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Article

A Generic Composite Hypothesis Using Horizontal and Vertical Frameworks for AWGN Blind Detection in a Cognitive Radio System

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Abstract: Classifying the Additive White Gaussian Noise (AWGN) and the Primary User (PU) transmission signal has been a crucial area of research interest. For effective data transmission, the Secondary User (SU) detection threshold needs to be continuously adjusted to distinguish between the AWGN and PU signals at a very low Signal-to-Noise Ratio (SNR). The research analytically compared a proposed Vertical Hypothesis (VH) against the Horizontal Hypothesis (HH) of Spectrum Sensing (SS) within a Cognitive Radio (CR) framework. The developed model aims to increase SU sensitivity and specificity to AWGN and PU signal powers. The performance indices used are the composite hypotheses of spectrum detection P_d, missed detection P_{md}, to obtain a false alarm P_{fa}, and blind detection, P_{bd}. The results obtained clearly showed that the vertical approach, when varied, achieved a threshold of about 0.96 blind detection and 0.04 false alarm at -10 dB channel gain between PU and SU, which is an improvement over the IEEE guideline threshold of 0.9 spectrum detection and 0.1 false alarm, respectively. The vertical approach proved more efficient at optimizing radio spectrum utilization, potentially improving transmission quality in Fifth Generation (5G) and Sixth Generation (6G) wireless systems.

Keywords: Binary Hypothesis; Composite Hypothesis; Horizontal Hypothesis; Vertical Hypothesis; Spectrum Sensing
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1 Introduction

Cognitive Radio (CR) represents a pioneering, intelligent technology proposed to optimize and support the frameworks of both Fifth Generation-Advanced (5G-A) and Sixth Generation (6G) wireless networks [1]. It is a transformative technology designed to enhance dynamic spectrum access and interference management. Its flexible architecture has demonstrated the capability to meet the requirements of the proposed next-generation wireless resources [2]. CR is defined as an intelligent radio system that has the capability of studying the licensed spectrum owner's white holes and capitalizing on its transmission without causing any harmful interference to the licensed owner [3, 4]. It is also referred to as a wireless spectrum optimizer. Technology is conceived to address problems arising from the scarcity of radio spectrum caused by static radio policies, which poses a danger to the commercial band for prospective futuristic wireless services/devices [5, 6]. Forecasts indicated that more than 50 billion smart devices would demand internet connectivity by 2025. Access to all these Internet of Things (IoT) devices cannot be granted due to static radio spectrum management [7]. To achieve its mandates, the CR opened additional research branches, including Spectrum Sensing (SS). It is the most crucial task in establishing a CR-based communication mechanism [3]. Spectrum sensing in CR is designed to be invariant to noise power, reliable in the detection and differentiation of the Primary User (PU) signal from noise, even under low Signal-to-Noise Ratio (SNR) conditions [8]. Most research on SS, as seen, focuses its investigation on two to three detection metrics, including spectrum detection, P_d missed detection, P_{md}, and false alarm, P_{fa} [9]. In addition to these three SS uncertainties, this research proposes to also explore a fourth metric, which is the blind detection, P_{bd}.

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The blind detection is also referred to as null detection [10]. The primary objective of this research is to identify an optimal threshold capable of reliably discriminating between the signal features of AWGN and the PU, even at low SNR. It will be achieved by effectively evaluating and validating the relationship between a proposed Vertical Hypothesis (VH) and conventional Horizontal Hypothesis (HH) frameworks. In CR, the "VH framework," often referred to as hierarchical, multi-stage, or two-level hypothesis testing is a spectrum sensing architecture designed to overcome the limitations of the HH single-stage detectors in low Signal-to-Noise Ratio (SNR) environments. In the blind detection hypothesis, if the PU is inactive, the received signal will contain only Gaussian noise [11]. In this case, the Secondary User (SU) senses and watches proactively when the PU would require its channel. The proposed approach is a blind sensing technique, meaning it optimizes transmission efficiency without requiring any knowledge of PU signal parameters. Rather, its threshold handle is activated on alert, with high sensitivity and specificity to accurately distinguish PU signal beeps from AWGN channel pulses.

The novelty in this work is in the conception and development of the VH model of SS to obtain an improved blind detection, P_{bd} threshold at a very low SNR. The method can be deployed to solve wireless communication problems in areas such as spectrum sensing, timing, low throughput, inefficient energy use, interference mitigation, bandwidth utilization, and many more.

Over a decade of conducting CR research, different approaches to the application of the SS composite hypothesis have been presented. These earlier methods recorded tremendous successes but are also characterized by inherent limitations. This work is based on an SS model that can effectively overcome these limitations by increasing spectrum sensitivity, improving transmission bandwidth, and mitigating malicious activities in the wireless channel [6]. This is obtained by running a comparative test between the conventionally set horizontal hypothesis thresholds of CR spectrum sensing versus its vertical approach. In view of this presentation, this research has made the following significant findings and contributions to knowledge by:

- Elaborating on the two major categories of hypotheses (binary and composite) of the CR-SS algorithms in an approach never seen presented by earlier works.
- Modeling the proposed horizontal and vertical hypotheses of composite classes of SS in a manner that has not been seen presented elsewhere.
- Analyzing the interoperability between the proposed horizontal hypothesis and the vertical hypothesis.
- Comparing the results obtained using comparative analysis between the proposed horizontal and vertical hypotheses of CR-SS to prove system efficacy.
- Validating the result of the proposed vertical hypothesis with a conventional IEEE guideline of spectrum detection, P_d and false alarm, P_{fa}. This is to ascertain the improvement in spectrum sensitivity and specificity that could enable effective differentiation between AWGN signal pulses and the PU signal's power.
- Validating the developed system throughput with the conventional design guideline threshold of 0.9 spectrum detection and 0.1 false alarm, at -10 dB channel gain between the PU and SU.

This paper adopts the following organizational framework: It starts by introducing the research background, core tools, significant academic value, motivations, and economic importance. An overview of existing literature is provided in Section 2 to establish the context and validate the research gap addressed in this study. Section 3 outlines the methodology, detailing the means for achieving the research objectives, screening criteria, and analytical processes for proffering solutions. The results presented in Section 4, which presents the evaluations and validations of the adopted method. Section 5 is the summary and conclusion of the research activity.

2 Related Work

The quest to make this research more effective prompted the search for related literature that presented direct and/or relevant ideas to the research gap in this work. This is an attempt to study the methods they adopted, the tools used, and the results obtained. The limitations of the methods adopted in this literature also inform the organization of this work to clearly present its improvements and originality.

Ilgun *et al.* [12] presents a statistical approach known as hypothesis testing theory. The research evaluated spectral holes and successfully facilitated dynamic access for multiple users by applying a fuzzy hypothesis-based approach. The results showed that the system's detection agility increased with each additional PU user. However, this method could only sense the availability of the PU. To address limited knowledge of primary signal availability, Subekti *et al.* [11] introduced a blind spectrum sensing framework for cognitive radio systems, using the Jarque-Bera test statistic to distinguish idle from active frequency bands. The method effectively identifies active primary signals by detecting deviations from Gaussian noise without requiring prior knowledge of signal characteristics. While computationally efficient and robust against noise uncertainty, this method faces performance degradation in low-sample scenarios and under impulsive non-Gaussian noise conditions. Abdelbaset *et al.* [13] enhanced the accuracy and efficiency of spectrum sensing by integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This also aims to identify and utilize underused frequency bands. The approach offers high adaptability to unknown signals through autonomous feature extraction. Although, it introduces computational overhead and relies heavily on high-quality training datasets. Kocakaya *et al.* [14] enhanced spectrum sensing performance; this study introduces a novel threshold determination technique driven by an online learning algorithm. The primary objectives were to minimize total error probability and enhance spectrum sensitivity, particularly in low-signal-to-noise-ratio environments with noise uncertainty. The method was rigorously evaluated across both non-fading and various fading channels. The method offers robust, low-complexity detection across various fading channels. However, it faces limitations regarding performance at low SNR, reliance on simulations, and computational latency. Addressing spectrum scarcity in rapidly advancing wireless networks, Vaduganathan *et al*. [2] introduced a Component-Specific Cooperative Spectrum Sensing Model (CSCSSM). Experimental results verified that this model provides superior efficiency and robustness compared to traditional cognitive radio network methods. This distributed approach enhances detection robustness, though it introduces higher computational complexity and communication overhead compared to traditional methods. Islam *et al*. [9] developed low-power Matched Filter (MF), Cyclostationary Feature (CF), and Hybrid Filter Detection with Inverse Covariance (HFDIC) techniques for Ambient Backscatter Communication (AmBC), enhancing user detection speed and accuracy. The HFDIC method showed superior performance improvements across all assessed parameters, including P_d, P_{md}, and P_{fa} to increase throughput. While offering superior detection probabilities and improved throughput, this approach faces challenges in high computational complexity and dependence on varying ambient RF environmental conditions. Gowda *et al*. [15] developed a selective channel assignment technique for cognitive radio systems that minimizes erroneous handovers by combining blocking and unnecessary probabilities. Simulations demonstrated that this method reduces interference and outperforms traditional random assignment approaches. The algorithm successfully compensates for noise uncertainty and performs well even in low SNR and fading environments. However, the results rely heavily on simulations; real-world hardware deployment might introduce latency, interference, and calibration challenges not accounted for in the model.

These reviewed works have further revealed limitations in methods, tools, and results of earlier research aimed at improving the spectrum sensitivity of wireless systems. These limitations have clearly called for the need for more cutting-edge approaches. With this, the research gap of this work is conceived and carefully formulated to proffer a better solution using the vertical hypothesis method of spectrum sensitivity. Additional findings from recent articles that necessitate this research are juxtaposed in Table 1.

Table 1: Related work

Author	Work done	Method used	Pros	Cons
Halaki *et al.* (2023) [16]	Introduced an advanced spectrum sensing technique to help cognitive radios detect signals more accurately, even in harsh, heavy-tailed noise	Used P-Norm Detector (PND) and a Geometric Power Detector (GPD) under Generalized Gaussian Distribution (GGD) noise	Improves both detection accuracy in heavy-tailed noise and overall system performance by using an optimized PND threshold	It requires higher computational complexity than standard energy detection methods
Musuvathi *et al.* (2024) [17]	Aimed at optimizing limited radio frequencies to handle the explosion of IoT devices	Used Machine Learning (ML) to accurately detect weak, noisy signals (-25 dB to -10 dB), ensuring highly reliable wireless communication	The K-Nearest Neighbors (KNN) algorithm is highly easy to implement and delivers 94.5% accuracy in tough conditions.	While KNN is simple, it can be computationally expensive/slow during the inference phase
Rassomakhin and Brifman (2025) [18]	Proposed analog-discrete method mathematically generates noise in the frequency domain before applying filters, resulting in a functionally accurate representation	Simulated noise as a continuous analog process, passed it through an analog filter, and then sampled it to convert it into discrete data	It improves noise power calculation by preventing presampling filtering errors, while being faster and easier to implement	To properly simulate and filter continuous noise, the method requires higher oversampling rates, which increase simulation time
Valadao *et al.* (2025) [19]	Addressed the criticality of spectral congestion by deploying efficient dynamic spectrum access in cognitive radio (CR) networks	Deployed Machine Learning (ML)- based approach to predict environmental parameters of noise levels and the distance between users	The models achieved impressive correlation coefficients: over 0.98 for noise prediction and 0. 82 for distance	Its validation relies on simulated data, as such, real-world implementation in noisy, dynamic environments may show lower metrics.
Lan *et al.* (2026) [20]	Developed an ATC model that enhances spectrum hole detection in complex cognitive radio environments.	Combined graph networks, CNNs, and Transformers to capture spatial, structural, and time-based features	It has the advantage of simulating real-world datasets and improves detection accuracy over existing benchmarks	It introduces high computational complexity as a tradeoff

2.1 Theoretical Background

Cognitive radio is a nature-inspired wireless technology that acts like a digital chameleon. It continuously scans its surroundings, seamlessly shifts to vacant frequencies to avoid interference, and adapts its transmission parameters in real time. Computer scientist Joseph Mitola III introduced the innovative concept of cognitive radio. He initially presented it at an academic seminar at Stockholm's KTH Royal Institute of Technology in 1998, and subsequently co-published the foundational paper with Gerald Q. Maguire, Jr. in 1999, thereby revolutionizing the field of wireless communications. A chameleon is known for its ability to change its reflective (cognitive) image to match its current environment without affecting the original owner. Bio-inspired technologies have proven to be among the safest and most achievable in terms of perfection when deployed. As such, the CR is coded using Software-Defined Radio (SDR) for its superior decision-making. It is designed with such characteristics to proactively change its transmission parameters to suit every radio-induced environment. Its architecture is designed to accommodate both contentious and non-contentious cases in both coherent and non-coherent wireless domains. Theoretical and experimental analyses conducted by researchers have demonstrated the uniqueness of cognitive radio compared with other prospective 22$^{\text{nd}}$-century wireless technologies. As such, it is envisaged to effectively drive Beyond Fifth Generation (B5G) objectives. The most common attributes of CR relative to a chameleon are environmental sensing for PUs detection, decision-making for channel selectivity, mobility in surfing vacant channels, and sharing channel information with other CR users/base stations [21, 22].

Among these attributes of the CR system, spectrum sensing remains the most crucial for determining the original owner's transmission channel conditions before taking action. It is a prior analysis that helps verify the PU's activity before transmission, thereby averting harmful interference.

Cognitive radio, aside from being one of the prospective technologies for B5G, has an HH model that enabled the establishment of wireless protocols like WiFi (IEEE 802.11), Zigbee (IEEE 802.15.4), and WiMAX (IEEE 802.16), which are already deeply integrated with CR Software-Defined Radio (SDR) systems [23, 24]. This HH model is also used in the evaluation of channel availability between peers or adjacent networks in the same tier (e.g., unlicensed devices sharing the same Wi-Fi or IoT band) to facilitate peer-to-peer dynamic spectrum access. Conversely, the VH model is projected to assess channel states across different network tiers or layers (e.g., sharing a microcell layer with a femtocell or terrestrial systems leasing from satellite networks) to manage hierarchical spectrum access. The VH model is envisioned to enable a wide range of potential real-world IoT applications, including vehicular communication, security, health care, and Satcom deployment [3, 25]. Furthermore, it is proposed to drive the premier global CR standard, IEEE 802.22, which is designed to operate on specific real-world radio frequencies.

3 Methodology

This section presents a paradigm shift in the relationship between the two major categories of the CR-SS hypothesis, using an approach not presented in previous research. These categories of SS hypotheses are the binary and the composite hypotheses [12]. Unlike the three normal uncertainties of the composite hypothesis of, P_d, P_{md} and P_{fa} analyzed that are presented in most research conducted in this area, this research presented a fourth composite uncertainty, which is the P_{bd}. The P_{bd} can be continuously fine-tuned and optimized to effectively sense and differentiate between AWGN signal power and the PU signal power. It can function effectively without the prior knowledge of the PU transmission characteristics.

3.1 Spectrum Sensing Hypotheses

The reliability and accuracy of the decisions the SU system makes to optimize spectrum sensing depend on two philosophical hypotheses of binary and composite [26]. In view of this assertion, the research analytically hybridized the two major categories of SS hypotheses to further improve system efficacy by developing a comparative test.

3.1.1 Binary Hypothesis

In this binary hypothesis test, the null hypothesis, H_0 denotes the non-existence of PU, while the alternative hypothesis, H_1 denotes its occurrence [27].

3.1.2 Composite Hypothesis

In this study, the composite hypotheses for Spectrum Sensing (SS) encompass four key probabilities: P_d, P_{md}, P_{fa}, and P_{bd}. The P_d denotes the likelihood of a correct detection, P_{md} represents the chance of missing a busy channel as idle, P_{fa} represents the false alarm probability, and P_{bd} indicates the high probability of blind detection of an idle channel (or the absence of the primary user). Table 2 is a summary of composite hypothesis parameters as presented by this work.

Table 2: Composite Hypothesis Parameters

Parameter	Description	Meaning
P_{fa}	False Positive (Incorrect detection)	Considering that PU is active while it is absent.
P_d	True Positive (Correct detection)	Considering that PU is active, while it is truly active.
P_{md}	False Negative (Incorrect detection)	Considering that PU is absent while it is active.
P_{bd}	True Negative (Correct detection)	Considering that PU is absent while it is truly absent.

For clarity, Figure 1 presents graphical representations of the priority regions for the composite hypothesis analysis considered in this work. The probability of P_{bd} and P_d can be affected by both P_{fa} and P_{md}. For optimal sensing, P_{fa} and P_{md} must be kept very low in accordance with the IEEE set guideline of 0.1 maximum [28]. Conversely, P_{bd} and P_d are required to be kept higher in accordance with the IEEE set design guideline of 0.9 minimum [28]. In the vertical analysis, continued minimization of P_{fa} and P_{md} coherently maximized P_{bd} and P_d. To accurately differentiate between the PU signal and AWGN signals, the P_{fa}^{min} is designed to achieve efficient spectrum sensitivity and specificity. By adopting the conventional equation of a straight-line method, $y = f(x)$ simply shows that in every decremental effect on the input signal there will be a detrimental change at the output, and vice versa.

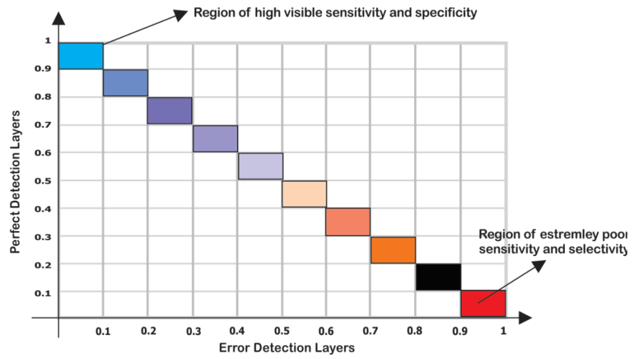

Figure 1: The Proposed Composite Uncertainty Layers

3.2 Spectrum Sensing System Model

Spectrum sensing is a proactive method of detecting channel occupation of signals in CR networks, which is regarded as a problem based on two major binary uncertainties of H_0 and H_1 [4, 29]. H_0 connotes the absence of the PU and H_1 denotes the presence of the PU. The received signal samples, $y_s(n)$ of a CR-SS can mathematically be modeled as follows:

$$y_s(n) = \begin{cases} s_n + z_n & : H_1 \\ z_n & : H_0 \end{cases} \tag{1}$$

where s_n is the data-carrying symbol, which also represents the primary signal transmitted over a wireless channel, while z_n refers to the Additive White Gaussian Noise (AWGN) channel interjection along the transmission path. Figure 2 demonstrates the schematic workflow of a wireless channel handle induced by a cognitive CR algorithm.

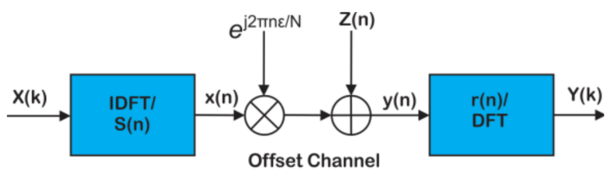

Figure 2: Wireless Channel Model

To further decompose Equation (1), the data-carrying symbol is computed by [18] as:

$$s_n(n) = [s_n(0), s_n(1), s_n(2), \ldots, s_n(N-1)]^H \tag{2}$$

where N corresponds to the number of Inverse Discrete Fourier Transform (IDFT) samples and $[.]^H$ is the Hermitian transpose.

N is the product of a function of the spectrum sensing period τ, and the sampling frequency f_s, whose relationship is expressed in Equation (3) as Ref. [4]:

$$N = \tau f_s \tag{3}$$

Also, z_n only affects the baseband signal in the time domain; as such, it is considered to be a circularly symmetric complex Gaussian random variable with mean zero and noise variance as:

$$z_n(n) = [z_n(0), z_n(1), z_n(2), \ldots, z_n(N-1)]^H \tag{4}$$

Its noise variance denoted as σ_a^2 is assumed to be the same for all cognitive users.

At the receiver side, the received signal response in the time domain, $y_s(n)$, after passing through the offset channel, is taken to be the same as the signal impulse response, $r_s(n)$ which is further synthesized as:

$$r_s(n) = [r_s(0), r_s(1), r_s(2), \ldots, r_s(N-1)]^H \tag{5}$$

Its final signal waveform at the output is generated using Discrete Fourier Transform (DFT) conversion from the time domain to the frequency domain at the Kth subcarrier and is presented as:

$$Y(n) = \sum_{n=0}^{N-1} y_s(n) e^{-j2\pi kn/N} \tag{6}$$

Equation (6) also depicts the SS signal model as obtained in this work.

To determine if the PU is present or not, the received signal's energy is compared to the detection threshold using energy detection test statistics, E, as follows:

$$E_y(n) = \frac{1}{N} \sum_{n=0}^{N-1} |y(n)|^2 \tag{7}$$

3.2.1 Spectrum Sensing Parameters

Spectrum sensing is a factor of the original signal variance σ_s^2, noise variance σ_a^2, the sensing decision threshold λ_s, and the number of IDFT samples, N. From these parameters, the composite relationships of P_d and P_{fa} are formulated. Since the analysis is based on signal-magnitude power detection for the AWGN and the PU, the conventional Equations (8) and (9) are derived by taking the modulus on both sides to mitigate errors and negative values that may arise in implementations. Therefore;

$$P_d = Q^2 \left(\frac{\lambda_s - N(\sigma_a^2 + \sigma_s^2)}{2N\sqrt{(\sigma_a^2 + \sigma_s^2)^2}} \right) \tag{8}$$

$$P_{fa} = Q^2 \left(\frac{\lambda_s - N\sigma_a^2}{\sqrt{2N\sigma_a^2}} \right) \tag{9}$$

where $Q(.)$ denotes the Q-function of the complementary distribution function of the standard Gaussian. The $Q(x)$ is computed in Equation (10):

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{+\infty} \exp\left(-\frac{y^2}{2}\right) dy, \tag{10}$$

The threshold for the probability of blind detection is determined by an optimized signal plus noise distribution (H_1), and is formulated as:

$$\lambda_s = Q^{-1}(P_{bd}^{min})\sqrt{E\sigma_n^2} \tag{11}$$

where Q^{-1} is the inverse Q-function.

To maintain specificity in the false alarm rate, the threshold is computed based on the noise distribution (H_0) only.

$$\lambda_s = Q^{-1}(P_{fa}) \tag{12}$$

3.2.2 Proposed Horizontal and Vertical Analysis of Spectrum Sensing

In this work, the hybridization of the two detection hypotheses (binary and composite) aims to explore and exploit the full bandwidth of the PU signal while avoiding harmful interference with the SU [10, 26, 30]. In this light, this research framework presents a comparative analysis of the horizontal and vertical composite hypotheses. These are the two classical modes of spectrum sensing, each encompassing four outcomes: true negative, true positive, false negative, and false positive. This is a generic framework that depends solely on research preferences. Figure 3 demonstrated the interoperability of the four composite hypotheses as proposed by the work. It is interpreted as:

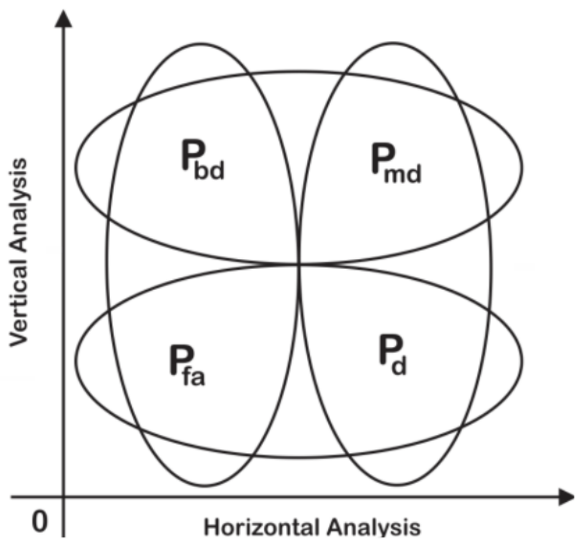

Figure 3: Proposed Horizontal and Vertical Frameworks of the Spectrum Sensing Model.

- The two-bisectional relationship between perfect detection tools of P_{bd} versus P_d and imperfect detection of P_{md} versus P_{fa}, have been established and estimated among the areas that require further research clarity in the near future.
- The analytical tradeoff or constraints of the four uncertainties between P_{fa} versus P_d, P_{fa} versus P_{bd}, P_{md} versus P_d, and P_{md} versus P_{bd} have been the areas of extreme focus that require exploration and exploitation in research to maximize spectrum resource utilization.
- This research focuses on the P_{fa} versus P_{bd} constraint of the spectrum sensing hypothesis model to optimize transmission efficacy. The developed model uses VH model, which allows the SS threshold handle to be varied to meet desired signal specifications.

The empirical analysis for the trade-off between the decremental and incremental values of error decision and perfect sensing is presented in Equations (13–19).

The formula to combine the uncertainties of making a wrong decision (either missing a busy channel or falsely alarming an idle one) is computed using the overall probability of error, P_e as:

$$P_e = \pi_0 P_{fa} + \pi_1 P_{md} \tag{13}$$

where π_0 is the prior probability of the channel being idle and π_1 is the prior probability of the channel being busy, which is considered as:

$$\pi_0 + \pi_1 = 1 \tag{14}$$

In this work, the limiting cases of error are computed from the perspective of false negatives and false positives as:

False negative: incorrect detection probability, considering that PU is active, by:

$$P_{md}^{th} = Pr(H_0|H_1) = \frac{\partial y}{\partial t}(1 - |P_{bd}|) \tag{15}$$

where, $0.9t$ is considered the minimum detection probability for P_{bd}. This work considers each coefficient as an incremental index value in every t shift. Where $t = 0.01$, the interval of every shift.

False positive: false alarm probability, considering that PU is absent and variable, as:

$$P_{fa}^{th} = Pr(H_1|H_0) = \frac{\partial y}{\partial t}(1 - |P_d|) \tag{16}$$

at $t = 0.01$, with P_{fa} having a $0.1t$ maximum detection probability in every t slot.

In general, the vertical analysis provides high assurance in distinguishing wanted from unwanted scenarios between the PU signal and the AWGN power. It is formulated in terms of the true-positive and true-negative hypotheses. By considering the signal response on the vertical axis, its incremental value is obtained by taking the derivative at each t-shift. Therefore,

True positive: correct detection probability, considering that PU is active and variable, as:

$$P_d = Pr(H_1|H_1) = \left(1 - P_{md}^{th}\right), \tag{17}$$

True negative: correct detection probability, considering that PU is totally absent, is given as:

$$P_{bd} = Pr(H_0|H_0) = \left(1 - P_{fa}^{th}\right), \tag{18}$$

Equation (18) is the blind detection technique often involved in analyzing the covariance matrix of the received signal, $y(n)$ to calculate the eigenvalue ratio, which does not require prior information about the PU signal or noise power. If the blind detector decides the current channel k is active (busy), the channel index k is updated to $k+1$ In the next time slot, search for an idle channel.

Since this scenario involves identifying optimal parameters among two outcomes, the uncertainty is often heightened by noise variance uncertainty (σ_a^2). The effective detection threshold and thus of the uncertainty in P_{fa}^{th} and P_{bd} incremental/decremental values, is modified by the factor in Equation (19) as:

$$\text{Threshold}_{\text{Actual}} = \text{Threshold}_{\text{nominal}} \pm \sigma_a^2 \tag{19}$$

This simply means that, to improve spectrum efficiency, P_{fa}^{th} is set to be no greater than P_{fa}. This alteration is determined by the threshold obtained from the integrated CRN and the induced IDFT/DFT channel access waveform. Minimizing P_{fa} is equal to maximizing $\Sigma_{i=1}^{N} w_i h_i^2$ as follows:

$$\Sigma_{i=1}^{N} w_i h_i^2 \leq \sqrt{\Sigma_{i=1}^{N} w_i^2 \Sigma_{i=1}^{N} h_i^2} = \sqrt{\Sigma_{i=1}^{N} h_i^4}, \tag{20}$$

Finally, the minimal P_{fa} for the spectrum sensing blind detection, P_{bd}^{th} induced by the IDFT/DFT waveform in the CRN architecture is achieved as follows:

$$P_{fa}^{min} \leq Q[\sqrt{2\delta}\xi + Q^{-1}(P_d^{th})] + \xi\sqrt{\frac{T_{Sm}}{2} f_s \Sigma_{i=1}^{k} Z_i |h_i|^4}, \tag{21}$$

where:
T_{Sm} is the sensing length time.
f_s is the wideband sampling frequency.
ξ is the ratio to SNR
K is the number of Satellite to Earth Station (SES) channels.
δ is the measurement matrix at l^{th} slot of k^{th} SU.
h_i is the channel gain and obeys the Gaussian distribution function with a mean of zero and a variance of one.
Z_i is the AWGN and is given as:

$$Z_i = \frac{|h_i|^2}{\sqrt{\Sigma_{i=1}^{k} |h_i|^4}} \tag{22}$$

Therefore,

$$P_{bd}^{th} = 1 - P_{fa}^{min} \tag{23}$$

3.3 Generic Spectrum Sensing Procedures

This section presents summaries of the procedures followed to achieve the methodology of this work, using a coded algorithm and flowchart. These are generic procedures that can be constantly varied and modified to meet peculiar needs. The algorithm gives guidance on the harmonization of the research tools, while the flowchart explicitly demonstrates the methods that guided the procedures. The results obtained are plotted to improve clarity and ensure reproducibility.

3.3.1 Procedure

One of the most common challenges encountered by previous blind detection approaches is the inability of their models to detect environmental characteristics of wireless signals at very low SNR. This work has significantly improved on this limitation by developing an adaptive model capable of calibration to a region with high sensitivity (0.9 detections) and high specificity (0.1 false positives). To enable a clearer distinction between the AWGN and the PU transmission signals, the SU sensing handle needs to be continually varied to high levels to detect low signal power while autonomously reducing false detection errors.

Figure 4 presents a discrete incremental trade-off model for blind detection, where the system can initialize a threshold within the high-detection region's probability to significantly distinguish between noise and the required signal. This discrete incremental value has made this work robust to SNR discrimination by overcoming challenges associated with noise uncertainty. With this highsensing alert achievement, the SU using the vertical-hypotheses model can operate without detailed and preexisting knowledge of the PU, which is remarkable, especially when the signal parameters are unknown. In view of this, the procedures as presented start by initializing an adaptive sensing threshold region (0.9 and 0.1) and an incremental value (0.01).

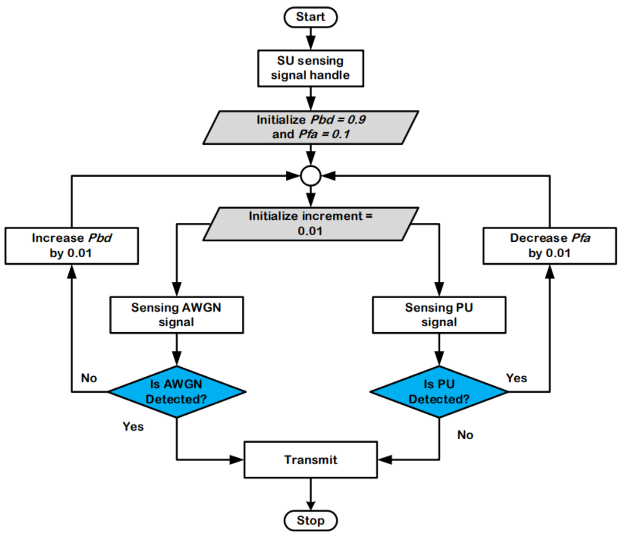

Figure 4: The Proposed AWGN Blind Detection Model

4 Results and Discussion

This Section presents simulations conducted to further validate the literature reviewed, the research gap unveiled, the methodology adopted, and the analysis performed in this work to achieve results. The channel condition adopted is the Rayleigh channel model, due to its ability to support communication between the transmitter and receiver without line-of-sight. The simulation is performed using PyCharm 3.10.2 IDE for Python scripts. In accordance with the IEEE 802.22 standard of end-to-end delay for 5G networks, transmission length time, T_s should be no longer than 2 ms for terrestrial networks and a minimum of 25 ms for LEO satellite round-trip, with a $P_{fa} = 0.1$ and a $P_d = 0.9$. This is also considered the horizontal hypothesis threshold for SS, as demonstrated in this work's methodology. Its vertical analysis is obtained using P_{fa}^{min} and P_{bd}^{th}.

The key features of the simulation include:

- **Low SNR Handling**: Specifically tests at -10 dB to simulate realistic, challenging channel conditions.
- **Vertical Hypothesis (VH) Logic**: The code sets a dynamic threshold based on the average energy of both signal scenarios, mimicking the proposed improvement over fixed IEEE thresholds.
- **Performance Metrics**: Uses energy detection (np.sum(signal^{**2})) to compute the threshold and classify the presence of the PU, achieving high sensitivity.
- **Visualization**: Displays the difference between noisy PU signals and pure AWGN to visualize/improve detection performance.

The key simulation parameters are summarized in Table 3.

Table 3: Key Simulation Parameters

Parameter	Value
Channel	Rayleigh(-10 dB)
AWGN	-10 dB
Number of PUs Channels, N	4096
Channels gain between PU and SU, h	-10 dB
Channels gain among SUs, g	0 dB
Wideband sampling frequency, f_s	4.8 MHz
Ratio to SNR, ξ	-10 dB to 0 dB
Signal power	1
IEEE SS standard	P_d=0.9, P_{fa}=0.1

This is the summary of the results obtained from the simulations. Figure 5 presents the composite received signal waveform, as formulated in Equations (1–7) and shown in Figure 1. The image visualizes the nature of the received signal after passing through an offset channel. It encompasses a mixture of the original signal (PU) and the natural channel noise (AWGN), which requires special tools and techniques to identify/decode in order to avoid SU interference with the PU. Figures 6 to 9, simply display the interpretation of the result in Figure 5 using the VH model, as developed by this work. The VH model is a generic tool that is continuously fine-tuned to increase the visibility of the signal pattern to decode its source. The performance of the VH model is compared with that of the HH model in Table 4.

The final result is presented as throughput to indicate the amount of data that can be transmitted per unit time, considering the demand for advanced frequencies. The theoretical analysis and simulations are presented in percentages and validated using the conventional IEEE set standard thresholds of $P_{fa} = 0.1$ and $P_d = 0.9$. The percentage improvement of data transmitted per time is compared with that of the conventional model using Equation (24). The result is shown in Figure 10, and the improvement in research performance is presented in Table 4.

$$\text{Percentage Improvement} = \frac{\sum \text{New Scheme} - \sum \text{Original Scheme}}{\sum \text{Original Scheme}} \times 100\% \qquad (24)$$

4.1 Horizontal and Vertical Hypotheses Evaluation

This section details the simulation results comparing the blind detection probability, P_{bd} and minimum false alarm rate, P_{fa}^{min} on the vertical axis against the probability of detection, P_d and false alarm rate, P_{fa} on the horizontal axis. This is evaluated and tested over a -10 dB channel gain between PU and SU. To improve the spectrum efficiency, $P_{fa}^{min} \leq P_{fa}$ is achieved. By theoretical analysis, minimizing P_{fa} as P_{fa}^{min} is equal as maximizing P_{bd}. Therefore, the lower the P_{fa}^{min}, the higher the spectrum sensitivity and selectivity of the P_{bd} model.

4.1.1 Sensing of Composite Signal Using a Conventional Sensing Model

Figure 5 presents the simulation results obtained under the conventional hypothesis. The simulation result obtained at $-10dB$ channel gain shows a sensing handle operating within the IEEE standard's required threshold, with average sensing abilities of about 0.9 and 0.1, respectively. This is expected to be within the 5G system's safety deployment threshold. Although the sensing threshold seems suitable for transmission in higher frequencies, its constraint includes the inability of the model to effectively discriminate between the wanted PU signal and the unwanted AWGN signal. With this kind of transmission pattern, the safety of the PU signal cannot be assured, and the quality of the SU signal could be jeopardized. Raw or composite signal transmission properties can be defined by color patterns, but they do not always yield accurate predictions. This has been shown here that at -10 dB and below, it is not clearly safer for an SU to transmit its data without prior information about the PU signal power to avoid harmful interference.

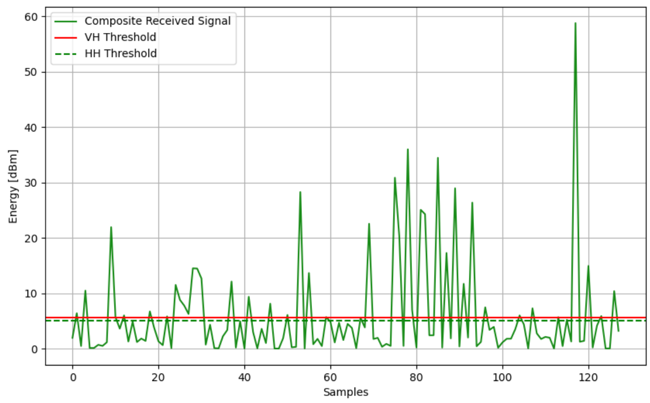

Figure 5: Mixture of PU plus AWGN Signal Powers in a Conventional Hypothesis mode.

4.1.2 Spectrum False Alarm Detection Using Vertical Versus Horizontal Hypotheses

Consistent with the conventional model, Figure 6 also shows a simulation of the false-alarm sensitivity of VH relative to the HH method at -10 dB. The results show that the VH model has a minimal false alarm rate of 0.04, while the HH model has 0.15, using the same parameters. This means the VH model has outperformed the HH model in terms of spectrum prior knowledge sensitivity and specificity. This indicates that when VH analysis is activated, the SU can transmit data without prior knowledge of the PU's spectrum requirements or occupancy. It is also possible to avert harmful interference, even at very low signal transmission power. This is seen from the VH adaptability to accurately interpret and distinguish between the PU transmission pulse and the AWGN signal power.

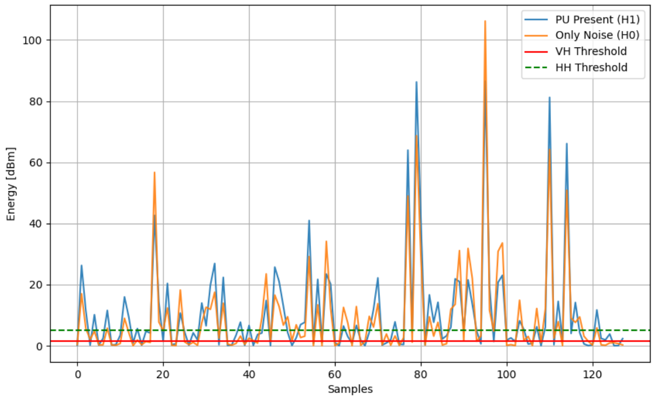

Figure 6: VH versus HH Visualization of P_{fa} and P_{fa}^{min} pulse

The summary of the results obtained and plotted in Figure 6, from the VH versus HH generated data at P_{fa} and P_{fa}^{min} are presented as follows:

- - -Spectrum Sensing Analysis at -10 dB- - -
Vertical Approach: P_{bd}=0.96, P_{fa}=0.04
Horizontal Approach: P_{bd}=0.85, P_{fa}=0.15
- - -Simulation Results (SNR: -10 dB)- - -
Vertical Approach (VH) Blind Detection (P_{bd}): Passed
Vertical Approach (VH) False Alarm (P_{fa}): High
Horizontal Approach (HH) Blind Detection (P_{bd}): Failed
Horizontal Approach (HH) False Alarm (P_{fa}): Low
- - -Results at -10 dB SNR- - -
Vertical Hypothesis: P_{bd} = 0.3286, P_{fa} = 0.2836
Horizontal Hypothesis: P_{bd} = 0.3582, P_{fa} = 0.3118
- - -Spectrum Sensing Results (-10 dB)- - -
Proposed HH Threshold: 1.5088
Sensitivity (P_{bd}): 0.3807
Specificity (P_{fa}): 0.3573

Furthermore, the research runs a simulation comparing VH and HH for perfect detection, as shown in Figure 7. From the results displayed, it is also evident that the VH performed better than the HH, achieving a perfect detection of about 0.96, while the HH achieved 0.85. This is also a function of the system, increasing sensitivity and specificity. This indicates that when VH is activated, the SU can transmit data without raising an alarm about the PU's absence, within the context of -10 dB and below.

The summary of the results achieved and plotted in Figure 7, from the VH versus HH generated data at P_{bd} and P_{bd}^{th} are presented as follows:

Vertical Approach: P_{bd} = 0.96, P_{fa}= 0.04
Horizontal Approach: P_{bd} = 0.85, P_{fa} = 0.15
- - -Simulation Results (SNR: -10 dB)- - -
Vertical Approach (VH) Blind Detection (P_{bd}): Passed
Vertical Approach (VH) False Alarm (P_{fa}): High
Horizontal Approach (HH) Blind Detection (P_{bd}): Failed
Horizontal Approach (HH) False Alarm (P_{fa}): Low
- - -Results at -10 dB SNR- - -
Vertical Hypothesis: P_{bd} = 0.3260, P_{fa} = 0.2887
Horizontal Hypothesis: P_{bd} = 0.3574, P_{fa} = 0.3158
- - -Spectrum Sensing Results (-10 dB)- - -
Proposed VH Threshold: 8.4226
Sensitivity (P_{bd}): 0.7094
Specificity (P_{fa}): 0.6987

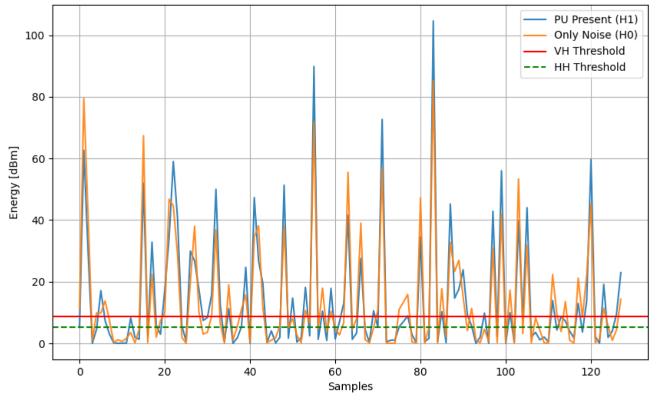

Figure 7: VH versus HH hypothesis Plots of P_{bd} and P_{bd}^{th}

Table 4 compares the simulation results from the newly developed VH model with those from the HH traditional approach, as summarized in Figures 6 and 7. The comparison metrics are structured based on P_{bd}^{th} versus P_{bd} and P_{fa}^{min} versus P_{fa}. It is recorded that varying the sensing threshold values using the VH method yielded an improvement of 0.96 for P_{bd}^{th} and 0.04 for P_{fa}^{min}, against the 0.85 for P_{bd} and 0.15 for P_{fa} obtained by the HH approach. With this, the SU, using the VH model, could safely transmit data without prior information (blind detection) about the PU's presence, owing to its ability to sense and specify signal patterns with very low power input. On the other hand, a sharp discrepancy is noticed on the transmission waveforms sampling handles, where the HH patterns are appreciated higher than the VH. This is a result of improper screening of transmission pulses that amount to the misinterpretation of the PU and AWGN signal powers, causing a false positive alert. This is one of the limitations experienced from the HH model.

Finally, it is clear that the VH method also outperformed the HH approach in terms of system sensitivity and specificity, achieving 0.7094 and 0.7031, compared with 0.3807 and 0.3573, respectively.

4.1.3 VH Data Sampling of Individual Signal Pulses

Figures 8 and 9 present the optimized visualization of the individual PU signal sampled separately from the individual AWGN signals by the VH model. The capability of the VH algorithm is to continuously fine-tune 0.1 and 0.9 to achieve the P_{fa}^{min} and higher P_{bd}^{th} values. The results presented at this threshold clearly demonstrate their scalability for achieving safer transmission. This has improved the sensing scale, thereby increasing system selectivity, which in turn has autonomously increased the SU's transmission bandwidth. Achieving such improvements in high-spectrum sensitivity and specificity also demonstrates the VH method's capability to better differentiate the PU signal power from the AWGN signal power than is obtainable with the traditional HH.

Table 4: Comparison of VH and HH Spectrum Sensing Handles

At -10 dB SNR	**VH**	**HH**
Spectrum Sensing Threshold Curations:		
P_{bd}	0.96	0.85
P_{fa}	0.04	0.15
Blind Detection Navigation Test:		
P_{bd}	passed	Failed
P_{fa}	High	Low
Composite Signal Sampling:		
P_{bd}	0.3260	0.3574
P_{fa}	0.2887	0.3158
AWGN vs PU Individual Signal Power Detection		
Sensitivity, P_{bd}	0.7094	0.3807
Specificity, P_{fa}	0.7031	0.3573
Threshold:	8.4226	1.5088

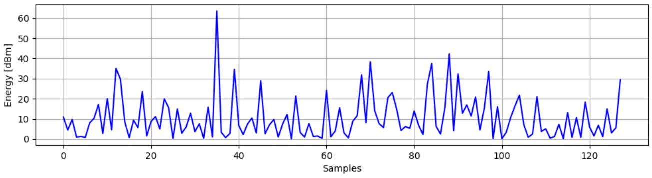

Figure 8: Extracted PU Signal Power Pattern using the VH model.

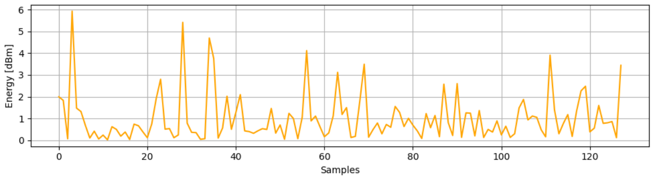

Figure 9: Pure AWGN Signal Power using the VH model

4.2 System Throughput Validation

Figure 10 and Table 5 present the simulation results for the system throughput in the perfect-channel stage of the VH algorithm, validated against the IEEE HH standard for a CR system. It was observed from the result that both models perform closely when at low packet transmission, P_{tra} level, but when the P_{tra} is large enough, a wide variation is observed. The throughput using VH analysis outperformed that of IEEE HH analysis by 22.6% in terms of P_{tra}. This was because the IEEE HH method achieved less than 3 Gbps throughput, whereas the VH method achieved about 3.6 Gbps. The HH approach is also observed to exhibit inefficiency in system scalability, as the system begins to degrade in functionality with every increase in data above 2.4 Gbps. In an IDFT-based structural design for 5G network setups, each wireless system resource block contains 14 symbols, and each symbol contains 8 bits of data.

Table 5: Percentage Improvement of Throughput for P_{bd} over P_d

Hypothesis	**Average Throughput**	**Average % Improvement over IEEE Design Guide**
Horizontal Analysis	2.21 Gbps	–
Vertical Analysis	2.71 Gbps	22.6%

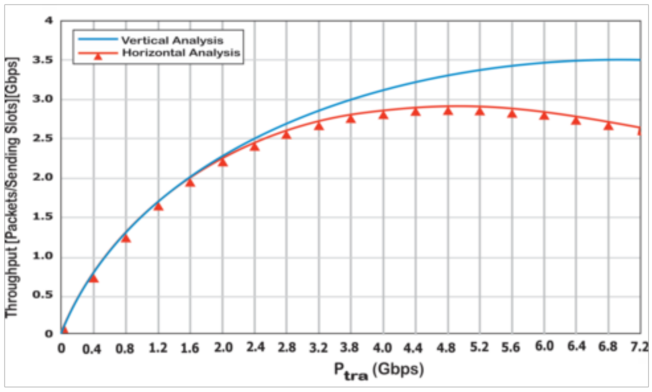

Figure 10: Plot of Throughput with P_{bd} versus P_d at -10 dB fixed Channel State

5 Conclusion and Future Work

The need to increase spectral sensitivity to avoid harmful interference between the PU and SU in a CR system cannot be overemphasized. This research developed an SS model that effectively distinguishes between AWGN and PU signal powers to improve transmission quality in 5G and 6G wireless systems. The techniques deployed to solve this problem are the VH developed by this work and validated with the IEEE HH approach. The performance indices used are the spectral detection, P_d missed detection, P_{md} to obtain a false alarm, P_{fa} and blind detection, P_{bd}. The results obtained show an improvement in the spectral sensing capability of the newly developed VH method over the HH approach. This also justifies the VH method's ability to exhibit high spectral selectivity between the PU signal power and the AWGN signal pulses. The research scoped its analysis of vertical analysis on spectral blind detection, P_{bd} against the false positive, P_{fa}. As such, there is a need to further explore and exploit the vertical analysis of miss detection, P_{md} and spectrum detection, P_d as an area for further work.

List of Abbreviations

5G	Fifth Generation
6G	Sixth Generation
AmBC	Ambient Backscatter Communication
AWGN	Additive White Gaussian Noise
B5G	Beyond Fifth Generation
CF	Cyclostationary Feature
CNNs	Convolutional Neural Networks
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSCSSM	Component-Specific Cooperative Spectrum Sensing Model
dB	Decibel
DFT	Discrete Fourier Transform
PU	Primary User
FFT	Fast Fourier Transform
GAT	Graph Attention Networks
GGD	Generalized Gaussian Distribution
GPD	Geometric Power Detector
HFDIC	Hybrid Filter Detection with Inverse Covariance
HH	Horizontal Hypothesis
IDFT	Inverse Discrete Fourier Transform
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
KNN	K-nearest Neighbors
MF	Matched Filter
ML	Machine Learning
PND	P-Norm Detector
RNNs	Recurrent Neural Networks
SDR	Software Defined Radio
SNR	Signal-to-Noise Ratio
SS	Spectrum Sensing
SU	Secondary User
VH	Vertical Hypothesis

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Authors' contribution

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

The data that supports the findings in this paper are available from the corresponding author upon request.

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