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Analysis of Varied Ambient Conditions on Energy Detection-Based Spectrum Sensing Using RTL SDR 2832U

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ABSTRACT

Efficient utilization of spectrum has become increasingly important in the last few decades. This trend is due to the expansion of communication applications and users. This has given scope for the shift to explore technologies such as cognitive radio and software defined radio (SDR) for dynamic access. By utilizing SDR architectures to provide a programmable environment with novel detection schemes, such as energy detection (ED). Energy detection using SDR makes it appealing for real-world sensing, yet its performance is susceptible to low signal-to-noise ratio (SNR), noise uncertainty, and fading. This experiment evaluates energy detection using a Realtek-based software defined radio (RTL SDR) in six diverse environments—moderately noisy urban, high-noise industrial, suburban or mixed-rural, interference-prone, deep-fading, and rural sparse signal contexts—by measuring detection probability (Pd) and false alarm probability (Pfa). The findings reveal that differences over environments, with the obtained Pd ranging from 1.37% to 67.84%, and Pfa from 8.86% to 68.32%, and the SNR ranging from -10.72 dB to -32.75 dB. These results demonstrate the detection probability in six diverse environments and the comparative study of various SNR. The results gained a better balance with the high detection rate and a reasonably low false alarm rate and a suitable SNR value of -15.69 dB in the 'Interference Prone' environment. The real-time signals were extracted using RTL SDR 2832U hardware in six diverse environments using the energy detection spectrum sensing method. Further, the results have been simulated in Matrix Laboratory 2024b, and pd and pfa performance parameters have been plotted for different SNR values obtained by the experimental analysis.

1. INTRODUCTION

Spectrum sensing efficiently detects the available frequency bands, enabling dynamic spectrum access in cognitive radio systems. Cognitive radio has emerged as a transformative paradigm, allowing secondary users to opportunistically access unused licensed spectrum while avoiding interference with primary users. Central to CR's effectiveness is spectrum sensing, which assesses whether frequency bands are occupied. Among the primary spectrum sensing methods, such as energy detection, matched filtering, and cyclostationary feature detection methods, energy detection is to be used efficiently in both time and frequency domains.

Energy detection has been the topic of interest for many researchers during the last five decades, particularly related to spectrum sensing in SDR and CR environments. The concept of energy detection was stated in 1967 by Urkowitz [1], with the help of Shannon's sampling formula, by addressing the detection of unknown signals.

In this paper several time-bandwidth products are drawn using several receiver operating curves (ROC) and extended to chi-square cumulative probability for calculating detection probabilities and false alarms. Building on these early findings, Digham et al. [2] in 2003 investigated the problem of energy detection over different fading channels. Here it performed different diversity schemes on detection probability, false alarm, and SNR and could not find much improvement in these parameters. Shortly after, Hoven et al. [3] showed that the trade-off between power and space for secondary users and interference protection for primary users leads to the detection of signals with the combination of quantization and noise uncertainty. In 2005, Haykin [4] addressed the cognitive tasks such as radio scene analysis, channel state estimation and predictive modelling, transmit power control, and dynamic spectrum management, which underscored the operational simplicity of energy detection. Cabric et al. [5] analyzed the cyclostationary feature detection method and found out it has more advantages over all other sensing methods because of its ability to differentiate modulated signals, interference, and noise under low SNR values. Ghasemi and Sousa [6], in 2005, studied the challenges faced to find out the unlicensed spectrum and proposed a collaborative spectrum sensing method to improve the sensing performance.

These findings guided this research for considering the probability of detection, the probability of false alarm, and SNR parameters to take into consideration for this research work.

Further, Akyildiz et al. [7] did the survey on next-generation wireless networks, cognitive radio networks, and dynamic spectrum access. Tandra and Sahai [8] in 2008 contributed a simple mathematical model on the concept of SNR walls, revealing fundamental performance limits for energy detection. Responding to these concerns, A detailed study has been done on the cooperative spectrum sensing, and its various sensing methods were done in 2009 by Yucek and Arslan [9]. Baldini et al. [10] did a survey on security aspects in software-defined radio and cognitive radio. The survey summarizes the main security threats and challenges and the related protection techniques in SDR and CR. Sasipriya et al. [11] analyzed spectrum sensing detection based on the correlation sum method by utilizing the multiuser multiple input multiple output technique over fading and Additive White Gaussian Noise (AWGN) channel. In 2020, Bhattacharjee et al. [12] proposed an energy-efficient multicasting in hybrid cognitive small cell networks and compared the proposed method with the conventional approach and proved the new scheme contributes much more energy efficiency than the conventional one. Jain and Taneja [13] explained about various hardware and software packages in SDR. Salahdine et al. [14] provided certain techniques that handle the uncertainty of cognitive radio.

These findings lead to the identification of the research gap for considering an efficient method in CR spectrum sensing to be merged with SDR to analyse real-time signals to take into consideration for this research work.

Recent studies reported from Federal Communications Commission (FCC) measurements that some channels are heavily used while others are sparsely used, as represented in Figure 1.

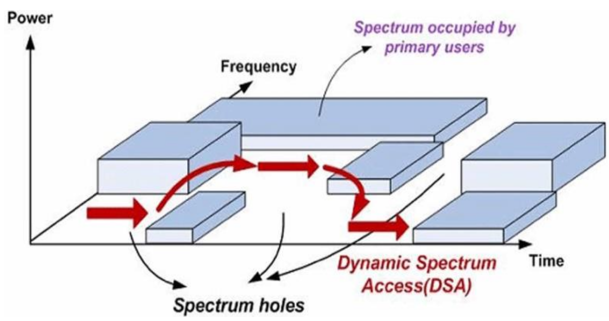


Figure 1. Dynamic spectrum access [15]

Recent years have witnessed a shift toward leveraging machine learning and hybrid techniques for improved performance. In 2022, research [16] introduced fuzzy-based, energy-efficient cognitive radio schemes for IoT and IRS-aided spectrum sensing strategies to enhance SNR through weighted energy detection. Lin et al. [17] highlighted a new intelligent reflecting surface (IRS)-aided spectrum sensing scheme which improves the performance gain. Usman et al. [18] developed a two stage spectrum sensing using energy detection which outperforms single stage spectrum sensing schemes.

By 2023, deep learning-driven multistage thresholding [19] achieved remarkably low false alarms and missed detections by dynamically estimating detection thresholds. The most recent studies states by Sabrina et al. [20] proposed a CNN-LSTM model which provides a high detection rate under low SNR. In 2024, study [21] explored the integration of K-Nearest Neighbours (KNN) and convolutional neural networks (CNNs) for spectrum sensing. KNN achieves classification accuracy at low SNR, and CNN-based approaches demonstrate substantial improvements in AWGN environments.

Another CNN based approach proposed by Abdelbaset et al. [22] outperforms the accuracy to identify the unused frequency bands precisely. The studies by Venkatapathi et al. [23] discusses cooperative spectrum sensing approach to enhance the long-term overall performance of the Secondary User. Most recent study done by Mokhtar [24] employs machine learning with feature extraction and random forest classifier to enhance the individual secondary user energy detection accuracy in presence of a high level noise power density.

SDR-based implementations of hybrid CNN-LSTM models showed real-time detection reliability across FM, GSM, and OFDM applications. It shows hybrid energy-and-entropy two-stage approach demonstrated clear advantages over single-stage methods. Rao and Sahaai [25] developed an adaptive and residual hybrid network (A-RHN) to enable more efficient use of the available spectrum by avoiding transmitting on frequencies that are already in use in the year 2025.

From the literature gaps identified, there are indications of possibility in exploring varied ambient conditions on energy detection-based spectrum sensing in this work. In energy detection, most of the existing works rely on analytically generated or simulated signals under idealized noise and channel conditions. The novelty in this work is the multi-environment performance analysis of energy detection focused on real-world signal acquisition using Realtek-based software defined radio (RTL SDR).

In this work, an evaluation of the real-world performance of the energy detector across varied environmental conditions has been proposed. This analysis fills that gap by capturing real-time signals with the RTL-SDR in six representative environments, such as moderately noisy urban, high-noise industrial, suburban or mixed-rural, interference-prone, deep-fading, and rural sparse signal environments, and assessing energy detection's performance in terms of probability of density and probability of false alarm.

This paper is organized as follows: Section 2 speaks for the design methodology of the work, followed by the experimental methodology. Section 3 represents the experimental setup and the simulation results, succeeded by comparison plots of obtained Pd, Pfa, and SNR values for six diverse environments. This section also shows the comparison table for the obtained parameters, limitations, and future scope.

2. ENERGY DETECTION METHOD

A low-cost RTL-SDR connected to a broadband antenna was used to capture in-phase/quadrature (IQ) samples across multiple frequency bands in six diverse environments: moderately noisy urban, high-noise industrial, suburban/mixed-rural, interference-prone, deep-fading, and rural sparse-signal contexts. These environments were considered to represent a comprehensive range of actual conditions affecting signal quality, interference, and channel characteristics. Using an energy detection strategy, the captured signals were processed by determining the squared magnitude of received samples across fixed observation periods. Detector thresholds were derived from estimated noise variance. A detection decision was made if observed energy exceeded the threshold. Performance metrics—probability of detection (Pd) and probability of false alarm (Pfa)—were estimated through repeated measurements and varied by environmental conditions and measured SNR.

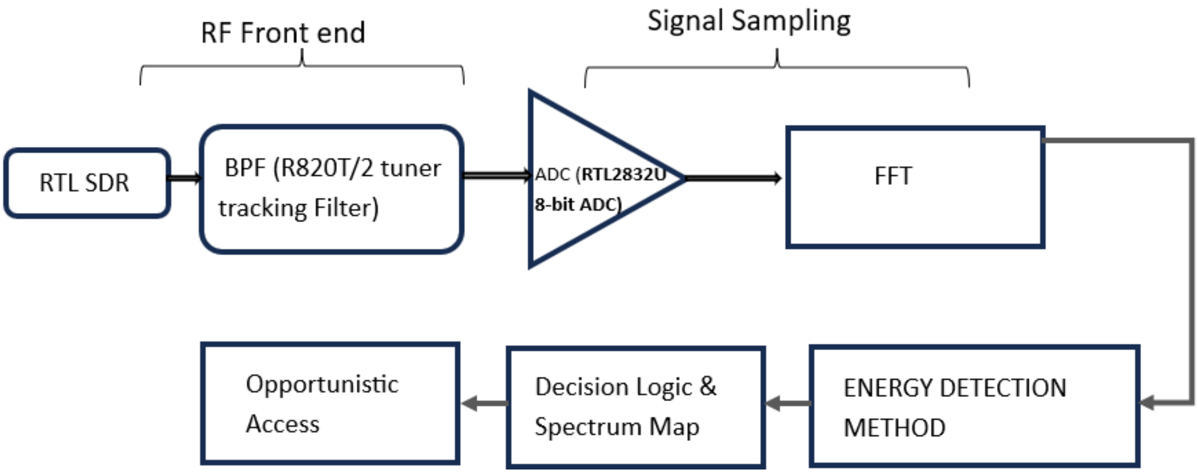


Figure 2. Design methodology for energy detector using RTL SDR 2832U

The proposed design methodology, represented in Figure 2, an RTL SDR 2832U was used in the receiver front-end to receive the real-time signal for further processes. The specifications of this hardware are stated as it is an adaptable software defined radio (SDR). It uses a Realtek RTL2832U chip, which acts as a wideband radio receiver. The technical specifications for accurate signal processing using this device are mentioned with its parameters, such as a tuner frequency of 100 MHz and a tuner gain of 25 dB. Its sampling rate is between 1 MHz and 2.4 MHz, and it is expected to get high-resolution signal capture. For substantial data handling capacity, the data frame size provides 4096. Maintaining a tuner PPM correction of '0' and utilizing a 'single' data type.

2.1 Methodology/ conditions

The methodology employed in this work is centred on the use of an energy-detection-based spectrum-sensing framework implemented with an RTL-SDR receiver. Among the spectrum sensing techniques, such as energy detection, cyclostationary feature detection, and matched filter detection, energy detection was preferred to evaluate real-time signals in this work because it can be used in various environments, making it suitable for practical SDR experiments. In this approach, the decision on whether a frequency band is occupied is based on the total energy of the received signal over a fixed observation interval, which is compared against a predetermined detection threshold. The energy detection model is explained in Figure 3.

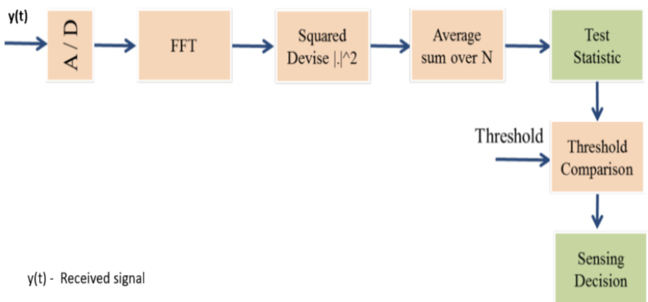


Figure 3. Energy detection model [14]

The steps involved in energy detection are as follows: Conventionally, the received signal is modelled as a binary hypothesis test given by y(t) in Eq. (1):

$$y(t) = \begin{cases} n(t), & H0 \text{ (noise only)} \\ S(t) + n(t), & H1\ (Signal + noise) \end{cases} \qquad (1)$$

where, n(t) denotes Additive White Gaussian Noise (AWGN) with zero mean and variance σ_n^2 , and S(t) represents the transmitted signal.

Under hypothesis H0, the band is unoccupied since it consists of only noise signal, while under hypothesis H1, the band is occupied by a primary user transmission since it consists of the combination of signal and noise signals.

Theoretical framework of energy detection:

The test statistic of the energy detector is defined as the accumulated energy, E of the received samples from 1 to N given by Eq. (2):

$$E = \sum_{i=1}^{N} |y(i)|^2 \qquad (2)$$

where, N represents the number of samples in one observation window. This test statistic is then compared with a threshold λ to determine the channel occupancy according to the rule given in Eq. (3).

$$E = \begin{cases} H0, & E < \lambda \\ H1, & E > \lambda \end{cases} \qquad (3)$$

Eq. (3) indicates:

If the measured energy exceeds the threshold - H_1 - signal present.

If the measured energy is less than the threshold - H_0 - only noise is present.

The Received Signal Strength (RSS) in decibels was also calculated as RSS_{dB} to normalize the energy values and facilitate interpretation which is represented Eq. (4):

$$RSS_{dB} = 10\log_{10}(E) \qquad (4)$$

To estimate the signal-to-noise ratio (SNR) represented in Eq. (5), the captured signal was divided into two regions: the initial portion of the dataset, assumed to contain noise only, and the final portion, assumed to contain the signal. The average noise power and signal power were computed, and the SNR was obtained as:

$$SNR_{dB} = 10\log_{10}(P_{signal}/P_{noise}) \tag{5}$$

The probability of detection (P_d) is the probability of correctly declaring a signal when it is present. The probability of false alarm was estimated experimentally by applying a range of thresholds to the noise-only portion of the signal and calculating the fraction of windows exceeding the threshold.

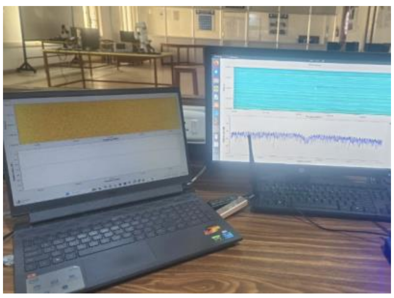
In defiance of its limitations, energy detection is favored for its fast and simple implementation. It is highly suitable for real-time applications in cognitive radio and dynamic spectrum access systems in view of SNR. The practical implementations and simulation results have been explained in Section 3 as follows.

3. EXPERIMENTAL SETUP AND RESULTS

Signals were captured over a duration of a few seconds to several minutes in each environment. The acquired complex I/Q samples were stored for offline processing in '.mat' format. The samples were segmented into non-overlapping windows of 1024 samples, and the energy for each window was computed using the energy detection model expression.

In this section, the evaluation of energy detector analysis for the performance of a spectrum sensing algorithm by examining its probability of detection (Pd) and probability of false alarm (Pfa) across six different SNR values ranging from –32.75 dB to –10.72 dB. Figure 4 shows the experimental setup:

Probability of detection, probability of false alarm and Signal to Noise Ratio are crucial in cognitive radio applications to identify spectrum availability as accurate as necessary for reliable communication without interfering with licensed users.



(a) Signal acquisition using RTL SDR 2832U

(b) Elements of RTL SDR 2832U

(c) Signal processing using RTL SDR 2832U

Figure 4. Experimental setup of energy detection scheme

In Figure 5, the yellow-coloured spectrogram indicates regions of extremely high power where the signal is strongest, such as a carrier or dominant tone. Here, an SNR of -10.72 dB and a detection rate of 40.71% demonstrate a relatively balanced performance. The Pd of 61.90% and Pfa of 33.64% suggest that the signal is detectable despite moderate noise, making this environment best described as a moderately noisy urban environment. It represents typical city conditions where multiple overlapping signals and moderate noise are present.

Figure 6 exhibits a much lower detection rate of 17.23% and an indigent Pd of only 1.37%, even though its total energy (0.0788 J) and average power are not the lowest among the sets. Here the spectrogram indicates still strong power levels. The high PFA of 22.52% combined with an SNR of -24.55 dB indicates a high-noise industrial environment, where strong electromagnetic interference (EMI) is corrupting the signal. Such environments are common in manufacturing zones, power plants, or near heavy electrical equipment.

In contrast, Figure 7 shows a detection rate of 33.61% and a high Pd of 67.84% at an SNR of -15.69 dB. The moderate PFA (22.21%) and mid-level energy consumption in this suburban or mixed-rural environment suggest a good balance between sensitivity and reliability, but it is occasionally impacted by environmental noise.

Figure 8 represents the highest detection rate of 68.05%. The spectrogram indicates strong power levels. However, it also shows an excessively high false alarm rate of 68.32%, which points to an over-aggressive detection threshold. These findings exhibit a relatively low SNR of -19.64 dB and the lowest among all energies in other sets (0.0107 J). This depicts an interference-prone environment, which is certainly found in military applications and also in misconfigured sensing systems.

The lowest among all SNR values is represented in Figure 9 as -32.75 dB. This spectrogram typically represents medium power, where the signal is present but not as dominant. Here the detection rate is just 9.11%, and the obtained Pd (9.35%) and Pfa (8.86%) are minimal, which shows that the signal is deeply buried in noise. This deep fading environment is typically found in shielded locations such as tunnels, basements, etc.

There is a unique scenario with low energy (0.0059 J) represented in Figure 10, which gives the lowest average power of 9.85e-04 W. With an SNR of -14.03 dB and a detection rate of 28.67%, it has a moderately high PFA of 47.00% despite a poor Pd of 10.34%. These values imply the presence of weak or infrequent transmissions in a quiet but sensitive setting. This depicts a low-power device environment, a rural sparse signal scenario, where devices transmit infrequently or from long distances.

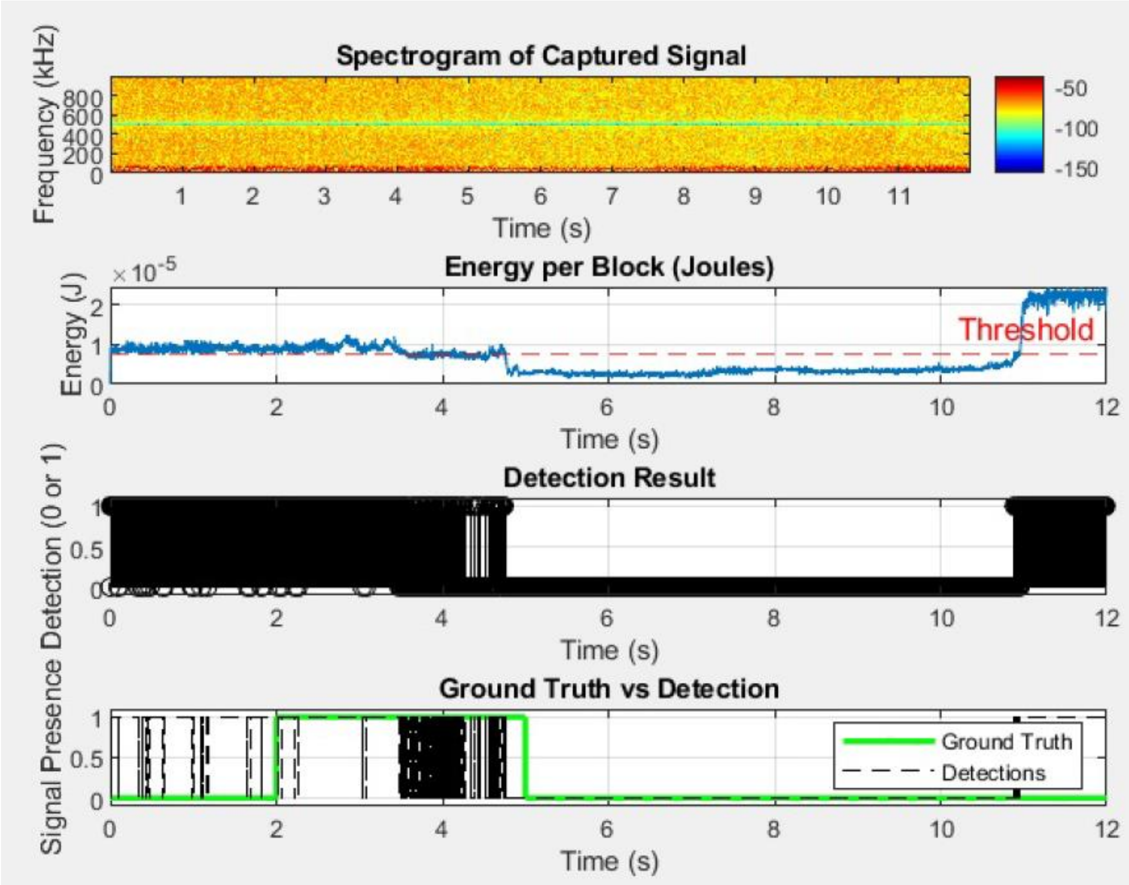


Figure 5. Moderately noisy urban environment energy detector

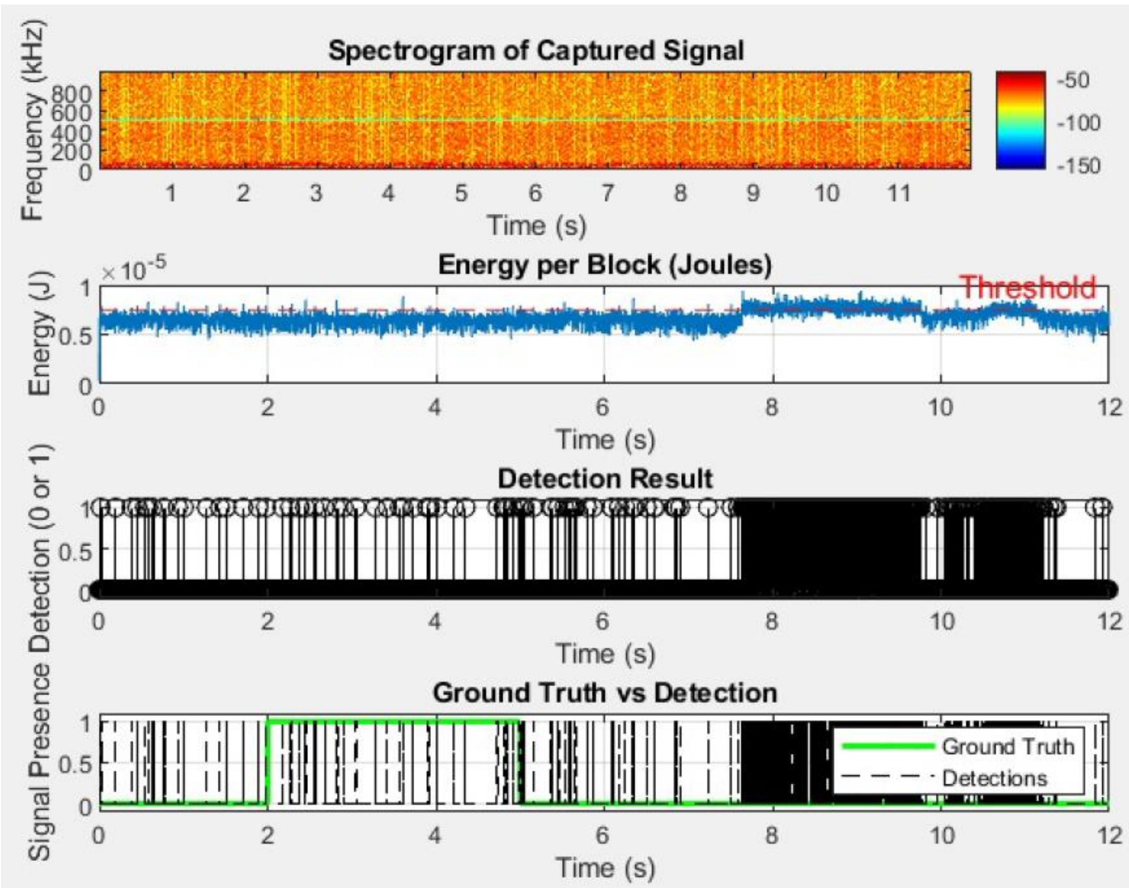


Figure 6. High-noise industrial environment energy detector

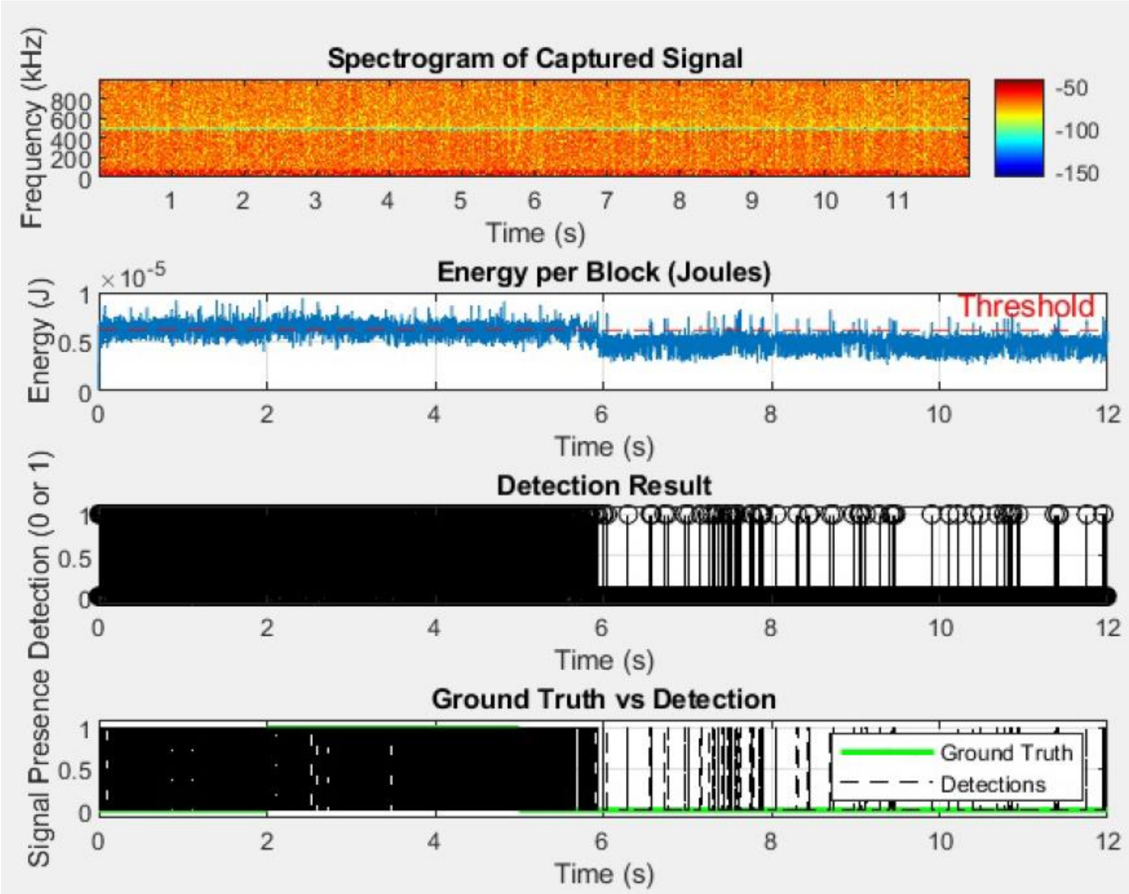


Figure 7. Suburban or mixed-rural environment energy detector

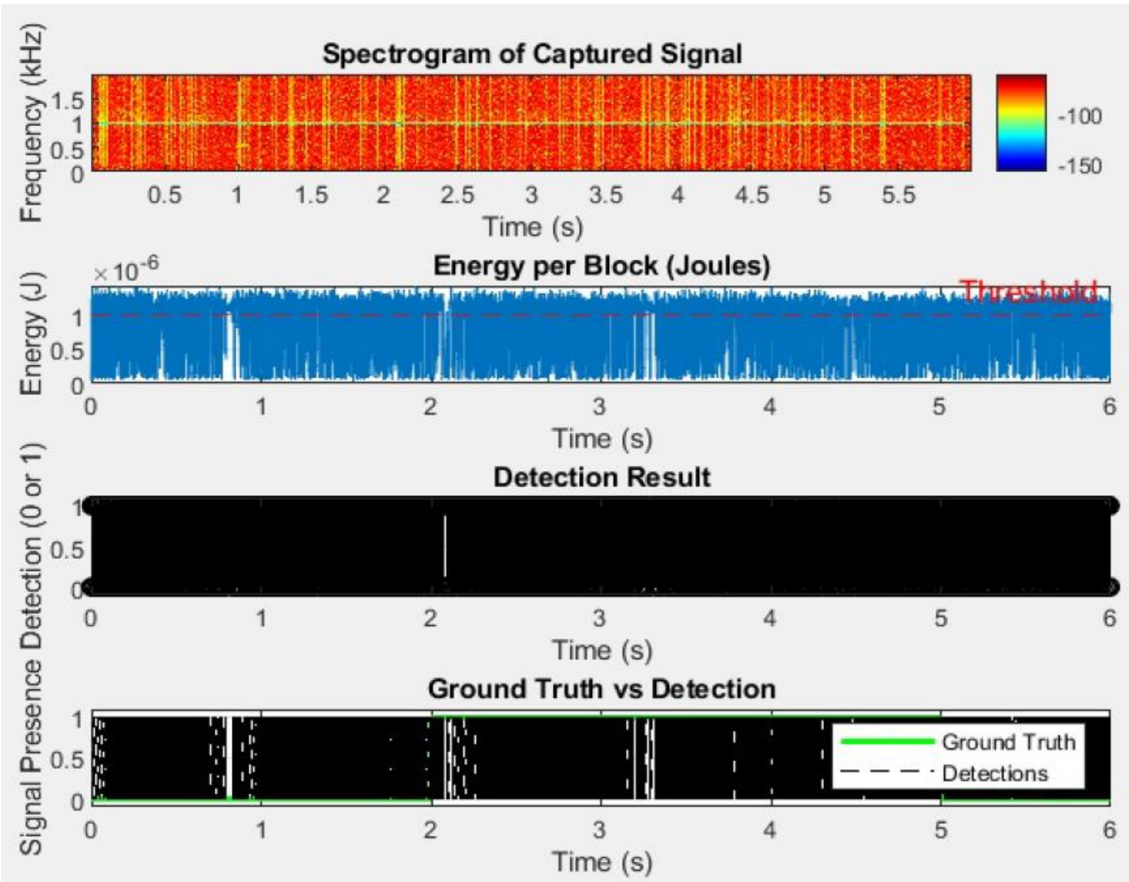


Figure 8. Interference-prone energy detector

The simulation results in Figure 5 to Figure 10 have been summarized in Table 1. This experimental analysis explains the sensitivity of energy detection to various channel and environmental conditions.

Figure 11 depicts low detection probability in urban noisy and industrial environments and gives better ranges in rural and interference-prone areas.

Probability of false alarm is equally significant to probability of detection for steady sensing represented in Figure 12, which determines the rate of occurrence of the detector misidentifying noise as a valid signal. A high false alarm rate leads to inefficient spectrum utilization because secondary users may unnecessarily abandon channels that are truly free.

The rural sparse signal case had the best performance balance among the six environments, with a false alarm rate of about 34% and a detection probability of about 62%. Although not ideal, these values imply that acceptable performance could be attained with threshold optimization and the potential application of cooperative sensing, which involves several secondary users sharing sensing results. Despite a false alarm rate of more than 22%, the detection probability decreased to almost zero (1.37%) in the worst-case scenario, which was the high-noise industrial environment. This suggests that energy detection by itself cannot provide dependable spectrum sensing in extremely noisy or interference-rich environments.

Figure 13 highlights that energy detection endeavours in very noisy or faded environments (low Pd, sometimes high Pfa). In high-noise industrial settings (dB), Pd drops to 1.37%, and Pfa rises to 22.52%, while rural sparse signals (dB) achieve Pd of 61.90% and Pfa of 33.64%. Detection is more successful in rural/spread-out signals and interference-prone regions, but often at the cost of increased false alarms. High SNR (less negative) improves detection, but trade-offs remain between Pd and Pfa depending on environmental conditions.

Table 1. Comparison of performance metrics in varied ambient conditions

Environment	SNR (dB)	Pd (%)	Pfa (%)
Moderately Noisy Urban	-32.75	9.35	8.86
High Noise Industrial	-24.55	1.37	22.52
Suburban/Mixed Rural	-19.64	67.78	68.32
Interference Prone	-15.69	67.84	22.21
Deep Fading	-14.03	10.34	47.00
Rural Sparse Signals	-10.72	61.90	33.64

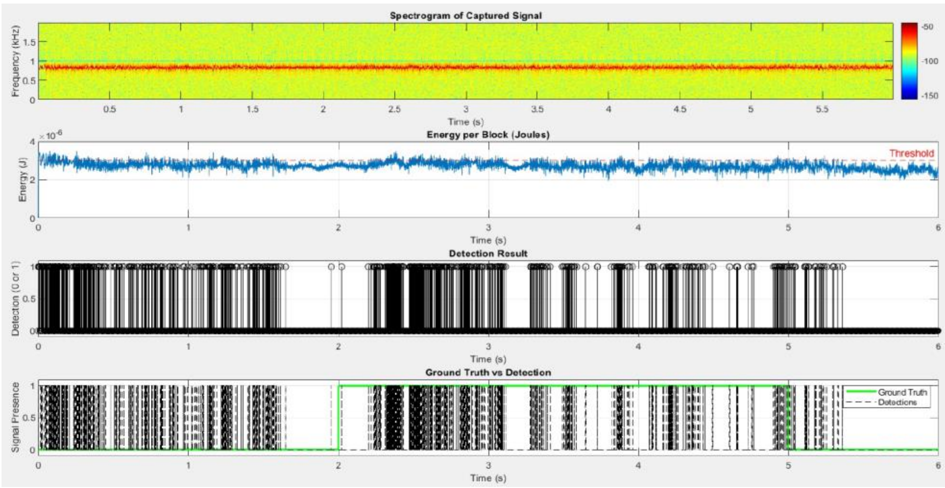


Figure 9. Deep fading environment energy detector

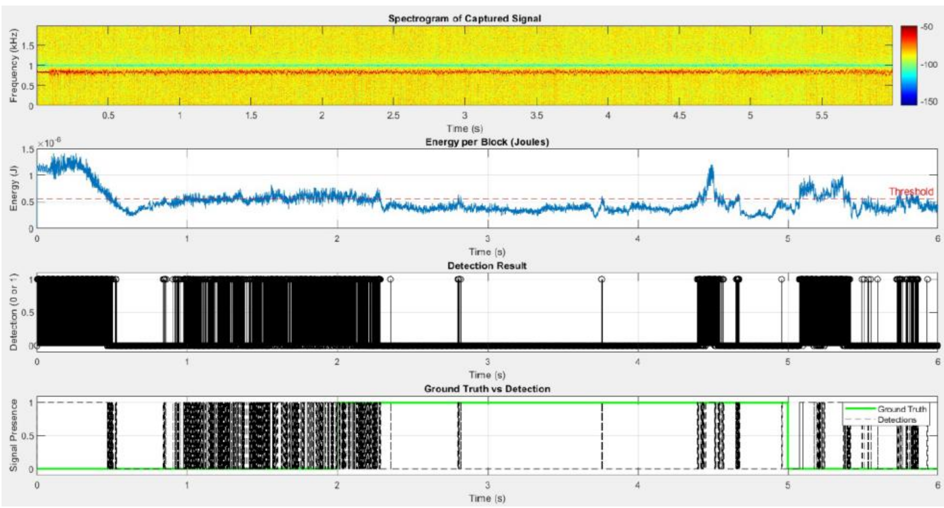


Figure 10. Rural sparse signals energy detector

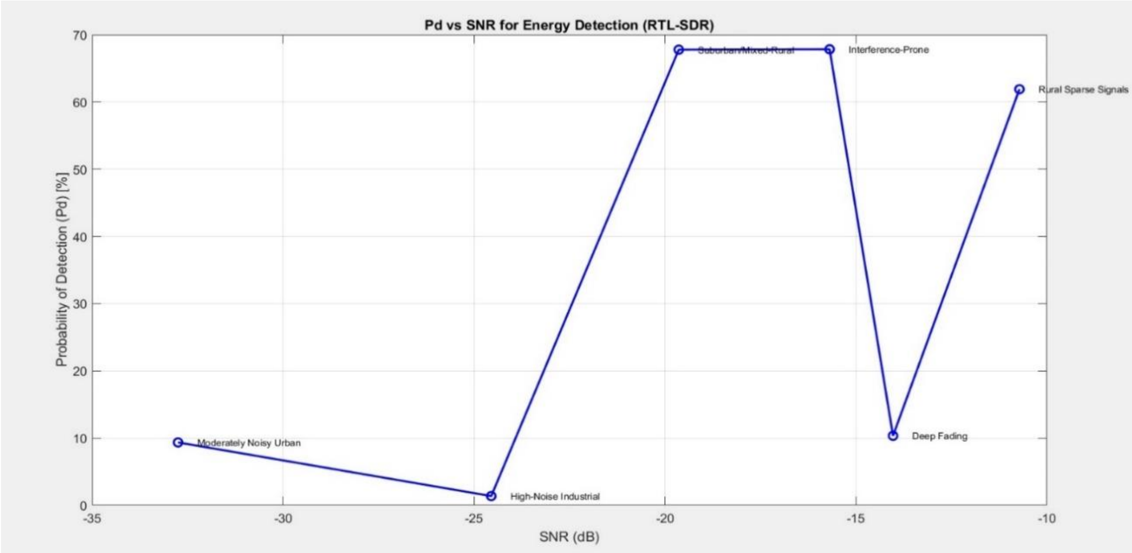


Figure 11. Probability of detection across environments

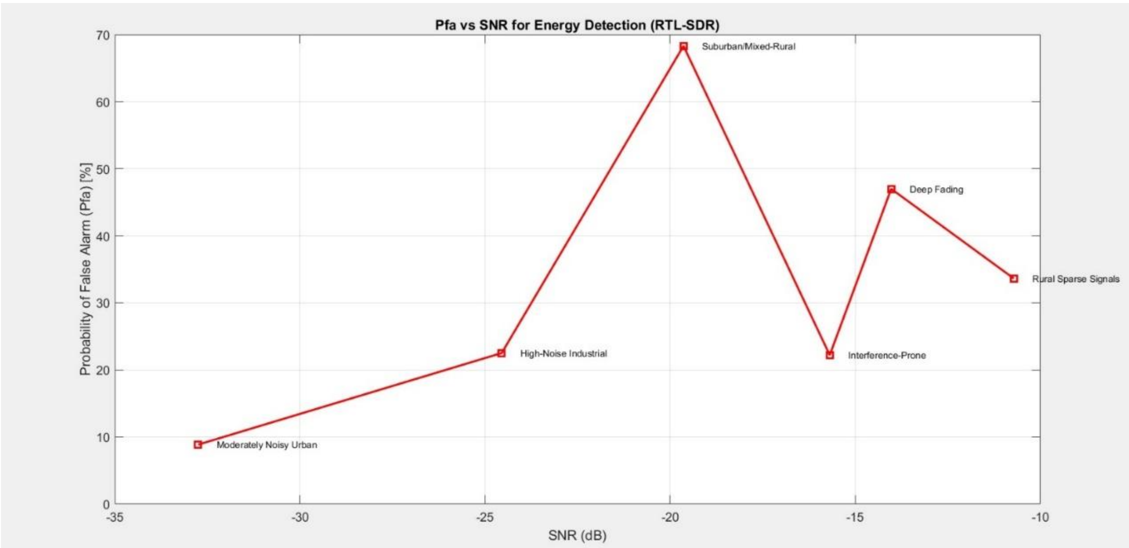


Figure 12. Probability of false alarm across environments

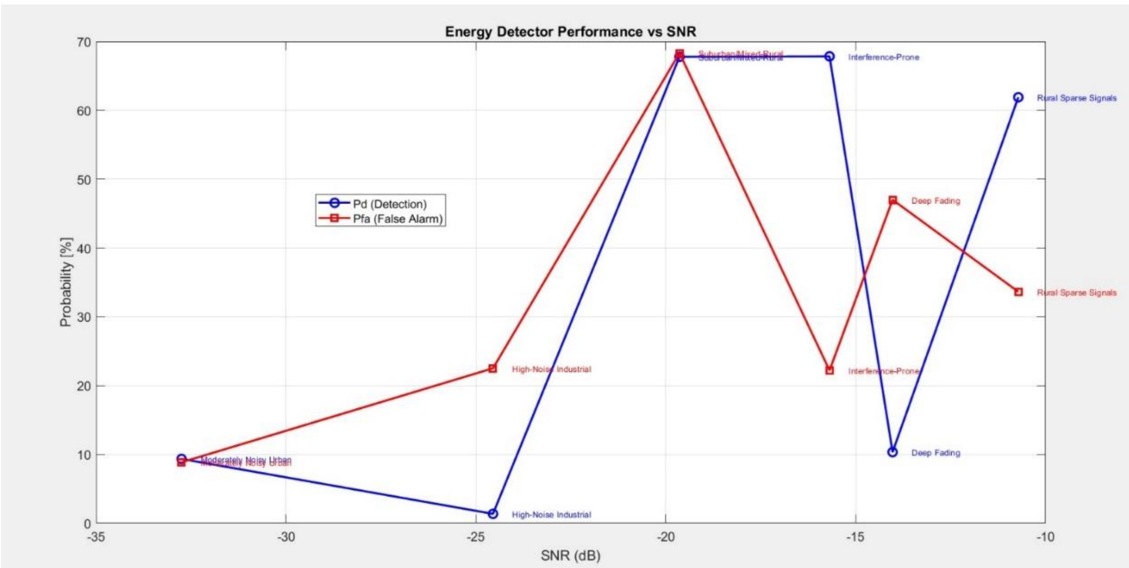


Figure 13. Pfa and Pd across environments in different SNR

4. CONCLUSION

This work was focused on studying the impact of different ambient conditions from the signal acquisition to the energy detection stage of SDR. Energy detection was chosen due to its simplicity and cost-effectiveness for various research applications. It also provides the joint analysis of SNR, Pd, and Pfa. This study provides the gap between theoretical analysis and practical implementation. There are key findings observed in this experimental analysis using performance metrics such as SNR, Pfa, and Pd. It has been observed that a reasonable SNR value was obtained, which suggests a better environment as a rural sparse signal environment, i.e., -10.72 dB, and an interference-prone area, i.e., -15.69 dB.

However, there are limitations in this work; even though real-time signal acquisition from different ambient conditions is taken, the occurrence of false alarms may not be avoidable. The accuracy obtained in this experiment is limited by scope to detect the signal efficiently in these varied ambient conditions.

This experimental analysis shall be further extended by surpassing these limitations for achieving better accuracy with methods such as integration of multiple classifiers. Further investigation will be directed towards mitigating the SNR ranges and reducing false alarm rates. Hybrid spectrum sensing methods can be explored with the combination of energy detection and cyclostationary feature detection or energy detection and matched filtering to enhance the performance in deep fading environments. Additionally, a paradigm shift in choosing different SDR platforms such as ADALM-Pluto, USRP B200/B210, Lime SDRmini, and Hack RF gives a performance comparison of hardware architectures for real-world cognitive radio deployments.

REFERENCES

[1] Urkowitz, H. (2005). Energy detection of unknown deterministic signals. Proceedings of the IEEE, 55(4): 523-531. https://doi.org/10.1109/PROC.1967.5573

[2] Digham, F.F., Alouini, M.S., Simon, M.K. (2003). On the energy detection of unknown signals over fading channels. In IEEE International Conference on Communications, ICC'03, Anchorage, AK, USA, pp. 3575-3579. https://doi.org/10.1109/ICC.2003.1204119

[3] Hoven, N., Tandra, R., Sahai, A. (2005). Some fundamental limits on cognitive radio. Wireless Foundations EECS, University of California at Berkeley, 1-11.

[4] Haykin, S. (2005). Cognitive radio: Brain-empowered wireless communications. IEEE Journal on Selected Areas in Communications, 23(2): 201-220. https://doi.org/10.1109/JSAC.2004.839380

[5] Cabric, D., Mishra, S.M., Brodersen, R.W. (2004). Implementation issues in spectrum sensing for cognitive radios. In Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, USA, pp. 772-776. https://doi.org/10.1109/ACSSC.2004.1399240

[6] Ghasemi, A., Sousa, E.S. (2005). Collaborative spectrum sensing for opportunistic access in fading environments. In First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, DySPAN 2005, Baltimore, MD, USA, pp. 131-136. https://doi.org/10.1109/DYSPAN.2005.1542627

[7] Akyildiz, I.F., Lee, W.Y., Vuran, M.C., Mohanty, S. (2006). NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey. Computer Networks, 50(13): 2127-2159. https://doi.org/10.1016/j.comnet.2006.05.001

[8] Tandra, R., Sahai, A. (2008). SNR walls for signal detection. IEEE Journal on Selected Topics in Signal Processing, 2(1): 4-17. https://doi.org/10.1109/JSTSP.2007.914879

[9] Yucek, T., Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Communications Surveys & Tutorials, 11(1): 116-130. https://doi.org/10.1109/SURV.2009.090109

[10] Baldini, G., Sturman, T., Biswas, A.R., Leschhorn, R., Godor, G., Street, M. (2011). Security aspects in software defined radio and cognitive radio networks: A survey and a way ahead. IEEE Communications Surveys & Tutorials, 14(2): 355-379. https://doi.org/10.1109/SURV.2011.032511.00097

[11] Sasipriya, S., Vigneshram, R. (2016). An overview of cognitive radio in 5G wireless communications. In 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Chennai, India, pp. 1-5. https://doi.org/10.1109/ICCIC.2016.7919725

[12] Bhattacharjee, S., Acharya, T., Bhattacharya, U. (2020). Energy-efficient multicasting in hybrid cognitive small cell networks: A cross-layer approach. IEEE/ACM Transactions on Networking, 28(1): 262-274. https://doi.org/10.1109/TNET.2019.2962309

[13] Jain S., Taneja, N. (2014). Evolution from SDR to cognitive radio. Indian Journal of Applied Research, 4(8): 248-253.

[14] Salahdine, F., Kaabouch, N., El Ghazi, H. (2017). Techniques for dealing with uncertainty in cognitive radio networks. In 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, pp. 1-6. https://doi.org/10.1109/CCWC.2017.7868352

[15] Alotaibi, A.M., AlQahtani, S.A. (2017). Routing protocol for cognitive radio Ad Hoc networks. International Journal of Interdisciplinary Telecommunications and Networking (IJITN), 9(3): 45-60. https://doi.org/10.4018/IJITN.2017070104

[16] Chithaluru, P., Stephan, T., Kumar, M., Nayyar, A. (2022). An enhanced energy-efficient fuzzy-based cognitive radio scheme for IoT. Neural Computing and Applications, 34(21): 19193-19215. https://doi.org/10.1007/s00521-022-07515-8

[17] Lin, S.E., Zheng, B.X., Chen, F.J., Zhang, R. (2022). Intelligent reflecting surface-aided spectrum sensing for cognitive radio. IEEE Wireless Communications Letters, 11(5): 928-932. https://doi.org/10.1109/LWC.2022.3149834

[18] Usman, M.B., Singh, R.S., Rajkumar, S. (2022). Stage spectrum sensing technique for cognitive radio network using energy and entropy detection. Wireless Power Transfer, 9: 1978. https://doi.org/10.1155/2022/7941978

[19] Bedir, O., Ekti, A.R., Ozdemir, M.K. (2023). Exploring deep learning for adaptive energy detection threshold determination: A multistage approach. Electronics, 12(19): 4183. https://doi.org/10.3390/electronics12194183

[20] Sabrina, Z., Djamel, T., Camel, T., Ammar, M., Said, S., Okba, N. (2023). SDR implementation of spectrum sensing using deep learning. International Journal of Sensors Wireless Communications and Control, 13(4): 226-236. https://doi.org/10.2174/2210327913666230719152400
[21] Musuvathi, A.S.S., Archbald, J.F., Velmurugan, T., Sumathi, D., Renuga Devi, S., Preetha, K.S. (2024). Efficient improvement of energy detection technique in cognitive radio networks using K-nearest neighbour (KNN) algorithm. EURASIP Journal on Wireless Communications and Networking, 2024(1): 10. https://doi.org/10.1186/s13638-024-02338-8
[22] Abdelbaset, S.E., Kasem, H.M., Khalaf, A.A., Hussein, A.H., Kabeel, A.A. (2024). Deep learning-based spectrum sensing for cognitive radio applications. Sensors, 24(24): 7907. https://doi.org/10.3390/s24247907
[23] Venkatapathi, P., Khan, H., Rao, S.S., Immadi, G. (2024). Cooperative spectrum sensing performance assessment using machine learning in cognitive radio sensor networks. Engineering, Technology & Applied Science Research, 14(1): 12875-12879. https://doi.org/10.48084/etasr.6639
[24] Mokhtar, R.A. (2025). Adaptive based machine learning approach for cooperative energy detection in cognitive radio networks. Journal of Electrical Engineering, 76(2): 106-115. https://doi.org/10.2478/jee-2025-0011
[25] Rao, R.K., Sahaai, M.B. (2025). Optimal spectrum sensing framework for cognitive radio networks using attention-based autoencoder with multi-scale capsule network. International Journal of Communication Systems, 39(1): e70300. https://doi.org/10.1002/dac.70300

NOMENCLATURE

E	Accumulated energy
Pd	Probability of detection
Pfa	Probability of false alarm
SNR	Signal to noise ratio
RSS	Received signal strength
P	Power