Collaborative Spectrum Detection in Cognitive Radio Networks

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Abstract

The explosive growth in wireless communications has led to a scarcity of available spectrum resources. Cognitive Radio (CR) technology offers a solution by enabling dynamic spectrum access, allowing secondary users to opportunistically utilize underutilized spectrum bands without causing interference to primary users. Cooperative spectrum sensing, is a key component of CR, which leverages collaboration among multiple CRs to improve the accuracy and reliability of spectrum sensing. This paper explores the principles, techniques, challenges and solutions of co-operative spectrum sensing in cognitive radios. Irrespective of the challenges associated with the collaborative spectrum sensing approach, it is the key solution to hidden node problems and detection probability in cognitive radio sensing can be significantly improved in a heavily shadowed environment. The system model deployed in this paper used the OR and AND rules in collaboration with the fusion center for fusion center decisions be taken with respect to PU spectrum detection in an environment of multiple SUs, depending on the majority voting rule. The outcomes of various simulations helped in the identification of energy detection, detection and false alarm probabilities, cognitive radio decisions and fusion center rules as well as fusion center decisions based on different fusion rules are graphically represented in this paper.

Keywords: Cognitive Radio, Cooperative Spectrum Sensing, Detection Probability, Majority rule voting, Fusion Center Decision

I. Introduction

The increasing demand for wireless communication services has put immense pressure on the limited radio frequency spectrum. Traditional static spectrum allocation policies lead to inefficient spectrum utilization, with many licensed bands remaining underutilized. Cognitive Radio (CR) technology has emerged as a promising solution to this problem by enabling dynamic spectrum access (DSA). CRs can sense the spectrum environment, identify underutilized bands, and adapt their transmission parameters to exploit these opportunities without interfering with licensed (primary) users [1]

One of the fundamental tasks in CR technology is spectrum sensing. Spectrum sensing involves detecting the presence or absence of primary users in a given frequency band. However, individual CRs may face challenges such as shadowing, multipath fading, and hidden terminal problems, which can degrade the sensing accuracy. Cooperative spectrum sensing, where multiple CRs collaborate to sense the spectrum, has been proposed to address these challenges.

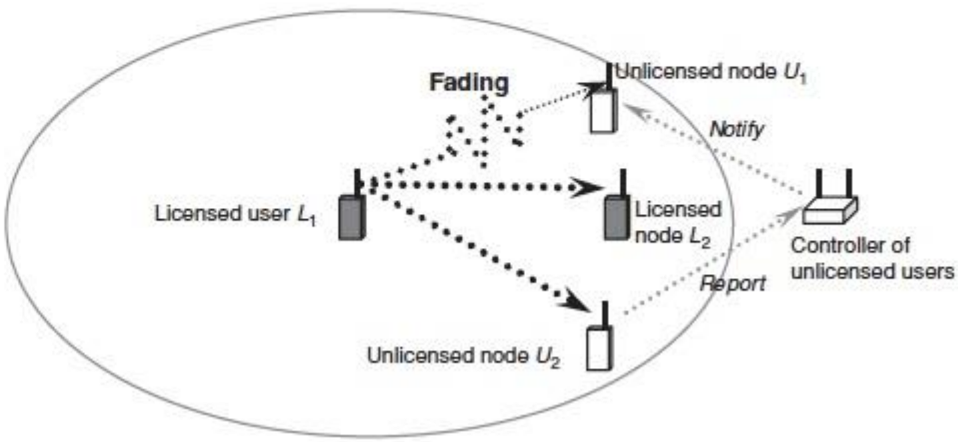

Fig 1 Cooperative Spectrum Sensing [2]

Principles of Cooperative Spectrum Sensing

Cooperative spectrum sensing involves multiple CRs sharing their local sensing information to make a collective decision about the presence of primary users. The cooperation can be classified into centralized and distributed approaches [3]:

1. Centralized Cooperative Sensing: In this approach, CRs send their local sensing results to a central entity, often referred to as the Fusion Center (FC). The FC processes the received data and makes a final decision regarding the presence of primary users. This method can achieve high accuracy but may suffer from high communication overhead and delays. Unlicensed users monitor the target channels and report their sensing results to the central controller.

2. Distributed Cooperative Sensing: Here, CRs exchange sensing information with their neighbors and make decisions based on local processing without relying on a central entity. This approach reduces communication overhead and delays but may require sophisticated algorithms to ensure robust performance. Unlicensed users share their sensing results with each other, and each unlicensed user makes the decision on spectrum access locally.

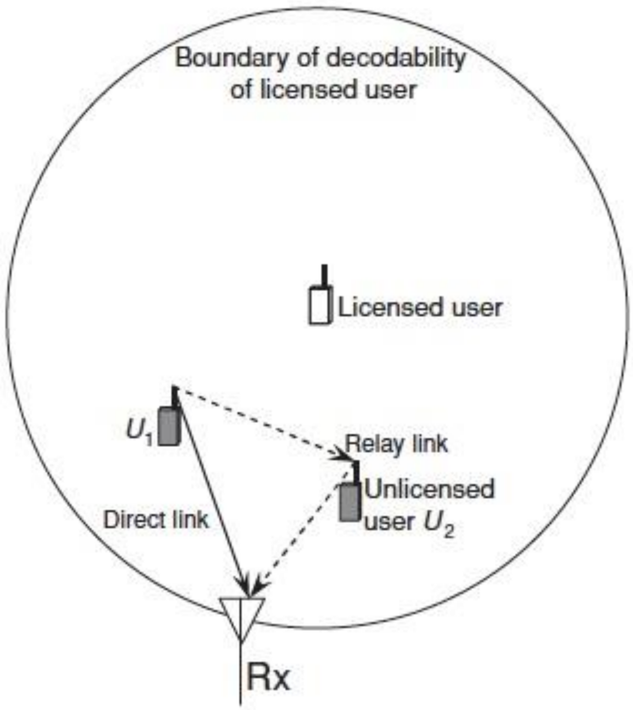

Fig 2 Cooperation in a Cognitive Radio Network [2]

Techniques for Cooperative Spectrum Sensing

Several techniques have been developed to enhance the performance of cooperative spectrum sensing. Some of the prominent techniques include:

1. Energy Detection: This is the simplest and most widely used technique where CRs measure the energy in the spectrum band and compare it with a predefined threshold. While easy to implement, it is sensitive to noise uncertainty and may not differentiate between primary user signals and noise.

2. Matched Filtering: This technique correlates the received signal with a known pattern (reference signal) to detect the presence of the primary user. It provides optimal performance but requires prior knowledge of the primary user's signal characteristics.

3. Cyclostationary Feature Detection: This technique exploits the cyclostationary features of the primary user signals, which are not present in noise. It offers robust performance even in low signal-to-noise ratio (SNR) conditions but is computationally intensive.

4. Eigenvalue-Based Detection: This method uses the eigenvalues of the received signal's covariance matrix to detect the presence of primary users. It is effective in distinguishing

between noise and primary user signals but requires accurate estimation of the covariance matrix [4]

Challenges in Cooperative Spectrum Sensing

Despite its advantages, cooperative spectrum sensing faces several challenges [5]:

1. Synchronization: Accurate synchronization among cooperating CRs is crucial for reliable performance. Any misalignment can lead to erroneous sensing results.

2. Communication Overhead: The exchange of sensing information among CRs can lead to significant communication overhead, especially in centralized approaches.

3. Security and Privacy: Cooperative sensing is vulnerable to security threats such as data falsification and eavesdropping. Ensuring the integrity and confidentiality of sensing data is essential.

4. Computational Complexity: Advanced sensing techniques like cyclostationary feature detection and eigenvalue-based detection require substantial computational resources, which may not be feasible for all CRs [5].

Motivation and Technical Contribution

The motivations for this paper are as follows;

1. Improving Spectrum Utilization

Spectrum is a limited resource, and its efficient use is critical for accommodating the growing number of wireless devices and services. Traditional spectrum management techniques lead to underutilization.

2. Mitigating the Hidden Terminal Problem associated with non-cooperative spectrum sensing.

Individual cognitive radios may fail to detect primary users due to the hidden terminal problem, where obstacles prevent reliable signal reception.

3. Enhancing Detection Accuracy in Low SNR Environments with less complex and costive technique like the collaborative spectrum detection.

Low signal-to-noise ratio (SNR) environments pose challenges for reliable spectrum sensing, leading to high false alarm and miss detection rates.

Technical contributions for this research are as follows;

1. Fusion Algorithms: Development of advanced fusion algorithms to combine sensing data from multiple cognitive radios effectively. These algorithms can include hard decision fusion (e.g., AND, OR, majority voting) and soft decision fusion (e.g., weighted combining).

2. Optimal Sensor Selection: Designing techniques to select the optimal subset of cognitive radios for sensing, balancing between detection performance and resource utilization.

3. Robustness to Fading and Shadowing: Ensuring that cooperative sensing algorithms are robust to varying channel conditions such as fading and shadowing, which affect individual radios differently.

By addressing these motivations and making these technical contributions, cooperative spectrum sensing in cognitive radio networks can significantly improve spectrum efficiency, reliability, and adaptability, ensuring optimal use of the spectrum resource in various conditions.

This research commences with introduction in section I whiles the review of related works constitute section II. The system model comes under section III with section IV handling the results and discussions. Finally section V is made up of the future research directions and conclusion.

II. Related Works

Literature Review on Cooperative Spectrum Sensing in Cognitive Radios is as follows;

This paper [6] focuses on energy-efficient cooperative spectrum sensing techniques, proposing a method that reduces energy consumption without compromising detection accuracy. The study shows that the proposed method is particularly effective in large-scale cognitive radio networks

The authors in [7] explore the application of machine learning algorithms to improve the accuracy and efficiency of cooperative spectrum sensing. Their results demonstrate that machine learning can significantly enhance the detection of primary users, even in challenging environments.

This study [8] introduces a reinforcement learning-based approach for adaptive cooperative spectrum sensing. The proposed method dynamically adjusts sensing parameters based on the network environment, leading to improved sensing performance and resource utilization.

The paper [9] presents a novel approach using blockchain technology to enhance the security and reliability of cooperative spectrum sensing. The authors show that blockchain can effectively prevent malicious attacks and ensure the integrity of the sensing data.

This research [10] explores deep learning models to improve the performance of cooperative spectrum sensing. The results indicate that deep learning can significantly improve detection accuracy, especially in scenarios with high noise and interference levels.

The authors in [11] propose an optimized cooperative spectrum sensing scheme tailored for 5G networks. Their approach uses advanced signal processing techniques to enhance sensing accuracy and reduce the overhead associated with cooperative sensing.

This paper [12] addresses the challenge of latency in cooperative spectrum sensing for cognitive radios within the context of IoT networks. The authors propose a method that minimizes latency while maintaining high detection accuracy, making it suitable for time-sensitive applications.

The study in [13] proposes a hybrid cooperative spectrum sensing scheme that combines traditional sensing methods with machine learning techniques. The hybrid approach improves the robustness of spectrum sensing in diverse and dynamic environments.

This paper [14] introduces a distributed consensus algorithm to enhance cooperative spectrum sensing. The proposed method achieves high detection accuracy and robustness against false sensing information, making it suitable for large-scale cognitive radio networks.

The authors in [15] explore multi-objective optimization techniques for balancing trade-offs between sensing accuracy, energy efficiency, and latency in cooperative spectrum sensing. Their approach shows that it is possible to achieve a good balance among these competing objectives.

This forward-looking paper [16] discusses the integration of AI into cooperative spectrum sensing for future 6G networks. The authors demonstrate that AI can significantly enhance the adaptability and efficiency of spectrum sensing in highly dynamic and complex environments.

This survey paper [17] reviews the security challenges associated with cooperative spectrum sensing in cognitive radio networks. The authors discuss various attack vectors and propose countermeasures to enhance the security and reliability of cooperative sensing.

The study in [18] presents a joint spectrum sensing and resource allocation framework that leverages cooperative strategies to optimize network performance. The authors show that their approach improves both spectrum utilization and network throughput.

This paper [19] proposes a fuzzy logic-based approach for cooperative spectrum sensing, which accounts for uncertainties in the sensing environment. The results indicate that fuzzy logic can enhance decision-making accuracy in complex and uncertain conditions.

The authors in [20] introduce a quantum-inspired cooperative spectrum sensing technique that leverages quantum computing concepts to improve sensing accuracy and efficiency. The study shows promising results, particularly in terms of speed and energy efficiency.

This paper by [21] focuses on developing an efficient cooperative spectrum sensing method for Cognitive Radio Networks (CRNs) using the Rényi entropy and an optimal likelihood ratio approach. The study addresses one of the key challenges in CRNs: reliably detecting the presence of primary users (PUs) to avoid interference while maximizing spectrum usage for secondary users (SUs).

Summary of related works

The reviewed literature highlights significant advancements in cooperative spectrum sensing for cognitive radio networks. Researchers have explored a wide range of approaches, including machine learning, deep learning, blockchain, and quantum-inspired techniques, to improve the accuracy, efficiency, and security of spectrum sensing. The studies consistently demonstrate that cooperative spectrum sensing is crucial for enhancing the performance of cognitive radio networks, particularly in the context of 5G and future wireless communication systems.

III System Model

Cooperative Spectrum Sensing (CSS) in Cognitive Radios involves multiple cognitive radio users working together to detect the presence or absence of primary users in the spectrum. This improves the detection performance compared to individual sensing by mitigating issues like shadowing, fading, and hidden node problems. Below are the detailed models for CSS:

1. Network Setup

Primary Users (PUs) are licensed users with priority access to the spectrum.

Cognitive Radio Users (CRs) are unlicensed users that opportunistically use the spectrum without causing interference to PUs.

Spectrum Sensing Channel is the channel through which CRs observe the presence of PUs.

Reporting Channel is the channel through which CRs report their sensing results to a Fusion Center (FC).

2. Communication Model

Signal representation deals with channel characterization between PU and SUs in the presence of noise.

PU Signal: s(t)

Received Signal at CR i:

$$y_i(t) = h_i s(t) + n_i(t) \tag{1}$$

Where h_i is the channel gain between the PU and CR i, and n_i (t) is the noise at CR, i.

Hypotheses comprise of either PU absent or PU present as shown below;

H_0: PU absent

$$y_i\ (\mathrm{t}) = n_i\ (\mathrm{t}) \tag{2}$$

H_1: PU present

$$y_i\ (\mathrm{t}) = h_i \mathrm{s}(\mathrm{t}) + n_i\ (\mathrm{t}) \tag{3}$$

Energy Detection deals with the test statistic between the hypotheses and the number of samples N.

$$T_i = \frac{1}{N} \sum_{t=1}^{N} |y_i(t)|^2 \tag{4}$$

Where N is the number of samples

Threshold λ:

$$T_i \begin{matrix} > & H_1 \\ < & H_0 \end{matrix} \lambda \tag{5}$$

3. Cooperative Spectrum Sensing (CSS) Model

Fusion Center (FC) Model combines the sensing results from multiple CRs to make a final decision on the presence of the PU. Fusion Rules comprise of the OR rule and the AND rule which help in fusion center decision.

OR Rule: The fusion center decides that the PU signal is present if any node detects the signal.

$$\text{FC Decision} = \begin{cases} H_1 \ if\ any\ T_i\ > \lambda \\ H_0 \quad\ Otherwise \end{cases}$$

AND Rule: The fusion center decides that the PU signal is present only if all nodes detect the signal.

$$\text{FC Decision} = \begin{cases} H_1 \ if\ all\ T_i\ > \lambda \\ H_0 \quad Otherwise \end{cases}$$

Majority Rule: In the majority voting rule, the fusion center decides that, the PU signal is present if a majority of nodes detect the signal.

$$\text{FC Decision} = \begin{cases} H_1 \; if \; majority \; T_i \; > \lambda \\ H_0 \qquad\qquad Otherwise \end{cases}$$

4. Computational Model

Detection Probability P_d handles the probability of correctly detecting the presence of the PU:

$$P_d = \text{P} \; (T_i \; > \lambda | H_1) \tag{6}$$

False Alarm Probability P_{fa} handles the probability of falsely detecting the presence of the PU:

$$P_{fa} = \text{P} \; (T_i \; > \lambda | H_0) \tag{7}$$

Global Detection Probability P_d handles the overall detection probability considering all CRs and the fusion rule:

$$P_D = \text{P} \; (FC \; Decision = \; H_1 | H_1) \tag{8}$$

Global False Alarm Probability P_{FA} handles the overall false alarm probability considering all CRs and the fusion rule:

$$P_{FA} = \text{P} \; (FC \; Decision = \; H_1 | H_0) \tag{9}$$

The goal of the fusion center decision is to improve the accuracy and reliability of spectrum sensing, reducing the probability of false alarms and missed detections. By combining data from multiple nodes, the fusion center can take advantage of spatial diversity and improve the overall performance of the cooperative or collaborative spectrum sensing system. The fusion center decision making process typically involves data collection, data fusion and decision making.

IV Results and Discussion

Receiver Operating Characteristic (ROC) Curve: Plots P_d vs. P_{fa} to evaluate the trade-off between detection and false alarm probabilities with respect to performance analysis.

Mathematical Analysis

1. **Energy Detector Performance:**

Under H_0:

$$T_i \sim \mathcal{N}\left(\sigma_n^2, \frac{\sigma_n^4}{N} \right) \tag{10}$$

Under H_1:

$$T_i \sim \mathcal{N}\left(\sigma_n^2 + \frac{P_s}{N} \sum_{i=1}^{N} h_i^2, \frac{\sigma_n^4}{N} \right) \tag{11}$$

2. **Probabilities:**

P_{fa}:

$$P_{fa} = \mathrm{Q}\left(\frac{\lambda - \sigma_n^2}{\sigma_n^2/\sqrt{N}} \right) \tag{12}$$

P_d:

$$P_d = \mathrm{Q}\left(\frac{\lambda - (\sigma_n^2 + \frac{P_s}{N} \sum_{i=1}^{N} h_i^2)}{\sigma_n^2/\sqrt{N}} \right) \tag{13}$$

Here, Q(x) is the Q-function also known as the Gaussian tail probability or complementary cumulative distribution function (CCDF), is a mathematical function that calculates the probability that a standard normal random variable exceeds a given value.

In conclusion, Cooperative Spectrum Sensing in Cognitive Radios utilizes the collaboration of multiple CRs to improve the accuracy and reliability of detecting primary users. By leveraging the sensing information from multiple nodes and combining them through a fusion center, CSS can significantly enhance detection performance, mitigate the effects of channel impairments, and ensure efficient spectrum utilization.

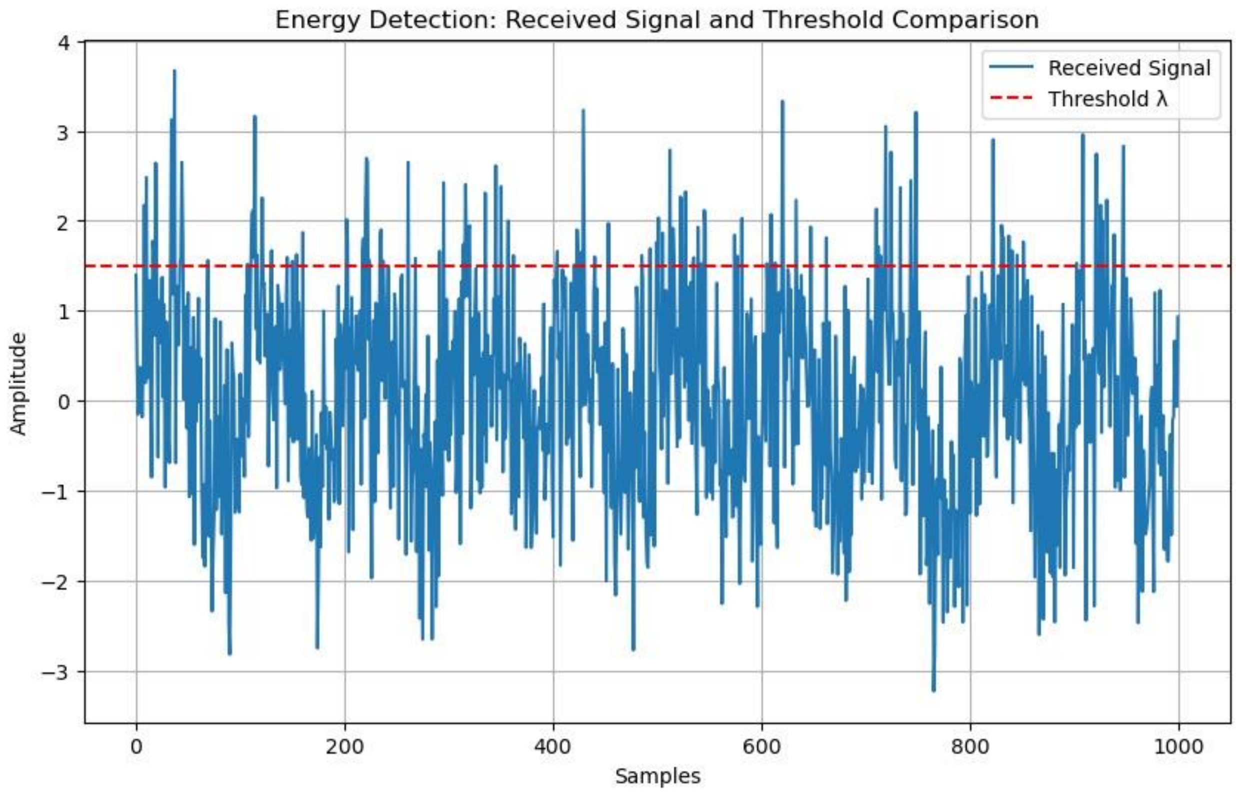

Fig 1: Energy Detection (Received Signal and Threshold Comparison)

Test Statistic (Energy): 1362.23; Threshold (λ): 1.5

Detection Result: PU is present

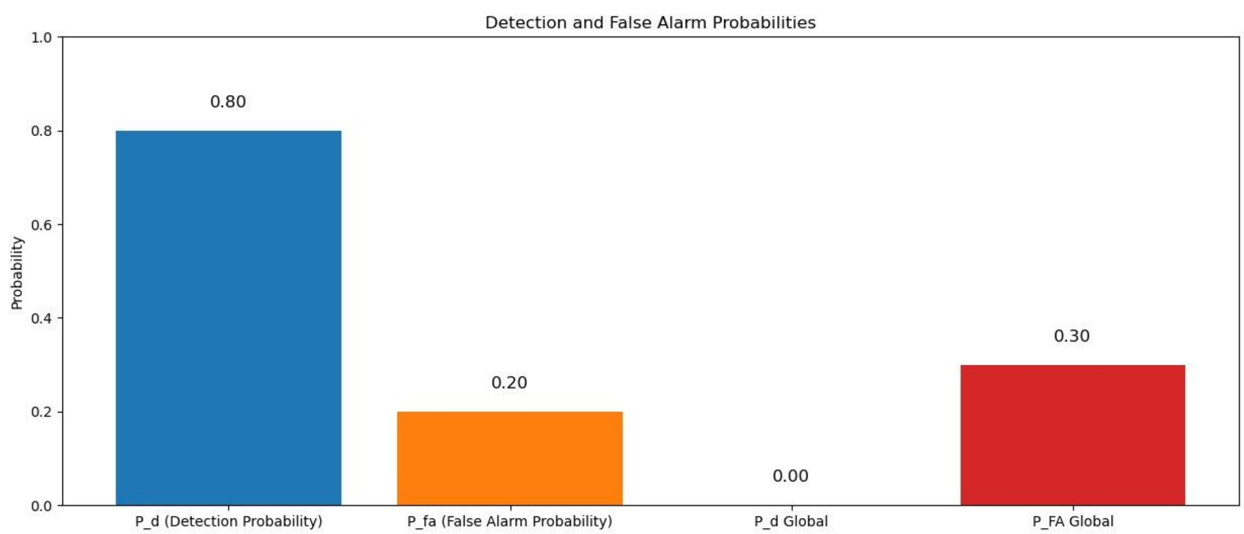

Fig 2: Detection and False Alarm Probabilities

True PU state: Absent

Cognitive Radio Decisions: [0 1 0 0 0 0 1 0 0 1]

OR Rule Decision: PU Present

AND Rule Decision: PU Absent

Majority Rule Decision: PU Absent

Global Detection Probability (P_d): 0.00

Global False Alarm Probability (P_FA): 0.30

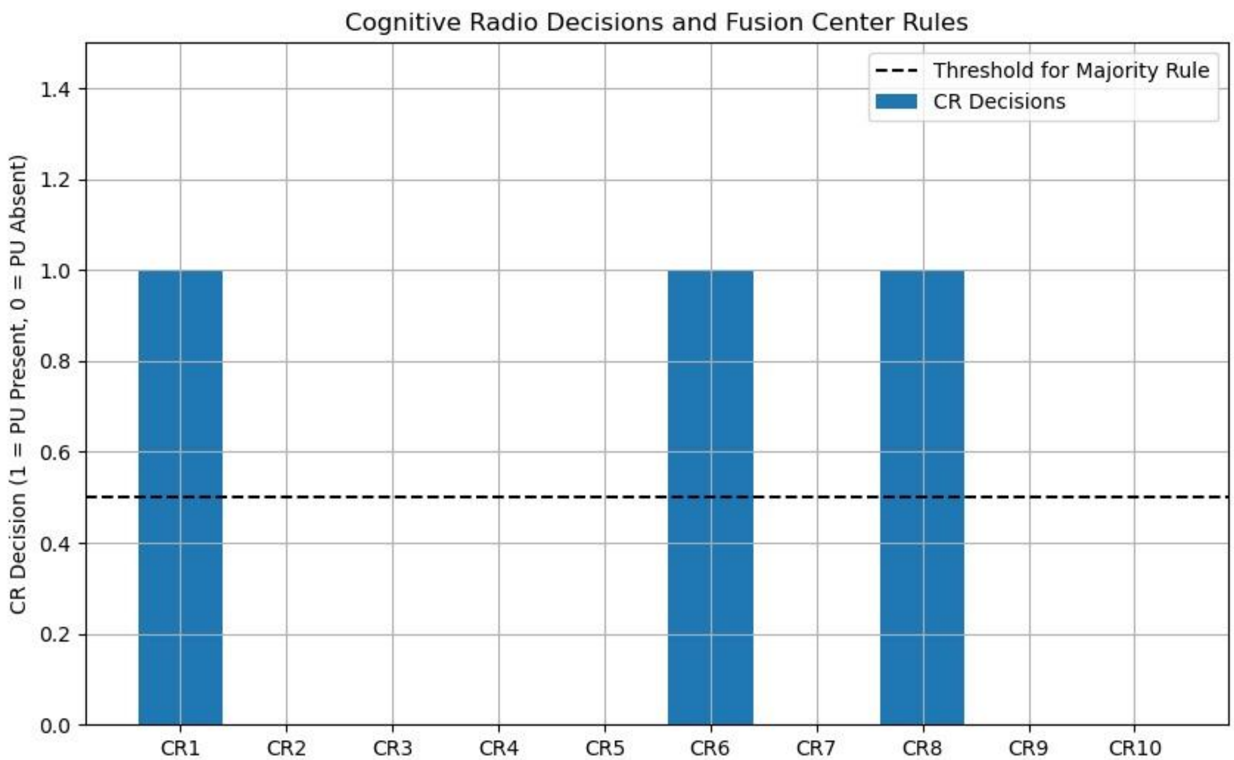

Fig 3: Cognitive Radio Decisions and Fusion Center Rules

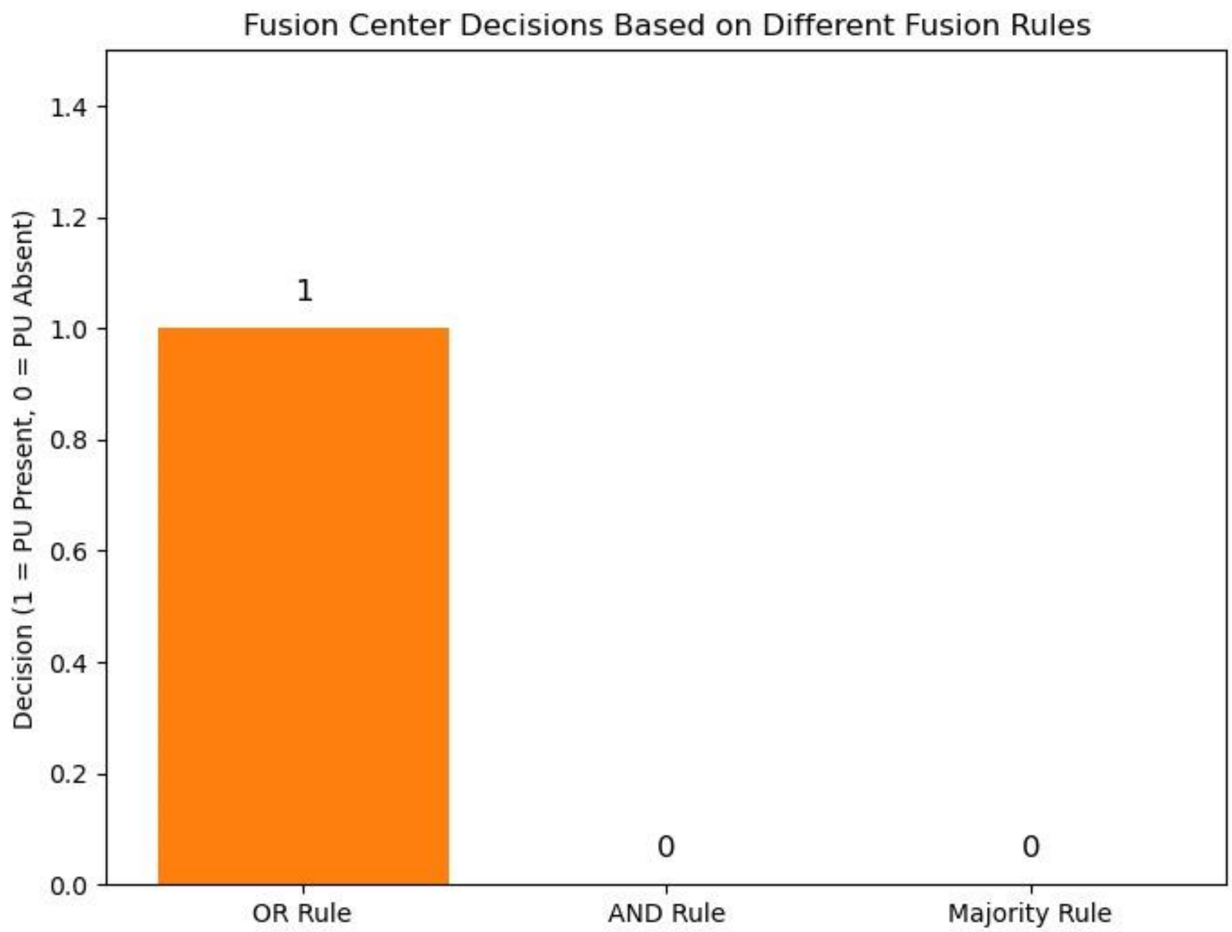

Fig 4: Fusion Center Decisions Based on Different Fusion Rules

True PU State: Absent

CR Decisions: [1 0 0 0 0 1 0 1 0 0]

OR Rule Decision: PU Present

AND Rule Decision: PU Absent

Majority Rule Decision: PU Absent

V. Future Research and Conclusion

Cooperative spectrum sensing is a vital component of cognitive radio technology, enhancing spectrum utilization and mitigating the challenges associated with individual or non-cooperative sensing. By leveraging collaboration among multiple CRs, cooperative sensing improves the accuracy and reliability of detecting primary users. However, it also introduces challenges such as synchronization, communication overhead, security, and computational complexity. Addressing these challenges through innovative algorithms and efficient protocols is crucial for the successful deployment of cognitive radio networks. Future research will likely continue to focus on optimizing trade-offs between sensing accuracy, energy efficiency, latency, and security in cooperative spectrum sensing.

Conflicts of Interest: The authors declare no conflicts of interest regarding the publication of this paper.

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