



ORIGINAL RESEARCH ARTICLE

ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING (OFDM) SUB-BAND
CHANNEL CLASSIFICATION BASED ON ADAPTIVE THRESHOLDING

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ABSTRACT

The radio frequency (RF) spectrum has experienced increased congestion due to a growing number of wireless devices and escalating demand for higher data rates. Cognitive radio (CR) enables wireless devices to sense their environment and efficiently utilize available spectrum resources. However, spectrum sensing in CR systems still remains a challenge due to the increased demands for higher data rates and efficiency. Existing research often trades complexity for accuracy, however a balance between accuracy and complexity is required for a good wireless communication. This study proposes a low-complexity, high-accuracy spectrum sensing method for Orthogonal Frequency Division Multiplexing (OFDM)-based cognitive radio. It combines a Fast Fourier Transform (FFT) filter bank for signal decomposition with a novel convex-optimized adaptive threshold algorithm to classify sub-band occupancy. Then, an optimal Adaptive threshold technique is designed through convex optimization, enhancing classification accuracy by optimizing statistical properties. Simulation results show improved accuracy compared to other related works, with a higher probability of detection achieving a probability of detection (P_d) of 0.9686 at a probability of false alarm (P_{fa}) of 0.1 and an SNR of 10 dB indicating the proposed technique's promise for efficient spectrum utilization.

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1.0 Introduction

The electromagnetic radio spectrum serves as a renewable resource for radio communication systems, enabling repeated use. Its reusability and capacity to accommodate numerous concurrent users make it a valuable asset. However, the increasing congestion in the radio frequency (RF) spectrum is a recent challenge, attributed to advancements in wireless communication technology (Dibal et al., 2018). The congestion in wireless networks, exacerbated by new technologies like 5G and internet of things (IoT), has led to a demand for improved spectral efficiency and high data rates (Lorincz et al., 2021b; Wahla et al., 2019). To address this issue, the concept of cognitive radio (CR) was introduced as a promising candidate for improving spectral efficiency in multicarrier communication. Cognitive radio is designed to be aware of its radio frequency (RF) surroundings and efficiently utilize available spectral resources. Its main component is spectrum sensing, which involves detecting and sharing unutilized spectrum to enhance dynamic spectrum access. However, spectrum sensing remains a challenge in CR systems due to the recent demand for higher accuracy and efficiency (Lorincz et al., 2021b; Shi et al., 2014; N. Wang et al., 2014). Hence, this spectrum sensing process requires high accuracy and high efficiency to effectively utilize the available spectrum resources. Figure 1 illustrates how system complexity, detection accuracy, and processing time are important in the detection process.

Orthogonal frequency division multiplexing (OFDM) is a widely used modulation and multiplexing technology that serves as the foundation for various telecommunication standards such as wireless LANs, digital terrestrial television (DTT), and digital video broadcasting (DVB) globally. OFDM is a multi-carrier transmission technology that transforms high-speed serial data into parallel transmission streams using frequency division multiplexing. This involves splitting the channel into independent sub-channels, modulating each with data, and

subsequently re-multiplexing to generate the OFDM carrier (Abbaszadeh et al., 2018; Bhardwaj et al., 2012). The key advantages of OFDM technique includes its high spectral efficiency, ability to support higher data rates, and robustness against inter-symbol interference (ISI).

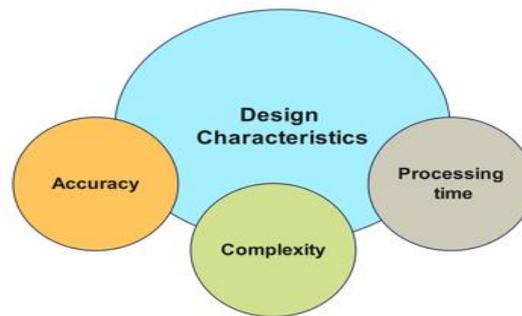


Figure 1: Design characteristics of a cognitive radio (CR) system showing the trade-off among complexity, detection accuracy, and processing time.

Recognized for its high spectral efficiency, OFDM meets the criteria of cognitive radio (CR). As a result, it is considered a promising choice for implementing the physical layer of cognitive radio due to its ability to transmit high data rates and achieve high spectral efficiency (Pan et al., 2020; Xu et al., 2016; Bhardwaj et al., 2012). Researchers have extensively explored efficient methods for classifying OFDM sub-band channels to meet the growing demand for faster and more reliable wireless networks. Traditional modulation classification techniques such as maximum-likelihood (ML) estimators (Yucek and Arslan, 2004) and machine learning approaches (Siva et al., 2024), including support vector machines (SVM) (Mahanta et al., 2022), have been applied to enhance classification performance. However, both likelihood-based and machine-learning methods often face challenges in real-world conditions, including high computational costs and poor generalization (Hong et al., 2019). Deep learning classifiers can automatically learn complex features and achieve high accuracy, but they demand substantial volumes of labelled data and high processing power, limiting their practicality in resource-constrained environments.

In parallel, researchers have investigated feature-based algorithms and traditional spectrum sensing techniques for efficient sub-band channel detection. Matched filter sensing, for instance, provides optimal performance when the primary user (PU) signal is known, as it maximizes the signal-to-noise ratio (SNR) at the detector output (Salahdine et al., 2016). However, this technique requires perfect knowledge of the PU signal and a dedicated receiver for each user, which limits its applicability. Cyclostationary feature detection exploits the periodic statistics of modulated signals and is more accurate than simple energy detection but suffers from high computational complexity and longer sensing times (Qin et al., 2012.). Conversely, conventional energy detection requires no prior information about the PU signal and therefore achieves low implementation complexity (Helif et al., 2015). Its performance can be improved through the adoption of adaptive or dynamic thresholds (Onumanyi et al., 2018).

Several recent studies have introduced adaptive and hybrid approaches to address these trade-offs. Qin et al., (2012) and Youn et al., (2014) used the Discrete Wavelet Packet Transform (DWPT) to decompose wideband channels into sub-bands and compared their energies against fixed thresholds. Alom et al. (2017) proposed an enhanced spectrum sensing technique based on energy detection that reduced sensing time but achieved lower classification accuracy. Salam et al. (2019) improved detection performance by combining adaptive thresholding with optimal frame duration for multi-layer sensing, albeit at the expense of higher computational complexity. Saleh et al. (2021) developed a 5G cognitive radio system using asynchronous spectrum sensing, which enhanced throughput but degraded detection accuracy at high SNR. Similarly, Wang et al. (2022) presented an adaptive energy detection method for L-band aeronautical systems, offering reliable performance but slower decision speed due to its reliance on likelihood functions.

The reviewed literature reveals a consistent trade-off between detection accuracy and computational complexity in OFDM sub-band classification and spectrum sensing. Some methods achieve high accuracy but are computationally intensive, while others are lightweight but less precise. Striking a balance between these two objectives remains an open challenge. To address these shortcomings, this work proposes a method that leverages the low-complexity of FFT-based energy detection while employing a per-sub-band, convex-optimized adaptive threshold to regain high accuracy. This is achieved by formulating threshold selection as a constrained optimization problem. The proposed method employs a fast Fourier transform (FFT)-based sub-

band decomposition to reduce computational workload and an optimized adaptive threshold combined with histogram analysis to enhance detection accuracy.

2. Materials and Methods

Simulations were performed in MATLAB R2021b using the Signal Processing Toolbox (FFT/filter bank, spectral analysis), the Optimization Toolbox (fmincon), and the Statistics and Machine Learning Toolbox (perfcurve for ROC).

2.1 The Flow Diagram of the Methodology

The process involves taking a wideband signal, such as long-term evolution (LTE), and passing it through a filter bank. This wideband signal was created by combining multiple narrowband signals distributed across a broad frequency range. The wideband signal was decomposed into narrowband frequencies using the fast Fourier transform filter bank (MATLAB FFT). The motivation to use this technique is based on the fact that energy detection is attractive for low complexity, while adaptive thresholds mitigates SNR sensitivity and convex optimization yields a data-driven threshold per sub-band therefore improving accuracy. The subsequent signal classification was achieved through an Adaptive Thresholding Algorithm, which was tailored based on the statistical properties of coefficients from sub-band channels in the OFDM filter bank. Design parameters for this algorithm were optimized using convex optimization. The classified signals are analyzed at the output using a histogram. Each OFDM sub-band channel was plotted according to the adaptive thresholding of its coefficients. Through histogram analysis, each sub-band channel in the OFDM filter bank is classified as either carrying information or containing noise based on the gathered information. The flow diagram of the methodology is shown in the Figure 2. The various stages of the workflow in Figure 2 are discussed extensively in the following section.

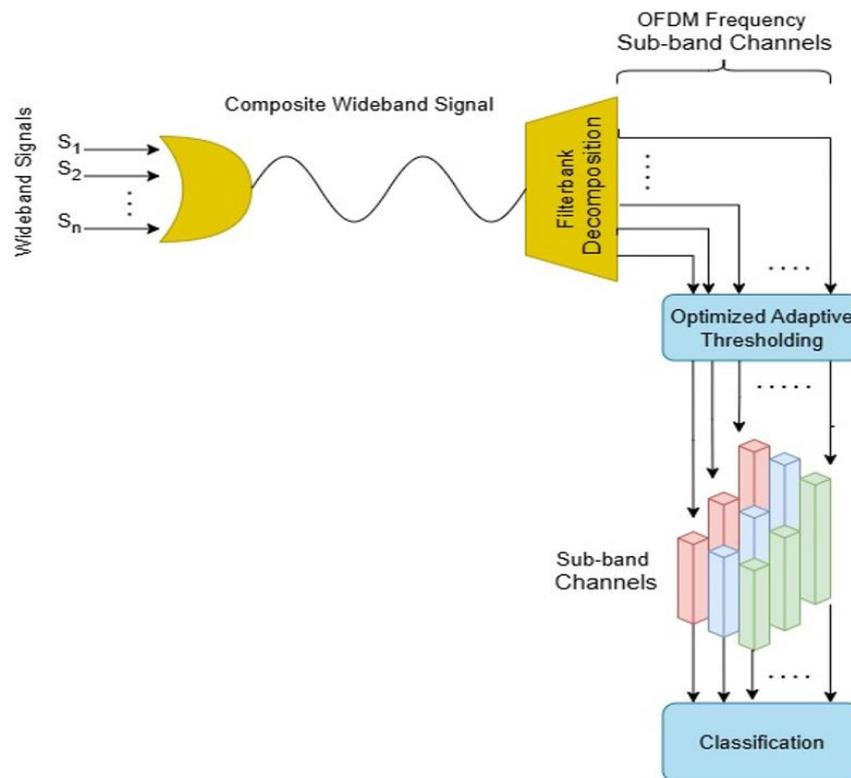


Figure 2: Flow diagram of methodology

2.2 Composite Wideband Signal Generation

This wideband signal was created by combining multiple narrowband signals distributed across a broad frequency range. The input signal is a wideband signal, like a long-term evolution (LTE) signal which was fed into the filter bank. They are defined by (Park et al., 2009)

$$s = A \sin(2\pi ft) \quad \text{or} \quad s = A \cos(2\pi ft)$$

2.3 Filter Bank Decomposition

This step involves the decomposition of the LTE/wideband signal into sub band channels using the fast Fourier Transform filter bank. The fast Fourier transform (FFT) filter bank was used to decompose the signal into sub-band channels. Mathematically, the FFT is expressed as

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi nk/N}$$

2

From the equation (1), the structure for the FFT filter bank is derived as shown in equation 2. The distribution of each sub band channel after the decomposition is shown in Figure 3.

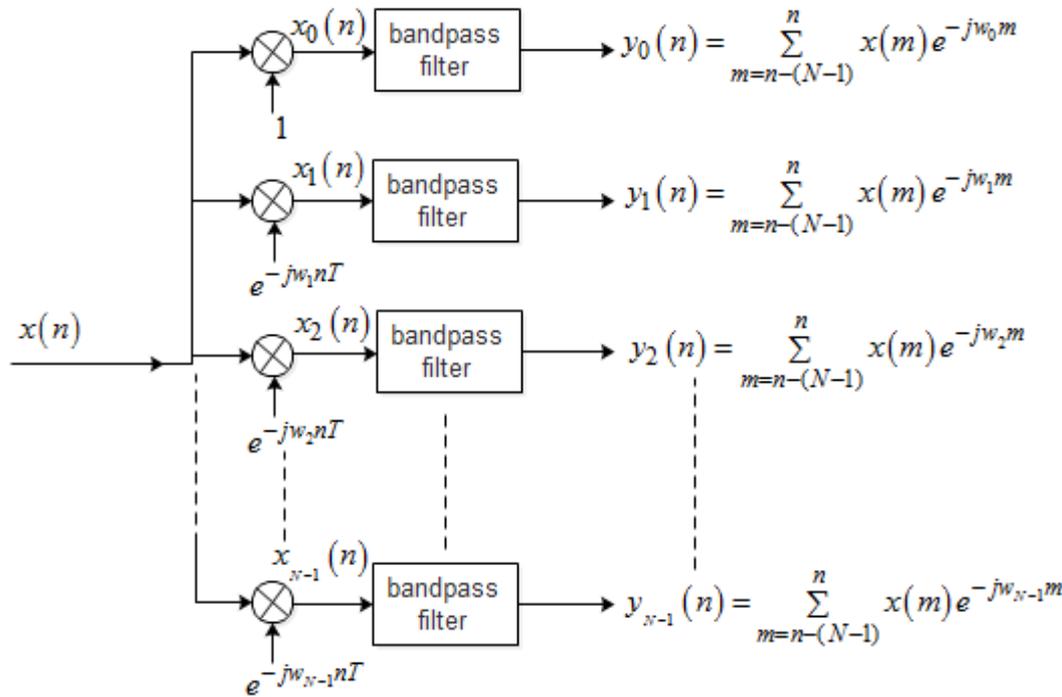


Figure 3: FFT Filter Bank

2.4 Adaptive Thresholding

In this step, an adaptive threshold was designed based on the statistical properties of the coefficients of the sub-band channels in the OFDM filter bank. Typical properties that was explored include the variance of the coefficients, mean of the magnitude of the coefficients as a function of signal-to-noise ratio (SNR), the energy in the sub-band channel under observation as a function of SNR. The statistical properties of each sub-band channel were used, an appropriate adaptive threshold was designed for the sub-band channel. The flow of the energy detection and adaptive threshold process is shown in Figure 4.

In order to achieve reliable spectrum classification across all OFDM sub-bands, an adaptive thresholding algorithm was developed to automatically adjust the detection threshold according to the instantaneous signal characteristics. The algorithm estimated the sub-band energy of the received wideband signal and compared it against an optimized threshold derived from convex optimization principles. The adaptive threshold was designed to balance the trade-off between detection probability P_d and false alarm probability P_{fa} , thereby improving classification accuracy at varying SNR conditions.

The adaptive threshold selection in this work was formulated as a convex optimization problem. The goal was to determine a set of thresholds T_k for each sub-band k that best separates occupied and idle channels while keeping the computational complexity low.

A composite wideband OFDM signal was generated and divided into $N=32$ sub-bands using an FFT-based filter bank.

The energy in each OFDM sub-band channels can be expressed as

$$E_k = \sum_{n=0}^{L-1} [X_K(n)]^2$$

3

Where $E_k =$ Energy in the sub – ban k , $X_k(n) =$ FFT output samples in sub – band k , $L =$ number of samples

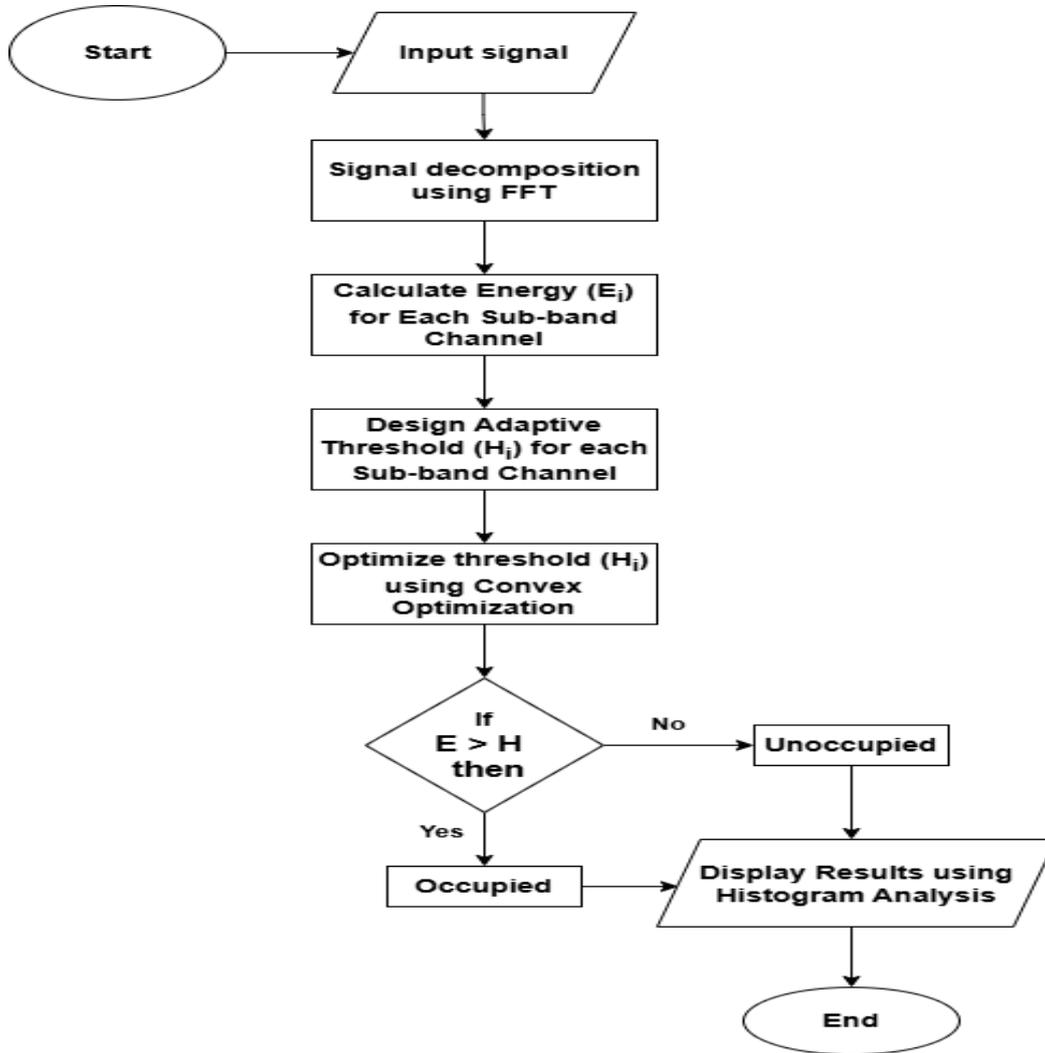


Figure 4: The flow chart of the Energy detection and Adaptive threshold process

The decision rule for spectrum occupancy is defined as:

$$\text{Decide } H_1(\text{occupied}) \text{ if } E_k > \Gamma_k,$$

$$\text{Decide } H_0(\text{Vaccant}) \text{ if } E_k < \Gamma_k$$

4

A sub-band is declared occupied if $E_k > \Gamma_k$, and vacant otherwise.

Where $H_1 =$ sub – band is occupied, $H_0 =$ sub – band is not occupied, $\Gamma_k =$ adaptive threshold for sub – band k

The design parameters were optimized using convex optimization which helped to derive an optimum threshold for the sub-band channel under observation. To obtain an optimal set of thresholds Γ_k , a convex optimization model was established. The objective is to minimize the deviation between the computed sub-band energies and the adaptive thresholds so that the decision boundary adapts to signal conditions. The optimization problem is expressed as

$$\min_{\Gamma_k} \sum_{k=1}^N [E_k > \Gamma_k] \text{ subject to } 0 \leq \Gamma_k \leq \alpha_1 E_k + \alpha_2 \Phi_k$$

5

Where $E_k = \text{Energy in the sub-band } k$, $\Gamma_k = \text{adaptive threshold for sub-band}$, $N = \text{Number of samples}$. Here, Φ_k denotes the signal-to-noise ratio (SNR) or the variance metric of the k -th sub-band, and α_1, α_2 are positive scaling factors that control the upper bound of each threshold. Typical values of α_1, α_2 used in this work ranged between 0.5 and 1.5. Equation 4 ensures that each threshold Γ_k is positive and limited by a linear combination of its corresponding energy and SNR, guaranteeing convexity of the feasible region. The optimization problem in Equation 4 was solved using MATLAB's `fmincon` function from the Optimization Toolbox.

For normalized evaluation, an equivalent bound can be expressed as

$$0 < \Gamma_k \leq \alpha \left(E_k + \frac{\Phi_k}{\sum_{j=1}^N \Phi_j} \right), \quad k = 1, 2, \dots, N, \quad 6$$

where α is a global scaling factor (0.5–1.5) controlling the sensitivity of the threshold relative to the total SNR across all sub-bands.

Finally, the adaptive decision rule of 4 combined with the optimized thresholds from 5 to 6 gives the convex-optimized thresholding algorithm summarized by

$$\Gamma_k^* = \arg \min_{\Gamma_k} [E_k - \Gamma_k] \quad \text{subject to } 0 \leq \Gamma_k \leq \alpha_1 E_k + \alpha_2 \Phi_k \quad 7$$

The resulting optimal Γ_k^* adapt dynamically to the instantaneous energy and noise level of each sub-band, improving detection accuracy while maintaining low computational complexity. Equation 7 defines the feasible range of the adaptive threshold for each sub-band channel. The threshold Γ_k is linearly dependent on the sub-band energy E_k and the corresponding signal-to-noise ratio Φ_k . The parameters α_1 and α_2 are positive scaling constants, typically within the range 0.5–1.5, that adjust the sensitivity of the threshold to variations in energy and noise. This formulation ensures that the threshold increases proportionally with both the power and quality of the received signal in each sub-band. By maintaining independent bounds for every sub-band, the optimization remains fully convex and computationally efficient when solved using MATLAB's `fmincon` function (Optimization Toolbox). The approach aligns with the assumptions of the simulation testbed described in Section 2.4, where each sub-band experiences independent AWGN conditions. As a result, the adaptive threshold responds dynamically to real-time energy and SNR fluctuations, improving the probability of detection while minimizing false alarms across all 32 sub-bands.

Following the convex optimization stage, the optimized thresholds Γ_k^* were applied to the energy values of each sub-band to determine channel occupancy decisions. To validate the reliability of these decisions, a histogram-based analysis was performed. The histogram represents the distribution of energy samples across all sub-bands, illustrating the separation between noise-dominated and signal-dominated regions. By observing the spread and clustering of energy levels around the optimized thresholds, the algorithm dynamically adjusts to varying noise conditions and improves the distinction between occupied and unoccupied channels. The resulting decision map for all 32 sub-bands forms the basis for the performance evaluation presented in the subsequent section.

2.5 Sub-band Channel Classification and Analysis

This stage of the work involves plotting a histogram for each OFDM sub-band channel based on the adaptive thresholding of the coefficients of the channel. The analysis was based on the spread of data in the histogram. Using the histogram and analysis information, the stage classified each sub-band channel of the OFDM filter bank as either a channel with information or a channel without information. Channels whose sub-band energy have higher magnitude than their corresponding Adaptive threshold are said to be occupied, while channels with lower magnitude than their corresponding Adaptive threshold would be said to be unoccupied.

3. Results and Discussion

the performance of the proposed algorithm was evaluated in a MATLAB simulation environment. A synthetic wideband OFDM signal was generated with a total bandwidth of 20 MHz, divided into $N=32$ sub-bands using an FFT-based filter bank. Each sub-band contained OFDM symbols modulated with QPSK or 16-QAM, with 64 sub-carriers and a cyclic prefix of 1/8. The primary user (PU) activity was modelled as random occupancy of a subset of the sub-bands, while the secondary user (SU) attempted to detect spectrum holes. The received

signal was transmitted over an additive white Gaussian noise (AWGN) channel, and the signal-to-noise ratio (SNR) was varied from -10 dB to $+10$ dB in steps of 5 dB. For each SNR value, 1000 Monte Carlo trials were conducted to obtain reliable estimates of the detection probability P_d and false alarm probability P_{fa} . Receiver operating characteristic (ROC) curves were generated by sweeping the adaptive threshold values across the valid range. Processing time was measured from the MATLAB execution environment.

The following assumptions were made:

- (i) The noise is Gaussian and stationary
- (ii) Perfect synchronization between transmitter and receiver is available
- (iii) The channel is flat fading or AWGN without multipath.
- (iv) The FFT size and sub-band partitions are known at the receiver.
- (v) The PU signal is modelled as standard OFDM without advanced coding or multiple antennas.

These assumptions are common in spectrum sensing studies and provide a controlled baseline for evaluating detection algorithms.

3.1 Signal Decomposition

Figure 5 shows the distribution of coefficients in 32 sub-band channels after decomposition of input signal by FFT filter bank. Figure 6 shows the energy profile of the 32 sub-band channels with varying energy values that can be observed across each sub-band channel, with sub-band channels 16 to 18 having the lowest energy. These channels are vacant as they are characterized by noise. Sub-band channels 9 and 25 have the highest energy values.

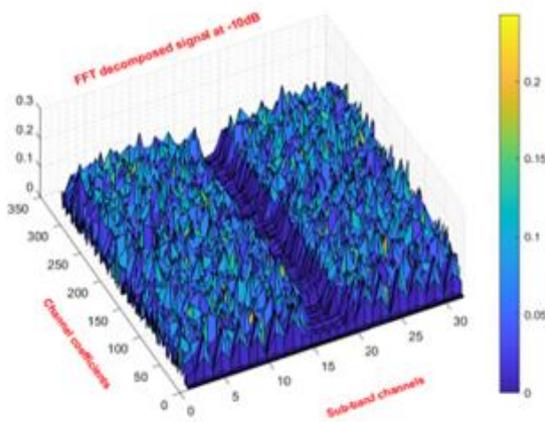


Figure 5: Distribution of coefficients in 32 sub-band channels after decomposition of input signal by FFT filter bank

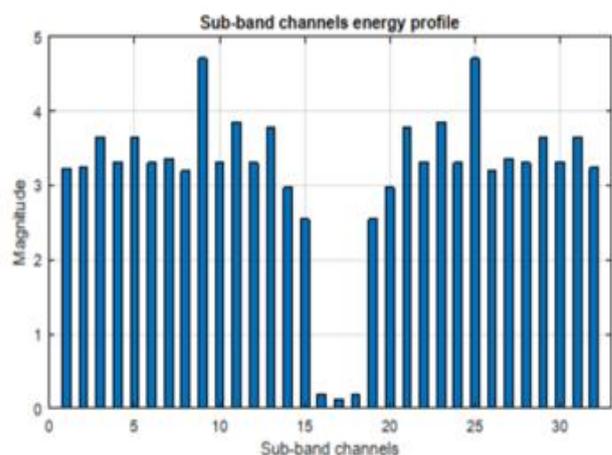


Figure 6: Energy profile in sub-band channels

The histogram analysis of these channels is shown in Figures 7a and 7b, where the sub-band channels with strong signal values have larger number of bins than sub-band channels with weak or no signal values.

3.2 Threshold design

Figures 8–12 illustrate the energy distribution across the 32 FFT sub-bands for SNR values of -10 dB, -5 dB, 0 dB, 5 dB, and 10 dB respectively. These plots were generated from the simulation testbed described in Section 3.0, using OFDM-modulated signals with random PU occupancy. As assumed, the channel was AWGN and synchronization was perfect, which allows the sub-band energy to closely reflect the effect of noise at low SNRs. At -10 dB as shown in Figure 8, only two sub-band channels were correctly identified as occupied due to the low SNR and noise significance. With an increase to -5 dB as shown in Figure 9, ten sub-band channels were identified. At 0 dB as shown in Figure 10, more channels were identified as occupied.

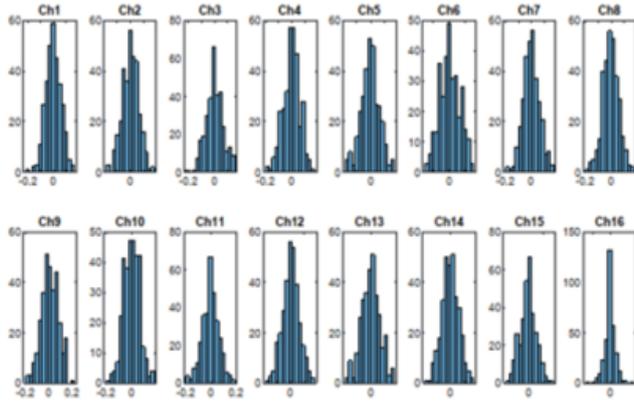


Figure 7a: Histogram analysis of sub-band channels 1 to 16

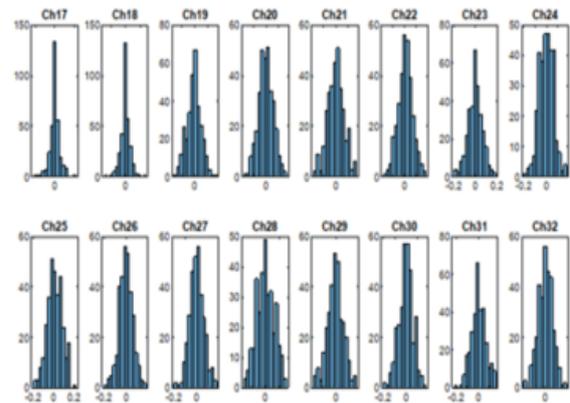


Figure 7b: Histogram analysis of sub-band channels 17 to 32

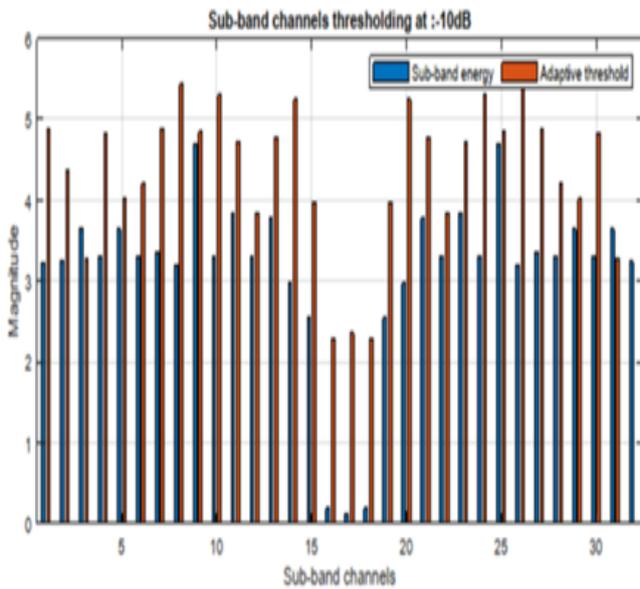


Figure 8: Thresholding at -10dB with 2 channels correctly identified as Occupied

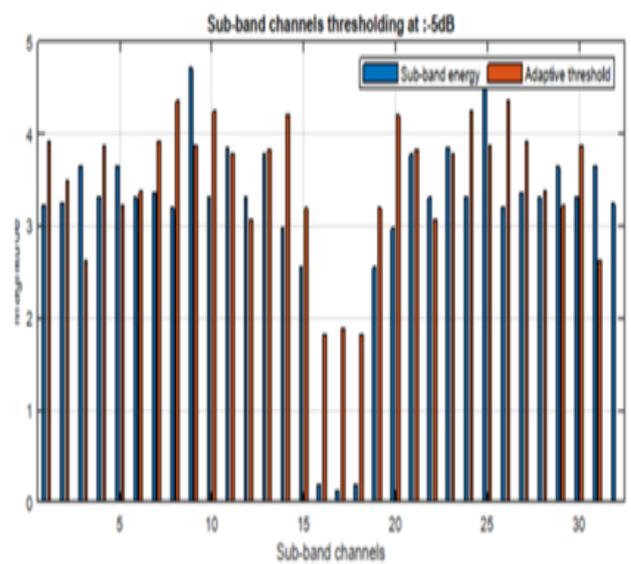


Figure 9: Thresholding at -5dB with 10 channels correctly identified as Occupied

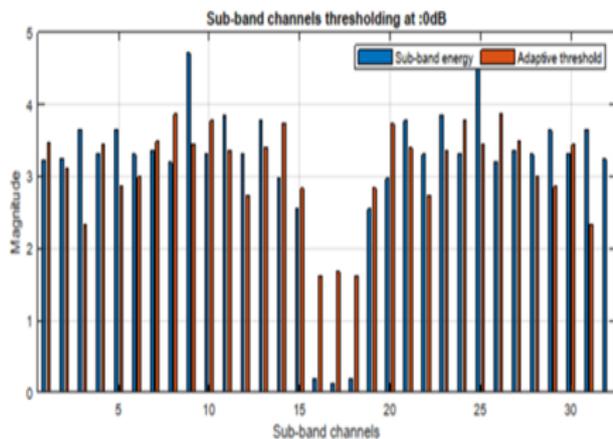


Figure 10: Thresholding at 0dB, 15 channels were correctly identified as Occupied.

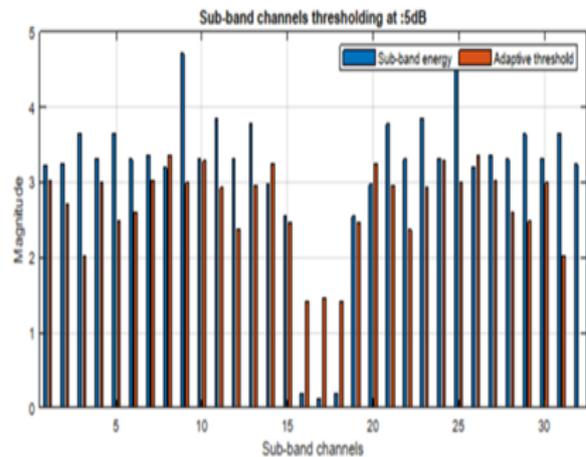


Figure 11: Thresholding at 5dB, 23 channels were correctly identified as Occupied

Further increasing the SNR to 5dB as shown in Figure 11 resulted in more accurate identification of occupied channels. In Figure 12, almost all channels were identified at 10dB SNR except for channels 16 to 18. As the SNR increases, the threshold is able to make better decisions since the difference between the signal and noise energy in each sub-band channel is becoming clearer.

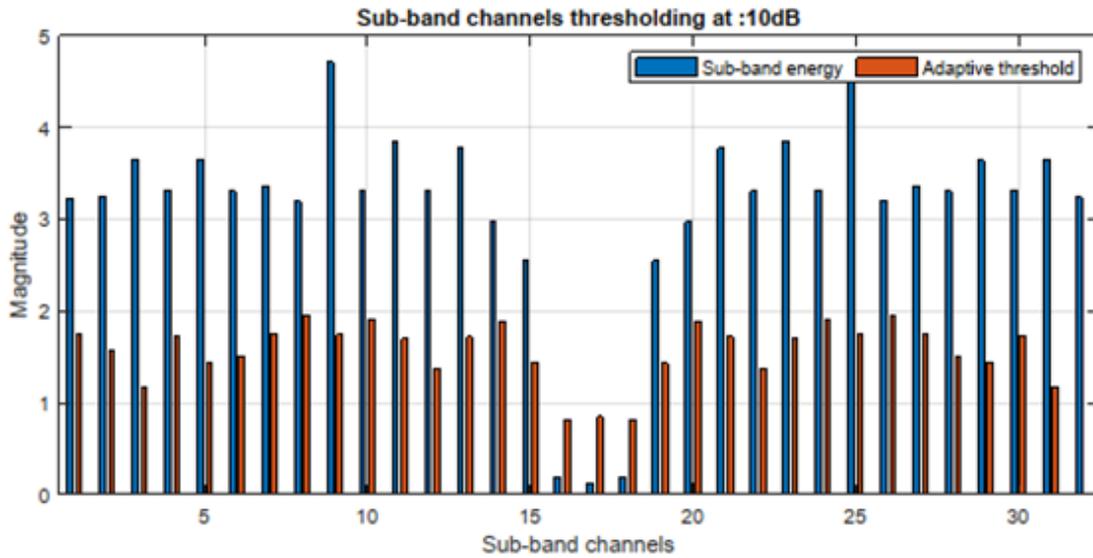


Figure 12: Thresholding at 10dB, all channels are correctly identified

3.3 ROC Curve Analysis

The ROC characteristics of the thresholding system at different SNR values and for varying probability of false alarm P_{fa} with corresponding probability of detection P_d is shown in Figure 13. The ROC curve shows the accuracy of the probability of detection, curves closer to the top-left corner indicate a better performance. The curve for a SNR of 10 dB appears at the top-left corner shows that the accuracy is higher at higher SNR. For the case of varying the probability of detection against SNR, the ROC curve indicates the ability of the system to distinguish between the signal and the noise. It evaluates the performance of the classification system as shown in the ROC curve in Figure 14.

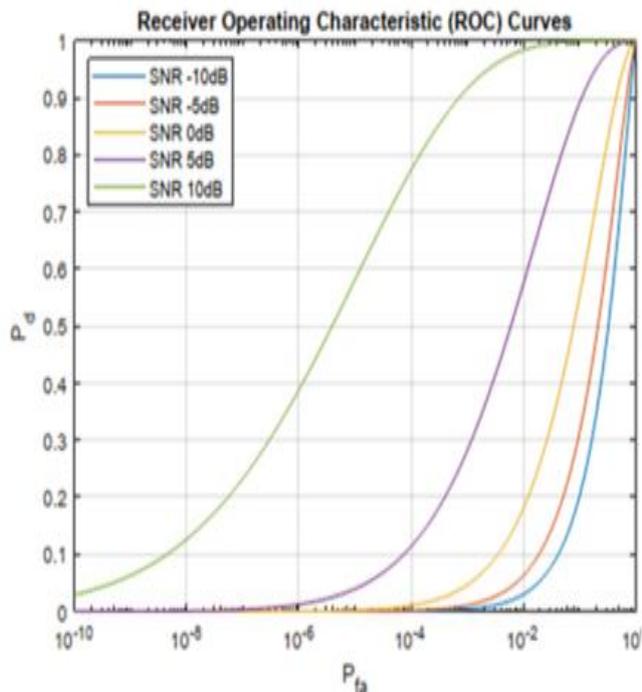


Figure 13: ROC performance P_d against p_{fa}

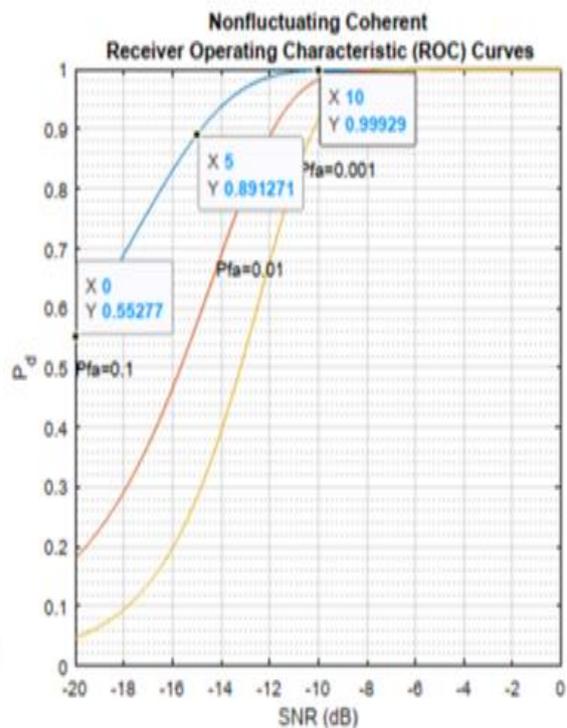


Figure 14: ROC performance for varying SNR values

3.5 Performance Evaluation

Figure 13 presents the ROC performance derived from 1000 Monte Carlo trials per SNR value, using the synthetic wideband OFDM signal described in the testbed. The ROC curves confirm that the convex-optimized adaptive threshold improves the trade-off between P_d and P_{fa} compared with fixed threshold

detection under the AWGN assumption. Despite AWGN's mathematical convenience, real-world channels diverge from it in ways that reduce this straightforward categorization technique's efficacy. Figure 14 shows the detection probability P_d as a function of SNR, computed using the testbed assumptions (AWGN channel, 32 sub-bands, random PU activity). Results demonstrate that at higher SNRs (≥ 0 dB), nearly all sub-bands were correctly classified as occupied, consistent with the expectation under Gaussian noise. At 10 dB, the algorithm achieved $P_d=0.9686$ for $P_{fa}=0.1$. Table I shows a performance comparison of results obtained from related work (Alom 2017; Saleh 2021; Wang 2022); the results are compared by taking into consideration various parameters. Some of the work show that the sensitivity of the ROC characteristics to be low, while some have high sensitivity. For the accuracy, the probability of detection P_d was varied with SNR at fixed values of probability of false alarm P_{fa} . The probability of false alarm was chosen at 0.1, and it was observed that the probability of detection P_d decreases as the SNR decreases. The probability of detection also increases with increase in the SNR.

For performance benchmarking, the proposed FFT-based convex optimization method was compared with the adaptive energy detection approach reported by Wang *et al.* (2022), which employed a similar wideband OFDM configuration and operated within the L-band frequency range under comparable SNR conditions (-10 dB to 10 dB). This alignment in system parameters makes Wang *et al.*'s works an appropriate baseline for evaluating the effectiveness of the proposed algorithm.

Table I: Performance comparison of spectrum sensing methods under AWGN, 32 sub-bands, SNR $\in [-10, 10]$ dB, and $P_{FA} = 0.1$

Method (Ref)	Technique / Feature	Threshold Type	Complexity	P_D @ -10 dB	P_D @ 0 dB	P_D @ 10 dB	Notes
Alom 2017	Adaptive Energy Detection	Adaptive (statistical)	Low	0.3482	0.5731	0.7863	Reduces sensing time but suffers at low SNR
Saleh 2021	Asynchronous Cooperative Sensing	Fixed / Cooperative	High	0.4121	0.6243	0.8671	Improved Pd via cooperation, but latency issues
Wang 2022	Adaptive ED (L-band)	Adaptive	Medium	0.5542	0.8713	0.9284	Good trade-off but requires iterative update
Proposed (This Work)	FFT Sub-band + Convex Optimized Threshold	Adaptive (Convex optimization)	Low	0.6781	0.8973	0.9686	Improved accuracy due to the optimization.

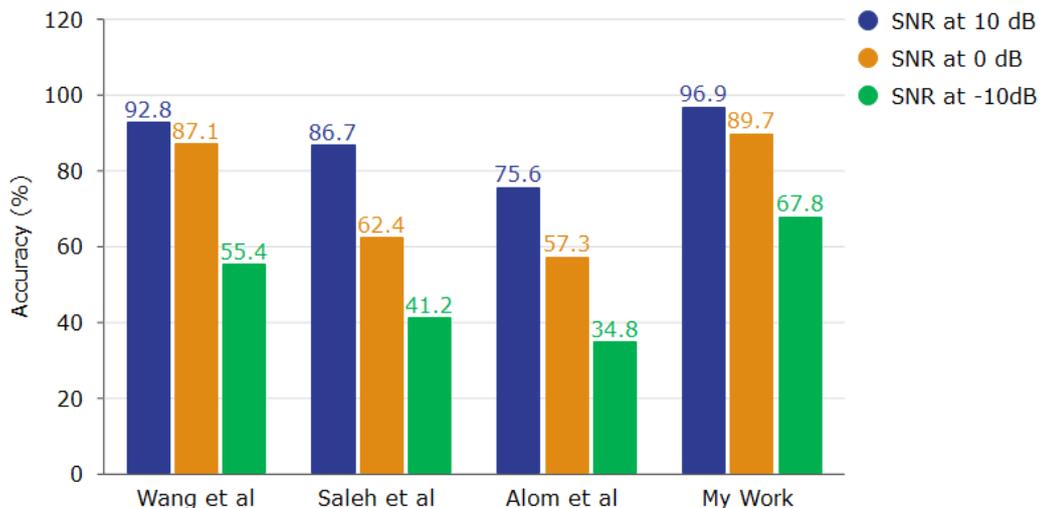


Figure 15: Accuracy performance comparison with related works

Figure 15 compares the accuracy of the proposed method with related work (Alom 2017; Saleh 2021; Wang 2022). The same testbed parameters were applied to all simulations to ensure fairness of comparison: AWGN channel, 32 sub-bands, SNR $\in [-10, 10]$ dB, and Monte Carlo averaging. The improved accuracy of the

proposed method at higher SNRs is attributed to the convex optimization of thresholds, whereas competing methods either rely on fixed thresholds or more complex likelihood tests under the same assumptions. We compared against Alom 2017 (adaptive ED, reduced sensing time), Saleh 2021 (asynchronous sensing), and Wang 2022 (adaptive ED for L-band). We report P_d at fixed $P_{fa}=0.1$ across $\text{SNR} \in \{-10, -5, 0, 5, 10\}$ dB. Our method attains $P_d=0.9686$ at 10 dB with low processing time due to FFT-based decomposition, outperforming the baselines at high SNR. Differences are attributable to convex-optimized per-sub-band thresholds (better separation) vs fixed thresholds or likelihood tests (slower) in baselines.

4. Conclusion

In the scope of this work, the problem of spectrum underutilization which is associated with wireless communication was identified. Cognitive radio was identified as an ideal solution due to its ability to share unoccupied channels. The OFDM technology was also introduced due to its ability to improve spectral efficiency and transmit higher data rates. Most of the work reviewed tend to trade-off low complexity for classification accuracy, while some authors trade-off classification accuracy for low complexity.

When compared to alternative techniques, the proposed method of adaptive thresholding for OFDM sub-band channel classification is more economical in system resource utilization, providing the best possible balance between cheap computational cost and adequate performance for the majority of commercial applications. In addition to being substantially less expensive and more power-efficient than sophisticated methods like machine learning or compressive sensing, which give declining returns for most use cases, it greatly beats straightforward fixed-threshold approaches with little additional complexity. Because of this, adaptive thresholding is the preferred option for consumer Wi-Fi, IoT, and cellular systems where simplicity, power consumption, and implementation cost are crucial. It maintains its position as the most practical and cost-effective option in the wide wireless market by acting as a flexible foundational technique that can be improved with lightweight intelligence for future systems.

Additionally, this technique's introduction of a critical layer of channel-aware intelligence into OFDM systems at a surprisingly cheap computing cost is one of its key contributions. By converting the physical layer from a static conduit into an adaptive, self-optimizing resource, it directly increases throughput accuracy by an average of about 4.1% and 4.03% for both efficiency and reliability while opening the door to more sophisticated features like fine-grained multi-user scheduling and cognitive radio. By striking a balance between very low complexity and moderate accuracy, adaptive thresholding for OFDM sub-band classification achieves an ideal engineering compromise, placing itself at the "knee of the curve" where performance gains per unit of additional cost are maximized. The proposed method avoids the disproportionate complexity of advanced techniques like machine learning or compressive sensing, which offer diminishing accuracy returns, and performs significantly better than simpler fixed-threshold methods with only a slight increase in computational load—using basic statistics and comparisons. Because of this, it is the most popular and affordable option for mainstream wireless systems. It offers enough accuracy to allow adaptive modulation and reliable resource allocation in typical frequency-selective channels, but its equilibrium is upset by highly non-Gaussian interference or extreme mobility, which calls for more sophisticated techniques.

The use of convex optimization technique to optimize the data points of the OFDM signal improved the classification accuracy. The results of this work were compared with other similar work, our work showed improved accuracy and also low processing time.

With the rapid growth of cellular technology, various investigations are being carried out to continue ensuring the sustainability of mobile communication services. The results of this research point to an intriguing path, which can be pursued in future work. Some areas to be considered may include, testing the algorithm in fading channel models (e.g., Rayleigh, Rician) to evaluate robustness, Investigating the integration of machine learning for online estimation of the optimization parameters and implementing the algorithm on a software-defined radio (SDR) testbed for validation with real RF signals. There is still room for improvement in the areas of spectral efficiency. Hence, the new variants of the Orthogonal Multiple Access (OMA) technique which can further improve the spectral efficiency can be used towards the realization of 6G.

References

Abbaszadeh, MH., Khalaj, BH. and Haghbin, A. 2018. Optimum low complexity filter bank for generalized orthogonal frequency division multiplexing. <https://doi.org/10.1186/s13638-017-1017-x>

- Alom, MZ., Godder, TK., Morshed, MN. and Maali, A. 2017. Enhanced spectrum sensing based on Energy detection in cognitive radio network using adaptive threshold. Proceedings of 2017 International Conference on Networking, Systems and Security, NSysS 2017: 138–143. <https://doi.org/10.1109/NSysS.2017.7885815>
- Bhardwaj, M., Gangwar, A. and Soni, D. 2012. A Review on OFDM: Concept, Scope & its Applications. In IOSR Journal of Mechanical and Civil Engineering (IOSRJMCE), 1(1).
- Dibal, PY., Onwuka, EN., Agajo, J. and Alenoghena, CO. 2018. Application of wavelet transform in spectrum sensing for cognitive radio: A survey. Physical Communication, 28: 45–57.
- Helif, S., Abdulla, R. and Kumar, S. 2015. A review of energy detection and cyclostationary sensing techniques of cognitive radio spectrum. 2015 IEEE Student Conference on Research and Development, SCORED 2015, September 2016: 177–181. <https://doi.org/10.1109/SCORED.2015.7449319>
- Hong, S., Zhang, Y., Wang, Y., Gu, H., Gui, G. and Sari, H. 2019. Deep Learning-Based Signal Modulation Identification in OFDM Systems. IEEE Access, 7:114631–114638.
- Lorincz, J., Ramljak, I. and Begušić, D. 2021. A survey on the energy detection of OFDM signals with dynamic threshold adaptation: Open issues and future challenges. Sensors, 21(9). <https://doi.org/10.3390/s21093080>
- Mahanta, M., Taparugssanagorn, A. and Pati, BM. 2022. Assessment of spectrum sensing using support vector machine combined with principal component analysis. International Journal of Sensor Networks, 39(4): 256-278.
- Onumanyi, AJ., Abu-Mahfouz, AM. and Hancke, GP. 2018. A comparative analysis of local and global adaptive threshold estimation techniques for energy detection in cognitive radio. Physical Communication, 29: 1–11. <https://doi.org/10.1016/j.phycom.2018.04.008>
- Pan, G., Li, J. and Lin, F. 2020. A Cognitive Radio Spectrum Sensing Method for an OFDM Signal Based on Deep Learning and Cycle Spectrum. International Journal of Digital Multimedia Broadcasting, 2020. <https://doi.org/10.1155/2020/5069021>
- Park, S., Won, YS., Choi, YC., and Kim, JH. 2009. Molecular Design of Organic Dyes with Double Electron Acceptor for Dye-sensitized Solar Cell. Energy & Fuels, ACS Publications
- Qin, Z., Wang, N., Gao, Y. and Cuthbert, L. 2012. Adaptive Threshold for Energy Detector Based on Discrete Wavelet Packet Transform. 2:2–6.
- Salahdine, F., Ghazi, H. El, Kaabouch, N. and Fihri, W. F. 2016. Matched filter detection with dynamic threshold for cognitive radio networks. International Conference on Wireless Networks and Mobile Communications, WINCOM 2015. <https://doi.org/10.1109/WINCOM.2015.7381345>
- Salam, AOA., Sheriff, RE., Al-Araji, SR., Mezher, K. and Nasir, Q. 2019. Adaptive threshold and optimal frame duration for multi-taper spectrum sensing in cognitive radio. Elsevier - ICT Express, 5:31–36. <https://doi.org/10.1016/j.icte.2018.02.002>
- Saleh, MM., Abbas, AA. and Hammoodi, A. 2021. 5G cognitive radio system design with new algorithm asynchronous spectrum sensing. 10(4): 2046–2054. <https://doi.org/10.11591/eei.v10i4.2839>
- Shi, Z., McLernon, D., Ghogho, M., & Wu, Z. 2014. Improved spectrum sensing for OFDM cognitive radio in the presence of timing offset. Eurasip Journal on Wireless Communications and Networking, 2014(1), 1–9. <https://doi.org/10.1186/1687-1499-2014-224>
- Silva, PEG., Moualeu, JM., Nardelli, PH., Li, Y. and de Souza, RA. 2024, June. An Efficient Machine Learning-Based Channel Prediction Technique for OFDM Sub-Bands. In 2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring): 1-5.

Wahla, AH., Member, S., Chen, LAN. and Lee, M. 2019. Automatic Wireless Signal Classification in Multimedia Internet of Things: An Adaptive Boosting Enabled Approach. *IEEE Access*, 7: 160334–160344. <https://doi.org/10.1109/ACCESS.2019.2950989>

Wang, L., Liu, M., Zhang, J. and Li, D. 2022. Adaptive Threshold Energy Detection Spectrum Sensing Method for L-Band Digital Aeronautical Communication System. *Hindawi - Security and Communication Networks*, 2022: 1–7. <https://doi.org/10.1155/2022/4325515>

Wang, N., Gao, Y. and Cuthbert, L. 2014. Spectrum sensing using adaptive threshold based energy detection for OFDM signals. 2014 IEEE International Conference on Communication Systems, *IEEE ICCS 2014*: 359–363. <https://doi.org/10.1109/ICCS.2014.7024825>

Xu, W., Xiang, W., Elkashlan, M. and Mehrpouyan, H. 2016. Spectrum Sensing of OFDM Signals in the Presence of Carrier Frequency Offset. *IEEE Transactions on Vehicular Technology*, 65(8): 6798–6803. <https://doi.org/10.1109/TVT.2015.2478517>

Youn, Y., Jeon, H. and Lee, H., Discrete wavelet packet transform based energy detector for Cognitive radios. 2007 IEEE 65th Vehicular Technology Conference-VTC2007-Spring, 2007.

Yücek, T. and Arslan, H. 2004. A Novel Sub-Optimum Maximum-Likelihood Modulation Classification Algorithm for Adaptive OFDM Systems