International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 6, December 2025, pp. 5401~5410
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i6.pp5401-5410

Enhanced spectrum sensing in MIMO-OFDM cognitive radio networks using multi-user detection and square-law combining techniques

Srikantha Kandhgal Mochigar[1,2], Rohitha Ujjini Matad[1], Premachand Doddamagadi Ramanaik[2]
[1]Department of Electronics and Communication Engineering, Proudhadevaraya Institute of Technology Hosapete, affiliated to Visvesvaraya Technological University, Belagavi, India
[2]Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management Ballari, affiliated to Visvesvaraya Technological University, Belagavi, India

Article Info

Article history:

Received Sep 23, 2024
Revised Jul 9, 2025
Accepted Sep 14, 2025

Keywords:

Cognitive radio
Energy detection
Multiple-input multiple output
Multi-user detection square-law combing
Orthogonal frequency division multiplexing
Spectrum sensing

ABSTRACT

Spectrum sensing (SS) is essential for cognitive radio (CR) networks to enable secondary users to opportunistically access unused spectrum without interfering with primary users. This article proposes a novel multi-user detection (MUD) and square-law combining (SLC) framework for SS in multiple-input multiple-output (MIMO) and orthogonal frequency division multiplexing (OFDM) CR networks. Traditional SS methods, especially energy detection (ED), often underperform in low signal-to-noise ratio (SNR) conditions, resulting in high false alarm rates due to noise uncertainty and multi-user interference. The multi-user detection-square-law combining (MUD-SLC) framework addresses these limitations by using MUD to separate user signals and SLC to combine energy from multiple antennas, significantly improving probability of detection (PD) while maintaining a low false alarm probability (Pfa). Simulation results show that the proposed approach achieves a PD of 0.81 at Pfa=0.15 and SNR=15 dB, outperforming conventional and advanced SS methods. Moreover, MUD-SLC demonstrates a considerable boost in detection performance, even in the presence of severe interference and noise uncertainty, leading to more reliable spectrum utilization in systems. The framework also maintains a lower Pfa, especially in dynamic wireless environments. This research work contributes to improving the efficiency and reliability of SS in CR networks.

Corresponding Author:

Srikantha Kandhgal Mochigar
Department of Electronics and Communication Engineering, Proudhadevaraya Institute of Technology, Hosapete, affiliated to Visvesvaraya Technological University
Belagavi-590018, Karnataka, India
Email: srikanthkm2019@gmail.com

1. INTRODUCTION

The rapid expansion of wireless communication has resulted in an increasingly congested radio spectrum, creating challenges for efficient spectrum utilization. Conventional static spectrum allocation techniques fail to effectively address this challenge, as licensed frequency bands are often underutilized. To overcome this limitation, cognitive radio (CR) systems have emerged as a promising solution by enabling dynamic spectrum access (DSA), which allows secondary users (SUs) to opportunistically access idle licensed spectrum without interfering with primary users (PUs) [1], [2]. As highlighted in a comprehensive survey on next generation CR networks [3], CR systems utilize DSA techniques to analyze the radio environments, identify spectrum gaps and permit SUs to occupy these idle frequency bands. This approach not only enhances spectrum utilization but also facilitates the creation of more flexible and adaptive network frameworks. Effective spectrum sensing (SS) is crucial SUs to exploit underutilized spectrum in CR networks. Energy detection (ED) is widely used due to its simplicity and adaptability to diverse communication scenarios. However, ED-based techniques often face challenges in low signal-to-noise ratio (SNR) conditions, where noise uncertainty (NU) can result in higher false alarm and missed detection rates [4], [5].

Advanced spectrum sensing techniques are being developed, focusing on signal characteristics that distinguish licensed signals from background noise. By analyzing spatial and temporal signal properties, these methods enhances detection accuracy [6]. Several enhancements to ED have been proposed, such as dynamic thresholding, to improve performance under varying noise levels. For example, Ye *et al.* [7] demonstrated that adaptive threshold adjustments based on real-time noise variance could significantly improve SS reliability. By factoring in noise variance estimates, the researchers demonstrated that the system can produce more precise detection outcomes, even in environments with significant noise and uncertainty. Additionally, highlights that conventional ED methods, which use fixed thresholds, are prone to increased false alarm probability (Pfa) and missed detection, particularly when noise levels fluctuate [8]. The presence of multiple antennas in multiple-input multiple-output (MIMO) systems improves signal detection in low-SNR conditions. While orthogonal frequency division multiplexing (OFDM) optimizes spectrum utilization by breaking the signal into orthogonal subcarriers. The integration of MIMO and OFDM technologies in CR systems has proven to be a practical approach to improving both spectral efficiency and overall system performance cognitive radios (CRs) allow dynamic access to underutilized spectrum, while MIMO and OFDM offer advantages like spatial diversity and increased resilience to multipath fading [9]–[15].

In Rawat's study [16], the performance of CR users in multiple-input multiple-output-orthogonal frequency division multiplexing (MIMO-OFDM) wireless networks is assessed, with a particular focus on how these technologies improve SS and data transmission in CR systems. The research shows that the combination of MIMO and OFDM greatly enhances the reliability of SS by utilizing spatial diversity and frequency selectivity. ED faces notable challenges, particularly in environments with NU, which arises due to factors such as temperature variations, interference and imperfect filtering. These fluctuations can exceed predicted values, causing the performance of ED to degrade, especially under low-SNR conditions. Additionally, the trade-offs among critical parameters like the number of samples, NU levels, and Pfa require careful calibration to maintain consistent detection performance. Addressing these challenges is essential to enhance ED's applicability and ensure its robustness in diverse and dynamically changing wireless environments [17]. While Deep-CRNet demonstrates impressive performance in accurately detecting PU activity and identifying spectrum holes in CR networks, certain challenges remain. The systems reliance a deep learning method such as multi-kernel convolutions and residual connections, introduces a significant computational burden. Additionally, the detectors performance may depend heavily on the quality and diversity of training data, potentially making it vulnerable to variations in transmission patterns or network dynamics that were not considered during the training process [18], [19].

The integration of intelligent reflecting surface significantly enhances SS accuracy by leveraging its ability to manipulate reflections and strengthen weak signals from the PUs. This result in more reliable detection outcomes even in challenging environments. Techniques such as block coordinate descent, successive convex approximation and semidefinite relaxation are computationally intensive and may increase system latency [20]. Full-duplex operation modes enable simultaneous transmission and reception, reducing SS delays while improving throughput compared to traditional half-duplex methods. These modes significantly enhances the networks responsiveness to changes in frequency availability [21]. Sivagurunathan *et al.* [22] reviews various SS technique, their classification and their underlying methodologies. It explores the strengths and weaknesses of these approaches, offering valuable insights into potential improvements. The survey also identifies key challenges and opportunities in the field, providing a roadmap for enhancing existing SS techniques [22]. Recent advancements have incorporated antenna diversity techniques such as square-law selector and square-law combining (SLC), to enhance detection accuracy. These methods have been analytically evaluated to understand their impact on detection performance. However, practical challenges like radio frequency (RF) impairments and fading models complicate the hardware implementation of these techniques [23]. This section reviews the existing research on ED and SS in MIMO-OFDM-based CR networks, highlighting both their benefits and limitations.

Lorincz *et al.* [24] developed an algorithm to simulate the ED process in cognitive MIMO-OFDM systems using the SLC technique. The SLC technique is employed to enhance the ED process by combining signals from multiple antennas. This method improves the overall SNR, making it easier to detect the presence of signals. However, the study did not comprehensively investigate the impact of variations in noise uncertainty (NU) and the adjustments to the dynamic detection threshold (DT) on the performance of ED and it was confined to a particular MIMO-OFDM system model. The analysis does not explore the potential benefits of advanced modulation schemes on detection performance.

Lorincz *et al.* [25] introduced an innovative algorithm to simulate ED process using SLC, evaluating its performance across different operational scenarios. Their findings highlighted that enhancing the number of receive antennas od the SU side significantly improves ED performance compared to increasing the number of transmit antennas on the PU side. Nevertheless, their study was confined to ED, making it less effective in scenarios with low SNR or severe channel fading. Furthermore, the impact of the advanced modulation techniques on detection performance was not explored in their analysis.

Lorincz *et al.* [26] developed a mathematical model aimed at exploring the relationship between key parameters and detection performance, with a focus on optimizing the detection threshold to enhance the reliability of SS. The study examined how variations in the DT and NU influence the effectiveness of ED in MIMO-OFDM CR systems. However, the analysis failed to consider the potential interference from other users or external sources, which could notably impact the performance of ED.

Pan *et al.* [27] introduced a framework that harnesses deep learning techniques to improve the accuracy and reliability of SS in dynamic wireless environment. It proposes a new method for SS in CR Networks, employing deep learning and cycle spectrum analysis to identify OFDM signals. However, the learning approach demands considerable computational resources and expertise in model training, this could create difficulties for deployment in environments with limited resources.

Al-Amidie *et al.* [28] developed a generalized likelihood ratio test (GLRT) detector using a Bayesian framework to tackle uncertainties in the noise covariance matrix and channel gain. Their work presents a robust SS detector designed for MIMO CR systems, particularly when the Channel State Information (CSI) is imperfect. The proposed solution effectively addresses SS uncertainties under the given assumptions. However, the study focuses solely on the SS challenge, without accounting for additional factors such as resource allocation or throughput optimization within CR networks. Additionally, the robust detector may involve higher computational complexity.

Zaimbashi [29] proposed a SS method for multi-antenna CR systems using a one-step likelihood test (LRT) based on the covariance matrix of the received signal. The proposed E-SSE detectors outperformed traditional methods like SSE and MME in simulation environments. However, the work assumes ideal conditions and does not account for real world issues such as hardware imperfections, mobility or interference. Additionally, it does not address signal detection in OFDM systems or multi-user scenarios. In contrast, the work introduces a multi-user detection-square-law combining (MUD-SLC) framework tailored for MIMO-OFDM networks, capable of handling interference and dynamic spectrum conditions effectively.

Overall, current cognitive SS approaches face challenges, robust detection methods often lead to increased computational complexity. Additionally, many of these approaches are restricted to basic ED, which can underperform in low-SNR conditions or with significant channel fading. The impact of interference in SS is also frequently overlooked, which can result in reduced efficiency due to elevated false alarm rates.

In this research, the MUD-SLC technique to create a robust and efficient SS solution for MIMO-OFDM CR networks. The important findings of this research are listed as.

a. Separation of signals: MUD plays a critical role in separating signals from multiple users. This is especially important in multi-user CR environments where primary and secondary users share the same spectrum. By reducing the interference between users, MUD enhances detection performance.
b. Combining energy for robust detection: SLC boosts detection performance by combining the received signal energy from multiple antennas or subcarriers, thus improving SNR and making the system more resilient to noise and fading. This facilitates a more dependable detection process, even in adverse conditions.
c. Improved spectrum utilization: by enhancing the detection performance in multi-user environments, the system enables secondary users to more effectively access unused spectrum, improving overall spectrum utilization in CR networks.
d. Increased network reliability: the integration of MUD and SLC ensures that spectrum holes are detected with high accuracy, even in challenging environments such as low-SNR or fading channels. This leads to more reliable network performance, with fever missed detection opportunities and false alarms.

The structure of the research paper is as follows: section 2 outlines the proposed methodology; section 3 provides an analysis of the results along with the discussion and section 4 offers the conclusions drawn from the research.

2. PROPOSED METHOD

In this research, MUD-SLC technique is proposed for the SS in MIMO-OFDM CR network, where SS is enhanced using MUD and SLC techniques. The objective of the system is to efficiently detect the presence of PU in a shared spectrum environment while allowing SUs to access available spectrum without causing harmful interference. The schematic representation of MUD-SLC technique is presented in Figure 1.

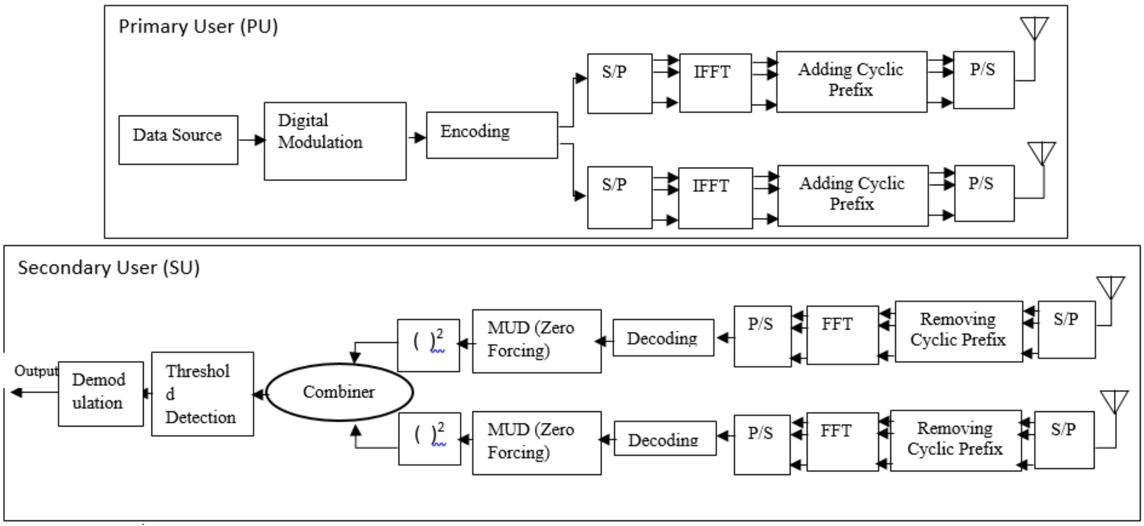

Figure 1. Functional components of the MIMO-OFDM communication system utilizing ED for SS, Implemented through MUD-SLC technique

2.1. System model

The proposed framework operates within a MIMO-OFDM CR network, leveraging spatial and frequency diversity to enhance SS. The system consists of N_t transmit antennas at the PU and N_r receive antennas at the SU. MIMO technology enables spatial diversity, while OFDM mitigates frequency-selective fading by dividing the signal N orthogonal subcarriers. The received signal at the i^{th} antenna is expressed as

$$y_i = H_i x + n_i \quad (1)$$

where H_i represents channel matrix modelling path loss, fading and interference. x represents vector of transmitted signals from PU antennas, modulated using QPSK or QAM. n_i represemts noise with zero mean and variance σ^2. To mitigate interference, the proposed system employes MUD to separate overlapping signals from multiple users. SLC aggregates the energy across N_r antennas to improve the effective SNR for reliable detection.

2.2. Multi-user detection (MUD)

Multi-user detection (MUD) is a enhance technique in wireless communication systems, particularly in scenarios where multiple users transmit data simultaneously over shared channels. The goal of MUD is to decode the signals of multiple users by accounting for the interference between them, thus improving overall system performance. MUD is especially critical in code- division multiple access (CDMA), OFDM and MIMO systems, where users or antennas share the same frequency band. The zero-forcing (ZF) detector eliminates interference by multiplying the received signal by the pseudo-inverse of the channel matrix H. The ZF solution is given by:

$$\hat{X} = (H^H H)^{-1} H^H \quad (2)$$

where $\hat{X}$ is the estimated transmitted signal vector, and H is the aggregate channel matrix across all users. While ZF effectively removes interference, it can amplify noise when the channel matrix H is ill conditioned.

2.3. Square-law combining

Square-law combining (SLC) is a diversity-combining technique often used in communication systems to improve detection performance under fading channels. SLC is typically applied in ED for SS, where the signals energy is combined across multiple branches (*e.g.* antennas or subcarriers). SLC computes the energy of the received signal and sums the energy from all branches. This is particularly effective when the signal is weak, as it can improve the probability of detection (PD) without needing to decoding the exact transmitted data. Consider a communication system with N_r receive antennas and let the received signal on the i^{th} branch be denoted by $r_i(t)$. The SLC output is the sum of the squared magnitudes of the received signals, given by:

$$E_{combined} = \sum_{i=1}^{N_r} |y_i|^2 \tag{3}$$

where, $|y_i|^2$ represents the energy of the signal received on the i^{th} branch. The decision on whether a signal is present or absent is made by comparing the combined energy E with a threshold λ.

$$Dicision: E \begin{cases} > \lambda\, Signal\ present \\ \leq \lambda\, Signal\ absent \end{cases} \tag{4}$$

For SLC, the effective SNR after combining is given by:

$$SNR_{COMBINED} = \frac{1}{N_r} \sum_{i=1}^{N_r} SNR_i \tag{5}$$

This shows that combining the energy across N_r branches improve the overall SNR, thereby enhancing the detection performance, particularly in fading environments. In CR networks, SLC is often used for SS. It helps detect the presence of PU by measuring the energy of the received signal across multiple antennas or subcarriers. This makes SLC a valuable technique in dynamic spectrum access scenarios where reliable detection is crucial.

2.4. OFDM transmission

In the OFDM-based CR system, the wideband channel is segmented into several orthogonal subcarriers, enabling the system to mitigate frequency-selective fading. The transmitted signal x consists of modulated symbols on each subcarrier. The signal on the k^{th} subcarrier at time t is given by:

$$x_k(t) = \sum_{n=0}^{N-1} X_n e^{j2\pi nk/N} \quad k = 0,1, \dots \dots, N-1 \tag{6}$$

where, X represents the modulated data symbol on the n^{th} subcarrier, N is the number of OFDM subcarriers, the exponential term represents the subcarrier modulation. At the receiver, after MUD and SLC are applied, the system combines the received signal energies across multiple antennas and subcarriers for SS. Spectrum sensing process as:

a. Signal transmission: multiple SUs transmits their data using OFDM over shared bands.
b. Signal reception: the received signals, subject to multi-user interference and noise, are processed using MUD techniques such as ZF or MMSE.
c. Energy combining: SLC is applied to combine the energy of the received signals across multiple antennas and/or subcarriers.
d. Decision making: the combined energy is compared against the detection threshold to decide whether the spectrum is occupied by a PU or available for SU.

2.5. Computational complexity

The computational complexity of the MUD-SLC framework primarily arises from MUD algorithm and SLC energy aggregation. The ZF detector used in MUD involves matrix inversion with a complexity of $O(N_r^3)$, while SLC adds linear complexity proportional to the number of antennas $(O(N_r))$. While these operations are more efficient than data-intensive machine learning models, optimizing MUD-SLC for real-time applications is a focus for future research.

3. RESULTS AND DISCUSSION

This section presents the experimental findings and their interpretation, emphasizing the efficiency of the proposed MUD-SLC framework for SS in MIMO-OFDM CR networks. By integrating results with discussion, to provide a comprehensive understanding of how the proposed framework addresses SS challenges, particularly in low-SNR and interference-heavy scenarios. The implementation process was executed with the help of MATLAB software on a system with an intel i7 processor, windows 11 operating system and 8Gb of random-access memory (RAM). The simulation parameters for the proposed approach are outlined in Table 1.

Table 1. Simulation parameters of the proposed method

Parameters	Values
PU signal type	OFDM
NU factor ρ	1.02
DT factor ρ′	1.01
OFDM modulation type	QPSK, 16 QAM, 64 QAM
Detection sample numbers	128, 512, 256
PD and Pfa range	[0 to 1]
PU Tx branches number	1 to 2
SU Rx branches number	1 to 2
SNR at SU point (dB)	-30 to -10

3.1. Performance analysis

In this section, the efficiency of the proposed approach is evaluated using various parameters, as listed in Table 1. Figure 2 illustrates the receiver operating characteristic (ROC) curve, depicting the PD versus SNR for a 2×2 MIMO system under NU and DT conditions, with the PU transmitting at 1 W and 100 mW. Figure 3 shows the ROC curve of PD versus Pfa for a MIMO system under NU and DT factors, with the PU transmitting at 1 W. Figure 2 displays the ROC curve for a 2×2 MIMO system, showing the relationship between PD and SNR for NU and DT factors, with parameters set as Pfa=0.15, N=128, P_{TX}=1W and 100 mW.

The results indicate that as the SNR improves, the PD increases significantly, highlighting the enhanced SS performance of the MUD-SLC framework. For instance, Figure 2 illustrates the ROC curve for a 2×2 MIMO system under NU and DT conditions, showing that an SNR of -15 dB and a Pfa of 0.15, the proposed method achieves a PD of 0.81. The result outperforms conventional SLC-based methods in low-SNR scenarios, which achieve PD values of 0.77 and 0.70. The integration of MUD enables effective separation of user signals, mitigating co-channel interference, while SLC aggregates energy from multiple antennas, further boosting the overall SNR. However, NU and DT adjustment present challenges, particularly at lower SNR levels. These factors highlight the importance of designing robust algorithms to address real-world impairments in wireless environments.

Figure 3 presents the ROC curve for the same 2×2 MIMO system, illustrating the PD versus Pfa at SNR levels of -15 dB and -10 dB, with N=128 and P_{TX} =1 W. The results reveal a trade-off between the PD and the Pfa. As the SNR increases from -15 to -10 dB, the ROC curve moves toward the top-left corner of the plot, signifying an improvement in PD while maintaining the same Pfa. This trend is anticipated, as higher SNR conditions facilitate more reliable detection of PU signals.

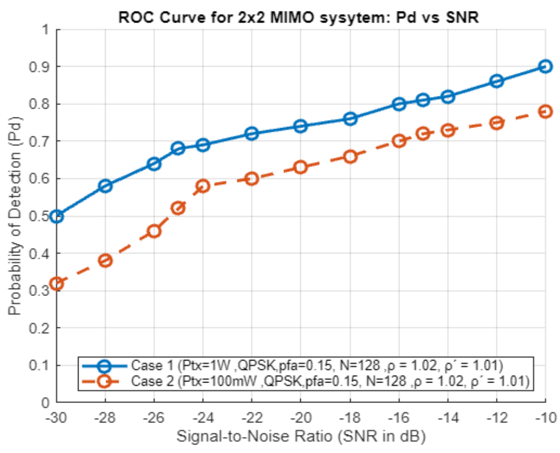

Figure 2. ROC curve of PD versus SNR for 2×2 MIMO under NU and DT factor at P_{TX} = 1 W and 100 mW

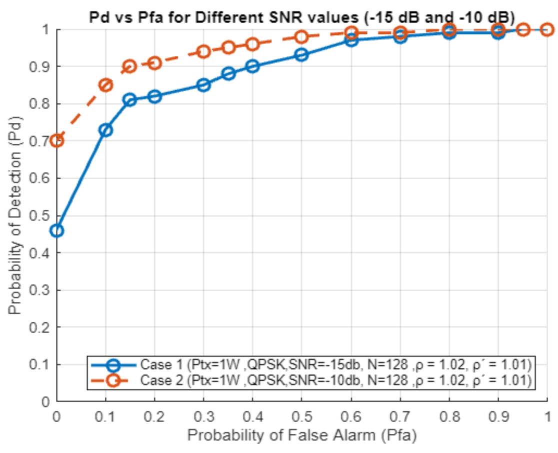

Figure 3. ROC curve of PD versus Pfa for 2×2 MIMO under NU and DT factor at P_{TX} = 1 W

The findings provide valuable insights into the effectiveness of ED for SS in MIMO-OFDm CR Networks. By evaluating factor such as noise uncertainty, dynamic threshold adjustment, and the interplay between detection and false alarm probabilities, these findings can inform the development and refinement of SS algorithms for practical implementation.

3.2. Comparative analysis

Table 2 outlines the simulation parameters for various scenarios, with scenarios 1 and 2 representing SLC [24] and SLC [25] respectively. Table 3 provides a comparative analysis of the proposed MUD-SLC framework against existing SLC-based methods in [24] and [25] by evaluating PD at various SNR levels. The results demonstrate the superior performance of the proposed method. For instance, at an SNR of -10 dB, the MUD-SLC framework achieves a PD of 0.90, compared to 0.88 [24] and 0.85 [25]. Similarly, at SNR=-15 dB, the proposed method achieves a PD of 0.81, surpassing 0.77 [24] and 0.70 [25].

Table 4 further illustrates the performance comparison for PD versus Pfa at SNR=-15dB. Notably, the MUD-SLC method achieves a PD of 0.90 at Pfa=0.4, exceeding the results of [24] (0.89) and [25] (0.85). These findings highlight the robustness of the MUD-SLC framework in handling low-SNR conditions and achieving a favorable trade-off between PD and Pfa. Table 5 summarizes the PD of the proposed MUD-SLC framework compared with advanced methods, including improved ED and deep learning-based spectrum sensing (DL-SS), at Pfa=0.15 and SNR=-15 dB.

Table 2. Simulation parameters with the different scenarios

Parameters	Scenario	
	1	2
NU factor ρ	1.02	1.02
DT factor ρ′	1.01	1.01
SNR in dB	-30 to -10	-15
Target Pfa	0.15	0 to1
PU Tx branches number	1 to 2	1 to 2
SU Rx branches number	1 to 2	1 to 2
Number of samples	128	128

Table 3.Comparison of PD versus SNR for the proposed MUD-SLC framework and existing methods ([24], [25]) at Pfa=0.15

Scenario	Parameters	SLC [24]	SLC [25]	Proposed MUD - SLC
1	SNR= -10dB	0.88	0.85	0.9
	SNR= -15dB	0.77	0.7	0.81
	SNR= -25dB	0.65	0.6	0.68
	SNR= -30dB	0.55	0.5	0.57

Table 4. Comparison of PD versus Pfa for the proposed MUD-SLC framework and existing methods ([24], [25]) at SNR=-15 dB

Scenario	Parameters	SLC [24]	SLC [25]	Proposed MUD - SLC
2	Pfa=0	0.42	0.35	0.46
	Pfa=0.2	0.79	0.73	0.82
	Pfa=0.3	0.84	0.8	0.85
	Pfa=0.4	0.89	0.85	0.9
	Pfa=0.8	0.98	0.96	0.99

Table 5. Comparison of proposed MUD-SLC with advanced spectrum sensing methods

Scenario	Method	PD at Pfa=0.15	Computational complexity
3	Conventional ED	0.7	Low
	Improved ED	0.75	Moderate
	DL-SS	0.8	High
	Proposed MUD-SLC	0.81	Moderate

3.3. Real-world applicability

While simulation results confirm the robustness of the proposed MUD-SLC framework, real world validation remains a crucial step to assess its practical effectiveness. In real deployments, additional factors such as hardware imperfections, non-linearities, user mobility and rapidly changing spectrum environments can significantly influence system performance. Future work will focus on implementing the framework in a physical testbed to evaluate its reliability under such non-ideal conditions. This includes testing with real cognitive radio hardware platforms, measuring detection accuracy in the presence of dynamic interference and observing performance in varying mobility scenarios such as UAV-assisted or vehicular networks. These experiments will help bridge the gap between theoretical simulations and practical deployment, ensuring the frameworks adaptability to 5G and beyond wireless systems.

3.4. Discussion

The proposed MUD-SLC SS framework effectively addresses key challenges faced by traditional ED methods, particularly under low-SNR conditions and in multi-user environments. By integrating MUD, the framework separates signals from multiple users, significantly reducing co-channel interference. Additionally, the SLC technique aggregates energy across spatial paths, resulting in a higher PD even in the presence of fading and noise uncertainty.

Comparative analysis with prior studies further underscores the advantages of the proposed method. Unlike [24] and [25], which rely solely on SLC for ED, the MUD-SLC framework combines MUD for interference mitigation and SLC for energy aggregation, achieving superior performance. For instance, at an SNR of -15 dB, the proposed method achieves a PD of 0.81, compared to 0.77 for [24] and [25], respectively. Similarly, at a Pfa of 0.4 the proposed system attains a PD of 0.90, exceeding the performance of the reference systems. The proposed MUD-SLC framework demonstrates superior detection performance, achieving a PD of 0.81 at Pfa=0.15, compared to 0.75 for improved ED and 0.80 for DL-SS. Unlike DL-SS, which demands high computational resources, the MUD-SLC method balances performance and efficiency, making it more suitable for resource-constrained environments.

While the framework demonstrates significant improvements in PD, it introduces additional computational complexity due to the MUD process. Future research could explore adaptive thresholding techniques or machine learning approaches to optimize the framework for real-time applications. This refinement could further enhance the applicability of the MUD-SLC framework in CR networks, particularly in dynamic and resource constrained environments. While the dataset is based on simulation, the framework is designed to operate in dynamic real-world environments. Future research will confirm its validity performance using experimental testbeds to account for hardware imperfections, mobility and interference from external sources.

4. CONCLUSION

This research presents a robust SS framework for MIMO-OFDM CR networks, combining MUD and SLC techniques. The proposed system delivers superior detection performance, especially in low-SNR and interference-prone environments. Key findings indicate that the MUD-SLC framework achieves a PD of 0.81 at an SNR of -15 dB, significantly outperforming existing SLC-based methods. At a Pfa of 0.15 and an SNR of -15 dB, the framework surpasses conventional and advanced approaches. By reducing interference through MUD and enhancing signal aggregation using SLC, the system improves spectrum utilization and network reliability in dynamic and challenging conditions. Although the approach provides substantial benefits, the computational complexity could present difficulties for real-time deployment. However, the balance between computational efficiency and performance makes it practical for various applications. Future research could focus on developing adaptive algorithms and conducting testbed validations to further optimize complexity and enhance real-world performance. These advancements will support the integration of CR systems in next-generation wireless networks, including 5G and beyond.

REFERENCES

[1] Y. Zeng, Y.-C. Liang, A. T. Hoang, and R. Zhang, "A review on spectrum sensing for cognitive radio: challenges and solutions," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, no. 1, p. 381465, Dec. 2010, doi: 10.1155/2010/381465.

[2] A. Ghasemi and E. S. Sousa, "Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 32–39, Apr. 2008, doi: 10.1109/MCOM.2008.4481338.

[3] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, Sep. 2006, doi: 10.1016/j.comnet.2006.05.001.

[4] M. Z. Alom, T. K. Godder, and M. N. Morshed, "A survey of spectrum sensing techniques in cognitive radio network," in *2015 International Conference on Advances in Electrical Engineering (ICAEE)*, IEEE, Dec. 2015, pp. 161–164, doi: 10.1109/ICAEE.2015.7506821.

[5] P. C. Sofotasios, E. Rebeiz, L. Zhang, T. A. Tsiftsis, D. Cabric, and S. Freear, "Energy detection based spectrum sensing over κ−μ and κ−μ extreme fading channels," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 3, pp. 1031–1040, Mar. 2013, doi: 10.1109/TVT.2012.2228680.

[6] G. Vazquez-Vilar, R. Lopez-Valcarce, and J. Sala, "Multiantenna spectrum sensing exploiting spectral a priori information," *IEEE Transactions on Wireless Communications*, vol. 10, no. 12, pp. 4345–4355, Dec. 2011, doi: 10.1109/TWC.2011.101211.110665.

[7] Z. Ye, G. Memik, and J. Grosspietsch, “Energy detection using estimated noise variance for spectrum sensing in cognitive radio networks,” in *2008 IEEE Wireless Communications and Networking Conference*, IEEE, Mar. 2008, pp. 711–716, doi: 10.1109/WCNC.2008.131.

[8] W.-L. Chin, “On the noise uncertainty for the energy detection of OFDM signals,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7593–7602, Aug. 2019, doi: 10.1109/TVT.2019.2920142.

[9] T. M. Getu, W. Ajib, and R. Landry, “A Simple F–test based spectrum sensing technique for MIMO cognitive radio networks,” in *2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, IEEE, Oct. 2018, pp. 1–8, doi: 10.1109/WiMOB.2018.8589123.

[10] T. M. Getu, W. Ajib, R. Landry, and G. Kaddoum, “Toward overcoming a hidden terminal problem arising in MIMO cognitive radio networks: a tensor-based spectrum sensing algorithm,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 10, pp. 9833–9847, Oct. 2019, doi: 10.1109/TVT.2019.2933857.

[11] J. Zhang, L. Liu, M. Liu, Y. Yi, Q. Yang, and F. Gong, “MIMO spectrum sensing for cognitive radio-based internet of things,” *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8874–8885, Sep. 2020, doi: 10.1109/JIOT.2020.2997707.

[12] M. S. Miah, M. Schukat, and E. Barrett, “Sensing and throughput analysis of a MU-MIMO based cognitive radio scheme for the Internet of Things,” *Computer Communications*, vol. 154, pp. 442–454, Mar. 2020, doi: 10.1016/j.comcom.2020.03.003.

[13] M. Jin, Q. Guo, J. Xi, Y. Li, and Y. Li, “On spectrum sensing of OFDM signals at low SNR: new detectors and asymptotic performance,” *IEEE Transactions on Signal Processing*, vol. 65, no. 12, pp. 3218–3233, Jun. 2017, doi: 10.1109/TSP.2017.2688967.

[14] G. L. Stuber, J. R. Barry, S. W. McLaughlin, Ye Li, M. A. Ingram, and T. G. Pratt, “Broadband MIMO-OFDM wireless communications,” *Proceedings of the IEEE*, vol. 92, no. 2, pp. 271–294, Feb. 2004, doi: 10.1109/JPROC.2003.821912.

[15] H. Harkat, P. Monteiro, A. Gameiro, F. Guiomar, and H. F. Thariq Ahmed, “A Survey on MIMO-OFDM systems: review of recent trends,” *Signals*, vol. 3, no. 2, pp. 359–395, Jun. 2022, doi: 10.3390/signals3020023.

[16] D. B. Rawat, “Evaluating performance of cognitive radio users in MIMO-OFDM-based wireless networks,” *IEEE Wireless Communications Letters*, vol. 5, no. 5, pp. 476–479, Oct. 2016, doi: 10.1109/LWC.2016.2587262.

[17] J. Lorincz, I. Ramljak, and D. Begušić, “A review of the noise uncertainty impact on energy detection with different OFDM system designs,” *Computer Communications*, vol. 148, pp. 185–207, Dec. 2019, doi: 10.1016/j.comcom.2019.09.013.

[18] X. Fernando and G. Lăzăroiu, “Spectrum sensing, clustering algorithms, and energy-harvesting technology for cognitive-radio-based Internet-of-Things networks,” *Sensors*, vol. 23, no. 18, p. 7792, Sep. 2023, doi: 10.3390/s23187792.

[19] R. Ahmed, Y. Chen, and B. Hassan, “Deep learning-driven opportunistic spectrum access (OSA) framework for cognitive 5G and beyond 5G (B5G) networks,” *Ad Hoc Networks*, vol. 123, p. 102632, Dec. 2021, doi: 10.1016/j.adhoc.2021.102632.

[20] W. Wu *et al.*, “Joint sensing and transmission optimization for IRS-assisted cognitive radio networks,” *IEEE Transactions on Wireless Communications*, vol. 22, no. 9, pp. 5941–5956, Sep. 2023, doi: 10.1109/TWC.2023.3238684.

[21] A. Nasser, H. Al Haj Hassan, J. Abou Chaaya, A. Mansour, and K.-C. Yao, “Spectrum sensing for cognitive radio: recent advances and future challenge,” *Sensors*, vol. 21, no. 7, p. 2408, Mar. 2021, doi: 10.3390/s21072408.

[22] P. Sivagurunathan, P. Ramakrishnan, and N. Sathishkumar, “Recent paradigms for efficient spectrum sensing in cognitive radio networks: issues and challenges,” *Journal of Physics: Conference Series*, vol. 1717, p. 012057, Jan. 2021, doi: 10.1088/1742-6596/1717/1/012057.

[23] L. Rodes, A. Kaushik, S. K. Sharma, S. Chatzinotas, and F. Jondral, “Square-law selector and square-law combiner for cognitive radio systems: an experimental study,” in *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*, IEEE, Sep. 2016, pp. 1–5, doi: 10.1109/VTCFall.2016.7881236.

[24] J. Lorincz, I. Ramljak, and D. Begusic, “Algorithm for evaluating energy detection spectrum sensing performance of cognitive radio MIMO-OFDM systems,” *Sensors*, vol. 21, no. 20, p. 6881, Oct. 2021, doi: 10.3390/s21206881.

[25] J. Lorincz, I. Ramljak, and D. Begušić, “Performance analyses of energy detection based on square-law combining in MIMO-OFDM cognitive radio networks,” *Sensors*, vol. 21, no. 22, p. 7678, Nov. 2021, doi: 10.3390/s21227678.

[26] J. Lorincz, I. Ramljak, and D. Begušić, “Analysis of the impact of detection threshold adjustments and noise uncertainty on energy detection performance in MIMO-OFDM cognitive radio systems,” *Sensors*, vol. 22, no. 2, p. 631, Jan. 2022, doi: 10.3390/s22020631.

[27] G. Pan, J. Li, and F. Lin, “A cognitive radio spectrum sensing method for an OFDM signal based on deep learning and cycle spectrum,” *International Journal of Digital Multimedia Broadcasting*, vol. 2020, pp. 1–10, Mar. 2020, doi: 10.1155/2020/5069021.

[28] M. Al-Amidie *et al.*, “Robust spectrum sensing detector based on MIMO cognitive radios with non-perfect channel gain,” *Electronics*, vol. 10, no. 5, p. 529, Feb. 2021, doi: 10.3390/electronics10050529.

[29] A. Zaimbashi, “Spectrum sensing in a calibrated multi-antenna cognitive radio: exact LRT approaches,” *AEU - International Journal of Electronics and Communications*, vol. 113, p. 152968, Jan. 2020, doi: 10.1016/j.aeue.2019.152968.

BIOGRAPHIES OF AUTHORS

Srikantha Kandhgal Mochigar is currently working as assistant professor in the department of electronics and communication engineering, Ballari Institute of Technology and Management Ballari, Karnataka, India. He has teaching experience of 13 years. He has published 3 journal and 2 conference papers. His area of research is spectrum sensing in cognitive radio networks. He is doing research in the Department of Electronics and Communication Engineering, Proudhadevaraya Institute of Technology, Hosapete, research center affiliated to Visvesvaraya Technological University, Belagavi, India. He can be contacted at email: srikanthkm2019@gmail.com.

Rohitha Ujjini Matad is currently working as professor and principal in PDIT-Proudhadevaraya Institute of Technology, Hosapete Karnataka, India. He has published 25 papers in referred international journals, 12 papers in national and international conferences. His area of research was spectrum sensing in cognitive radio networks. He can be contacted at email: rohithaujjini2010@gmail.com.

Premachand Doddamagadi Ramanaik is currently working as professor in the Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management Ballari, Karnataka, India. He has teaching experience of 22 years and industrial experience of 2 years. He has published 5 journal and 6 conference papers. His area of research is image compression with hardware realization. His areas of interest are in VLSI, image processing and microelectronics. He can be contacted at email: premchand.dr555@gmail.com.