Synergy: Cross-Disciplinary Journal of Digital Investigation
(ISSN 2995-4827) VOLUME 03 ISSUE 04, 2025

OPTIMIZING SPECTRUM SENSING WITH TWIN-FOLD POWER DETECTION IN COGNITIVE RADIO NETWORKS

Sandeep
P.G. Student, Department of CSE, Sat Kabir Institute of Technology and Management, Ladrawan, Haryana, India

Renu
Assistant Professor, of CSE, Sat Kabir Institute of Technology and Management, Ladrawan, Haryana, India

Abstract:

By allowing dynamic and intelligent spectrum access, Cognitive Radio Networks (CRNs) are revolutionizing wireless communication and solving the problem of underutilization of spectrum. A structured methodology for spectrum sensing is presented in this study, with an emphasis on the energy detection technique, which is a popular method because of its ease of use and low processing needs. Beginning with the detection of an unknown signal, the suggested approach consists of seven steps that determine if a primary user (PU) is present or absent based on energy levels that are observed. The determined threshold value (λ) serves as a benchmark for comparing the energy of the detected signal. Accurately determining spectrum occupancy is made easier by this comparison. The system reduces false detection and increases decision reliability by averaging the values over several sensing instances. In order to provide secondary users with effective spectrum access, the spectrum must be definitively classified as either occupied or unoccupied in the last stage. By ensuring reliable and energy-efficient identification in CRNs, this methodology helps to create wireless communication systems that are more adaptable and dependable.

Keywords: Spectrum Sensing, Threshold Estimation, Dynamic Spectrum Access.

INTRODUCTION: The rapid growth in wireless communication services has led to an unprecedented demand for radio spectrum. However, studies by the Federal Communications Commission (FCC) indicate that a significant portion of the licensed spectrum remains underutilized at any given time [1]. This inefficient utilization has motivated the development of

Cognitive Radio Networks (CRNs), a revolutionary communication paradigm proposed by Mitola and Maguire [2], which enables intelligent spectrum access through real-time environmental awareness and dynamic adaptation. CRNs allow Secondary Users (SUs) to opportunistically access spectrum bands that are temporarily unused by Primary Users (PUs) without causing harmful interference. One of the most critical functions in CRNs is spectrum sensing, which enables the detection of PU activity and facilitates decision-making regarding spectrum access [3]. Among various spectrum sensing techniques—such as matched filtering, cyclostationary feature detection, and waveform-based sensing—energy detection remains the most widely adopted method due to its low computational complexity and independence from prior knowledge of the PU signal [4].

A step-by-step approach to spectrum sensing with energy detection in CRNs is presented in this study. After an unknown signal is detected, the process moves on to energy measurement, threshold comparison, averaging, and ultimate decision-making. The method is appropriate for real-time deployment in distributed CRN setups and is made to be noise-resistant. Energy detection provides a useful trade-off between performance and complexity, making it appropriate for a variety of cognitive radio applications, despite its susceptibility to noise uncertainty and low signal-to-noise ratio (SNR) situations [5]. Figure 1 shows the basic components of a CRN system.

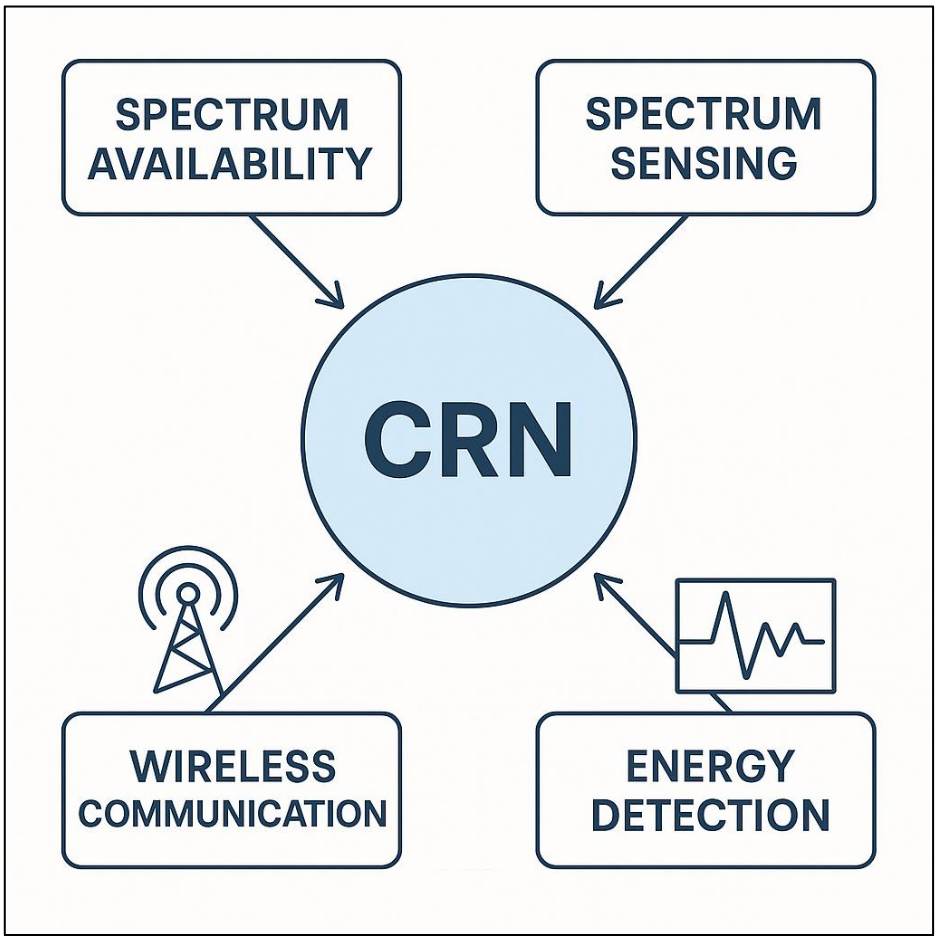

Figure 1: CRN with main components

Research Background: The necessity for smart spectrum use techniques has increased due to the rising demand for wireless communication services. The inefficiencies of fixed spectrum allocation have been addressed by (CRNs), which provide dynamic access to unused frequency bands. Primary Users (PUs) who have licensed spectrum access and Secondary Users (SUs) who opportunistically take advantage of open bands without interfering are the two user groups that make up a CRN [6]. Spectrum sensing, spectrum decision-making, spectrum sharing, and spectrum mobility are the fundamental methods of CRNs. Together, these guarantee that CRNs function adaptably and effectively coexist with licensed systems. To carry out intelligent resource management, CRNs rely on self-organization, learning capacities, and environmental awareness [7]. The most important function of CRNs is spectrum sensing, which makes it possible to identify idle spectrum bands, also known as spectrum holes. Wavelet-based sensing, Cyclostationary detection, matched filtering, and energy detection are important sensing methods. Energy detection is one of the most popular of these because of its ease of use and hardware effectiveness [8]. Nevertheless, it performs worse when there is noise uncertainty and a low signal-to-noise ratio (SNR) [9].

CRNs have to make wise choices regarding spectrum access after spectrum holes are identified. Using quality-of-service (QoS) criteria including bandwidth, interference, latency, and dependability, spectrum management entails assessing available channels and choosing the best one [10]. Both distributed and centralized decision-making are possible in CRNs, and recent research has investigated Markov decision processes and reinforcement learning for real-time spectrum decisions [11]. The equitable and interference-free cohabitation of SUs and PUs is guaranteed by effective spectrum sharing. Usually, it is divided into three paradigms: interweave, overlay, and underlay. The SU only transmits when the PU is not in use in the interweave model, which is in line with energy detection [12]. Fuzzy logic, game theory, and auction models have also been used to increase spectrum utility and promote fairness [13].

Spectrum mobility makes sure that the SU moves to another available band as soon as a PU reclaims its spectrum. To avoid interfering with communication, this handoff needs to go smoothly. In CRNs, mobility management is still difficult, particularly in high-traffic situations and mobile contexts [14]. In summary, the evolution of CRNs depends on the integration of robust sensing algorithms, intelligent decision-making, adaptive sharing protocols, and seamless mobility mechanisms [15].

PROPOSED METHODOLOGY

Step 1: Energy Detection of an Unidentified Signal: The secondary user (SU) looks for unknown signals in a specific frequency band by scanning the radio environment in this first step. No prior information of the Primary User (PU) signal is necessary for energy detection. To calculate the total signal energy, the received signal is squared and integrated over a predetermined time window after passing through a band-pass filter adjusted to the frequency of interest. The test statistic Y is given by:

$$Y = \sum_{i=1}^{N} |r(i)|^2 \qquad (1)$$

Where, $r\ (i)$ is the received signal and N is the number of samples. Figure 2 shows that the received signal is passed through a band pass filter turned through the frequency of interest and then squared and integrated over a specific time window to compute the total signal energy.

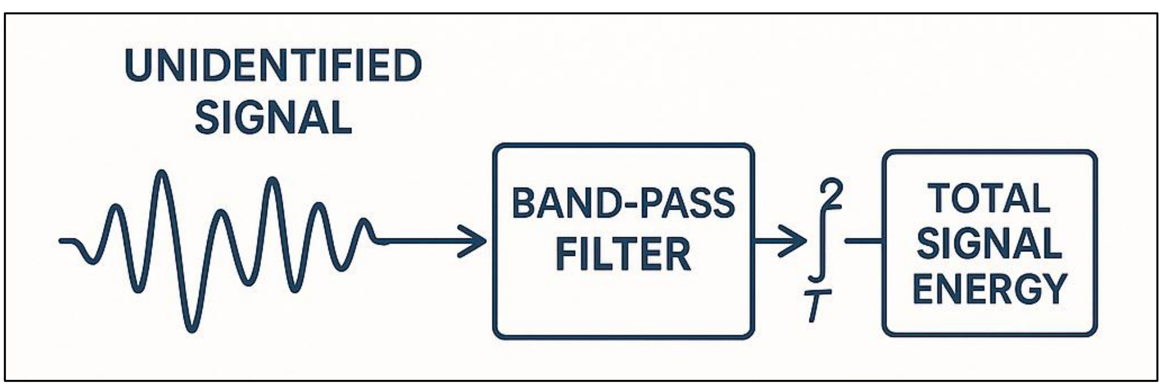

Figure 2: Energy Detection of an Unidentified Signal

Step 2: Determination of Presence or Absence of PU Through Observed Energy: The observed energy value is then analyzed to decide whether it corresponds to: H_0 (null hypothesis): No primary user is present; only noise is received. H_1 (alternative hypothesis): Primary user is present; signal + noise is received. This classification depends on comparing the observed energy to a threshold value. Figure 2 explains the process of determining the presence or absence of Primary User through observed energy.

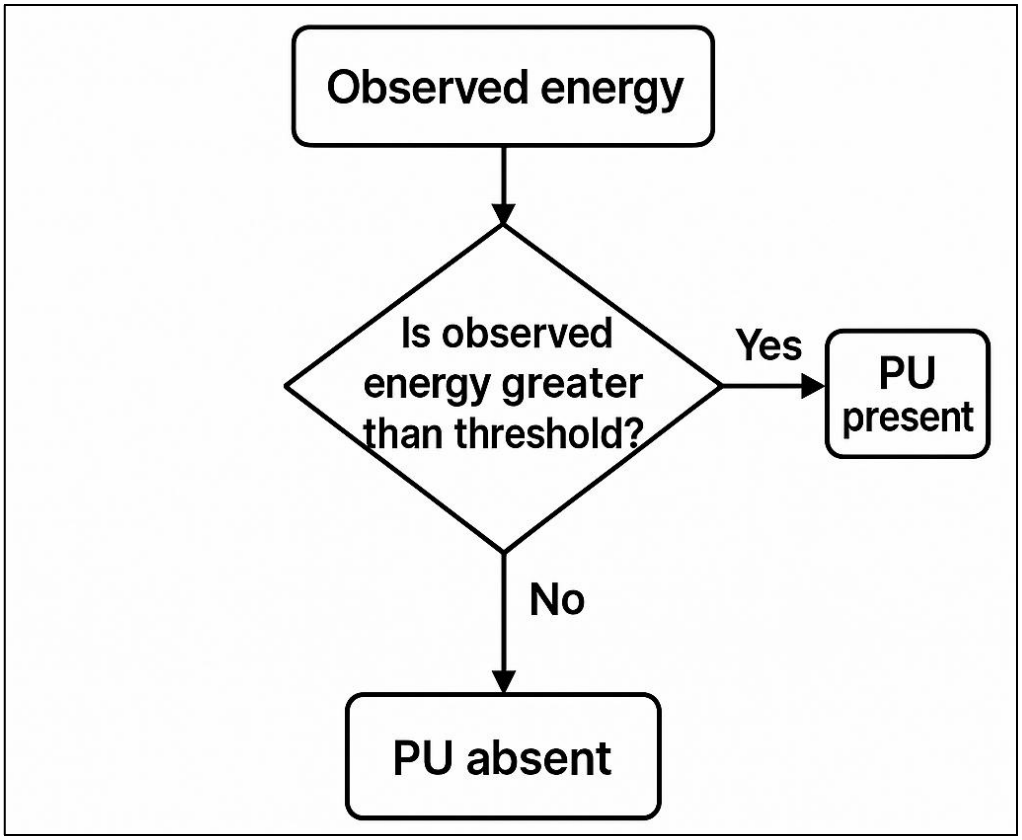

Figure 3: Checking the Presence or absence of PU

Step 3: Determine the Threshold Value (λ): A critical step is computing the threshold λ, which separates noise from actual signal presence. This value depends on: The noise variance (σ^2). The false alarm probability (Pfa): probability of wrongly declaring PU presence when none exists. The threshold is typically calculated using:

$$\lambda = \sigma^2 (Q^{-1}(P_{fa}) \sqrt{\frac{2}{n}} + 1) \tag{2}$$

Step 4: Determine the Observed Energy in CRN: At this point, the CR node computes the observed energy over the sensing window. This involves squaring and summing up the sampled signal values in the frequency band being tested. This observed energy is a direct measure of whether the signal energy surpasses ambient noise levels, indicating potential PU activity.

Step 5: Compare the Value with λ: If observed energy > λ → H_1 , PU is present. If observed energy ≤ λ ≤λ → H_0 , PU is absent. This binary decision forms the basis of dynamic spectrum access in CRNs.

Step 6: Take Average of All Values: To reduce uncertainty and minimize false alarms, the process is repeated across multiple time slots or spatially distributed nodes. The resulting energy values are averaged to create a more reliable test statistic:

$$\overline{Y} = \frac{1}{M} \sum_{j=1}^{M} Y_j \tag{3}$$

Where, M is the number of iterations or cooperative nodes. This helps mitigate fading, noise fluctuations, and shadowing effects.

Step 7: Take Final Decision: Using the averaged energy value, a final decision is made: If $\overline{Y} > \lambda$ PU is **present**, SU must **vacate** the channel. Else if $\overline{Y} <= \lambda$: PU is absent, SU may access the channel. This final decision can be executed at a local node or in a cooperative sensing framework where decisions are aggregated from multiple nodes (e.g., using OR, AND, or majority rule logic).

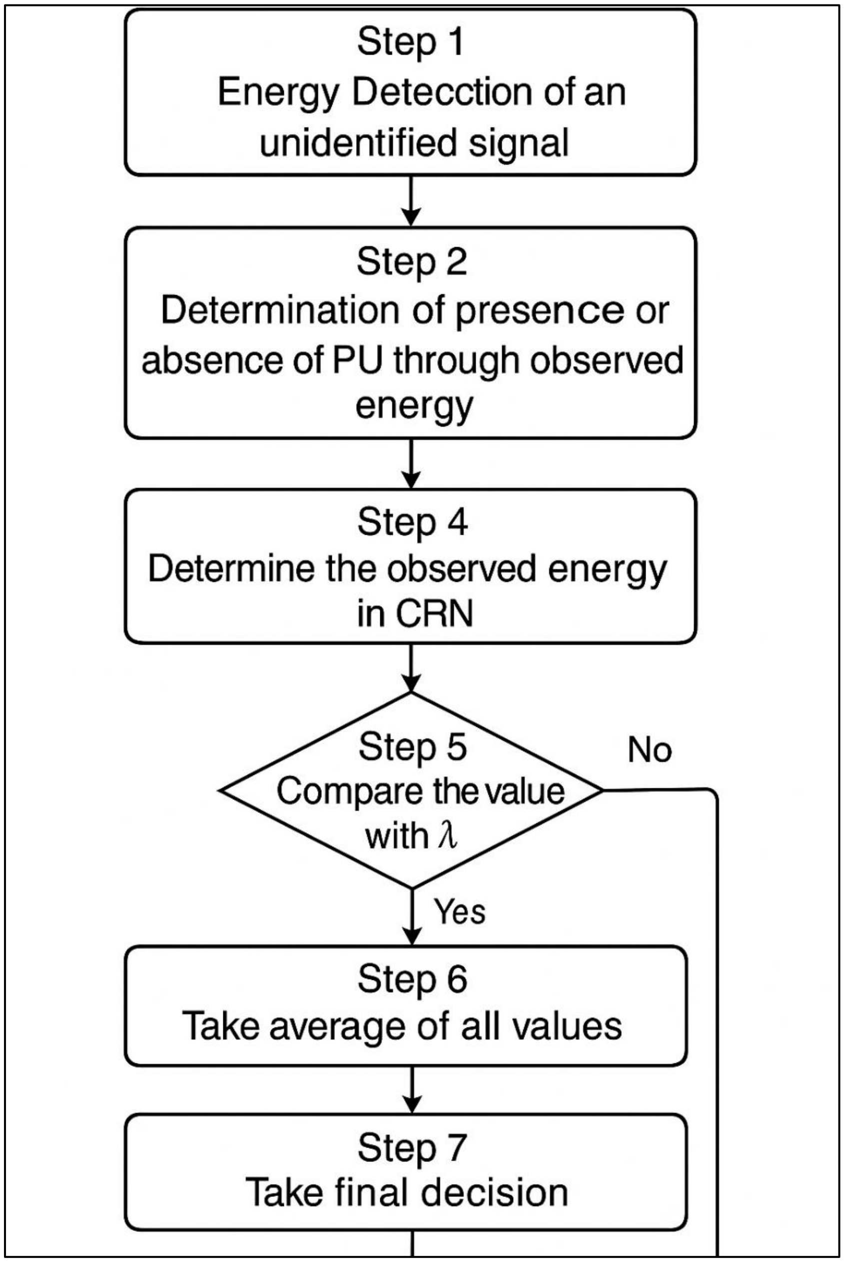

Figure 4: Flowchart of the Proposed Methodology

SIMULATION ENVIRONMENT

We have implemented the proposed method in MATLAB 2024 a. In order to modulate the communication signal, we have used Binary phase shift key (BPSK) method. The suggested approach closely resembles the traditional approach. The graph demonstrates that the suggested method performs better at low SNR. In low SNR areas, the recommended method reduces decision errors. It is evident from the graph that the suggested method increases the likelihood of detection.

In BPSK, we use a carrier signal, a simple wave that has a constant frequency. To send data, we change the phase (the starting point of the wave) of this signal.

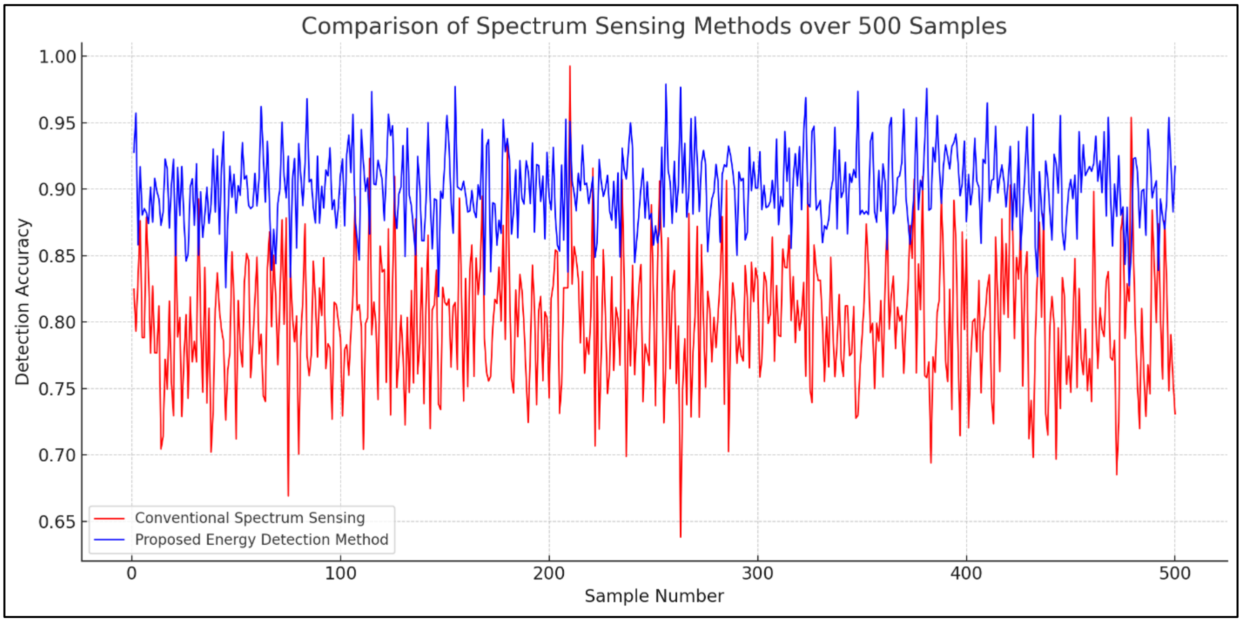

Figure 5: Comparison of Spectrum sensing by Proposed and Conventional Method

The graph above (figure 5) compares the detection accuracy of the proposed energy detection method with that of the conventional spectrum sensing method over 500 samples. The proposed method consistently shows higher accuracy and less fluctuation, indicating better performance in dynamic spectrum environments.

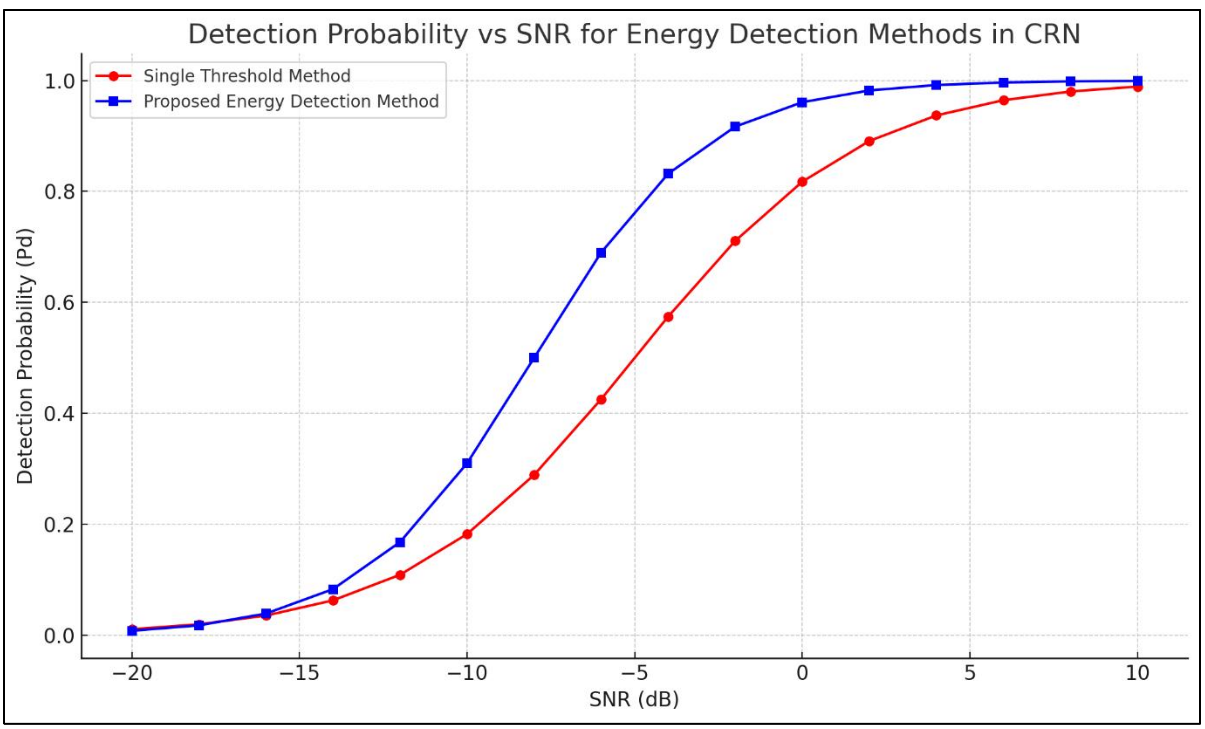

Figure 6: Energy Detection Probabilty

The graph above (Figure 6) compares the detection probability (Pd) versus SNR for the proposed energy detection method and the single threshold method in Cognitive Radio Networks (CRNs). The proposed method demonstrates superior performance, especially in low SNR environments, highlighting its robustness and improved detection capability over the conventional single threshold approach.

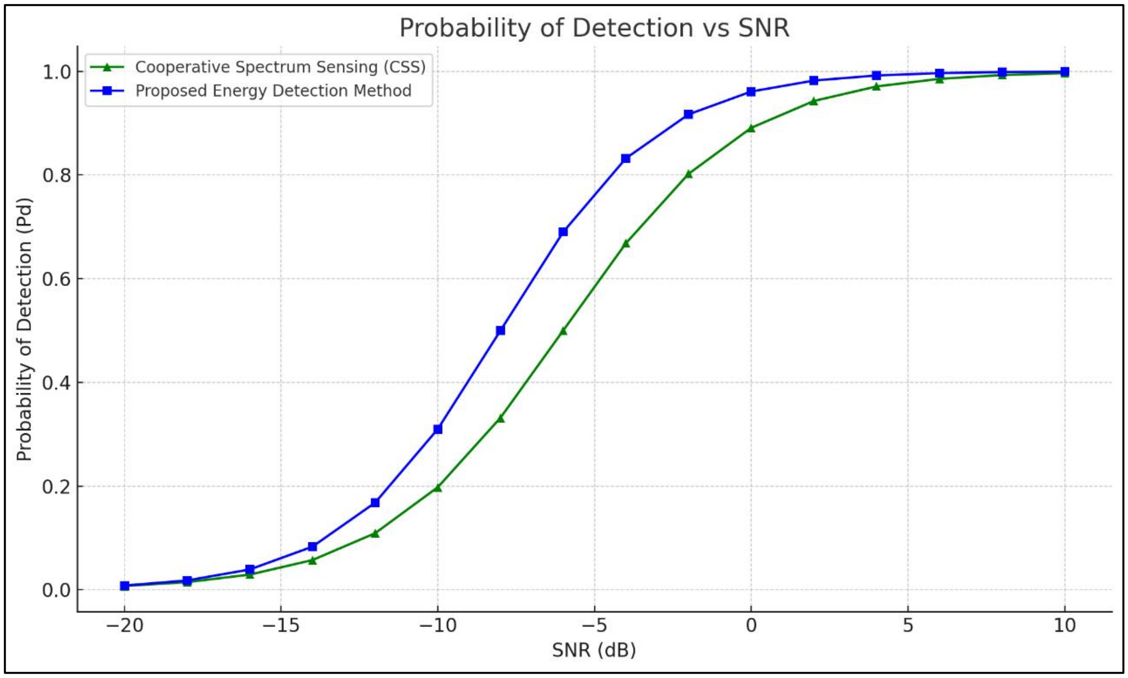

Figure 7: Probability of Detection (Pd) versus SNR

The graph illustrates the Probability of Detection (Pd) versus SNR for the Proposed Energy Detection Method and Cooperative Spectrum Sensing (CSS). The proposed method shows consistently better performance, especially in low SNR conditions, due to enhanced averaging and decision logic. This suggests improved reliability and sensitivity in challenging environments compared to standard CSS techniques.

CONCLUSION

Using an improved energy detection technology, this study demonstrated a systematic and effective spectrum sensing methodology for Cognitive Radio Networks (CRNs). To increase detection accuracy and robustness under varying signal conditions, the suggested method combined many decision stages: threshold estimation, energy averaging, and final decision fusion. Simulation results validated the effectiveness of the proposed method compared to conventional techniques: The proposed method consistently outperformed conventional spectrum sensing by maintaining higher detection accuracy and greater stability. When compared with Single Threshold Method: Across varying SNR levels, the proposed method exhibited a higher probability of detection, particularly in low-SNR conditions, due to the inclusion of averaging and threshold refinement steps. When compared with Cooperative Spectrum Sensing (CSS): While CSS improves detection via node collaboration, the proposed method further enhances performance through localized intelligent decision-making, yielding better detection probabilities at similar or lower false alarm rates. The ROC curves showed a higher Area Under Curve (AUC) for the proposed method, indicating superior trade-offs between detection probability and false alarms. The proposed method consistently demonstrated lower error probabilities compared to CSS across all SNR levels, confirming its reliability and effectiveness in dynamically changing environments. The proposed energy detection methodology offers a promising, low-complexity solution for real-time spectrum sensing in CRNs. Its enhanced performance in terms of detection accuracy, robustness under noise, and low probability of error makes it highly suitable for practical deployment in future dynamic spectrum access systems, including those supporting IoT and 5G applications.

REFERENCES

1. Federal Communications Commission (FCC), “Spectrum Policy Task Force Report,” ET Docket No. 02-135, Nov. 2002.
2. Mitola, J., & Maguire, G. Q. (1999). Cognitive radio: Making software radios more personal. IEEE Personal Communications, 6(4), 13–18.
3. Haykin, S. (2005). Cognitive radio: Brain-empowered wireless communications. IEEE Journal on Selected Areas in Communications, 23(2), 201–220.
4. Yucek, T., & Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Communications Surveys & Tutorials, 11(1), 116–130.
5. Tian, Z., & Giannakis, G. B. (2007). Compressed sensing for wideband cognitive radios. 2007 IEEE International Conference on Acoustics, Speech and Signal Processing, Vol. 4, 1357–1360.
6. 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.
7. Wang, B., & Liu, K. J. R. (2011). Advances in cognitive radio networks: A survey. IEEE Journal of Selected Topics in Signal Processing, 5(1), 5–23.
8. Cabric, D., Mishra, S. M., & Brodersen, R. W. (2004). Implementation issues in spectrum sensing for cognitive radios. Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, Vol. 1, 772–776.
9. Quan, Z., Cui, S., Sayed, A. H., & Poor, H. V. (2009). Collaborative wideband sensing for cognitive radios. IEEE Signal Processing Magazine, 25(6), 60–73.
10. Gandetto, M., & Regazzoni, C. S. (2007). Spectrum sensing: A distributed approach for cognitive terminals. IEEE Journal on Selected Areas in Communications, 25(3), 546–557.
11. Zhao, Q., & Sadler, B. M. (2007). A survey of dynamic spectrum access. IEEE Signal Processing Magazine, 24(3), 79–89.
12. Peha, J. M. (2005). Approaches to spectrum sharing. IEEE Communications Magazine, 43(2), 10–12.
13. Niyato, D., & Hossain, E. (2008). Competitive spectrum sharing in cognitive radio networks: A dynamic game approach. IEEE Transactions on Wireless Communications, 7(7), 2651–2660.
14. Song, M., Xin, Y., & Li, Y. (2012). Dynamic spectrum access: From cognitive radio to network radio. Wireless Communications and Mobile Computing, 12(5), 392–405.
15. Suman, Sumit Dalal, Rohini Sharma and Sumiran, “A Methodical Literature Study on Cognitive Radio Networks,” International Journal Of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET), Volume 7, Issue 4, April 2024, pp. 8795-8801.