents the likelihood of incorrect PU detection when only noise is present. Typical target values of Pfa range from 10^{-1} to 10^{-2} [36]. The relationship between these probabilities is interdependent in determining the optimal threshold value for best system performance.

2.2 Threshold Detection Model

A threshold is required to decide whether the target signal is absent or present. Improper adjustment of the threshold can lead to performance degradation, affecting detection accuracy. According to authors in [32], [34], the threshold λ is given by:

$$\lambda = \sigma_w^2\left(\frac{Q^{-1}(P_{fa})}{\sqrt{N}} + 1\right) \qquad (6)$$

where $Q^{-1}(\cdot)$ is the inverse Q-function. This threshold is influenced by the target probability of false alarm Pfa, the number of samples N, and the noise variance σw^2.

Therefore, determining an accurate threshold requires prior knowledge of the noise level or noise variance influencing the received signal [37]. The power representing integrator output Y is compared to the threshold λ. If $Y > \lambda$, hypothesis H_1 is accepted; otherwise, H_0 is accepted. The likelihood of correct detection (Pd) and false alarm (Pfa) are expressed as [30]:

$$Pd = P(Decision = H_1 \mid H_1) = P(Y > \lambda \mid H_1)$$

$$Pfa = P(Decision = H_1 \mid H_0) = P(Y > \lambda \mid H_0) \quad (7)$$

2.3 Receiver Operating Characteristics

Receiver Operating Characteristics (ROC) represent a plot of the correct detection rate against the false detection rate for various threshold values. Each threshold value corresponds to a pair of (Pd, Pfa), generating the ROC curve across a range of thresholds. This facilitates selecting an operating point that optimally balances detection accuracy with false alarm rates, thereby enhancing overall system performance. The curve is computed using Equation (4) based on the desired SNR to evaluate theoretical detection probability. In theoretical analysis, noise is commonly assumed to be AWGN with constant noise variance [31], [38]. Fading and shadowing are outside the scope of this study, which focusses on noise floor estimation and threshold selection from measured USRP data; the performance of ED over fading channels has been studied in [24], [25].

III. RESULTS AND DISCUSSION

Figure 4 shows a histogram plotting the count versus amplitude of the USRP dataset which reveals a distribution resembling a mountain-shaped curve, with most data concentrated between -65 dBm and -113 dBm. Given the assumption that the spectrum is underutilized, it is to interpret most of the observed power levels of the USRP data as noise.

The noise is estimated based on the Gaussian noise model, which is commonly used to characterize noise in communication systems. Thus, data within the dominant range (-65 dBm to -105 dBm) is treated as a noise-dominated region. By fitting a Gaussian distribution to this segment, the noise variance is extracted from the standard deviation. This approach involves isolating the noise-dominated region and applying statistical methods to calculate the mean and variance directly. The results are divided into theoretical analysis and empirical analysis.

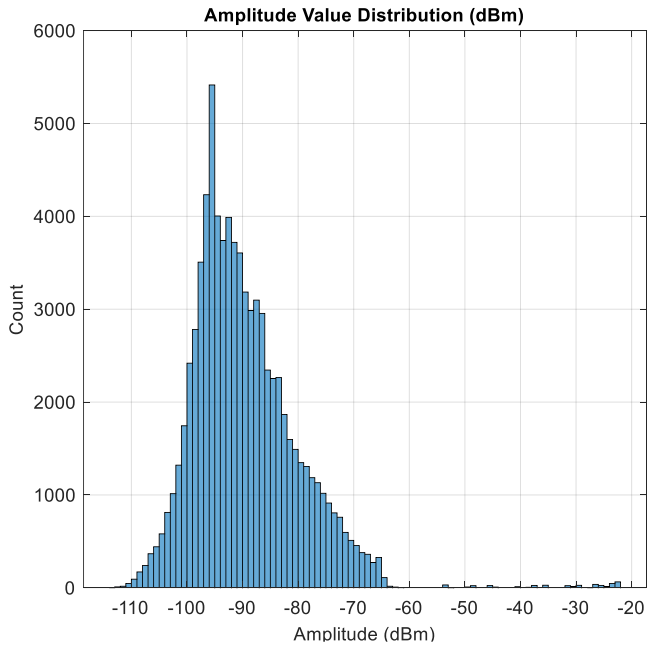


Figure 4. USRP data amplitude value distribution in dBm.

3.1 Theoretical Analysis

The theoretical analysis is applied to the energy detector algorithm to evaluate potential theoretical performance bounds under a constant noise environment, disregarding fluctuations in noise variance.

The theoretical ROC curve for ED is plotted in Figure 5 for the range of -18 dB to -30 dB SNR. The results indicate that the detector performs well at an SNR of -18 dB which obtained $P_d = 0.934$ for $P_{fa} = 0.01$.

As SNR drops below -18 dB, performance degrades significantly, as summarized in Table 2. Higher values of Pfa correspond to higher Pd across all SNR levels, indicating increased sensitivity at the expense of higher false alarm rates. When SNR decreases to -30 dB, Pd drops substantially to values between 0.0744 and 0.8743 for Pfa = 0.01 and Pfa = 0.9, respectively.

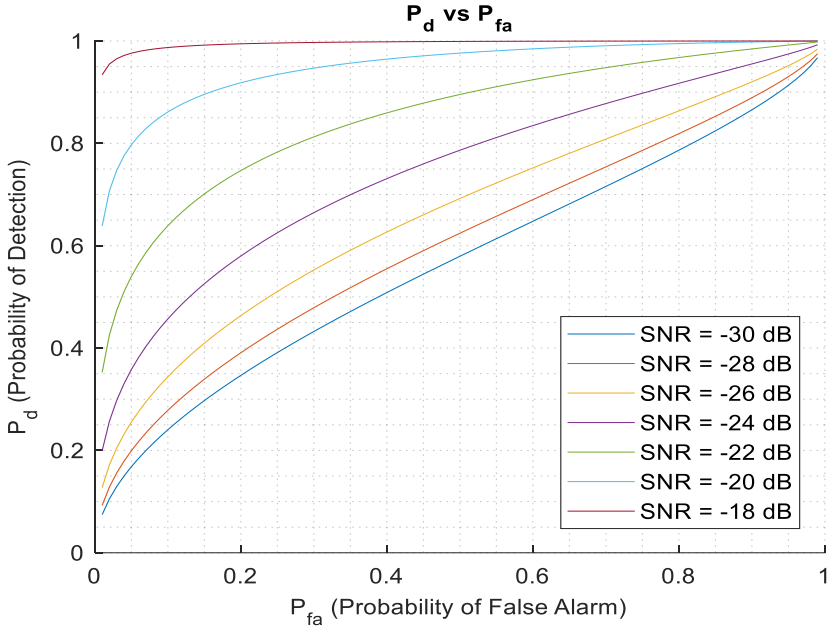


Figure 5. ROC curve of energy detector at different SNR at *N*=80250.

Table 2. Summary of theoretical Pd at different Pfa and SNR.

Pfa	-18 dB	-20 dB	-24 dB	-28 dB	-30 dB
0.01	0.9339	0.6385	0.199	0.0925	0.0744
0.1	0.9884	0.8696	0.4722	0.2915	0.2526
0.2	0.9948	0.922	0.5895	0.4003	0.3558
0.3	0.9972	0.949	0.6718	0.4868	0.4403
0.4	0.9984	0.9659	0.7369	0.5621	0.5157
0.5	0.9991	0.9772	0.791	0.631	0.5862
0.6	0.9995	0.9853	0.8391	0.6964	0.6544
0.7	0.9997	0.9911	0.8818	0.7604	0.7227
0.8	0.9999	0.9953	0.9211	0.8255	0.7939
0.9	0.9999	0.9982	0.9589	0.8968	0.8743

Figure 6 shows the relationship between P_{fa} and λ which are closely related and highly influenced by one

another. To strike an appropriate balance, the threshold should ideally minimize the P_{fa} while maintaining an acceptable P_D. A high threshold reduces P_{fa} which minimizes false alarms. A low threshold increases the sensitivity that gives a higher probability of detection in a low SNR environment. However, this sacrifices the high probability of false alarm which can lead to false alarms and inefficient use of the spectrum. This disrupts primary users and increases unnecessary transmission by secondary users. Conversely, this decreases P_d where the risk of missing active signals increases and leads to poor spectrum utilization.

The relationship of P_d with P_{fa} influenced is depicted in Figure 7 against SNR. A low P_{fa} prevent the system from falsely occupying the spectrum, thereby reducing interference with primary users and allowing better use of available spectrum [39], [40].

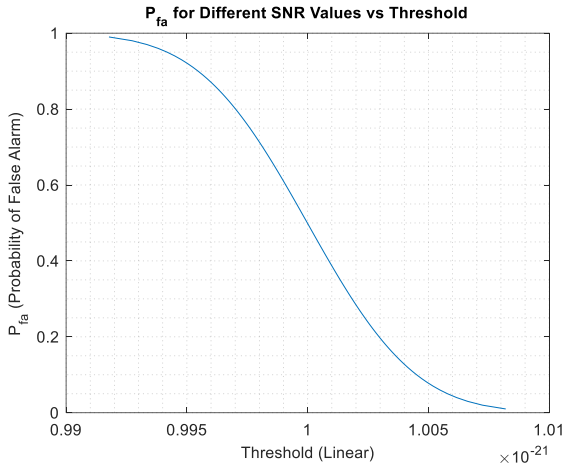


Figure 6. Probability of detection, P_d against threshold values, λ with different noise variance, σ_w^2 at $SNR = 20\ dB$, $P_{fa} = 0.01$, $N = 80250$.

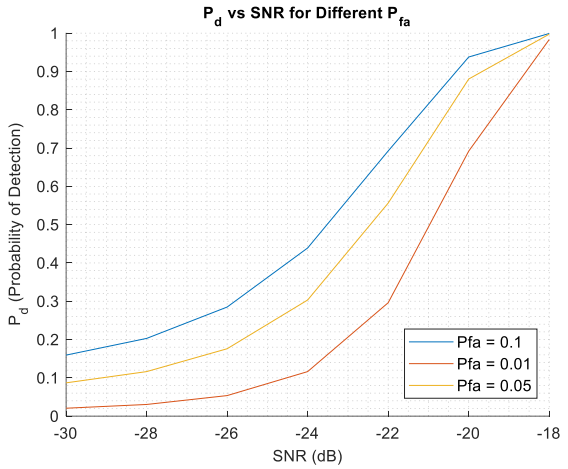


Figure 7. Probability of detection, P_d against SNR with different probability of false alarm, P_{fa} at $N = 80250$.

3.2 Empirical Analysis

The empirical analysis is performed using actual USRP measurements, considering real-world background noise variability.

With the pre-determined threshold value, the presence and absence of the spectrum is identified using the ED algorithm for the USRP data in consideration of the noise variance which is determined through the noise floor estimation with the average value of background noise present in the signal. In the USRP dataset, the noise is not uniform which introduces uncertainty when detecting weak signals which cause fluctuations. The presence of spectrum holes is inversely related to the signal detection rate. The spectrum utilization is depicted in Table 3 with noise floor estimation of –65 dBm, -85 dBm and -97 dBm. The highest noise floor of -65 dBm, resulted

in the sparsest signal of only 7.38% of spectrum usage while the decrease in noise floor led to an increase in spectrum usage.

Table 3. Spectrum Usage and Spectrum Holes at N = 80250 and Pfa = 0.01.

Noise floor (dBm)	Noise variance, σw^2 (linear)	Threshold, λ (linear)	Spectrum Usage (%)	Spectrum Holes (%)
-65	9.99×10^{-22}	1.00×10^{-21}	7.38	92.62
-85	1.04×10^{-24}	1.05×10^{-24}	44.31	55.69
-97.5	1.19×10^{-26}	1.18×10^{-26}	90.39	9.61

Referring to Figure 4, the USRP data amplitude distribution which accumulates in the range of -65 dBm to -110 dBm. As the threshold is lowered by decreasing the noise variance due to varying of noise floor, the system becomes more sensitive and capable of detecting weaker signals which results in an increase in spectrum usage.

Figure 8 shows the plots the spectrum utilization based on the noise variance chosen at -65 dBm noise floor reference point. This noise floor is utilized as a reference point which results the noise variance at 9.99×10^{22} in linear value. This threshold yields a detection rate where the spectrum is 7.38 % utilized and 92.62 % of the spectrum is available. The spectrum utilization is shown in detail where the absent of signal is represented by red line, H_0 while blue line represents the presence of PUs, H_1.

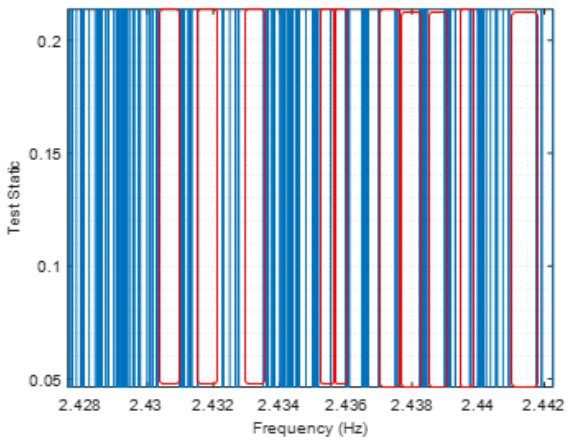


Figure 8. Indication of spectrum holes on USRP data plot at -89.513 dBm.

Table 4 shows the shows the probability of detection with the effect of noise floor which contributes to the noise variance with $N = 8000$. It has been shown that the performance of the energy detector improves as the noise variance lowered to -97 dBm, which obtained $P_d = 0.6820$ at -20dB SNR. This improves the SNR which allows the energy detector to more accurately detect the presence or absence of a signal. Similarly, the increase in the number of samples enhanced performance with more accurate estimation of the signal energy received. A larger sample size reduced the impact of random noise fluctuations depicted in Figure 4 and led to a more stable test statistic.

Table 4. Probability of detection for ED based on number of samples N and noise floor.

N	Noise floor (dBm)	Probability of Detection, Pd (Pfa = 0.01)
3000		0.5487
5000	-65	0.55
8000		0.5798
8000	-97.5	0.682

IV. CONCLUSION

Spectrum sensing is a critical component in modern wireless communication systems, essential for efficiently managing limited spectrum resources. The theoretical and empirical findings affirm the effectiveness of energy detection in identifying spectrum holes under varying noise floor conditions and SNR environments. Accurate noise floor estimation significantly influences detection performance and spectrum utilization. A higher noise floor estimate yields conservative detection with more available spectrum holes, whereas accurate noise floor tuning improves sensitivity and detection probability. The optimal decision threshold was identified as $\lambda = 1.18 \times 10^{-26}$ at Pfa = 0.01, yielding a detection probability Pd = 0.6820 at N = 8000 under a -97 dBm noise floor (Table 4). Furthermore, increasing sample size *N* mitigates random noise fluctuations. These findings underscore the necessity of noise-aware adaptive spectrum sensing strategies for dynamic spectrum access frameworks. Future work will extend the analysis to fading and shadowing channels, where the effect of channel fluctuation on Pd and on the adaptive threshold will be evaluated using measured channel data and cooperative sensing, together with other detection methods and dynamic interference in the 2.4 GHz band.

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REFERENCES

1. Alhumud, H., Zohdy, M., Debnath, D., & Olawoyin, R. (2019). Cooperative Spectrum Sensing for Cognitive Radio-Wireless Sensors Network Based on OR Rule Decision to Enhance Energy Consumption in Greenhouses. Wireless Sensor Network, 11, 1–11. https://doi.org/10.4236/wsn.2019.111001
2. Balachander, T., Ramana, K., Mohana, R. M., Srivastava, G., & Gadekallu, T. R. (2024). Cooperative Spectrum Sensing Deployment for Cognitive Radio Networks for Internet of Things 5G Wireless Communication. Tsinghua Science and Technology, 29(3), 698–720. https://doi.org/10.26599/TST.2023.9010065
3. Cotton, M. G., Vu, L. P., Eales, B., & Hicks, A. (2020). 3.45–3.65 GHz Spectrum Occupancy from Long-Term Measurements in 2018 and 2019 at Four Coastal Sites (Technical Report NTIA TR-20-548). U.S. Department of Commerce, National Telecommunications and Information Administration.
4. Deshmukh, M. N., & Padaganur, S. K. (2021). Comparative Analysis of Cognitive Radio Techniques for Sensing Spectrum. 2021 2nd International Conference for Emerging Technology (INCET), 1–4. https://doi.org/10.1109/INCET51464.2021.9456312
5. Joykutty, A. M., & Baranidharan, B. (2020). Cognitive Radio Networks: Recent Advances in Spectrum Sensing Techniques and Security. 2020 International Conference on Smart Electronics and Communication (ICOSEC), 878–884. https://doi.org/10.1109/ICOSEC49089.2020.9215360
6. Kumar, S. (2020). Wireless Sensor Network (WSN). GeeksforGeeks. https://www.geeksforgeeks.org/wireless-sensor-network-wsn/
7. M, S., & Sumithra, M. G. (2022). Overview of Spectrum Sharing and Dynamic Spectrum Allocation schemes in Cognitive Radio Networks. 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), 1, 934–937. https://doi.org/10.1109/ICACCS54159.2022.9785048
8. Muzaffar, M. U., & Sharqi, R. (2024). A review of spectrum sensing in modern cognitive radio networks. Telecommunication Systems, 85(2), 347–363. https://doi.org/10.1007/s11235-023-01079-1
9. Pal, A., Gayatri, G., Nandani, R., & Chatterjee, P. (2024). Evolution of Revolutionary CWSN from WSN. 2024 International Conference on Emerging Systems and Intelligent Computing (ESIC), 175–180. https://doi.org/10.1109/ESIC60604.2024.10481616
10. Poonguzhali, M., Rekha, M., Sumathi, A., Duraichi, N., Jeyalakshmi, K., & Sattanathan, S. (2023). Study of Cognitive Radio Techniques for Dynamic Spectrum Allocation. 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), 488–494. https://doi.org/10.1109/ICOSEC58147.2023.10276258

11. Salama, G. M., & Taha, S. A. (2020). Cooperative Spectrum Sensing and Hard Decision Rules for Cognitive Radio Network. 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS), 1–6. https://doi.org/10.1109/ICCAIS48893.2020.9096740
12. Sani, M., Tsado, J., Thomas, S., Suleiman, H., Shehu, I. M., & Shan'una, M. G. (2021). A Survey on Spectrum Sensing Techniques for Cognitive Radio Networks. 2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS), 1–5. https://doi.org/10.1109/ICMEAS52683.2021.9692412
13. Verma, G., Shukla, S., & Chauhan, S. S. (2020). Analysis of Time-Bandwidth Product in Cooperative Spectrum Sensing in Cognitive Radio Network. 2020 International Conference on Advances in Computing and Communication Engineering (ICACCE), 8138–8143. https://doi.org/10.1109/ICACCE49060.2020.9154988
14. Awin, F. A., Alginahi, Y. M., Abdel-Raheem, E., & Tepe, K. (2019). Technical Issues on Cognitive Radio-Based Internet of Things Systems: A Survey. IEEE Access, 7, 97887–97908. https://doi.org/10.1109/ACCESS.2019.2929915
15. Muchandi, N., & Khanai, R. (2016). Cognitive radio spectrum sensing: A survey. 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), 3233–3237. https://doi.org/10.1109/ICEEOT.2016.7755301
16. Sandya, H. B., Nagamani, K., & Shavanthi, L. (2018). A Review of Cognitive Radio Spectrum Sensing Methods in Communication Networks. 2018 International Conference on Communication and Signal Processing (ICCSP), 457–461. https://doi.org/10.1109/ICCSP.2018.8524489
17. Mohammed, D. A., & Sadkhan, S. B. (2021). Cooperative Cognitive Radio Sensing - Optimization: status, challenges and future Trends. 2021 1st Babylon International Conference on Information Technology and Science (BICITS), 164–169. https://doi.org/10.1109/BICITS51482.2021.9509918
18. Keerthika, J., AnandaKumar, H., Priya, V., Yuvalatha, S., & Gayathri, N. (2023). A Study of Dynamic Thresholds Power Detection Spectrum Sensing Techniques In CRN. 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), 1, 2251–2255. https://doi.org/10.1109/ICACCS57279.2023.10112923
19. Ali, D. M., & Abdulla, M. Y. (2022). Energy Detection Based Multi-Bands Spectrum Sensing Using Adaptive Threshold. 2022 Muthanna International Conference on Engineering Science and Technology (MICEST), 37–42. https://doi.org/10.1109/MICEST54286.2022.9790109
20. Lu, L., Zhou, X., Onunkwo, U., & Li, G. (2012). Ten Years of Research in Spectrum Sensing and Sharing in Cognitive Radio. EURASIP Journal on Wireless Communications and Networking, 2012, 28. https://doi.org/10.1186/1687-1499-2012-28
21. Reypnazarov, E., Khujamatov, H., Khasanov, D., & Allamuratova, Z. (2022). Research of Energy Detection Method in Spectrum Sensing in Cognitive Radio Networks. 2022 International Conference on Information Science and Communications Technologies (ICISCT), 1–6. https://doi.org/10.1109/ICISCT55600.2022.10146830
22. Semba Yawada, P., Wei, A. J., & Mbyamm Kiki, M. (2015). Performance evaluation of energy detection based on non-cooperative spectrum sensing in cognitive radio network. 2015 4th International Conference on Computer Science and Network Technology (ICCSNT), 1, 1036–1040. https://doi.org/10.1109/ICCSNT.2015.7490914
23. Sharma, G., & Ritu, S. (2015). A review on recent advances in spectrum sensing, energy efficiency and security threats in cognitive radio network. 2015 International Conference on Microwave, Optical and Communication Engineering (ICMOCE), 114–117. https://doi.org/10.1109/ICMOCE.2015.7489704
24. Kavaiya, S., & Patel, D. K. (2022). On the Performance of an Improved Energy Detector over Shadow Fading Channels for Vehicular Networks. 2022 14th International Conference on Communication Systems & Networks (COMSNETS), 275–279. https://doi.org/10.1109/COMSNETS53615.2022.9668367
25. Sharma, A., Pandit, S., & Kumar, R. (2024). Cooperative Spectrum Sensing Using Energy-Based Detection for Low SNR Regime over Rayleigh Fading Channel. 2024 International Conference on Integrated Circuits, Communication, and Computing Systems (ICIC3S), 1, 1–6. https://doi.org/10.1109/ICIC3S61846.2024.1060298
26. Godugu, K. K., & Vappangi, S. (2022). Performance Analysis of Wideband Spectrum Sensing (WSS) in Cognitive Radio Networks (CRN) over Erroneous Sensing and Reporting Channels. 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), 1–6.

https://doi.org/10.1109/ASIANCON55314.2022.9908624
27. lopez-Benitez, M., Casadevall, F., Umbert, A., Perez-Romero, J., Hachemani, R., Palicot, J., & Moy, C. (2009). Spectral occupation measurements and blind standard recognition sensor for cognitive radio networks. 2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications, 1–9. https://doi.org/10.1109/CROWNCOM.2009.5189204
28. P Arjoune, Y., Mrabet, Z. El, Ghazi, H. El, & Tamtaoui, A. (2018). Spectrum sensing: Enhanced energy detection technique based on noise measurement. 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), 828–834. https://doi.org/10.1109/CCWC.2018.8301619
29. Baradkar, H. M., & Akojwar, S. G. (2014). Implementation of Energy Detection Method for Spectrum Sensing in Cognitive Radio Based Embedded Wireless Sensor Network Node. 2014 International Conference on Electronic Systems, Signal Processing and Computing Technologies, 490–495. https://doi.org/10.1109/ICESC.2014.92
30. Hamdan, N. S., Mohamad, H., & Sali, A. (2021). Sensing and analysis of spectrum holes in ISM band using USRP testbed. TELKOMNIKA Telecommunication, Computing, Electronics and Control, 19(6), 1–7. https://doi.org/10.12928/TELKOMNIKA.v19i6.19888 [32] Lagunas, E., Sharma, S. K., Chatzinotas, S., & Ottersten, B. (2016). Compressive sensing based energy detector. 2016 24th European Signal Processing Conference (EUSIPCO), 1678–1682. https://doi.org/10.1109/EUSIPCO.2016.7760534
31. Ding, J., Guo, J., Qu, D., & Jiang, T. (2009). Novel multiple slots energy detection for spectrum sensing in cognitive radio networks. 2009 15th Asia-Pacific Conference on Communications, 81–84. https://doi.org/10.1109/APCC.2009.5375682
32. Koçkaya, K., & Develi, I. (2020). Spectrum sensing in cognitive radio networks: threshold optimization and analysis. EURASIP Journal on Wireless Communications and Networking, 2020, 1–4. https://doi.org/10.1186/s13638-020-01870-7
33. AL-Hussain, A., & Khudair, A. (2020). Spectrum sensing of wideband signals based on cyclostationary and compressive sensing. Indonesian Journal of Electrical Engineering and Computer Science, 20(3), 1361–1368. https://doi.org/10.11591/ijeecs.v20.i3.pp1361-1368
34. Liang, Y.-C., Zeng, Y., Peh, C. Y. E., & Hoang, A. (2008). Sensing-Throughput Tradeoff for Cognitive Radio Networks. IEEE Transactions on Wireless Communications, 7(4), 1326–1337. https://doi.org/10.1109/TWC.2008.060869
35. Ye, Z., Memik, G., & Grosspietsch, J. (2008). Energy Detection Using Estimated Noise Variance for Spectrum Sensing in Cognitive Radio Networks. 2008 IEEE Wireless Communications and Networking Conference, 711–716. https://doi.org/10.1109/WCNC.2008.131
36. Bhavana, B., Sabat, S. L., Namburu, S., & Panigrahi, T. (2023). Energy Detector for Spectrum Sensing using Robust Statistics in non-Gaussian Noise Environment. 2023 15th International Conference on COMmunication Systems & NETworkS (COMSNETS), 414–418. https://doi.org/10.1109/COMSNETS56262.2023.10041390
37. Ivanov, A., Stoynov, V., Mihaylova, D., & Poulkov, V. (2021). Energy detectors performance evaluation for interweave cognitive radio network scenario in 5G. IOP Conference Series: Materials Science and Engineering, 1032(1), 012010. https://doi.org/10.1088/1757-899X/1032/1/012010
38. Quan, Z., Zhang, W., Shellhammer, S. J., & Sayed, A. H. (2011). Optimal Spectral Feature Detection for Spectrum Sensing at Very Low SNR. IEEE Transactions on Communications, 59(1), 201–212. https://doi.org/10.1109/TCOMM.2010.112310.090306
39. Seshukumar, K., Saravanan, R., & Suraj, M. S. (2013). Spectrum sensing review in cognitive radio. 2013 International Conference on Emerging Trends in VLSI, Embedded System, Nano Electronics and Telecommunication System (ICEVENT), 1–4. https://doi.org/10.1109/ICEVENT.2013.6496549