Enhanced Detection of Intermittent Primary User Signals for Cognitive Radio-IoT Networks with Markov-Chain Modeled BPSK

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***Abstract*—This paper addresses the spectrum sensing challenges in Cognitive Radio-based Internet of Things (CR-IoT) networks, which are characterized by intermittent primary user (PU) activities. Unlike conventional approaches relying on fixed detection thresholds, we propose and evaluate an adaptive thresholding method within an Energy Detection (ED) framework, dynamically optimized based on real-time noise and signal characteristics. The PU activity is realistically modeled as a two-state Markov chain, with signals transmitted via Binary Phase Shift Keying (BPSK) modulation over an Additive White Gaussian Noise (AWGN) channel. Simulation results demonstrate that our adaptive threshold approach significantly enhances detection accuracy while reducing total error probability at low SNR conditions (from -25 dB to 0 dB), thus effectively increasing idle channel utilization compared to traditional fixed threshold techniques.**

***Index Terms*—Cognitive Radio, Internet of Things, Spectrum Sensing, Energy Detection, Adaptive Thresholding, Markov Chain, BPSK Modulation.**

I. Introduction

The wireless world is experiencing an unprecedented surge in connected devices, transforming the way we communicate. Technologies like Wi-Fi, Sigfox, Zigbee, and LoRaWAN power this revolution, supporting several IoT applications such as smart homes and e-health [1]. The increasing adoption of these technologies across various applications, coupled with the growing need for efficient wireless communication, is significantly intensifying the demand for the limited Radio Frequency (RF) spectrum, which serves as the driving force behind modern connectivity [2].

As is well-known, the RF spectrum is a finite resource, and many technologies operate within its unlicensed bands, creating an imbalance since the licensed spectrum is often underutilized due to static allocation methods [3]. Consequently, the RF spectrum faces several challenges, particularly in the crowded ISM (Industrial, Scientific, and Medicine) bands, where issues like congestion, interference, and spectrum scarcity are becoming increasingly critical. This mismatch between supply and demand accentuates the urgent need for more efficient spectrum management [4], [5].

Integrating Cognitive Radio (CR) functionalities into IoT ecosystems, known as CR-IoT networks, is a promising approach to address these challenges. By empowering these devices with sensing capabilities and dynamical access, CR-IoT endeavors to unlock unused frequencies; often termed ”spectrum holes” or ”white spaces”, without causing interference to primary license holders [6], [7]. CR-IoT paradigm revolves around an intelligent architecture designed to optimize spectrum usage.

These nodes continuously monitor their environment to identify idle frequency bands; i.e. free licensed channels on which primary users (PUs) operate. When suitable channels are identified, CR-IoT nodes transmit over these bands [8].

Spectrum Sensing (SS) is a key function in CR-IoT paradigm. It is a crucial component that enables the opportunistic use of the free licensed bands in the RF spectrum. Thanks to the decision made by the SS process, SUs or CR-IoT users can be informed about which spectrum holes to use for transmitting their concerned data. Various techniques exist in the literature for SS, including Energy Detection (ED), Cyclostationary detection, and techniques based on Artificial intelligence (AI) principles [9], [10], [11], [12].

ED is one of the most widely adopted techniques in SS due to its simplicity and low computational complexity, making it particularly suitable for resource-constrained IoT devices [13]. ED operates by comparing the received signal energy against a predefined threshold to determine the presence or absence of a PU. Conventional ED methods typically rely on a fixed threshold, which assumes a stable noise environment; an assumption that is often invalid in dynamic CR-IoT networks where noise levels and PU activity vary significantly over time [14]. This limitation frequently leads to high false alarm rates or missed detections, reducing spectrum utilization efficiency and increasing the risk of interference to PUs.

To address these shortcomings, adaptive threshold ED methods have been proposed, which dynamically adjust the detection threshold based on real-time noise and signal characteristics, offering the potential for improved detection accuracy in challenging environments [15], [16].

Recent studies in CR have explored adaptive threshold mechanisms to overcome the shortcomings of static-threshold, particularly under dynamic channel and low-SNR conditions.

One approach targets multi-carrier wave forms by dynamically adjusting thresholds in real time, thereby improving detection accuracy and reducing false alarms [17]. Another line of work ties primary user utilization to threshold adaptation, enhancing overall spectrum efficiency by calibrating detection sensitivity according to primary-user traffic levels [18]. A more nuanced solution employs a double-threshold method to tackle low-SNR challenges, refining the decision region between signal presence and noise to reduce error probabilities [19]. In parallel, an average energy detection scheme with adaptive thresholds shows that leveraging averaged signal statistics can mitigate transient noise fluctuations, outperforming purely instantaneous measurements [20].

To address these limitations, this paper proposes and evaluates a novel adaptive threshold energy detection approach specifically designed for CR-IoT environments characterized by intermittent PU signals modeled using a two-state Markov chain. Unlike previous fixed-threshold methods, our adaptive technique dynamically adjusts detection thresholds based on instantaneous noise and signal properties. We quantitatively demonstrate, through comprehensive simulations, significant performance improvements including enhanced detection accuracy, reduced false alarms, and higher idle channel utilization under challenging low SNR conditions

The remainder of this paper is organized as follows: Section II outlines the system model. Detection methodologies are given in section III detailing both the fixed and adaptive threshold ED formulations. Section IV presents simulation results of both approaches. Section V concludes the paper.

II. System Model

In this study, we consider a CR-IoT network where a SU performs SS to detect the presence or absence of a PU signal. To model the real dynamic behavior of transmitted signals over a channel, we model our PU's activity change as a two-state Markov chain. Moreover, the signal is modulated using Binary Phase Shift Keying (BPSK) over an Additive White Gaussian Noise (AWGN) channel. The detection technique employed by our SU to determine the PU's presence is the energy detection with both fixed and adaptive thresholding.

The SS problem is modeled as a binary hypothesis test as given in (1). Under the null hypothesis H_0, the PU is absent, and the received signal $y[n]$ contains only noise, $w[n]$, with variance σ_w^2. Under the alternative hypothesis H_1, the PU is active, and $y[n]$ includes both the transmitted BPSK modulated signal $x[n]$ and noise. We consider a normalized channel amplitude gain (h), to simplify the analysis [21].

$$y[n] = \begin{cases} h * x[n] + w[n] & : H_1; \text{PU Present} \\ w[n] & : H_0; \text{PU Absent} \end{cases} \tag{1}$$

where:

- $y[n]$: Received signal at the Secondary User .
- $x[n]$: Transmitted PU signal.
- $w[n]$: AWGN noise with variance σ_w^2.
- h: Channel amplitude gain, assumed to be 1.

A. Markov-Chain-Based PU Activity Model

The PU's activity is modeled as a two-state discrete-time Markov chain, representing the *busy* (ON, state 1) and *idle* (OFF, state 0) states.

To reflect realistic channel occupancy, The transition probabilities are given in the P matrix, which are adopted from a prior study on PU behavior modeling [22], :

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} = \begin{bmatrix} 0.8866 & 0.1134 \\ 0.5309 & 0.4691 \end{bmatrix} \tag{2}$$

where p_{ij} denotes the probability of transitioning from state i to state j. These values represent realistic transition dynamics that capture intermittent PU usage patterns. The ON duration is $T_{\text{on}} = 30\,\mu\text{s}$, and the OFF duration is fixed at $T_{\text{off}} = 90\,\mu\text{s}$. The sequence of states $s[n] \in \{0, 1\}$ is generated over a total sensing duration of $\Delta T = 0.1\,\text{s}$ with a sampling frequency $F_s = 10\,\text{MHz}$, resulting in $N = \Delta T \times F_s = 10^6$ samples.

B. Signal and Channel Model

When the PU is in the ON state ($s[n] = 1$), the transmitted signal is a BPSK-modulated signal with carrier frequency $f_c = 1\,\text{MHz}$. The BPSK symbols are randomly chosen as $b[n] \in \{+1, -1\}$ with equal probability. The PU signal $x[n]$ is expressed in (3), where n represents the sample index.

$$x[n] = \begin{cases} b[n] \cos(2\pi f_c n / F_s), & \text{if } s[n] = 1, \\ 0, & \text{if } s[n] = 0, \end{cases} \tag{3}$$

Under the alternative hypothesis H_1, the received signal at the SU is corrupted by AWGN, modeled as:

$$y[n] = x[n] + w[n], \tag{4}$$

where $w[n] \sim \mathcal{N}(0, \sigma_w^2)$ is the Gaussian noise with zero mean and variance σ_w^2. The signal-to-noise ratio (SNR) is set to $\text{SNR} = 10^{\text{SNR}_{\text{dB}}/10}$, where $\text{SNR}_{\text{dB}} = -20\,\text{dB}$. The noise variance is calculated as $\sigma_w^2 = \mathbb{E}[x^2[n]]/\text{SNR}$, where $\mathbb{E}[x^2[n]]$ is the average power of the PU signal.

III. Detection Methodologies

A. Energy Detection

The SU employs energy detection to determine the presence of the PU signal. In this study, we choose a sliding window size of $N_{wi} = 300$ samples, corresponding to the minimal expected duration of the PU activity (i.e., 30 µs at 10 MHz sampling frequency). This choice ensures that each window captures sufficient signal energy to reliably detect the presence or absence of the PU, optimizing the trade-off between sensing accuracy and computational complexity, a crucial consideration for resource-constrained IoT devices.

The test statistic is computed as the average power for each window as, for the k-th window:

$$P_k = \frac{1}{N_{wi}} \sum_{n=kN_w}^{(k+1)N_w - 1} |y[n]|^2. \tag{5}$$

The true state of the k-th window is defined as:

$$s_k = \begin{cases} 1, & \text{if } \exists \text{ n} \in [kN_w, (k+1)N_w - 1] \text{such that } x[n] \neq 0, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

To make a decision about the state of the channel, the ED detector compares the computed average power in a window to a predefined threshold.

- If $P_k \geqslant \lambda$, then H_1 is True; the PU is Active,
- Otherwise, if $P_k < \lambda$, then H_0 is True; No PU is Active,

This Threshold is a critical parameter for the detection process. Its value should be accurate to obtain a correct decision. Two types of thresholds are studied in this paper. In the following we study the static threshold; which is derived based on a desired P_d or P_{fa} and the dynamic threshold; which depends on the SNR values.

*1) **Fixed Threshold**:* The static threshold is theoretically derived based on a target probability of false alarm P_{fa} or a desired Probability of detection P_{d}.

According to [18], [21], [23], the theoretical threshold can be expressed under to approaches:

- λ_{P_d} for a Constant Detection Rate (CDR). In this case we ensure a very high probability of detection ($P_d \approx 1$), in the cost of high false alarms.

$$P_d = Q\left(\frac{\lambda_{P_d} - N_{wi}(\sigma_n^2 + \sigma_s^2)}{\sqrt{2N_{wi}(\sigma_n^2 + \sigma_s^2)^2}}\right) \tag{7}$$

Thus:

$$\lambda_{P_d} = (\sigma_w^2 + \sigma_s^2)\left(1 + \frac{Q^{-1}(P_d)}{\sqrt{\frac{N_{wi}}{2}}}\right) \tag{8}$$

- Or $\lambda_{P_{fa}}$ for Constant False Alarm Rate (CFAR). Here, we guarantee a very low false alarms, however the performance in term of P_d is moderate, and weak when SNR is very low.

$$P_{fa} = Q\left(\frac{\lambda_{P_f} - N_{wi}\sigma_n^2}{\sqrt{2_{wi}\sigma_n^4}}\right) \tag{9}$$

Thus:

$$\lambda_{P_{fa}} = \sigma_w^2\left(1 + \frac{Q^{-1}(P_f)}{\sqrt{\frac{N_{wi}}{2}}}\right) \tag{10}$$

$Q^{-1}(\cdot)$ represents the inverse Q-function given in (11), σ_s^2 and σ_w^2 are the signal and noise variance respectively and N_{wi} is the number of samples in each sliding window.

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-\frac{t^2}{2}}\,dt \tag{11}$$

For our simulation, we used the approximated formula using the following function as: $Q^{-1}(x) = \sqrt{2} \cdot erfinv(1 - 2x)$.

The decision rule is:

$$\hat{s}_k = \begin{cases} 1, & \text{if } P_k \geqslant \lambda, \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

*2) **Adaptive Threshold**:* The adaptive threshold is designed to account for the SNR, N_{wi}, σ_w^2 And α. it dynamically adjusts the detection threshold λ to achieve a balance between P_d and P_f, thereby maximizing spectrum efficiency for both PUs and SUs.

The optimization is formulated as **the minimization of the total error probability** P_e expressed as [16], [18], [20]:

$$P_e = \alpha\,(1 - P_d) + (1 - \alpha)P_{fa} \tag{13}$$

where α is the spectrum utilization ratio of the PU. α is defined as the ratio of PU consecutive "busy" slots by the total number of slots in the PU transmission cycle.

By substituting P_{fa} and P_d expressions using respectfully (7) and (9) in (13) we get :

$$\begin{aligned} P_e = \alpha\left[1 - Q\left(\frac{\lambda - N_{wi}(\sigma_n^2 + \sigma_s^2)}{\sqrt{2N_{wi}(\sigma_n^2 + \sigma_s^2)^2}}\right)\right] \\ + (1-\alpha)Q\left(\frac{\lambda - N_{wi}\sigma_n^2}{\sqrt{2_{wi}\sigma_n^4}}\right) \end{aligned} \tag{14}$$

The optimal decision threshold is then obtained by solving the equation in (15).

$$\frac{dP_e}{d\lambda} = 0 \tag{15}$$

This derivation yield to the quadratic equation that follows:

$$\begin{aligned} \left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)\lambda^2 + \left(-\frac{2\mu_1}{\sigma_1^2} + \frac{2\mu_0}{\sigma_0^2}\right)\lambda + \\ \left(\frac{\mu_1^2}{\sigma_1^2} - \frac{\mu_0^2}{\sigma_0^2} - 2\ln\frac{(1-\alpha)\sigma_0}{\alpha\sigma_1}\right) = 0 \end{aligned} \tag{16}$$

where:

- $\mu_0 = N_{wi}\sigma_n^2$
- $\sigma_0^2 = 2N_{wi}\sigma_n^4$
- $\mu_1 = N_{wi}(\sigma_n^2 + \sigma_s^2)$
- $\sigma_1^2 = 2N_{wi}(\sigma_n^2 + \sigma_s^2)^2$

The optimal threshold is the root given by :

$$\lambda_{ada} = \frac{\sigma_w^2\left[1 + \sqrt{1 + \frac{4}{N}\left(1 + \frac{2}{\text{SNR}}\right)\ln\left(\frac{(1-\alpha)(1+\text{SNR})}{\alpha}\right)}\right]}{\frac{(2+\text{SNR})}{(1+\text{SNR})}} \tag{17}$$

This expression depends on real-time estimates of the following parameters: SNR and α which represents the PU spectrum occupancy ratio. For the rest of our simulations, α is set to 0.5.

IV. Results and Discussion

In this section, we provide representative simulation results to illustrate the performance of both approaches in detecting free slots within the dynamic received signal. Note that these simulations were conducted in a Colab environment using Scipy library of python language. To simulate a real case scenario for our network, we first generate the dynamic (ON /

OFF) behavior of the PU signal over an AWGN channel. We then apply the ED detector to find out the free white spaces. Our aim is to highlight the out-performance of the adaptive thresholding in very low SNR environments which is the case for IoT devices. In this study, the SNR is treated as a known quantity. We first examine a challenging low-SNR case of -20 dB, synthesising the intermittent signal and benchmarking both detection schemes against the ground truth. The analysis is then extended to a broader range, from -25 dB to 0 dB, where performance is assessed in terms of the probability of detection P_d, the probability of error P_e, and the percentage of idle-channel utilisation.

A. Detection Performance at - 20 dB

Fig. 1 shows the PU signal states based BPSK modulation, AWGN Channel, and received signal at an SNR of -20 dB, which is heavily distorted due to the presented noise, making it difficult to distinguish the original PU signal. This visual representation emphasizes the challenge of signal detection in noisy environments and underscores the necessity of adaptive thresholding techniques to mitigate the impact of noise, thereby improving detection performance in CR-IoT networks.

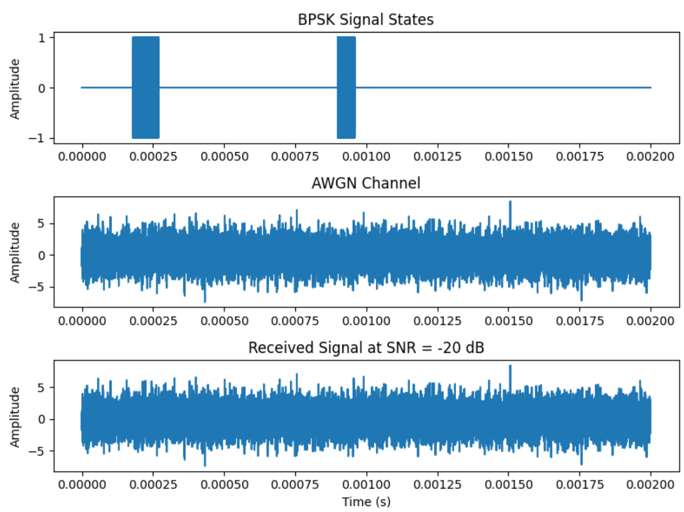

Fig. 1. BPSK Signal, AWGN Channel, and Received Signal at SNR = -20 dB.

In Fig. 2 we examine a typical scenario of the dynamic detection procedure at a weak SNR of -20 dB, with a sampling rate of 10 MHz over multiple windows using fixed and adaptive thresholds. This figure provides a detailed view of the windowed power, threshold's values and detection decisions declared by the ED detector based on the three thresholds types.

The performance of the ED algorithm based three different thresholds; (λ_{Pd}; Constant Detection Rate (CDR), λ_{Pfa}; Constant False Alarm Rate (CFAR), and λ_{ada} (adaptive threshold) was evaluated at a challenging condition due to dominant noise. The windowed average power, depicted in the top panel of Figure 2, fluctuates around the threshold's values (λ_{Pd}, λ_{Pfa} and λ_{ada}) with the following colors respectfully (blue,

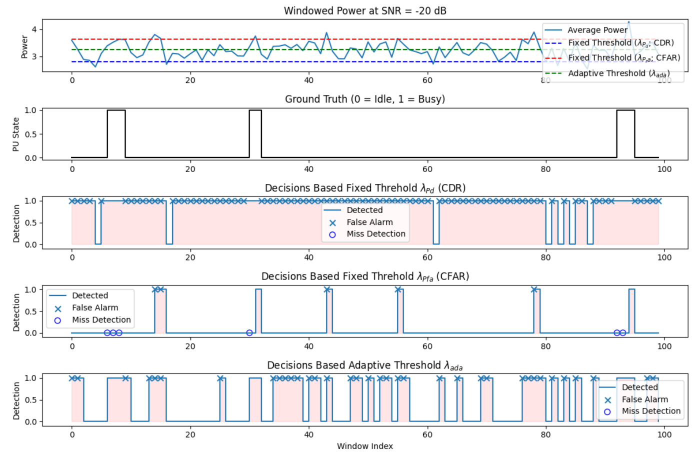

Fig. 2. A typical scenario of the dynamic detection procedure at a Weak SNR = -20 dB, with a sampling rate at 10MHz over multiple windows using fixed and adaptive thresholds.

red and green). The ground truth, shown in the second panel, provides a binary reference (0 = idle, 1 = busy) for assessing detection accuracy.

The decisions based on λ_{Pd} reveal frequent detections alongside a high incidence of false alarms (marked with 'x') and non miss detection, these results are quite expected, as the theoretical value of the Pd was fixed at 0.95. By this case, the detector successfully declares PU presence, However, with the high false alarms it generates, there will be no spaces for a SU come along the channel. Conversely, results with λ_{Pfa} exhibits a conservative approach with fewer correct detections, resulting in significant miss detections (e.g., windows $20, 40$ and $60, 80$) and minimal false alarms, suggesting a trade-off favoring reduced false positives at the expense of sensitivity. The adaptive method λ_{ada} demonstrates a balanced performance, detecting most busy periods with moderate false alarms and miss detections, reflecting its ability to adapt to varying power levels.

At an SNR of -20 dB, all algorithms struggle due to noise interference. The CDR method's sensitivity leads to a high false alarm rate, rendering it unreliable for precise detection. The CFAR method, while reducing false positives, misses critical busy states, which could impair real-time spectrum utilization. The adaptive threshold λ_{ada} offers the most promising results, aligning closely with the ground truth, though further optimization is needed to minimize false alarms.

These findings underscore the limitations of current methods at low SNR and suggest the potential for developing enhanced algorithms or operating at higher SNR levels to improve detection reliability.

B. Probability of Detection vs. SNR

The performance in terms of probability of detection is evaluated across a range of SNR and is presented in Fig. 3. The probability of detection (P_d) was analyzed to assess the algorithms' effectiveness under varying noise conditions.

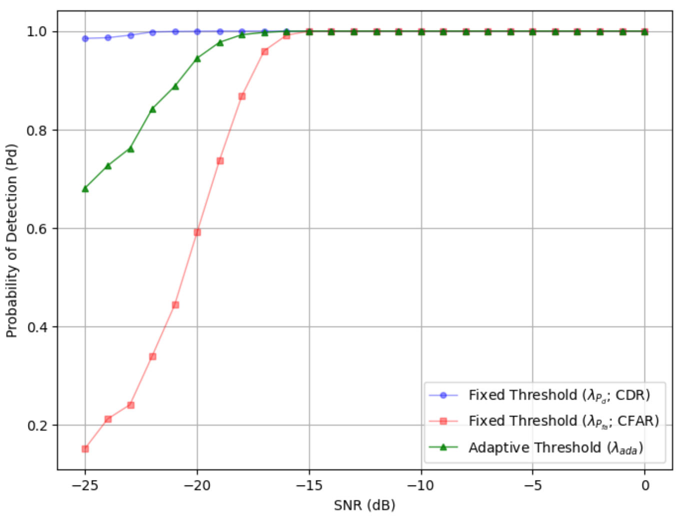

Fig. 3. Probability of Detection (P_d) vs. SNR of the Fixed (CDR & CFAR) and Adaptive Thresholds.

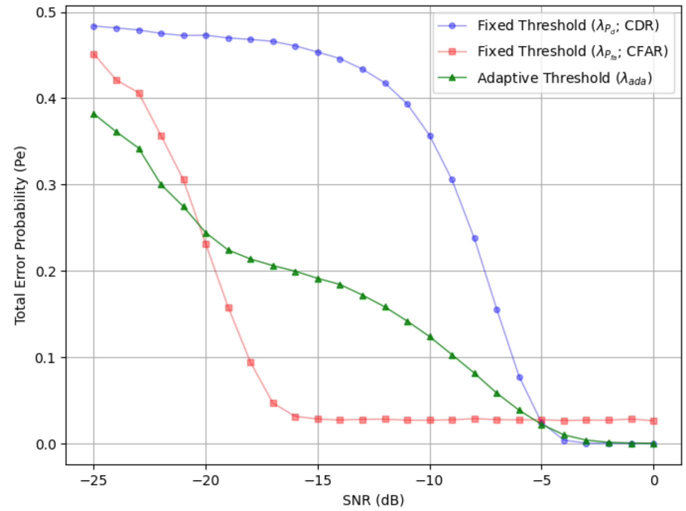

Fig. 4. Total Error Probability (P_e) vs. SNR.

Fig. 3 shows that the energy detector whose threshold is tuned by the λ_{Pd} rule keeps its probability of detection almost at unity across the entire low-SNR region under study. Such behaviour is desirable in scenarios where the first priority is to safeguard the PU by minimising missed detections.

In sharp contrast, the conventional CFAR detector suffers a marked performance collapse between -25 dB and -15 dB, plunging to $P_d \approx 0.10$ at -25 dB. The proposed adaptive detector also degrades as the SNR drops, but far more gracefully, still achieving $P_d \approx 0.68$ at the same SNR.

This intermediate performance highlights its ability to trade a moderate reduction in PU protection for a substantial gain in spectrum utilisation compared with the aggressive CFAR setting.

C. Total Error Probability vs. SNR

Moreover, the performance of the ED algorithm is further evaluated through the total error probability (P_e) as a function of SNR, as depicted in Figure 4. The total error probability encompasses both false alarms and miss detections, providing a comprehensive metric for assessing algorithm reliability across varying SNR conditions.

The CDR method (λ_{P_d}, blue curve) exhibits the highest P_e at low SNR values (e.g., -25 dB), starting at approximately 0.5 and decreasing gradually to around 0.05 at 0 dB. This indicates significant vulnerability to noise, likely due to its sensitivity to abrupt changes that are confounded by noise at low SNR. The CFAR method (λ_{pfa}, red curve) shows a moderate P_e, ranging from 0.4 at -25 dB to a stable 0.05 at -5 dB and beyond, reflecting a conservative approach that reduces errors as SNR improves but remains sub-optimal at extreme low SNR.

In contrast, the adaptive method (λ_{ada}, green curve) demonstrates the lowest P_e, starting at 0.38 at -25 dB and declining sharply to below 0.05 at -10 dB, maintaining this low level up to 0 dB, highlighting its superior adaptability and robustness.

D. Idle Channel Utilization

Finally, the efficiency of the three SS algorithms is assessed through the percentage of idle channel utilization as a function of SNR, as illustrated in Figure 5. Idle channel utilization percentage reflects the percentage of idle slots identified to be true by each algorithm, a critical metric in cognitive radio systems.

The Energy detector based CDR method (λ_{pd}) shows a gradual increase in idle channel utilization, rising from near 0% at -25 dB to approximately 80% at -5 dB, indicating moderate sensitivity to improving SNR conditions.

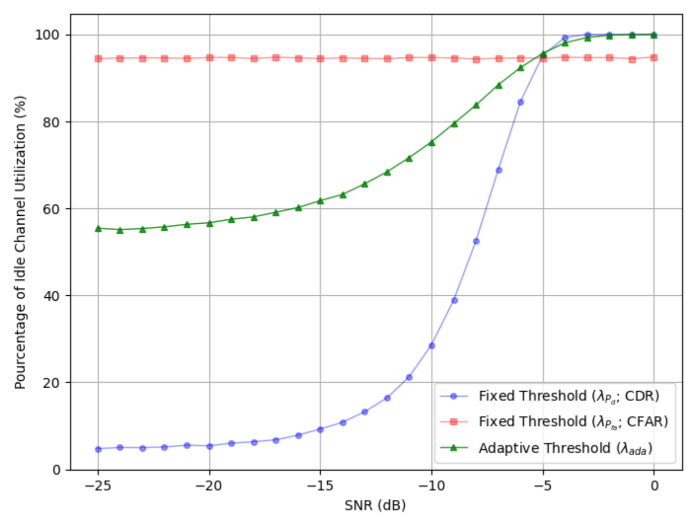

Fig. 5. Percentage of Idle Channel Utilization vs. SNR.

The CFAR method (λ_{pfa}, red curve) maintains a consistent utilization of around 100% across the SNR range, suggesting a highly conservative approach that may overestimate idle periods, potentially leading to inefficient spectrum use. In contrast, the adaptive method (λ_{ada}, green curve) demonstrates a sharp rise from 60% at -20 dB to 100% at -5 dB, reflecting its ability to dynamically adjust and maximize utilization as SNR improves.

These enhanced visualizations and quantitative analyses confirm that the proposed adaptive threshold method offers the best trade-off between detection accuracy, error probability, and spectrum utilization; particularly under the most challenging low-SNR conditions typical of CR-IoT deployments.

V. Conclusion and Future Work

The evaluation of ED algorithms based on three types of thresholds; fixed (CDR, CFAR methods) and the adaptive one, across low SNRs has revealed significant insights into their performance. The adaptive method consistently demonstrated superior robustness and efficiency, achieving the best trade - off between detection probabilities, error rates, and effective idle channel utilization. In contrast, CDR exhibited sensitivity to noise at low SNR, leading to elevated error rates, while CFAR's conservative approach resulted in missed detections and potentially inefficient spectrum use due to excessive false alarms. These findings underscore the critical role of adaptability in enhancing spectrum sensing accuracy and utilization in challenging environments.

The results affirm that the adaptive algorithm offers a promising foundation for optimizing spectrum management for CR-IoT systems. Future work will focus on implementing a cooperative spectrum sensing framework for IoT nodes, leveraging this adaptive approach to further improve detection reliability and efficiency through collaborative sensing among distributed nodes.

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