Entropy augmented energy detection for cognitive radio: robust spectrum sensing under fading channels

Lingeswari Ponnusamy, Marichamy Perumalsamy
Department of Electronics and Communication Engineering, P.S.R Engineering College, Sivakasi, India

Article Info

Article history:

Received Feb 12, 2025
Revised Oct 17, 2025
Accepted Dec 6, 2025

Keywords:

Cognitive radio detection
Energy detection
Energy-efficient cognitive radio
Entropy-based sensing
Low-signal-to-noise ratio
Spectrum sensing

ABSTRACT

Cognitive radio systems provide an intelligent solution to spectrum scarcity by dynamically accessing underutilized frequency bands licensed to primary users. Among various sensing techniques, energy detection (ED) is extensively adopted due to its inherent simplicity and minimal computational requirements, but suffers from poor performance at low signal-to-noise ratio (SNR) environments under channel impairments such as additive white gaussian noise (AWGN) and multipath fading. This paper proposes an enhanced spectrum sensing approach by integrating ED with entropy-based techniques, specifically Kapur and Renyi entropy measures. The proposed methods are evaluated under AWGN and various fading environments with binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) modulations. Simulation results demonstrate substantial improvements in detection performance. The results show that entropy-based enhancements significantly improve the reliability of spectrum sensing in cognitive radio (CR) systems operating under challenging channel conditions. Among the fading models, the Nakagami channel causes the greatest degradation in detection probability, followed by the Rayleigh fading channel. ED with Renyi entropy improves P_d by 15-fold and 8-fold, compared to ED under Nakagami and Rayleigh channels respectively.

Corresponding Author:

Lingeswari Ponnusamy
Department of Electronics and Communication Engineering, P.S.R Engineering College
Sivakasi, Tamilnadu, India
Email: lingeswari@psr.edu.in

1. INTRODUCTION

The unprecedented growth of wireless technologies has directed to an increased demand for radio spectrum, making spectrum scarcity a critical challenge for service providers in meeting the rising demands of modern communication services. According to the federal communications commission (FCC), even with optimal allocation, 80 to 90% of the licensed spectrum remains underutilized at any given time and location [1]. One creative way to make use of the unused spectrum is cognitive radio (CR) [2]. Wireless systems operate across both licensed and unlicensed frequency bands. For instance, CR utilizes the unlicensed industrial, scientific, and medical (ISM) bands, such as 902–928 MHz, 2.4–2.5 GHz, and 5.725–5.875 GHz, while licensed bands are used for applications such as AM radio (535 kHz–1.605 MHz), LTE (700 MHz–2.6 GHz), and marine/aerospace communication (300–535 kHz) [3]. Within the cognitive radio network (CRN), two categories of users are identified: primary users (PUs), who possess licensed access to exact spectrum bands, and secondary users (SUs), who opportunistically utilize vacant spectrum without causing interference to PUs [4], [5]. CRs address the issue of spectrum scarcity through dynamic and intelligent spectrum access, enabled by spectrum sensing (SS) techniques. SS detects spectrum holes (unoccupied frequency bands) that can be utilized by SUs [6]-[8]. Various techniques have been developed for SS, including matched filter detection (MFD), cyclostationary feature detection and energy detection (ED). Among these methodologies, ED is the most widely used due to its simplicity, fast implementation and independence from prior knowledge of PU signals [9], [10].

ED functions by comparing the energy of the received signal to a predefined threshold to determine availability of spectrum. While ED performs well in noise-stable environments, its effectiveness deteriorates at low signal-to-noise ratios (SNRs) and under noise uncertainty [11], [12]. Several enhancements have been proposed to address these limitations. The entropy-based detection has gained attention as a promising SS technique. It offers low complexity and robustness to noise without requiring prior knowledge of the PU signal. Since entropy quantifies signal uncertainty and reaches its maximum for uniform distributions, it serves as a useful criterion to differentiate between signal and noise [13], [14]. Numerous entropy-augmented ED methodologies have been proposed in the literature. For example, kernel principal component analysis has been used to implement adaptive threshold for ED under noise uncertainty, particularly in low SNR conditions [15]. Other studies have modelled the impact of sample size on noise ambiguity [16], and examined how fading, shadowing, and the hidden terminal problem influence ED performance [17], [18]. Hybrid matched filter detection (HMFD) [19], which combines MFD and ED is though effective, but introduces higher computational complexity. However, entropy-based techniques remain attractive due to their noise resilience and lower computational demands [20]. The histogram-based entropy estimators [21] and multi-stage detectors [22] balance complexity and performance. Techniques like the K-slot ED algorithm [23] and sample entropy for multiband sensing [24] enhance performance, but at the cost of increased computational load. The machine learning (ML) [25] and deep learning (DL) [26] methods also have been applied for SS. The ML methods have been explored to enhance detection accuracy under complex conditions like fading, shadowing and low SNR [26]. However, these approaches are less practical for lightweight CR devices due to high training costs, data requirements and computational complexity [27]. Most prior work has used Shannon entropy [28] along with the various sensing techniques. The ED methods and its variants that are reported in the literature are compared in Table 1.

Table 1. Comparison of the reported works in the literature

Authors (year)	Method	Remarks
Zhang *et al.* (2010) [12]	Frequency domain entropy-based SS scheme is studied and compared with ED and cyclostationary detectors	Studied for Shannon entropy only. Analyzed for additive white gaussian noise (AWGN) and Rayleigh channels. Used double sideband (DSB) and single sideband (SSB) modulation. Poor P_d at low SNR.
Prieto *et al.* (2018) [13]	Bartlett periodogram employed for entropy estimation	Shannon entropy only used. Studied for AWGN channel. Inferior performance at low SNR.
Prieto *et al.* (2019) [21]	ED with Shannon entropy	Shannon entropy used. No modulation. Poor performance at low SNR. AWGN channel only.
Tenorio *et al.* (2022) [24]	Sample entropy-based SS	Evaluated only for AWGN, ignores Rayleigh, Rician, and Nakagami channels.
Pandian *et al.* (2023) [26]	Random forest, logistic regression, support vector machine (SVM), and k-nearest neighbor (KNN)	Classical ML method used. No SNR effects and fading channel considered.
Usman *et al.* (2022) [28]	ED with Shannon entropy	Shannon entropy employed. No modulation. AWGN channel only.

Among the ED with different entropy methods, the ED with Shannon entropy shows better performance. Most of the studies have been carried out for AWGN channels only. Despite the progress in entropy-based detection and hybrid approaches, challenges remain in ensuring high detection accuracy at low SNR conditions, fading environments, and noise uncertainty while maintaining computational efficiency. The existing better performing ED method rely on Shannon entropy. This motivates the current study, which proposes a novel entropy augmented ED technique that incorporates Kapur and Renyi entropy methods. The proposed method aims to strike a balance between detection performance and computational complexity, offering robust sensing capabilities both under AWGN and various fading channels with different modulation methods.

The paper is structured as follows: following this introduction, section 2 presents the proposed entropy-augmented EDE method and presents the detection probability (P_d) under various channel conditions. Section 3 discusses the simulation and performance evaluations, including a comparison of the proposed techniques with the existing methods such as conventional ED and involving Shannon entropy. Finally, section 4 provides the conclusions and outlines future research directions.

2. METHOD

The proposed EDE method is shown in Figure 1. It has two distinct stages. The initial stage computes the energy of the received signal r(t) after band pass filtering through squaring and integration process. The second stage estimates the entropy. This entropy is then compared with the predefined threshold level to determine whether the spectrum is present or not. Both simulation and theoretical evaluation have been carried out and they are discussed.

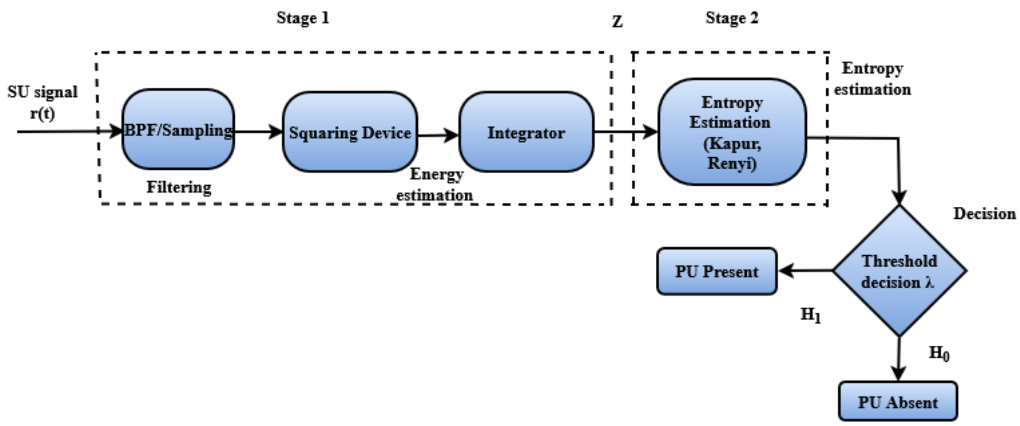

Figure 1. The proposed entropy-augmented ED method

2.1. Theoretical evaluation

P_d of signal for the spectrum holes is theoretically computed based on the equations obtained for the different channel conditions and the different entropy methods. The equations are obtained as:

– Representation of signals: the signal received by the SUs is described as a binary hypothesis (H_0 & H_1) testing to determine whether PU is in idle or busy state. H_0 denotes the absence of PU and H_1 denotes the existence of PU [29]. The signal received r(t) by SU is characterized by the subsequent two distinct hypotheses (1):

$$r(t) = \begin{cases} e(t); H_0 \\ k * m(t) + e(t); H_1 \end{cases} \tag{1}$$

m(t) represents the signal transmitted by PU and e(t) represents the noise component. k stands for the channel's amplitude gain and its value depends on the noisy environment. The value of k for AWGN channel is 1.

– Filtering: it is assumed that both the signal m(t) and noise e(t) are independent and identically distributed, exhibiting a mean of zero and variance σ_m^2 and σ_e^2 respectively. Further, m(t) is statistically independent of e(t) [30]. The signal r(t) received by SU is subjected to a band-pass filter with bandwidth B, and its transfer function is given as (2):

$$H(f) = \begin{cases} \frac{2}{\sqrt{N_0}}; |f - f_c| \le B \\ 0; |f - f_c| > B \end{cases} \tag{2}$$

where N_0 is power spectral density (PSD), f_c is carrier frequency, and B is bandwidth.

– Energy estimation: the filtered signal r(t) is subsequently squared and integrated over a time period T [31] to estimate its energy. The resultant energy (Z) is given as $\frac{1}{N_0}\int_0^{T} r^2(t)dt$. The estimated energy is considered to have a chi-square distribution with 2BwT degrees of freedom when there is only noise (H_0). If both signal and noise (H_1) are present, it is considered having non-central chi-square distribution, which has the same degrees of freedom and a non-centrality parameter that is based on the signal strength. The decision statistic for evaluating the energy of a signal is expressed as (3):

$$Z \sim \begin{cases} \chi_{2d}^2 \,; H_0 \\ \chi_{2d}^2(2\gamma); H_1 \end{cases} \tag{3}$$

The PDF corresponding to a chi-squared distribution in this case, labelled as Z, described by (4) [32]:

$$f_Z(z) = \begin{cases} \frac{1}{2^d \Gamma\text{(d)}} y^{d-1} e^{-\frac{y}{2}}\, ; H_0 \\ \frac{1}{2}(\frac{y}{2\gamma})^{\frac{d-1}{2}} e^{-\frac{2\gamma+y}{2}} I_{d-1}(\sqrt{2\gamma y})\, ; H_1 \end{cases} \tag{4}$$

Here, Γ(.) stands for the gamma function and Iu(.) stands for the u-th order modified Bessel function of the first kind [33].

- Entropy estimation: a measure of the average amount of information contained in each symbol is called entropy. For a continuous random variable, the entropy of PDF f(r) is as (5):

$$H(r) = -\int_{-\infty}^{\infty} f(r) log_2 f(r) dr \tag{5}$$

The Shannon entropy associated with a random variable is given by (6):

$$E_s(r) = -\sum_{r=-\infty}^{\infty} f(r) log_2 f(r) \tag{6}$$

Kapur's entropy with entropy order α is represented by (7):

$$E_k(r) = \frac{1-(\sum_{r=-\infty}^{\infty} f(r)^{1/\alpha})^{\alpha}}{1-\alpha} \tag{7}$$

Renyi entropy is represented by (8):

$$E_{r1}(r) = \frac{1}{1-\alpha} \log\,(\sum_{r=-\infty}^{\infty} f(r)^{\alpha}) \tag{8}$$

- Decision: the ED relies on a predefined threshold, which is important for evaluating aspects that contribute to its performance: i) probability of false alarm (P_f) and ii) detection probability (P_d). For a particular threshold, P_d and P_f can be described as (9):

$$P_d = P(H > \lambda/H_0)\ and\ P_f = P(H > \lambda/H_1) \tag{9}$$

P_d for different channel environments are evaluated as:

- AWGN channel: the probability of failure $P_{f,}$ is obtained for AWGN channel using the incomplete gamma function [33]. The P_d is obtained from the cumulative distribution function given in (4) involving the generalized Marcum Q-function, which depends on the SNR, $\mathrm{P_d} = 1 - \mathrm{F_Z(z)}$, where $F_z(z)$ is (10):

$$\mathrm{F_Z(z)} = 1 - \mathrm{Q_d}(\sqrt{2\gamma}, \sqrt{\mathrm{z}}) \tag{10}$$

Then P_d for an AWGN channel can be expressed as (11):

$$\mathrm{P_d} = \mathrm{Q_d}(\sqrt{2\gamma}, \sqrt{\lambda}) \tag{11}$$

where Q_d (.,.) signifies the generalized Marcum-Q function [34].

- Rayleigh fading channel: P_d under Rayleigh fading is determined by averaging in (10) over the SNR distribution using an integral involving the generalized Marcum Q-function. This occurs when the signal undergoes multipath scattering, causing its amplitude to follow a Rayleigh distribution, resulting in an exponential probability density function for the SNR γ.

$$\mathrm{P_{d\ Ray}} = \int_0^{\infty} \mathrm{Q_d}(\mathrm{r}, \sqrt{\lambda}) \frac{1}{\bar{\gamma}} e^{(-\frac{r^2}{2\bar{\gamma}})} r dr \tag{12}$$

substituting $p^2 = \frac{1}{\bar{\gamma}}$, m=d, a=1, and $b = \sqrt{\lambda}$ yields the P_d in Rayleigh channel given in (13):

$$\int_0^\infty \mathrm{dx.x.exp}\left(-\frac{\mathrm{p^2x^2}}{2}\right)\mathrm{Q_m(ax,b)} = \frac{1}{\mathrm{p^2}}\exp\left(-\frac{\mathrm{b^2}}{2}\right)\left\{\left(\frac{\mathrm{p^2+a^2}}{\mathrm{a^2}}\right)^{\mathrm{m-1}}\left[\exp\left(\frac{\mathrm{b^2}}{2}.\frac{\mathrm{a^2}}{\mathrm{p^2+a^2}}\right) - \sum_{\mathrm{n=0}}^{\mathrm{m-2}}\frac{1}{\mathrm{n!}}\left(\frac{\mathrm{b^2}}{2}.\frac{\mathrm{a^2}}{\mathrm{p^2+a^2}}\right)^{\mathrm{n}}\right] + \sum_{\mathrm{n=0}}^{\mathrm{m-2}}\frac{1}{\mathrm{n!}}\left(\frac{\mathrm{b^2}}{2}\right)^{\mathrm{n}}\right\} \tag{13}$$

$$\mathrm{P_{d\,Ray}} = \mathrm{e}^{-\frac{\lambda}{2}}\sum_{\mathrm{n=0}}^{\mathrm{d-2}}\frac{1}{\mathrm{n!}}\left(\frac{\lambda}{2}\right)^{\mathrm{n}} + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{\mathrm{d-1}}\left\{\mathrm{e}^{\frac{-\lambda}{2(1+\bar{\gamma})}} - \mathrm{e}^{-\frac{\lambda}{2}}\sum_{\mathrm{n=0}}^{\mathrm{d-2}}\frac{1}{\mathrm{n!}}\left[\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right]^{\mathrm{n}}\right\} \tag{14}$$

– Rician fading channel: the SNR has a PDF involving the modified Bessel function when the signal power follows a Rician distribution, which is defined by the Rician factor K. The average P_d under Rician fading, $P_{d\ Ric}$, is determined by averaging (10):

$$\mathrm{P_{d\,Ric}} = \int_0^\infty \mathrm{Q_d}(r,\sqrt{\lambda})\left(\frac{K+1}{\bar{\gamma}}\right)e^{\left(-K-\frac{(K+1)r^2}{2\bar{\gamma}}\right)}I_0\left(2\sqrt{\frac{K(K+1)r^2}{2\bar{\gamma}}}\right)rdr \tag{15}$$

For u=1, the corresponding solution may be solved using [35], which is provided in (16):

$$\int_0^\infty \mathrm{dx.x.exp}\left(-\frac{\mathrm{p^2x^2}}{2}\right)\mathrm{I_0(cx)Q(ax,b)} = \frac{1}{\mathrm{p^2}}\exp\left(\frac{\mathrm{c^2}}{2\mathrm{p^2}}\right)\mathrm{Q}\left(\frac{\mathrm{ac}}{\mathrm{p}\sqrt{\mathrm{p^2+a^2}}},\frac{\mathrm{bp}}{\sqrt{\mathrm{p^2+a^2}}}\right) \tag{16}$$

$$\mathrm{P_{d\,Ric}}|_{\mathrm{u=1}} = \mathrm{Q}\left(\sqrt{\frac{2\mathrm{K}\bar{\gamma}}{\mathrm{K}+1+\bar{\gamma}}},\sqrt{\frac{\lambda(\mathrm{K}+1)}{\mathrm{K}+1+\bar{\gamma}}}\right) \tag{17}$$

– Nakagami fading channel: when the signal follows a Nakagami distribution with fading parameter m [36], the average P_d under Nakagami fading is obtained by averaging (10) over this distribution using the change of variable $r = \sqrt{2\gamma}$.

$$\mathrm{P_{d\,Nak}} = \alpha\int_0^\infty \mathrm{Q_d}(r,\sqrt{\lambda})r^{2m-1}e^{\left(-\frac{mr^2}{2\bar{\gamma}}\right)}dr \tag{18}$$

Following the evaluation of the integral, $P_{d\ Nak}$ can be expressed in a closed form as described in (19):

$$G_M = \int_0^\infty dx.x^\rho \exp\left(-\frac{p^2x^2}{2}\right)Q_m(ax,b)\,;\rho > -1 \tag{19}$$

$$P_{d\,Nak} = \alpha\left[G_1 + \beta\sum_{n=1}^{d-1}\frac{\lambda/2}{2n!}F_1\left(m;n+1;\frac{\lambda}{2}*\frac{\bar{\gamma}}{m+\bar{\gamma}}\right)\right] \tag{20}$$

The confluent hypergeometric function is denoted by F1(:, :,.) [33], and (21) and (22) provide the representations of β and the solution of G1 [34].

$$\beta = \Gamma(m)\left(\frac{2\bar{\gamma}}{m+\bar{\gamma}}\right)^m e^{-\lambda/2} \tag{21}$$

$$G_1 = \int_0^\infty x^{2m-1}\exp\left(-\frac{mx^2}{2\bar{\gamma}}\right)Q(x,\sqrt{\lambda})dx \tag{22}$$

2.2. Simulation

The ED is evaluated through simulation considering various fading channels in MATLAB© platform. Primary user signals are randomly generated using rand function. Fading channel effects are obtained using Rayleigh Chan and Rician Chan for Rayleigh and Rician channels respectively. Nakagami-m fading is implemented with gamma distributed random variables. The hist function approximates the signals probability distribution for entropy calculation. A bandwidth of 12 kHz and a carrier frequency of 40 kHz are considered in our work based on existing literature [12]. These parameters are chosen to represent typical narrowband communication scenarios commonly used in CR applications with low SNR. A single user SS is considered to evaluate the fundamental performance of the EDE for improving PU detection, without involving multiple users [13], [18], [28]. P_d is evaluated for both binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) modulated signals with varying SNR levels. Monte Carlo simulations with 10,000 runs are done to get statistically robust results. The parameters and the assumptions made for the simulation is listed in Table 2.

Table 2. Simulation parameters

Simulation parameters	Type and value
Cognitive user	One user
Primary signal type	Random
Sensing method	ED with Shannon, Kapur, and Renyi entropy
P_f	0.1 to 1
Modulation type	BPSK and QPSK
Channel	AWGN, Rayleigh, Rician, and Nakagami
Number of samples and number of Monte Carlo simulations	1,000 and 10,000
Bandwidth	12 kHz
Carrier frequency	40 kHz
SNR in dB	-25 dB to 5 dB
Fading coefficient for Nakagami, m	3
Entropy order (Kapur, Renyi), α	2

The receiver operating characteristics (ROC) for both theoretical and simulation results are compared and found to be close. As an example, ROC curve for the Rician fading channel is shown in Figure 2. The simulated results are closely matches with the results obtained through theoretical evaluations with the deviation ranging 0 to 1.1%.

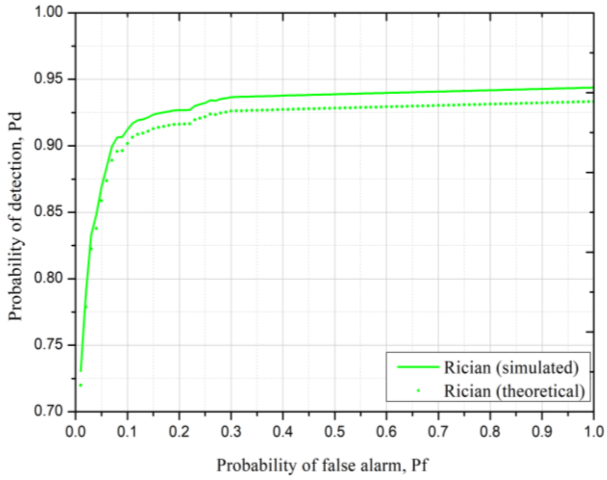

Figure 2. Simulated and theoretical P_d comparison for Rician channel at SNR=-25 dB

The computational complexity analysis for the Shannon, Renyi, and Kapur methods are shown in Figure 3. Shannon and Renyi entropies have linear computational complexity O(k) and takes a single pass-through k bin, executing one logarithm and a few multiplications offers efficient and robust performance for SS. While Kapur entropy involves higher complexity $O(k^2)$ with fixed threshold for SS [37].

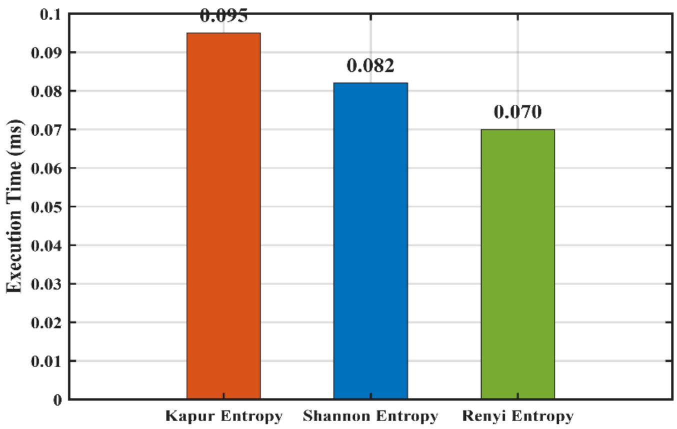

Figure 3. Computational complexity of entropy methods

3. RESULTS AND DISCUSSION

The performance of the method proposed in terms of P_d and SNR is analyzed, with results presented in Figures 4(a) to (d) for various channel fading environments using BPSK modulation. The detection capabilities of SU are evaluated by limiting the P_f to the lowest level, i.e., 0.1, in line with the IEEE 802.22 standard [13], [14], [21], [28]. The results indicate that P_d increases with rising SNR values across all scenarios. Among the channels, the Nakagami channel yields the lowest P_d, followed by the Rayleigh channel, while the AWGN and Rician channels shows better detection performance as 0.9149 and 0.9085 respectively for ED with Renyi entropy.

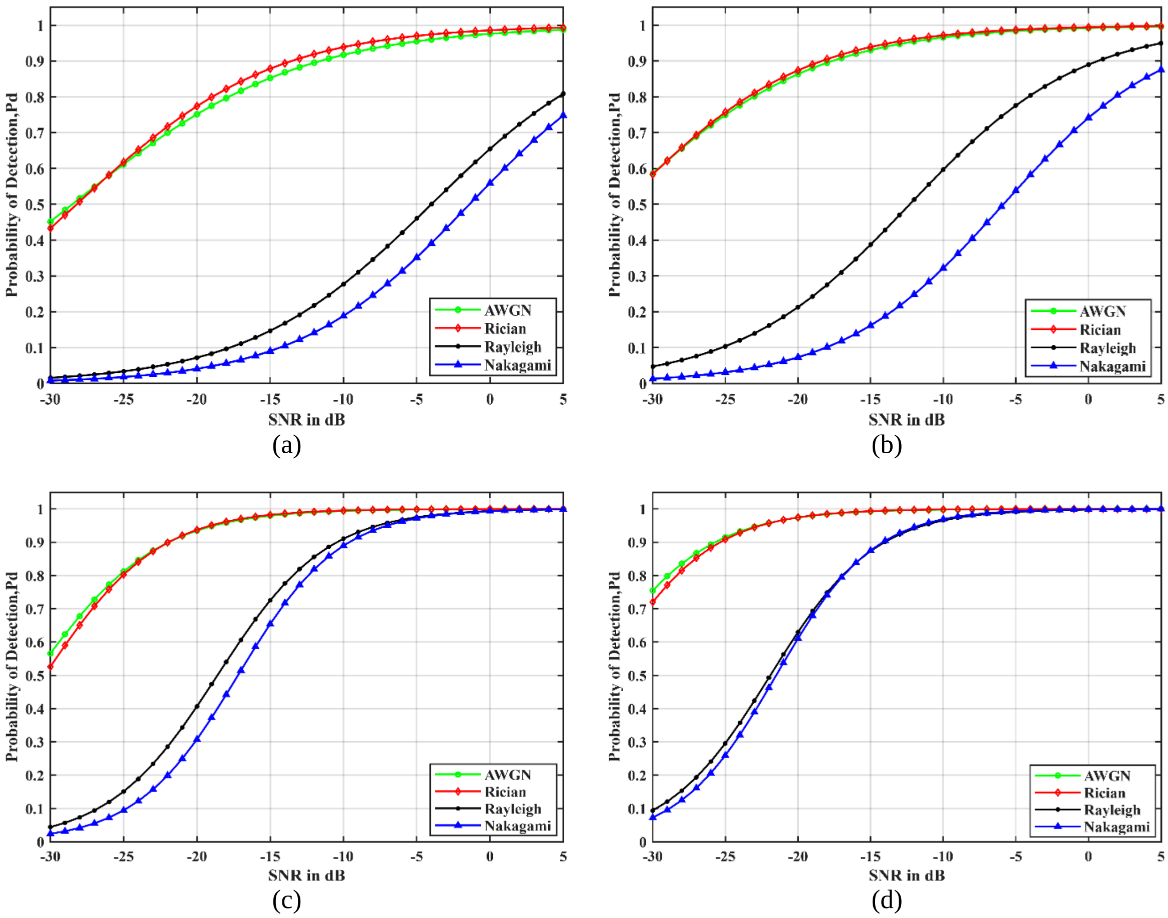

Figure 4. SNR vs P_d at P_f=0.1; (a) ED, (b) ED+Shannon, (c) ED+Kapur, and (d) ED+Renyi

The P_d values at a selected low SNR of –25 dB are summarized in Table 3. It is observed that ED with Renyi entropy consistently achieves the highest P_d across all SNR levels and channel conditions, followed by Kapur entropy, Shannon entropy, and ED. Renyi entropy performs better than Kapur entropy due to its tunable parameter alpha, which enhances adaptability to diverse statistical distributions and improves noise robustness. It also benefits from faster computation, as it has only power-law and logarithmic operations. The Nakagami channel causes the greatest degradation because it models severe multipath fading with higher fading depth than Rayleigh or Rician channels, leading to greater signal fluctuations and reduced detection performance in all the entropy methods.

Table 3. Performance of P_d for various ED+entropy method

Channel	Probability of detection (P_d) at P_f=0.1, SNR=-25dB			
	AWGN	Rayleigh	Rician	Nakagami
ED	0.6118	0.0336	0.6177	0.0178
ED+Shannon entropy	0.7493	0.1035	0.7569	0.0309
ED+Kapur entropy	0.8121	0.1508	0.8028	0.0943
ED+Renyi entropy	0.9149	0.2957	0.9085	0.2592

The performance of the EDE method considering both BPSK and QPSK modulation is analyzed in terms of P_f vs P_d at the fixed lower SNR of -25 dB in this section and shown in Figures 5(a) to (d) and Figures 6(a) to (d) respectively. The results indicate that a correlation exists among P_d and P_f. The probability of signal detection rises in proportion to P_f. The P_d is higher when the P_f increases. However, the spectrum quality gets worse when there is a high rate of false alarms affecting the system's overall performance.

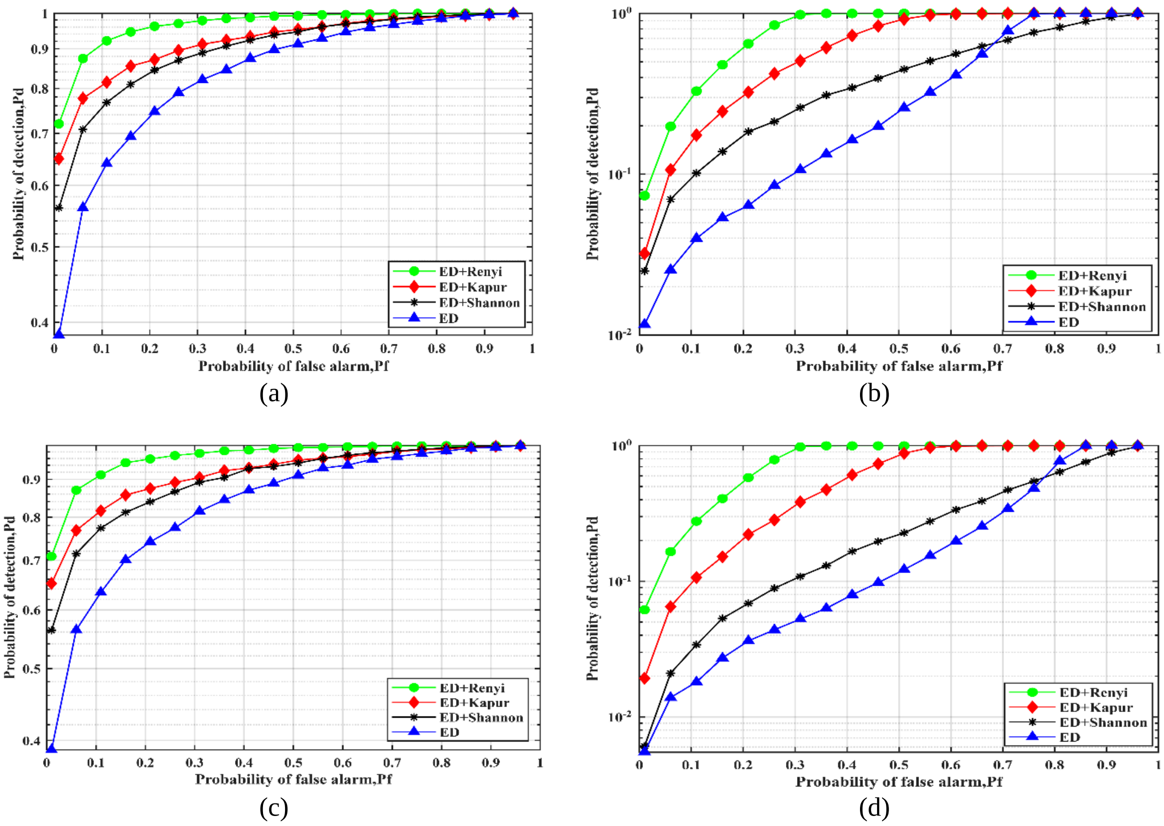

Figure 5. Performance of the detection methods under fading channels; (SNR=-25 dB, BPSK modulation); (a) AWGN channel, (b) Rayleigh channel, (c) Rician channel, and (d) Nakagami channel

3.1. Binary phase shift keying modulation

Figures 5(a) to (d) depicts the performance of the ED under various channel environments at a lower SNR of -25 dB considering BPSK modulated signals. The results obtained for the fixed P_f=0.1 are tabulated in Table 4. The results show that the proposed ED with Kapur and ED with Renyi techniques perform better than the conventional ED and the existing ED with Shannon method. The greatest improvement is observed in ED with Renyi method with gains of approximately 15-fold and 8-fold, compared to conventional ED under severely faded Nakagami and Rayleigh channels respectively. The BPSK modulation scheme, due to simpler constellation, is more robust to noise and fading compared and obviously provides higher P_d compared to QPSK.

3.2. Quadrature phase shift keying modulation

Figures 6(a) to (d) depicts the performance of the EDE under various channel environments at a lower SNR of -25 dB considering QPSK modulated signals. The results obtained for the fixed P_f=0.1 are tabulated in Table 5. As expected, P_d is lower than with BPSK, due to the denser constellation in QPSK which is more sensitive to noise and fading. However, QPSK provides better bandwidth efficiency. In all fading environments, Renyi entropy consistently outperforms Kapur and Shannon entropies because its greater sensitivity to the behavior of the probability distribution helps it better distinguish signals from noise, even under severe fading, resulting in significantly higher P_d.

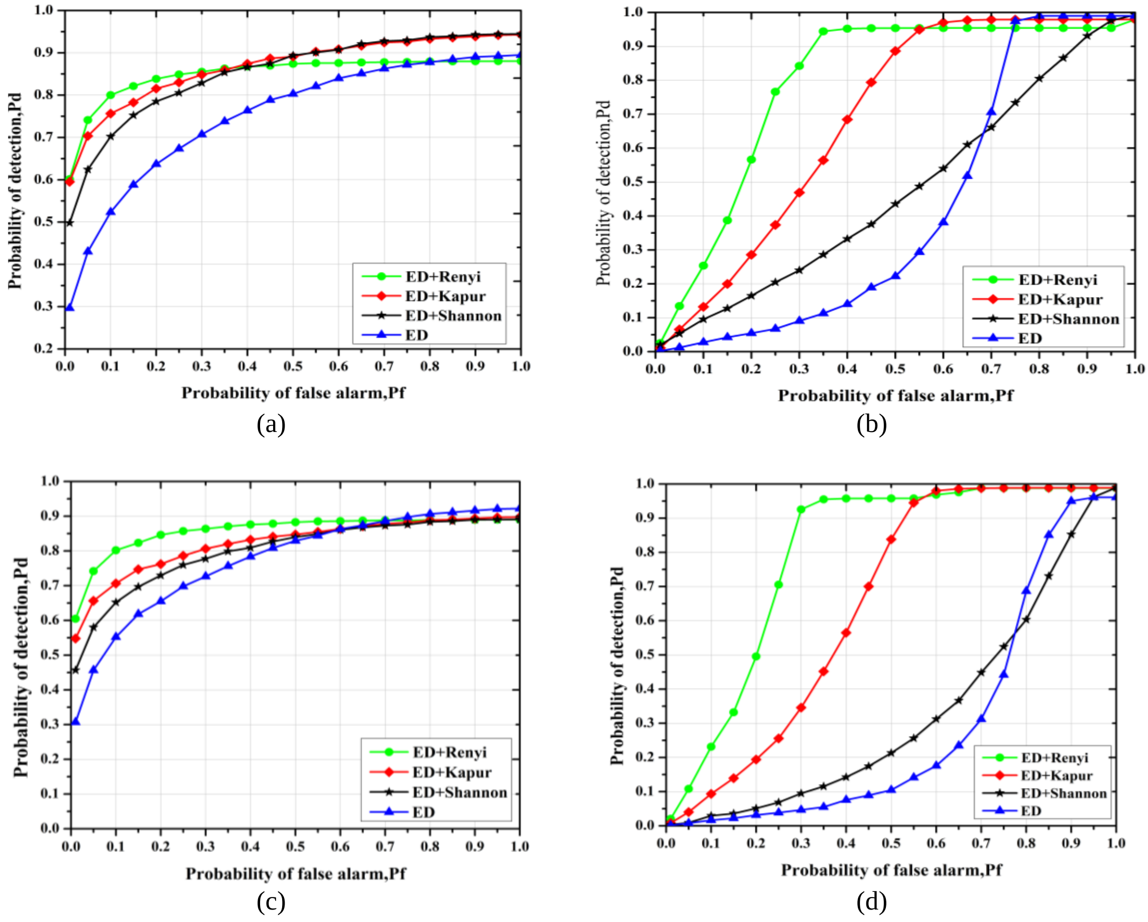

Figure 6. Performance of the detection methods under fading channels; (SNR=-25 dB, QPSK modulation); (a) AWGN channel, (b) Rayleigh channel, (c) Rician channel, and (d) Nakagami channel

Table 4. P_d Performance of the proposed EDE method (SNR=-25 dB, BPSK)

Channel	Probability of detection (P_d) at P_f=0.1			
	ED	ED+Shannon entropy	ED+Kapur entropy	ED+renyi entropy
AWGN	0.6284	0.7576	0.8136	0.9197
Rayleigh	0.0376	0.1024	0.1529	0.2994
Rician	0.6299	0.7610	0.8089	0.9120
Nakagami	0.0186	0.0316	0.0958	0.2604

Table 5. P_d Performance of the proposed EDE method (SNR=-25 dB, QPSK)

Channel	Probability of detection (P_d) at P_f=0.1			
	ED	ED+Shannon entropy	ED+Kapur entropy	ED+Renyi entropy
AWGN	0.5234	0.7021	0.7563	0.8000
Rayleigh	0.0275	0.0952	0.1321	0.2534
Rician	0.5521	0.6521	0.7065	0.8021
Nakagami	0.0165	0.0295	0.0934	0.2314

It is obvious that the ED method with QPSK modulation results in lower P_d compared to the BPSK modulation as the noise and fading level affects the signal constellation. However, it provides the benefit of higher bandwidth efficiency compared to the BPSK.

4. CONCLUSION

In this work, ED methods incorporating various entropy-based SS techniques are proposed to improve P_d of PUs. The effectiveness of the proposed approaches is evaluated across diverse channel environments. At an SNR of −25 dB, ED integrated with Kapur and Renyi entropy shows the P_d as 0.8089 and 0.9120, respectively, for BPSK modulation, 0.7065 and 0.8021 respectively, for QPSK modulation, under Rician fading channel. These results indicate that both Kapur and Renyi entropy-based ED methods significantly outperform the conventional ED and the Shannon entropy-based ED in terms of P_d. Among the two, ED with Renyi entropy exhibits superior performance. Furthermore, P_d is strongly influenced by the channel environment. The Nakagami channel exhibits the most significant degradation in P_d, followed by the Rayleigh channel. The effects of AWGN and Rician channels are comparatively less. The analysis of the present work is limited to single user environment.

The EDE approach can be further investigated by incorporating dynamically adaptive thresholds to enhance robustness in fluctuating signal conditions. Integration of ML and DL techniques presents a promising direction for future exploration. The practical deployment of the proposed methods can be evaluated using software-defined radios (SDRs). The current framework aligns with IEEE 802.22 standard requirements ($P_{f=}0.1$), ensuring reliable SS under low SNR conditions. Future work will focus on robustness analysis under noise uncertainty, hardware prototyping, and experimental validation to enhance real-world applicability.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	**C**	**M**	**So**	**Va**	**Fo**	**I**	**R**	**D**	**O**	**E**	**Vi**	**Su**	**P**	**Fu**
Lingeswari Ponnusamy	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Marichamy Perumalsamy	✓	✓				✓			✓	✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in https://github.com/lingeswari-2/Entropy-augmented-Energy-detection-in-Cognitive-radio.git.

REFERENCES

[1] S. Force, “Spectrum policy task force report, Federal communications commission (FCC),” vol. 135, no. 2, Washington DC, USA, 2002.

[2] Y. L. Zhang, Q. Y. Zhang, and T. Melodia, “A frequency-domain entropy-based detector for robust spectrum sensing in cognitive radio networks,” *IEEE Communications Letters*, vol. 14, no. 6, pp. 533–535, Jun. 2010, doi: 10.1109/LCOMM.2010.06.091954.

[3] S. Atapattu, C. Tellambura, and H. Jiang, “Energy Detection for Spectrum Sensing in Cognitive Radio,” *Energy Detection for Spectrum Sensing in Cognitive Radio*, pp. 11–27, 2014.

[4] K. Kockaya and I. Develi, “Spectrum sensing in cognitive radio networks: threshold optimization and analysis,” *Eurasip Journal on Wireless Communications and Networking*, vol. 2020, no. 1, p. 255, Dec. 2020, doi: 10.1186/s13638-020-01870-7.

[5] M. A. Abdulsattar, “Energy Detection Technique for Spectrum Sensing in Cognitive Radio: A Survey,” *International journal of Computer Networks & Communications*, vol. 4, no. 5, pp. 223–242, Sep. 2012, doi: 10.5121/ijcnc.2012.4514.

[6] T. Yücek and H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” *IEEE Communications Surveys and Tutorials*, vol. 11, no. 1, pp. 116–130, 2009, doi: 10.1109/SURV.2009.090109.

[7] A. Ahmed, Y. F. Hu, J. M. Noras, and P. Pillai, “Spectrum sensing based on Maximum Eigenvalue approximation in cognitive radio networks,” in *Proceedings of the WoWMoM 2015: A World of Wireless Mobile and Multimedia Networks*, Jun. 2015, pp. 1–6, doi: 10.1109/WoWMoM.2015.7158199.

[8] A. Mariani, A. Giorgetti, and M. Chiani, "SNR wall for energy detection with noise power estimation," in *IEEE International Conference on Communications*, pp. 1–6, Jun. 2011, doi: 10.1109/icc.2011.5963367.
[9] S. V. Nagaraj, "Entropy-based spectrum sensing in cognitive radio," *Signal Processing*, vol. 89, no. 2, pp. 174–180, Feb. 2009, doi: 10.1016/j.sigpro.2008.07.022.
[10] G. S. Tomar, A. Bagwari, and J. Kanti, "Introduction to cognitive radio networks and applications," *Boca Raton: Taylor & Francis, a CRC title, part of the Taylor &: Chapman and Hall/CRC*, 2016, doi: 10.1201/9781315367545.
[11] P. Lingeswari, P. Marichamy, S. Shenbagavalli, K. Pothiraj, S. Pandiaraj, and G. V. Kumar, "Adaptive Cooperative Spectrum Sensing with Double Thresholds for Noise Resilient Cognitive Radio Networks," in *3rd International Conference on Integrated Circuits and Communication Systems, ICICACS 2025*, pp. 1–5, Feb. 2025, doi: 10.1109/ICICACS65178.2025.10968537.
[12] Y. Zhang, Q. Zhang, and S. Wu, "Entropy-based robust spectrum sensing in cognitive radio," *IET Communications*, vol. 4, no. 4, pp. 428–436, Mar. 2010, doi: 10.1049/iet-com.2009.0389.
[13] G. Prieto, Á. G. Andrade, D. M. Martínez, and G. Galaviz, "On the Evaluation of an Entropy-Based Spectrum Sensing Strategy Applied to Cognitive Radio Networks," *IEEE Access*, vol. 6, pp. 64828–64835, 2018, doi: 10.1109/ACCESS.2018.2876499.
[14] N. Zhao, "A novel two-stage entropy-based robust cooperative spectrum sensing scheme with two-bit decision in cognitive radio," *Wireless Personal Communications*, vol. 69, no. 4, pp. 1551–1565, Apr. 2013, doi: 10.1007/s11277-012-0650-2.
[15] P. Venkatapathi, H. Khan, and S. S. Rao, "Performance Analysis of Spectrum Sensing in Cognitive Radio under Low SNR and Noise Floor," *International Journal of Engineering and Advanced Technology*, vol. 9, no. 2, pp. 2655–2661, Dec. 2019, doi: 10.35940/ijeat.f8703.129219.
[16] G. Mahendru, A. Shukla, and P. Banerjee, "A Novel Mathematical Model for Energy Detection Based Spectrum Sensing in Cognitive Radio Networks," *Wireless Personal Communications*, vol. 110, no. 3, pp. 1237–1249, 2020, doi: 10.1007/s11277-019-06783-3.
[17] A. D. Sahithi, E. L. Priya, Ravivek, and N. L. Pratap, "Analysis of energy detection spectrum sensing technique in cognitive radio," *International Journal of Scientific and Technology Research*, vol. 9, no. 1, pp. 1772–1778, 2020.
[18] H. Patil, S. V. Nekkanti, D. Negi, N. Masanagi, and S. More, "Spectrum Sensing Using Energy Detector in Rayleigh Fading Channel," *ITM Web of Conferences*, vol. 32, p. 02005, Jul. 2020, doi: 10.1051/itmconf/20203202005.
[19] A. Brito, P. Sebastiao, and F. J. Velez, "Hybrid Matched Filter Detection Spectrum Sensing," *IEEE Access*, vol. 9, pp. 165504–165516, 2021, doi: 10.1109/ACCESS.2021.3134796.
[20] X. Chen and S. Nagaraj, "Entropy based spectrum sensing in Cognitive Radio," in *7th Annual Wireless Telecommunications Symposium (WTS) 2008*, pp. 57–61, Apr. 2008, doi: 10.1109/WTS.2008.4547544.
[21] G. Prieto, Á. G. Andrade, and D. M. Martínez, "Numerical Analysis of Histogram-based Estimation Techniques for Entropy-based Spectrum Sensing," *IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India)*, vol. 37, no. 1, pp. 91–97, Jan. 2019, doi: 10.1080/02564602.2019.1566029.
[22] F. Mashta, M. Wainakh, and W. Altabban, "An integrated parallel multistage spectrum sensing for cognitive radio," *International Journal of Embedded and Real-Time Communication Systems*, vol. 12, no. 2, pp. 1–20, Apr. 2021, doi: 10.4018/IJERTCS.2021040101.
[23] C. Vladeanu, A. Martian, and D. C. Popescu, "Spectrum Sensing with Energy Detection in Multiple Alternating Time Slots," *IEEE Access*, vol. 10, pp. 38565–38574, 2022, doi: 10.1109/ACCESS.2022.3165556.
[24] Y. M. Tenorio, A. P. Guerrero, and R. A. Gonzalez, "Multiband Spectrum Sensing Based on the Sample Entropy," *Entropy*, vol. 24, no. 3, p. 411, Mar. 2022, doi: 10.3390/e24030411.
[25] S. E. Abdelbaset, H. M. Kasem, A. A. Khalaf, A. H. Hussein, and A. A. Kabeel, "Deep Learning-Based Spectrum Sensing for Cognitive Radio Applications," *Sensors*, vol. 24, no. 24, p. 7907, Dec. 2024, doi: 10.3390/s24247907.
[26] P. Pandian, C. Selvaraj, N. Bhalaji, K. G. A. Depak, and S. Saikrishnan, "Machine Learning based Spectrum Prediction in Cognitive Radio Networks," in *Proceedings of the 1st IEEE International Conference on Networking and Communications 2023, ICNWC 2023*, pp. 1–6, Apr. 2023, doi: 10.1109/ICNWC57852.2023.10127512.
[27] A. Kumar, N. Gaur, S. Chakravarty, M. H. Alsharif, P. Uthansakul, and M. Uthansakul, "Analysis of spectrum sensing using deep learning algorithms: CNNs and RNNs," *Ain Shams Engineering Journal*, vol. 15, no. 3, p. 102505, Mar. 2024, doi: 10.1016/j.asej.2023.102505.
[28] M. B. Usman, R. S. Singh, S. Mishra, and D. S. Rathee, "Improving Spectrum Sensing for Cognitive Radio Network Using the Energy Detection with Entropy Method," *Journal of Electrical and Computer Engineering*, vol. 2022, 2022, doi: 10.1155/2022/2656797.
[29] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40–48, Apr. 2008, doi: 10.1109/MCOM.2008.4481339.
[30] Y. C. Liang, Y. Zeng, E. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," in *IEEE International Conference on Communications*, pp. 5330–5335, Jun. 2007, doi: 10.1109/ICC.2007.882.
[31] H. Urkowitz, "Energy Detection of Unknown Deterministic Signals," *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523–531, 1967, doi: 10.1109/PROC.1967.5573.
[32] F. F. Digham, M. S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *IEEE Transactions on Communications*, vol. 55, no. 1, pp. 21–24, Jan. 2007, doi: 10.1109/TCOMM.2006.887483.
[33] I. S. Gradshteyn and I. M. Ryzhik, "Table of Integrals, Series, and Products," *Academic Press is an imprint of Elsevier*, New York, 7th edition, 2007.
[34] A. H. Nuttall, "Some Integrals Involving the QM-Function," *IEEE Transactions on Information Theory*, vol. 21, pp. 95–96, 1975.
[35] A. H. Nuttall, "Some Integrals Involving the Q-Function," *Naval Under water Systems Center (NUSC) technical report*, April, 1972.
[36] F. F. Digham, M. S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," in *IEEE International Conference on Communications*, vol. 5, pp. 3575–3579, 2003, doi: 10.1109/icc.2003.1204119.
[37] J. Acharya, A. Orlitsky, A. T. Suresh, and H. Tyagi, "The complexity of estimating Rényi entropy," *Proceedings of the Annual ACM-SIAM Symposium on Discrete Algorithms*, vol. 2015-January, no. January, pp. 1855–1869, 2015, doi: 10.1137/1.9781611973730.124.

BIOGRAPHIES OF AUTHORS

Lingeswari Ponnusamy received her M.E. degree in Communication Systems from National Engineering College, Kovilpatti and her B.E. degree in Electronics and Communication Engineering from Periyar Maniammai College of Technology for women, Thanjavur under Anna University, Chennai in the year 2012 and 2006 respectively. She has 13 years of Teaching Experience and now she is working as an Assistant Professor in P.S.R Engineering College, Sivakasi. Her research interest are wireless communication and cognitive radio. Presently, she is pursuing her Ph.D. under Anna University. She can be contacted at email: lingeswari@psr.edu.in.

Marichamy Perumalsamy is currently working as a professor and dean at the Department of Electronics and Communication Engineering, P.S.R. Engineering College. He holds a Ph.D. in Wireless Communication from IIT Kharagpur. His research areas include wireless networks, cognitive radio, logic systems, and biomedical engineering. He has published over 65 research articles in reputable journals. He has also presented at numerous conferences, contributing to advancements in his fields of expertise. Additionally, he holds four national patents, reflecting his innovative contributions to the fields. He can be contacted at email: pmarichamy@psr.edu.in.