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Article

Throughput Optimization Using Spectrum Sensing Vertical Hypotheses Integrated with F-OFDM Technique

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Abstract: The convergence of Satellite Mobile Networks (SMNs) with Terrestrial Wireless Networks (TWNs) has emerged as a significant area of research. Such integration is crucial for overcoming the current challenges of static spectrum assignment faced by earlier wireless network generations, including inefficient energy utilisation, insufficient bandwidth, increased latency, reduced reliability, limited connectivity, and restricted capacity. To address these issues, the potential of Cognitive Radio Networks (CRNs) has been exploited in Fifth Generation (5G), facilitating seamless interoperability among networks to sustain wireless communications. This paper presents a novel Vertical Hypothesis Uncertainty (VHU) method for optimising system throughput in CRN, leveraging the spectrum sensing false alarm, P_{fa} and null detection, P_{nd} hypotheses. This approach integrates the Filtered Orthogonal Frequency Division Multiplexing (F-OFDM) with Spectrum Sensing (SS) within a Satellite-Terrestrial Network (STN) domain. The performance of the proposed VHU was tested against the Hybrid Filter Detection with Inverse Covariance (HFDIC) and traditional spectrum sensing concepts. Results at –10 dB Signal-to-Noise Ratio (SNR) show that the VHU method remarkably outperforms HFDIC, achieving a 7.9% improvement in a fixed channel and a 15.84% improvement in a dynamic channel under perfect channel conditions.

Keywords: Centralized Cooperative Spectrum Sensing; Cognitive Links; F-OFDM; Interference Links; Null Detection; Vertical Hypothesis Uncertainty
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1 Introduction

Research and development for advanced Fifth Generation (5G) cellular communication networks is ongoing to mitigate problems arising from spectrum scarcity [1]. This is evident in the emergence of new technologies that complement the growing demand for bandwidth utilization and improve system throughput, as noted in [2]. 5G and beyond systems are expected to be more flexible in utilizing the limited spectrum to enhance wireless network efficiency [3]. Hence, developing techniques to establish a handshake between 5G Terrestrial Mobile Networks (TMN) and Satellite Mobile Networks (SMN) to enhance system throughput for big data transmission has been a significant challenge requiring research exploration [4]. This is also increasing the need to accommodate the growing proliferation of wireless devices and emerging technologies [5]. To overcome the spectrum shortage in beyond 5G systems, the SMN is envisioned to fully drive the Sixth Generation (6G) wireless resources. Some of the proposed driven demands for radio resources that spectrum channel shortages can hinder in 6G systems include Intelligent Healthcare (IH), Industry 5.0, and the Internet of Everything (IoE), among others [6].

In addition, the proposed 6G interoperation in SMN aims to enable significant features, including emergency communications and extensive global coverage. This should also meet the need for synergizing with TMNs for future Broadband Multimedia Communications (BMC) [7]. This implies that the cognitive scenario was proposed to ensure proper use of radio frequencies within the Electromagnetic Wave (EMW) spectrum, ranging from 3 kHz to 300 GHz [8], which encompasses both short- and long-distance communication. This is also intended to harmonize the coexistence of satellite-terrestrial nodes and improve the efficiency of overall spectral operations to enable big data transmission across different

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frequency bands of the spectrum [9]. Previously, 5G and Cognitive Radio (CR) research have received limited attention in the satellite context, as they have been discussed more extensively in the terrestrial context.

Among the interactive technologies proposed as pathways for 5G and beyond networks, CR has proven unique in supporting dynamic multi-user and single-user access for synchronous and asynchronous communications in both terrestrial and satellite networks [4]. It is referred to as a smart radio that seamlessly operates in unused licensed frequencies without posing a threat or causing any harmful interference to the original owner [3, 10, 11]. The original owners of this spectrum are the licensed owners, referred to as Primary Users (PUs), while the unlicensed owners are referred to as Secondary Users (SUs) [12]. Among other CR system conceptual attributes, the Spectrum Sensing (SS) technique remains an essential component for identifying unused frequency bands and leveraging them [13, 14].

In this context, this research aims to adopt the CR proactive SS method to convert interference links between SMNs and TMNs into cognitive links, thereby maximizing the throughput of wireless communication systems. This optimization is achieved by integrating Centralized Cooperative Spectra Sensing (CC-SS) into CR using the Filtered Orthogonal Frequency Division Multiplexing (F-OFDM) technique.

The novelty of this work lies in the deployment of the Vertical Hypothesis Uncertainty (VHU) method, which uses a null-detection variable to optimize the spectrum-sensing threshold. This milestone has enhanced the system's throughput, enabling it to support 5G frequencies and beyond. To the best of our knowledge, this approach has not been presented in previous literature/research. The following are the main research areas of significant contributions, which are:

- The work effectively obtained an improved threshold for spectrum false alarm and null detections. This is demonstrated by validating the results obtained with the VHU method against those recorded with Hybrid Filter Detection with Inverse Covariance (HFDIC) and traditional spectrum sensing approaches.
- The study achieved the conversion of interference links separating the different spectrum bands into cognitive links, thereby increasing the utilization of the bandwidth in wireless networks. With this, many technological inventions that could not be deployed due to insufficient bandwidth can now be deployed to enhance commercial use, military surveillance, exploration, effective healthcare services, and more.
- It also obtained an optimized system throughput in Gbps, which is scalable enough to drive 5G and 6G wireless network resources. This has matched the Third Generation Partnership Project (3GPP) mandate for 5G frequencies and beyond. This study unveiled the cross-link hypothesis of an imperfect channel of false alarm, P_{fa} versus missed detection, P_{md} and channel perfect detection, P_d versus null detection P_{nd} as recommended areas for further research work, this is to further enhance wireless system performance for decades.
- Finally, the research recommends the incorporation of AI-induced ML algorithms to improve further the spectrum sensibility, selectivity, and specificity between the PU and the AWGN signal. Among other benefits of using AI in CR-SS, it will also assist in analyzing complex and dynamic usage patterns, improve resource management, optimize spectrum allocation, and adapt to changing demands more effectively than conventional methods [15].

The study is organized as follows: to further substantiate the argument, Section 2 presents a detailed review of related works from earlier research, which helps to establish the uniqueness of the research gap. The theoretical background for the research's fundamental concept is presented in Section 3. Section 4 illustrates the methodology analogically. Sections 3 and 4 outline the methods to achieve the research objectives. Section 5 presents the research results and their corresponding discussions. Section 6 is the summary and conclusion of the research activity.

2 Related Works

This section presents varying overviews conducted by researchers using the SS technique of CR technology. The review presents the research methods employed by various works to enhance the management and utilization of wireless network resources, to increase bandwidth and throughput. This review has also helped identify the research gap, examine the limitations of various methods, and inform the development of this research topic, offering further solutions to improve system throughput in wireless systems.

To ensure secure network utilization against Malicious Users (MUs), [8] developed blockchain-based technology to identify and avert suspicious activities. The blockchain-based MU detection was deployed on an energy detection-based SS algorithm. By considering the Signal-to-Noise Ratio (SNR) at –5 dB, the proposed approach obtained detection probabilities of 3.125%, 6.5%, and 8.8% compared to other approaches when MUs are present. However, the method was observed to perform best only at –5 dB and to degrade when the threshold is increased. The work [16] conducted a review to optimize the smart attributes of the CR system using Machine Learning (ML). This initiative aims to enhance the safety and efficacy of transportation systems. The research explored cutting-edge approaches, including Vehicular Ad-hoc Networks (VANET), whose efficiency can be improved using ML-CR. This method exhibited low sensing processing time, which affects the end-to-end timing mandate required for 5G and the next generation of wireless systems. Taking the amplitude and phase components into consideration, [17] introduced a modified CRN's input signal. This consists of formulating the Mean Squared Deviation (MSD) and the Specific Adaptive Estimation (SAE). When the error calculation for the direct signal vectors was read, the proposed concept demonstrated better performance than the traditional methods.

Further experimental results demonstrated the efficiency and robustness of the proposed concept compared to conventional methods. However, the technique is only deployable in terrestrial networks, as no further analysis has been conducted to determine its effectiveness in the satellite wireless domain. To effectively analyze the trade-off between energy management and Quality-of-Service (QoS) in CRNs, [18] proposed a smart-sensing-enabled dynamic Spectrum Management (EDSM) scheme. By repeatedly sensing activities triggered by prior rules, the proposed scheme curtails energy consumption using refined fuzzy-based controllers to optimize the spectrum response time. The scheme is known for an intrinsic problem that arises from the complexity of the designs. This complexity negatively impacted the flexibility required in upcoming wireless networks.

The authors [19] implemented an eigenvalue-based Cooperative Spectrum Sensing (CSS) technique in conjunction with an Energy Detection (ED) scheme to evaluate CSS performance. The results showed that eigenvalue-based detection performed better at low SNR, while ED performed better at high SNR. The eigenvalue detector detected at an SNR of –9 dB, whereas the ED altogether detected signals at an SNR greater than –10 dB. These two techniques performed best at low signal-to-noise ratios but showed reduced efficiency when higher sample bits, like those required in a 5G system, were used. To maximize the detection precision of idle channels, [6] introduced a groundbreaking approach leveraging SS and Convolutional Neural Networks (CNNs). The performance and adaptability of this method surpassed those of traditional methods, including frequency-domain entropy-based methods and maximum–minimum eigenvalue-ratio-based methods.

Nevertheless, this method was observed to suffer from computational inefficiency due to the unavailability of the required data for its analysis. The work [2] used the correlation sum method to improve the efficacy of a cooperative CR-SS detection system. This is intended to explore and utilize the fading and Additive White Gaussian Noise (AWGN) channel using the Multi-User Multiple Input Multiple Output (MU-MIMO) technique. At low signal power, such as -10 dB and below, the detection efficiency of the Cooperative Correlation Sum (CCS) approach adopted in the analysis was superior to that of the Cooperative Energy Detection (CED) technique used for validation. However, this MU-MIMO technique in CCS was notable, with the drawback of not effectively discriminating between the AWGN variance power and the spectrum-licensed owner signals.

The literature reviewed has proven the need for advanced approaches in wireless communication. The drawbacks observed from the methods and techniques used by the reviewed articles led to the motivations behind the conception of this research work, which are:

- The quest to improve bandwidth utilization and, by extension, increase system throughput for present and upcoming generations of wireless systems.
- The need for the use of engineering and scientific approaches to synergize satellite-terrestrial networks to maximize wireless system bandwidth utilization and improve throughput.
- The need for the adoption of the false alarm versus the spectrum null detection vertical approach for optimal throughput analysis.
- The literature revealed that previous research conducted in this area to improve system throughput has always been on the false alarm versus spectrum detection horizontal hypothesis methods.

In summary, Table 1 presents the key related works that led to the formulation of this research gap, as well as the step-by-step method used to address it.

3 System Model

Figure 1 presents the schematic workflow of the research domain. As illustrated, the cognitive links can be from Fixed Service Station (FSS) to Onboard Satellite Terminals (OST), from OSTs to Satellite Constellation Terminals (SCTs), from SCTs to Terrestrial Base Stations (TBSs), from TBSs to Terrestrial User Terminals (TUTs), from TUTs to TBSs, and vice versa [4]. All of these encompass the SES wireless domain.

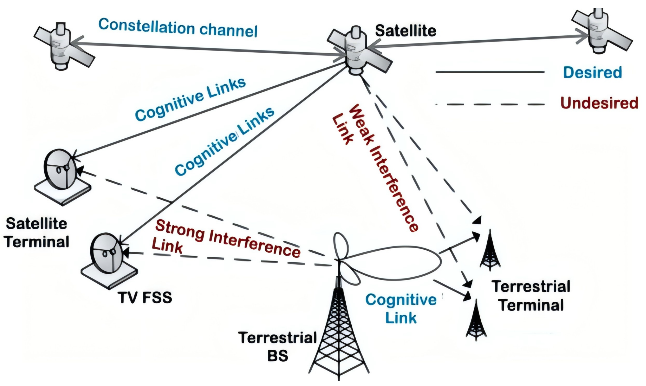

Figure 1: Cognitive and interference links interconnecting TMN nodes and SMN terminals.

3.1 Basic Spectrum Sensing Model

The response of an SS model in a discrete-time domain is formulated in [6, 22] as:

$$H_0 : y(n) = g(n) \quad (1)$$

$$H_1 : y(n) = h(n) * s(n) + g(n) \quad (2)$$

where:
$g(n)$ is the AWGN channel,
$h(n)$ corresponds to the channel gain,
$s(n)$ refers to the data samples,
H_0 connotes a null detection hypothesis, which indicates the absence of a signal,
H_1 denotes channel occupancy hypothesis, which refers to the presence of a signal,
$*$ represents the convolution operator in the time domain.

A decision metric, T, is derived to define the parameter to be determined and is written by [11, 23, 24] as:

$$T = \sum_{n=1}^{N} |y(n)|^2 \quad (3)$$

where T represents the cumulative signal energy decision metric and $y(n)$ is the receiver input samples based on the FFT tool after passing through the fading channel.

Table 1: Summary of related work

Author	Work Done	Method Used	Demerits	Merits
Jia et al. (2016) [7]	Developed an algorithm that could explore the Satellite-Earth Stations (SES) networks and make maximum use of the detection information to improve system throughput.	An upgraded Spread Slotted ALOHA (SSA) concept based on transmission techniques in multi-user channels.	Lack of scalability to drive higher data rates. The technique used is not suitable to drive the 5G NR resources mandate, as it could only be deployed for spectrum equalization in the Long-Term Evolution (LTE) system.	The method succeeded in synergizing satellite-terrestrial networks as prospected by upcoming wireless systems. The proposed SSA technique improved the system throughput better than the traditional "hard Combining" scheme.
Agus et al. (2016) [10]	Proposed a spectrum sensing threshold that could differentiate between inactive PU channels and the AWGN to avert interference and improve system throughput.	A blind spectrum sensing using the Jarque-Bera test statistics approach in a Fast Fourier Transform (FFT) access scheme.	The technique obtained a miss-detection threshold within 0.88 and 0.12 of Miss-Detection and False Alarm, which is less than the Institute of Electrical and Electronics Engineers (IEEE) set standard for 5G and subsequent generations of wireless systems.	The method used increases the system's spectral sensitivity and selectivity.
Islam et al. (2023) [20]	Developed a performance measure for system throughput at low power or low SNR, using three detection probability hypotheses of Detection, Missed Detection, and False Alarms.	A Novel Hybrid Filter Detection with Inverse Covariance (HFDIC) approach.	The technique lacks scalability to support 5G Frequency Resource 1 (FR1) resources. Its performance is seen dropping in every increase in packet transmission.	Under varying access of channels, the method optimizes spectrum access for various SUs using contentious training with a non-contentious iterations framework and is designed for multi-constraint
Bai et al. (2025) [21]	Aimed at addressing the issue of spectrum access in multiple opportunistic modes of cognitive radio networks, which results in low throughput.	Adopted various dynamic channel access concepts using self-attention multi-head and deep reinforcement learning multi-agent.	This method may not perform effectively in a complex network, especially those that require a high level of iterations for sample sizes of 4096 or 8192, which are necessary for 5G New Radio (NR) and upcoming generations.	The technique optimized the spectrum sensing threshold better than the traditional method. This results in a record of an appreciable increase in system throughput that matches the requirement for 5G NR resources.

This hypothesis in Equation (3) is best implemented on signal energy analysis, where prior knowledge about the PU transmission status is not needed.

Therefore, the decision based on the binary hypothesis for optimal sensing time is achieved by running a comparison test between T against a fixed decision threshold, λE, as expressed in [6, 23]:

$$H_1 : T \geq \lambda E; \quad \text{PU signal is present} \tag{4}$$

$$H_0 : T < \lambda E; \quad \text{PU signal is absent} \tag{5}$$

where λE denotes the sensing decision threshold, which depends on the AWGN noise variance, σ_n^2, and it is expressed in this work for a target false alarm, P_{th}^{fa}, in [14] as:

$$\lambda E = \sigma_n^2 \cdot \left[Q^{-1}(P_{th}^{fa}) \cdot \sqrt{2N} + N \right] \tag{6}$$

$Q(\cdot)$ and N refer to the Q-function of the standard distribution function and the minimum number of samples, respectively. These are defined in Equations (7) and (8) by [14] as:

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} \exp\left(\frac{-y^2}{2}\right) dy, \tag{7}$$

and,

$$N(x) = 2\left[(Q^{-1}(P_{th}^{fa}) - Q^{-1}(P_d))SNR^{-1} - Q^{-1}(P_d) \right]^2 \tag{8}$$

P_d refers to the likelihood of perfect spectrum detection.

Its SNR is expressed as:

$$\mathrm{SNR} = \frac{\sigma_s^2}{\sigma_n^2} \tag{9}$$

where σ_s^2 is the SU signal power.

3.2 Spectrum Detection Methods

Four uncertainties influence the accuracy in spectrum sensing: missed detection, false alarm detection, spectrum null detection, and spectrum detection [14, 24, 25]. Figure 2 is a demonstration of the relationship between these spectrum-sensing uncertainties. SU's efficient use of channel transmission can be affected by inaccurate information about the PU channel's status. Spectrum-sensing uncertainties are depicted in Figure 2.

It is evident in Figure 2 that there is a need to explore developing techniques or deriving methods that could enable transmission on the cross-link channels' imperfections of P_{fa} versus P_{md} and channel perfection of P_d versus P_{nd}. This may further improve the system's sensitivity and selectivity, and, in turn, improve its throughput.

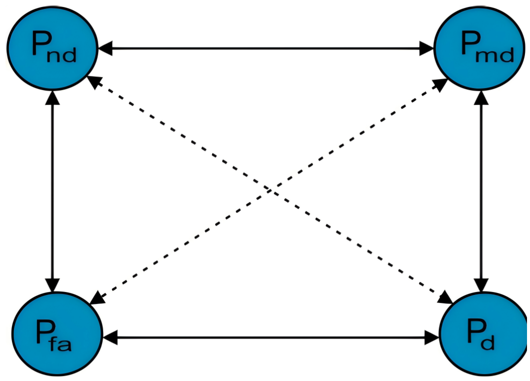

Figure 2: Spectrum sensing uncertainties.

3.2.1 Missed Detection

Spectrum sensing can be examined in terms of the likelihood of signal absence or presence [22, 26]. The probability of miss-detection (P_{md}) occurs when the spectrum sensor returns an idle value even while a signal is present. Declaring H_0 under H_1 hypothesis may cause interference and affect transmission efficiency [25]. The probability that the spectrum is missed detecting is mathematically formulated by [22, 26] as follows:

$$P_{md} = \Pr(T \leq \lambda E \mid H_1) \tag{10}$$

A fixed λE is defined for every σ_n^2 in the PU licensed channels to prevent the cognitive user from being misled by incorrect information from the spectrum sensor [23].

3.2.2 False Alarm Detection

Due to the risk of false alarms, signals detected may be erroneously reported [22, 26]. The spectrum sensor detects an idle channel or AWGN signal values and falsely reports that the spectrum has been used. Incorrect declaration of H_1 under H_0 hypotheses cause an increase in the number of iterations, increasing the time delay, which affects the quality of transmission [25]. The probability that the spectrum is tested incorrectly is written by [23, 26] as follows:

$$P_{fa} = \Pr(T \geq \lambda E \mid H_0) \tag{11}$$

3.2.3 Spectrum Perfect Detection

This is the likelihood that a spectrum is tested correctly. Two assumptions are made to maximize sensing and mitigate interference [27]:

- **Probability of Detection**: Correctly declaring H_1 under H_1 hypothesis causes the probability of detection [23]. When a PU is occupying the spectrum channel, the sensing slots are accurately analyzed to determine the number of spectrum channels detected as busy [23, 24] as:

$$P_d = \Pr(T > \lambda E \mid H_1) \tag{12}$$

- **Probability of Null detection**: Correctly declaring H_0 under H_0 hypothesis, the probability of detecting null in idle channels. When a PU is not occupying the spectrum channel, as in the case of interweave, more packets are transmitted, and the cognitive user's performance will be high. Here, the spectrum threshold is set to highly differentiate between the AWGN variance and the power of the PU signal. Equation (13) serves as the foundational hypothesis for this research work. It is formulated as follows:

$$P_{nd} = \Pr(T < \lambda E \mid H_0) \tag{13}$$

4 Methods

This section aims to achieve the research objectives by outlining the methods employed. This encompasses the integration of the F-OFDM algorithm in a cognitive radio domain. This section outlines the steps taken to achieve effective spectrum detection, thereby increasing transmission bandwidth and optimizing system throughput.

4.1 The Integration of F-OFDM Waveform with Spectrum Sensing Model

The mathematical characterization of the F-OFDM symbol is crucial for understanding the operations required at both the transmitter and receiver sides [28].

The F-OFDM time domain operation is a convolutional mode, and it is computed as follows [29]:

$$y(n) = S_{cp}(n) * F_{\varphi}(n) \tag{14}$$

where, $S_{cp}(n)$ is the discrete CP-OFDM signal and $F_{\varphi}(n)$ is its FIR spectrum shaping filter.

The signal formation at the received side is expressed as follows:

$$r(n) = \sum_{\varphi=0}^{M-1} y(n) * h_{\varphi}(n) + g_{\varphi}(n) \tag{15}$$

where, $M-1 = N$ refers to the number of data samples with 0 initial, and $y(n)$ is the F-OFDM received signal components after passing through the fading channel.

Equation (16) forms the F-OFDM impulse response, $r(t)$, which is obtained by mapping each sub-band filter folded version, $F_\varphi^*(-n)$ of each transmitted filter, $F_\varphi(n)$ with its corresponding receiver signal as follows:

$$r_\varphi(n) = r(n) * F_\varphi^*(-n) \tag{16}$$

Therefore, the integrated CRN with F-OFDM parameters is obtained from Equations (17) and (18) and expressed in [29] as:

$$H_0 : X_\varphi(n) = \Psi\left[g_\varphi(n)\right] \tag{17}$$

$$H_1 : X_\varphi(n) = \Psi\left[h_\varphi(n) r_\varphi(n) + g_\varphi(n)\right] \tag{18}$$

where, Ψ corresponds to the measurement matrix of k^{th} SU at l^{th} slot.

Finally, the integrated output signal, which is the decoded frequency domain waveform, $Y_k(e^{j\omega})$ at the receiver side is obtained by:

$$Y_k(e^{j\omega}) = \frac{k}{T_Q}\int_0^{T_q} X_\varphi(e^{j\omega})e^{-j\omega k\Delta ft}dt \tag{19}$$

where, $e^{j\omega}$ represent the frequency shift factor and T_q is the symbol's timing limit. $Y_k(e^{j\omega})$ can also be referred to as the air-piece audible signal.

The decision statistic, T, of a CC-SS detector in Equations (3), (4), and (5) is illustrated using Figure 3, and is extensively expressed in Equations (21) and (21) to achieve peculiarity in the null detection threshold. The spectrum sensing detector workflow presents the imagery of an F-OFDM transceiver waveform, $Y_k(n)$ integration with a spectrum sensing architecture. The hypothesis is formulated that if the received signal, $r_\varphi(n)$ decision statistic is less than the threshold, indicating effective null detection of idle spectrum channels; conversely, it is an effective spectrum detection.

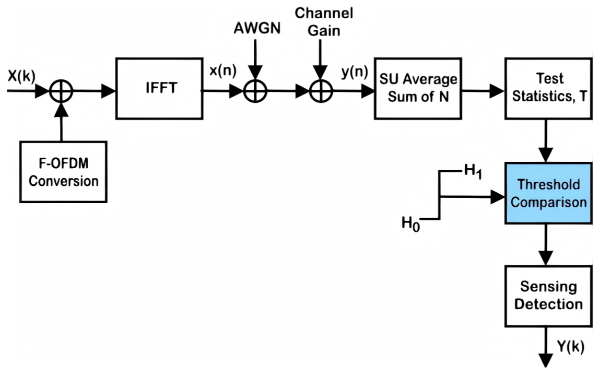

Figure 3: Optimized CC-SS Detector using F-OFDM.

4.2 The Analysis of Spectrum False Alarm and Null Detection Hypotheses

Null detection is the ability for a CR user to detect idle channels and/or unused frames with higher priority and accuracy. Starting from the joint distribution probability function of collaborative symbols, $f_x(t)$, the hypothesis H_0 and H_1 of the received samples are derived as follows:

$$f_0(T < \lambda E \mid H_0) = 2\pi^{-\frac{N}{2}}\left|\sigma_n^2\Psi\Psi^T\right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}y^T(\sigma_n^2\Psi\Psi^T)^{-1}y\right] \tag{20}$$

$$f_1(T > \lambda E \mid H_1) = 2\pi^{-\frac{N}{2}}\left|\sigma_n^2\Psi\Psi^T\right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(y-\Psi h_s)^T(\sigma_n^2\Psi\Psi^T)^{-1}(y-\Psi h_s)\right] \tag{21}$$

The Neyman–Pearson (NP) theorem of likelihood ratio for optimal decision rule obtained in the parameters in (20) and (22) [30] is adopted and normalized in (22) as:

$$V(y) = \frac{f_0(T < \lambda E \mid H_0)}{f_1(T > \lambda E \mid H_1)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{22}$$

where V denotes the SUs that accurately report PU's absence and γ is the null detection decision threshold. An equivalent test is obtained after taking logarithms on both sides, which is simplified as:

$$y^T(\Psi\Psi^T)^{-1}\Psi h_s \underset{H_0}{\overset{H_1}{\gtrless}} \sigma_n^2\log(N)\frac{1}{2}(h_s)^T\Psi^T(\Psi\Psi^T)^{-1}\Psi h_s = \gamma \tag{23}$$

where the output of the CC-SS detector is defined as:

$$T = y^T(\Psi\Psi^T)^{-1}\Psi h_s \tag{24}$$

Therefore, the P_{fa}, P_{md}, P_{nd}, and P_d at SU are computed by:

$$P_d = \Pr(T > \gamma \mid H_1) = Q\left(\frac{\lambda - (h_s)^T\Psi^T(\Psi\Psi^T)^{-1}\Psi h_s}{\sigma_n\sqrt{(h_s)^T\Psi^T(\Psi\Psi^T)^{-1}\Psi h_s}}\right) \tag{25}$$

$$P_{fa} = \Pr(T \geq \gamma \mid H_0) = Q\left(\frac{\lambda}{\sigma_n\sqrt{(h_s)^T\Psi^T(\Psi\Psi^T)^{-1}\Psi h_s}}\right) \tag{26}$$

$$P_{md} = \Pr(T \leq \gamma \mid H_1) = 1 - P_d \tag{27}$$

$$P_{nd} = \Pr(T < \gamma \mid H_0) = 1 - P_{fa} \tag{28}$$

Equations (25) and (26) are for the horizontal relationship between P_d and P_{fa}, while equations (27) and (28) are for the vertical relationship, all are set in conjunction with the standard threshold.

In order to adequately protect the PU, the analysis in equation (27) is mirrored below reference in equation (28) to increase the SU sensitivity, selectivity, and specificity.

In contrast to the analysis in [31], equation (28) is the targeted null detection probability, P_{nd}^{th} that provide proper PU protection. To achieve an effective P_{nd}, the parameter P_{fa} is varied as P_{fa}^{th} in relation to P_d^{th} in (29):

$$P_{fa}^{th} = Q\left[\sqrt{2\Psi}\xi + 1Q^{-1}(P_d^{th})\right] + \xi\sqrt{\frac{T_{smf_s}}{2}}\sum_{i=1}^{k} w_i|h_i|^2 \tag{29}$$

where ξ is the measure of the signal-to-noise ratio.

Finally, the variable false-detection, P_{fa}^{th} influence the achievement of perfect null detection, P_{nd} by the insertion of the values obtained in (29) into (30) as:

$$P_{nd} = 1 - P_{fa}^{th} \tag{30}$$

Assuming a frame duration T_F, the collaborative sensing duration and the reporting duration of individual sensors are denoted as T_R and T_S, respectively. The F-OFDM CC-SS will be performed concurrently by the SESs at the beginning of the channel. By considering a contentious network, each SES report results of local sensing to the Lower Earth Orbit (LEO) satellite in an eligible reporting time slot, N_R to avert conflict in transmission. For a given T_F, the longer the T_S, the shorter transmission time, T_T (β). Since $Q(x)$ is monotonically decreasing in x for a target P_{nd}^{th} at SU, optimizing T_S results in lower P_{fa}.

The research's primary purpose is to improve the spectrum sensing system by accurately varying the null detector threshold for the legal free spectrums to optimize system throughput. This is also to sufficiently protect the PU's legitimate signals and to maximize the SU transmission efficiency under a higher classification of AWGN variance. The optimization problem is expressed mathematically as:

$$\begin{aligned} \max : C(\alpha, K, P_{nd}^{th}) \\ \alpha, K, P_{nd}^{th} \\ \text{s.t.}, P, I, d \geq P_{nd}^{th} \\ P_{md} \leq \beta \\ P_{fa} \leq \delta \\ \alpha + K\eta \leq 1 \\ 0 \leq \alpha \leq 1 \\ 0 \leq K \leq N, \quad K \in \mathbb{Z} \end{aligned} \tag{31}$$

where, P_{nd}^{th} is the variable null detection hypothesis, which defines the safety of the PU signals. C is the spectral efficiency of the collaborative sensing time, T_S.

4.3 Optimal Sensing Threshold Algorithm

The optimal sensing threshold algorithm is given in Algorithm 1.

4.4 Procedure

Figure 4 presents the step-by-step procedures to achieve this work. After receiving the channel impulse responses, a comparison test is conducted to determine the signal type and its strength. A test statistic and an IEEE spectrum sensing standard are then initialized to back up the parameters address and the threshold of reference, respectively. If the test statistic value exceeds the system threshold, the iteration cycle automatically repeats to correct anomalies encountered during sensing the channel impulse response. In this situation, it is not safer for the SU to transmit because both the AWGN and the SU signal information overlap. If the test statistics fall below the threshold, the SU is free to transmit its data, albeit at the expense of the targeted threshold. To further improve the safety of the SUs' transmission by effectively discriminating between AWGN and PU signals, the system thresholds are increased by 0.01. The continuity of this increment depends on the scalability of the technique used.

Algorithm 1 Optimal Sensing Threshold Algorithm

Input: PFA_{Fixed}, PD_{Fixed}, SNR, σ_n^2, N, K
Output: T_{Output}

```
% Sense PU signal energy, T transmission to initialize P_nd variables
Initialize PFA_Fixed, PD_Fixed, SNR, σ_n^2, N
% Use equations (25), (26), and (27) for a targeted T_Output of equation (28)
Compute T_β, T_α, and T_δ
if T_β ≤ T_α then
    if T_β ≤ T_α ≤ T_δ then
        T_Output ← T_α
    else if T_α < T_β then
        T_Output ← T_β
    else
        T_Output ← T_δ
    end if
else if T_β > T_δ then
    T_Output ← T_α    (which is undesired)
    N* ← N
    Initialize K
    for each PD(PFA)_K do
        Compute T*_β, T*_α, and T*_δ for incremental K
        T*_β = T*_α = T*_δ
        T_Output ← T*_β = T*_α = T*_δ
    end for
    T_Output = PND_Variable
end if
```

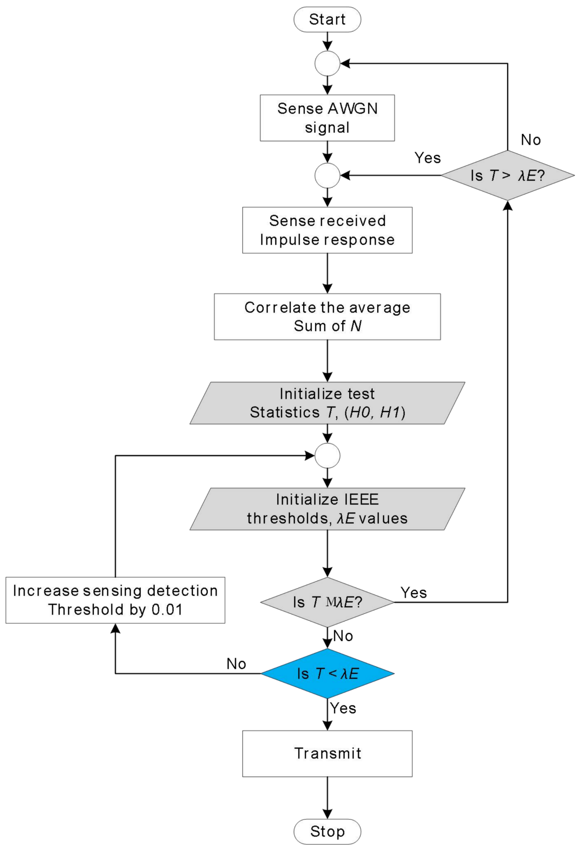

Figure 4: An optimized spectrum sensing workflow using vertical hypothesis.

5 Results and Discussion

This section presents the results of intensive computer simulations that assess the spectral efficiency of the developed model. Simulations carried out were to generate an F-OFDM signal waveform, and the generalized characteristics of P_{nd} in relationship with P_{fa} for optimal throughput in a fixed channel and dynamic channel stages of the CR domain. The parameters used are presented in Table 2. These parameters were obtained to effectively validate the proposed VHU method using HFDIC and traditional SS approaches to achieve optimal throughput.

Table 2: Simulation Parameters

Parameters	Values
Channel access technique	F-OFDM
Offset channel	Non-unity Gaussian
Mapping scale	256 QAM (8 bits)
Spectrum shaping tool	Hanning-induced Windowed filter
Number of PUs (FSS), N	10
Number of SES, K	6
Number of FC, LEO	1
Channel gain between PU and SU, h	–10 dB
AWGN channel	–10 dB
Channel gain among SUs, g	0
IEEE SS standard	$P_d = 0.9$, $P_{fa} = 0.1$
Transmission time, β	500 ms
Channel bandwidth	100 MHz
End-to-End delay	25 ms (LEO)
SNR, ξ	–10 to 0 dB

5.1 Probability of Perfect Detection

Figure 5 compares the proposed VHU method for SS null detection with the HFDIC and traditional methods over the range -10 to 0 dB. This comparison is expressed in the relationship between the null detection, P_{nd}^{th} of the variable false-alarm, P_{fa} and also detection, P_d of the parameter false-alarm, P_{fa} as illustrated in Figure 2 and analyzed in (28), (29), (30), and (31). The results obtained show that the VHU method adopted in this work outperformed all other cases. The VHU recorded a perfect detection probability of 0.92, compared to 0.81 and 0.69 for the HFDIC and the Traditional method, respectively. It is seen that the VHU obtained a high detection of 1 at -5 dB SNR, whilst the HFDIC and the traditional method provided 1 at -4 dB SNR.

5.2 Probability of False Detection

Conversely, Figure 6 presents the system false-detection probability obtained with the VHU method adopted in this work for optimal throughput. This is also compared with the HFDIC and traditional techniques to validate the effectiveness of the VHU method. Here, the result is interpreted to mean that the VHU approach of false alarm detection, P_{fa} recorded 0.08 uncertainty to generate 1 at -5 dB SNR, outperforming the 0.19 obtained by the HFDIC approach and 0.31 achieved by the traditional method, which both generated 1 at -4 dB SNR.

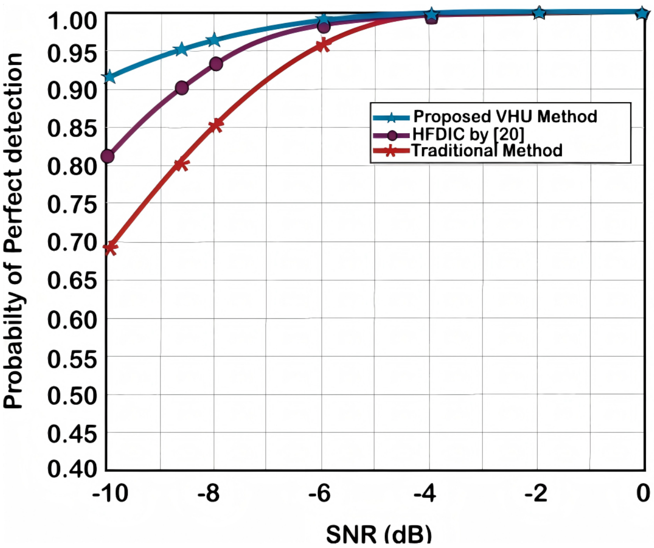

Figure 5: Perfect detection states.

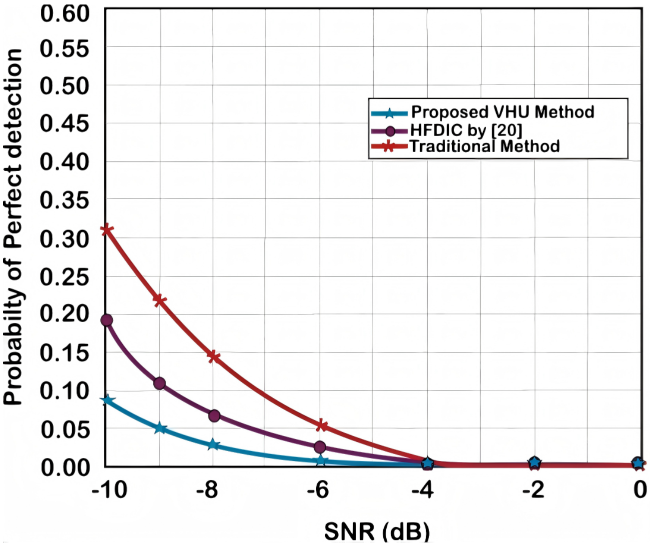

Figure 6: Imperfect detection condition.

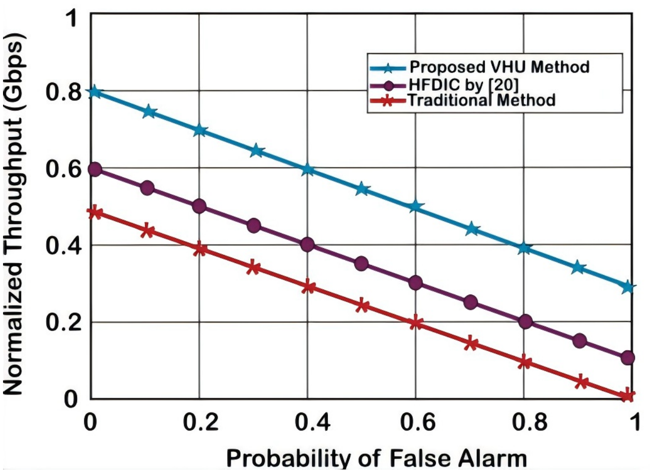

Figure 7: Normalized throughput.

5.3 Normalized Throughput

Figure 7 presents the simulation result obtained from the analysis in (22) of the proposed VHU, compared with the HFDIC and traditional methods. The metrics used here are the normalized throughput versus the false alarm at a 500-ms transmission time (β). The results show that the VHU method achieved a better normalized throughput of 0.8 Gbps, surpassing the HFDIC and conventional methods, which obtained 0.6 Gbps and 0.5 Gbps, respectively.

5.4 Throughput in a Fixed Channel State

The system throughput simulation in a fixed dormant channel state under perfect conditions is presented in Figure 8. An ideal channel condition in a fixed channel state is one in which the channel is free of PU activity but still affected by AWGN. At this point, the probability of the SU mistaking AWGN noise variance for PU-fixed transmission signals and increasing channel redundancy is high. Considering the improvement in Figures 4 and 5, where $P_{nd}^{th} = 0.69, 0.81$, and 0.92 and $P_{fa} = 0.31, 0.19$, and 0.08, respectively. Results recorded show all transmission dummies behaving the same at $P_{tra} \leq 0.3$, but the proposed VHU and HFDIC are seen maintaining the same trajectory to $P_{tra} \leq 0.4$, after which a variation is noticed. This is due to an increase in interference packages caused by the AWGN channel, which affects system scalability. The results in Table 3 show that the HFDIC method achieved a system throughput improvement of approximately 5.61% compared to the traditional method. However, the VHU outperformed both the HFDIC and conventional methods by 7.7% and 15.5%, respectively. This clearly shows that the proposed VHU approach outperforms the HFDIC and Traditional methods in terms of channel sensitivity and selectivity under perfect channel conditions, characterized by high AWGN noise presence.

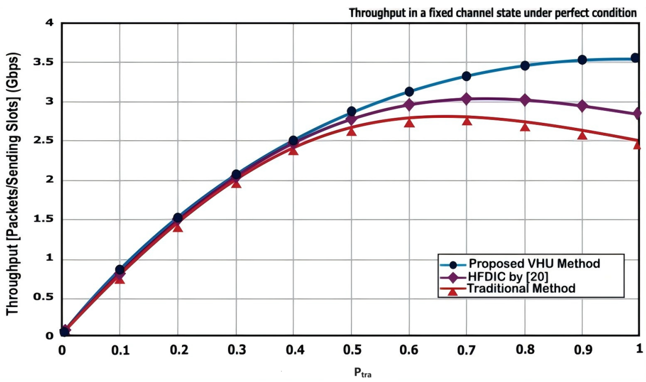

Figure 8: Throughput in a fixed channel under perfect conditions.

Table 3: Throughput Improvement in Fixed Channel State

Methods	**Average Throughput (Gbps)**	**Average % Improvement over the traditional Method**	**Average % Improvement over HFDIC Method**
Traditional	2.26	-	-
HFDIC	2.41	5.61%	-
Proposed VHU	2.67	15.6%	7.9%

5.5 Throughput in a Dynamic Channel State

Figure 9 shows the system throughput simulation in a dynamic channel state under perfect channel conditions. An ideal channel condition in a dynamic state is one in which the free channels are affected by AWGN noise, while the PU transmission channel is randomly occupied. At this point, the probability of the SU differentiating between the AWGN noise variance and the PU signal channel occupancy rate to reduce channel redundancies is low, primarily due to the complexity. Considering the improvement in Figures 4 and 5, where $P_{nd}^{th} = 0.69, 0.81$, and 0.92 and $P_{fa} = 0.31, 0.19$, and 0.08, respectively. Results recorded show that all transmission dummy trajectories behave differently from the initial ones $P_{tra} = 0$. The summaries in Table 4 show that the HFDIC method obtained 11.4% system throughput improvement over the traditional method; however, the VHU also performed better than the HFDIC and conventional approaches by 15.84% and 29.18%, respectively. The proposed VHU is seen as outperforming the HFDIG and traditional methods in terms of signal proactivity under dynamic channel conditions that include high AWGN noise and PU signals.

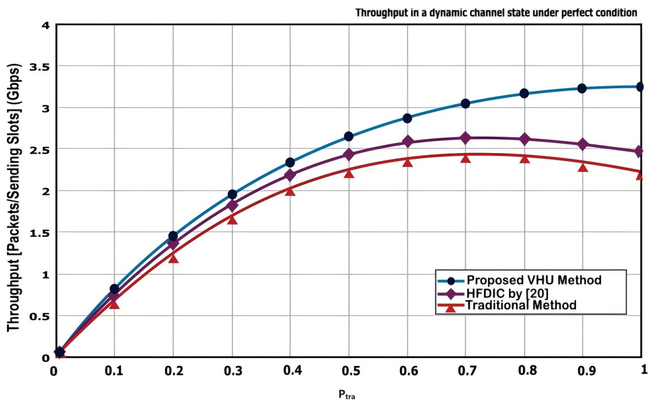

Figure 9: Throughput in a dynamic channel under perfect conditions

Table 4: Throughput Improvement in a Dynamic Channel State

Methods	**Average Throughput (Gbps)**	**Average % Improvement over the traditional Method**	**Average % Improvement over HFDIC Method**
Traditional	1.77	-	-
HFDIC	2.13	11.4%	-
Proposed VHU	2.48	29.18%	15.84%

6 Conclusions

The F-OFDM-generated signal was superimposed in a CR centralized network to produce an orthogonal signal waveform in an Electromagnetic Wave (EMW) induced environment. The CRN can adopt Chameleon-inspired technology that modifies its waveform to adapt and communicate effectively across every radio frequency environment. The integration of F-OFDM with the CC-SS technique in a CRN hybridizes a modified signal waveform, autonomously improving sensing capability to optimize system throughput.

This could also aid in meeting current and future wireless network requirements for quick access, optimal bandwidth, and maximum transmission duration. This has again underscored the need for full interoperability between SMNs and TMNs for effective Satellite-Terrestrial Communications (STC) proposed for 6G and future generations of wireless networks.

The simulation results show that the proposed VHU method is more scalable for data transmission than the HFDIC and traditional methods used as benchmarks. The results at $0.92\,P_{nd}$ and $0.08\,P_{fa}$ have also shown an improvement over the IEEE set threshold of $0.9\,P_d$ and $0.1\,P_{fa}$. In the area of future scope of this work, it is evident that there is a need to explore developing techniques and/or derive novel methods that could enable transmission on the cross-link hypothesis of channel imperfection of P_{fa} versus P_{md} and channel perfection of P_d versus P_{nd}.

Furthermore, by incorporating Artificial Intelligence (AI)-based ML algorithms into the VHU method, it is envisaged that this will increase the system's specificity, selectivity, and sensitivity, due to the demonstrated accuracy of AI in various fields of science. Considering the recommendations for further work may increase the system threshold and effectively discriminate between AWGN and PU signals, thereby improving the SU system's throughput.

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Author Contributions

The manuscript was written with contributions from all authors. Conceptualization, Z.A., and C.A.; methodology, Z.A., and C.A.; software, F.C.N., and A.L.I.; validation, J.R., and A.L.I.; formal analysis, Z.A., and C.A.; investigation, Z.A., C.A., F.C.N., and A.L.I.; resources, Z.A., and C.A.; data curation, Z.A., C.A., and J.R.; writing—original draft preparation, Z.A., C.A., F.C.N., J.R., and A.L.I.; writing—review and editing, Z.A., C.A., F.C.N., J.R., and A.L.I.; visualization, C.A.; supervision, A.L.I.; project administration, C.A., and A.L.I.; funding acquisition, C.A., and A.L.I. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

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.

Data Available

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

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