

Implementation of Artificial Neural Network for Spectrum Sensing & Spectrum Allocation in Cognitive Radio

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Abstract— The rapid expansion of wireless communication services has heightened the demand for efficient spectrum utilization. Cognitive Radio (CR) technology facilitates dynamic spectrum access by enabling secondary users to exploit unused spectrum. This project introduces an Artificial Neural Network (ANN)-based spectrum sensing and allocation technique for Cognitive Radio Networks. The proposed approach leverages the learning and adaptive capabilities of ANN to classify spectrum occupancy patterns and allocate available spectrum efficiently. The ANN model is trained to recognize primary user signals and distinguish them from noise with high accuracy. By incorporating adaptive learning, the ANN can adapt to varying signal conditions and improve spectrum sensing reliability. The project aims to enhance detection performance, reduce false alarms, and optimize spectrum allocation, demonstrating the effectiveness of the ANN-based approach in cognitive radio scenarios.

Index Terms—ANN, AI, Spectrum Sensing, Cognitive Radio

I. INTRODUCTION

The proliferation of smart devices, such as smartphones, IoT devices, wearable technology, and the expansion of wireless communication services have created an unprecedented surge in spectrum demand. This explosion of demand is compounded by the advent of 5G and the ongoing development of 6G, which promises even greater connectivity requirements. Traditional static spectrum allocation policies, which have been designed based on fixed assignments to specific users or services, are no longer sufficient to efficiently utilize the radio frequency spectrum. Studies reveal that despite the scarcity of available spectrum, a significant portion remains underutilized at any given time due to the static nature of traditional allocation strategies. The discrepancy between growing demand and static allocation methods has brought the need for more efficient and dynamic spectrum management solutions to the forefront.

To address these challenges, Cognitive Radio (CR) technology has emerged as a viable solution. CR enables dynamic spectrum access (DSA), allowing secondary users—unlicensed users—to opportunistically access

spectrum bands that are not being utilized by primary users (licensed users). This opportunistic access maximizes spectrum utilization, improves efficiency, and alleviates the issue of spectrum scarcity. The core functionality of a CR is its ability to sense the spectrum environment, detect the presence or absence of primary users, and decide on spectrum access without causing harmful interference to the primary users.

However, the success of Cognitive Radio hinges on its ability to accurately sense and detect idle spectrum bands. Spectrum sensing is one of the most critical tasks in cognitive radio networks, as it directly affects the system's ability to detect vacant channels and avoid interference with primary users. Effective spectrum sensing requires a reliable method that can differentiate between signals and noise, detect low-power signals, and adapt to changing environmental conditions. Conventional spectrum sensing techniques, such as energy detection and cyclostationary feature detection, have shown promise but also present several limitations.

Energy detection is widely used due to its simplicity and low computational cost. It involves measuring the energy of the received signal and comparing it to a predefined threshold. While this technique is computationally efficient and easy to implement, it is susceptible to noise uncertainty and unable to distinguish between noise and legitimate signals. This limitation often results in either missed detection or false alarms, particularly in low signal-to-noise ratio (SNR) environments. On the other hand, cyclostationary feature detection exploits the inherent periodic properties of modulated signals, making it more robust against noise and capable of differentiating between noise and primary user signals. However, cyclostationary detection is computationally intensive and requires prior knowledge of the primary user's signal characteristics, making it less practical for real-time spectrum sensing.

In recent years, Artificial Neural Networks (ANNs) have gained significant attention for their powerful pattern recognition and adaptive learning capabilities. ANNs are particularly suited to complex classification tasks where traditional methods struggle, as they can learn non-linear relationships between input features and adapt to changing signal conditions. The adaptive learning nature of ANNs allows them to continually improve their performance as they are exposed to more data, which is crucial in dynamic wireless environments. ANNs are capable of extracting intricate signal features, identifying patterns, and classifying spectrum occupancy based on learned experiences, which makes them a promising alternative for spectrum sensing in Cognitive Radio Networks.

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The proposed ANN-based spectrum sensing and allocation approach has several key advantages. Firstly, the neural network's adaptive learning capability allows it to recognize complex and evolving spectrum patterns, making it more robust in dynamic signal environments. Secondly, by combining spectrum sensing and allocation into a unified framework, the approach ensures seamless integration between detection and resource allocation, thereby enhancing overall spectrum utilization efficiency. Finally, the use of machine learning provides the flexibility to refine the model over time as new data is collected, improving detection reliability and responsiveness to changing conditions.

A. Objective

The primary objective of this project is to demonstrate that an ANN-based approach can achieve superior spectrum sensing performance compared to traditional methods, particularly in terms of detection accuracy, sensitivity, and false alarm rate. The secondary objective is to design a spectrum allocation strategy that optimizes the use of detected spectrum opportunities while minimizing interference. The proposed technique will be validated through simulations and evaluated across various scenarios, including different SNR levels, signal types, and noise conditions.

In conclusion, the ANN-based spectrum sensing and allocation technique presented in this project aims to address the limitations of conventional sensing methods by leveraging the adaptability and classification power of neural networks. By combining ANN-based spectrum sensing with dynamic spectrum allocation mechanisms, the proposed approach seeks to enhance spectrum utilization efficiency, improve detection reliability, and enable more intelligent spectrum management in Cognitive Radio Networks. This research has the potential to contribute significantly to the development of advanced cognitive radio systems capable of meeting the growing spectrum demands of future wireless communication networks.

II. LITERATURE SURVEY

The literature survey is carried out by different E-medias, IEEE journals, national and international conference paper-paper, research journals etc.

Introduction to cognitive Radio & Spectrum Utilization

The concept of cognitive radio (CR) was introduced in response to inefficiencies in traditional spectrum allocation, where static assignments lead to underutilization despite increasing demands on wireless networks. With the rapid growth in devices and applications, it became evident that fixed spectrum allocations could no longer accommodate evolving needs, driving the development of dynamic spectrum access (DSA) and cognitive radio technologies. Haykin (2005) framed cognitive radio as a "brain-empowered" wireless communication system that could sense, learn, and adapt to its environment, optimizing spectrum usage without interfering with primary (licensed) users.

Fundamental Cognitive radio Framework & Challenges

A. Cognitive Cycle & Functions

Cognitive radio operates through a "cognitive cycle," which includes spectrum sensing, decision-making, spectrum sharing, and mobility. The sensing stage is foundational, as it enables CR to identify vacant channels, or "spectrum holes,"

where it can operate. Studies, including that of Akyildiz et al. (2006), emphasize the role of spectrum sensing in detecting primary users and assessing channel availability, which are essential for ensuring interference-free coexistence with licensed users. Effective sensing, however, remains challenging due to environmental noise, interference, and power constraints, all of which can hinder detection accuracy.

B. Spectrum Sensing Techniques

Various spectrum sensing techniques have been explored to improve the efficiency and reliability of spectrum usage. Energy detection is widely used due to its simplicity, but it suffers from poor performance in low signal-to-noise ratio (SNR) conditions and is susceptible to noise uncertainty. Cabric, Mishra, and Brodersen (2004) discuss the limitations of energy detection, noting that while it requires less computational complexity, it struggles to differentiate between noise and primary signals, especially in challenging conditions. To address these limitations, other techniques, such as matched filtering and cyclostationary feature detection, have been developed.

C. Cyclostationary Detection & Cooperative Sensing

Cyclostationary detection, which detects signals based on inherent periodic properties of modulated signals, offers better noise resilience and can distinguish between noise and legitimate signals. However, it is computationally intensive, limiting its practicality for real-time applications. Cooperative sensing is proposed as an alternative or complement to individual sensing, as it combines observations from multiple CR devices to improve detection accuracy. Mishra, Sahai, and Brodersen (2006) highlight the benefits of cooperative sensing, especially in overcoming multipath fading and shadowing issues. Through cooperation, CR networks can aggregate data, thus increasing the likelihood of accurate channel assessments in complex environments.

Spectrum Management and Dynamic Access Models

A. Dynamic Spectrum Access Models

To maximize spectrum utilization, various dynamic access models have been proposed, such as underlay, overlay, and spectrum pooling. In the underlay model, secondary users operate concurrently with primary users at very low power levels, ensuring that interference stays below a defined threshold, a concept referred to as "interference temperature." The overlay model allows secondary users to access the spectrum only when it is unused by primary users, while the spectrum pooling model provides a framework for secondary users to "borrow" spectrum dynamically. Weiss and Jondral (2004) proposed spectrum pooling as a method for efficient spectrum sharing, where secondary users access frequency bands not being used at particular times. Spectrum pooling and similar models have been recognized for their potential to support CR systems, particularly as they avoid requiring changes to primary user systems.

A. Spectrum Management Function

Effective spectrum management requires CR to make real-time decisions on when and where to operate within the spectrum. Ghasemi and Sousa (2008) examine these requirements, addressing the need for reliable spectrum decision-making under noise constraints and proposing strategies for managing power to prevent interference. Spectrum management functions in CR systems are supported by spectrum decision algorithms, which determine

optimal operating parameters, and spectrum sharing strategies, which balance access among multiple secondary users to minimize conflicts. To enable real-time responsiveness, CR systems also incorporate spectrum mobility, allowing secondary users to vacate channels quickly if primary users resume transmission.

Advance sensing & Decision-making Technic

A. Machine Learning & Intelligence in CR

As CR technologies have evolved, researchers have begun incorporating machine learning (ML) and artificial intelligence (AI) to improve spectrum sensing and decision-making. AI-driven CR can learn from historical spectrum data, making adaptive decisions that optimize spectrum use and reduce interference over time. For instance, reinforcement learning (RL) enables CR to continuously refine its spectrum access strategies based on environmental feedback. Studies by Clancy et al. (2007) have shown that ML algorithms can significantly enhance spectrum sensing accuracy, predicting channel availability and selecting optimal channels more reliably than traditional methods.

B. Interface Management & Power Control

Interference management remains a critical aspect of CR, especially in shared spectrum environments. Power control techniques are essential to minimize the potential interference from secondary users to primary users. Hamdi, Zhang, and Letaief (2007) propose a power control approach based on sensing side information, whereby CRs adjust their transmission power according to interference constraints. This method ensures that CR systems maintain the balance between maximizing data throughput and minimizing interference. Similarly, Le and Liang (2007) introduced a fuzzy logic-based power control scheme that dynamically adjusts transmission power based on secondary users' interference levels observed at primary users' locations, improving compatibility with primary systems.

Application & Regulatory Implications

A. Standardization Effort & Policy Implication

Regulatory bodies, such as the Federal Communications Commission (FCC) and the International Telecommunication Union (ITU), have recognized the need for more flexible spectrum management policies to accommodate CR and DSA technologies. The FCC's report (2003) on spectrum policy reform encouraged research into CR and DSA, advocating for policies that would allow secondary users temporary access to licensed bands under strict conditions to prevent interference. These policies, including the FCC's spectrum sharing framework, set the stage for initiatives like the IEEE 802.22 standard, which supports CR operation in the TV white space band. The IEEE 802.22 standard, finalized in 2011, is the first standard to formally integrate CR capabilities for rural and underserved broadband access, establishing protocols for CR to operate in vacant TV channels

B. Global Spectrum Measurement & utilization Survey

Empirical studies have consistently shown underutilization across various spectrum bands. For example, the Shared Spectrum Company conducted extensive occupancy measurements across the U.S., revealing that most bands

between 30 MHz and 3 GHz were only sparsely occupied, with average utilization around 5.2%. Similar measurements in Europe have shown higher utilization rates but still indicate that substantial spectrum resources remain unused. These studies underscore the need for CR technologies that can capitalize on these gaps, dynamically accessing unoccupied spectrum bands to improve utilization while adhering to regulatory requirements. This real-world evidence has driven much of the research into spectrum sensing algorithms and spectrum awareness methodologies in CR systems.

Future Direction & Research challenges:

The ongoing research in CR technology seeks to address several challenges in achieving fully adaptive, interference-aware communication systems. One of the significant challenges is the speed and reliability of spectrum sensing and decision-making processes, as CR must operate in real-time to avoid interference with primary users. The hidden node problem, wherein CR may fail to detect a primary user due to signal shadowing or multipath fading, presents an additional obstacle. Solutions like cooperative sensing and advanced AI models, such as reinforcement learning, are under investigation to overcome these limitations.

Additional research is focused on developing robust multi-service, multi-technology, and multi-user CR environments, where CR systems must adapt to diverse applications without disrupting overall network stability. As AI and machine learning techniques become increasingly integrated into CR, the potential for autonomous and intelligent spectrum management grows, positioning CR to be foundational in future wireless systems, including 5G and beyond. However, challenges remain in scaling these technologies, maintaining regulatory compliance, & achieving hardware capabilities for wide-band sensing and rapid adaptation.

This survey provides a comprehensive overview of the state of cognitive radio research, covering foundational sensing and decision-making techniques, spectrum management functions, advanced AI integrations, and regulatory and practical challenges. The literature shows a consistent trend toward enhancing CR's autonomy, accuracy, and adaptability to meet the demands of modern and future wireless communication environments.

III. PROPOSED SYSTEM

Here's the revised cognitive radio spectrum sensing process diagram description with points 5 and 6 replaced by an ANN classification step:

Cognitive Radio Spectrum Sensing Process:

A. Received Signal

The process begins with the received signal, which is analyzed to identify potential spectrum occupancy by authorized or unauthorized users.

B. Cyclic Properties Identification

This step identifies cyclic properties within the signal. Cognitive radio systems leverage these properties, as modulated signals often exhibit specific cyclic features that can distinguish between noise and legitimate transmissions..

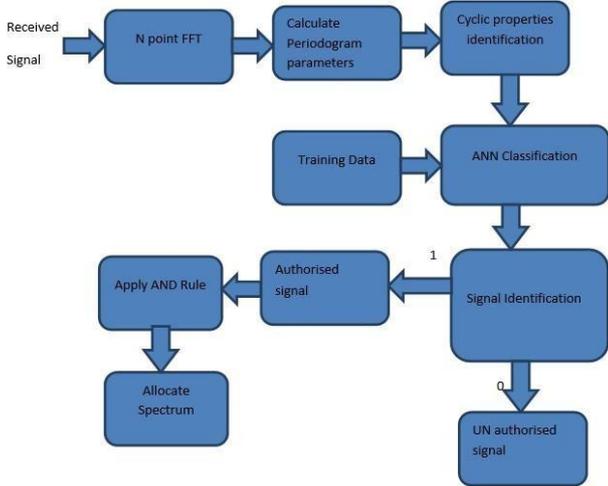


Fig.1 Block Diagram of Proposed System

C. Calculate Periodogram Parameter

Based on the cyclic properties, periodogram parameters are calculated to prepare signal for further frequency analysis. The periodogram he measure the power spectral density, which is crucial for identify energy peaks associated with transmitted signals.

D. N-Point FFT(Fast Furies Transform)

The signal undergoes an N-point FFT, converting it into the frequency domain to reveal periodic components. This transformation facilitates the detection of distinct frequency peaks that indicate active transmissions.

E. ANN Classification for Authorized Signal Detection

The ANN is trained to classify signals based on learned patterns of authorized and unauthorized transmissions. The ANN examines various spectral and cyclic features of the signal to determine if it matches authorized patterns.

F. Apply AND Rule:

An AND rule is applied to validate the ANN classification results. This rule ensures that the identified signal meets multiple criteria, such as specific spectral patterns and ANN output, to minimize false detections.

G. Decision - Authorized or Unauthorized Signal

If the signal passes the AND rule, it is classified as an Authorized Signal, and the system allows spectrum allocation accordingly.

If the signal fails to meet the criteria, it is classified as an Unauthorized Signal, resulting in no spectrum allocation to prevent interference.

H. Flowchart

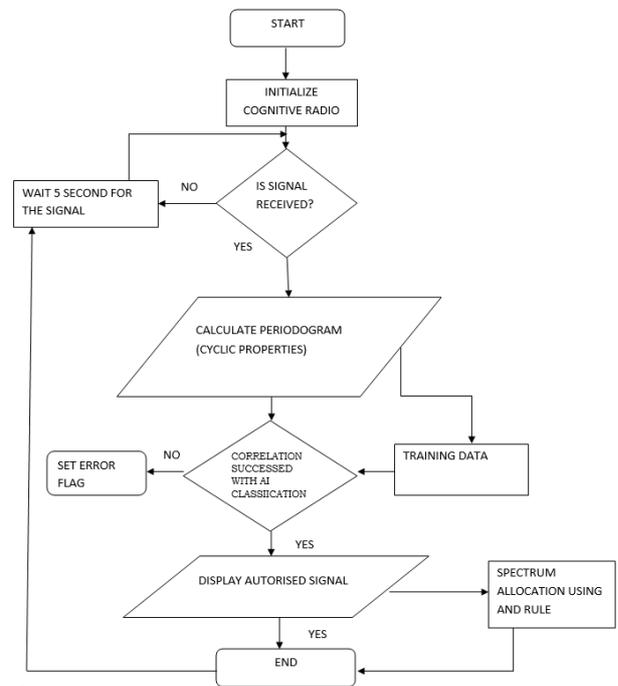


Fig. 2 Flowchart Diagram

I. Algorithm

1. Start
2. Initialize cognitive radio.
3. Calculate Periodogram, cyclic properties.
4. ANN classification.
5. For successful detection of authorized signal go to step 6, else go for step 7
6. Spectrum Allocation
7. Set error flag.
8. Wait for 5 second and go for step 3.
9. End

IV. RESULT

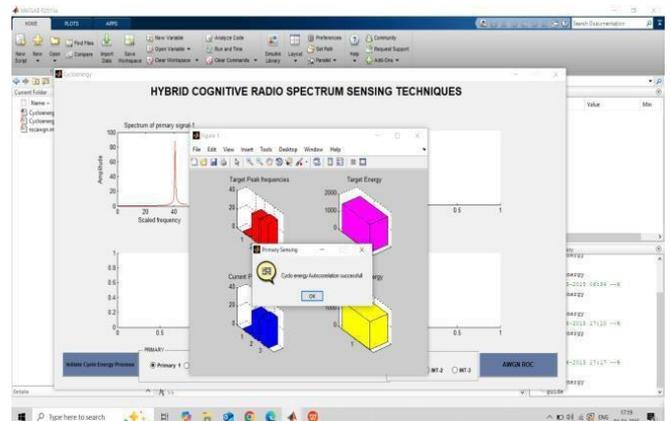


Fig.3. Hybrid Cognitive Radio Spectrum Sensing Techniques

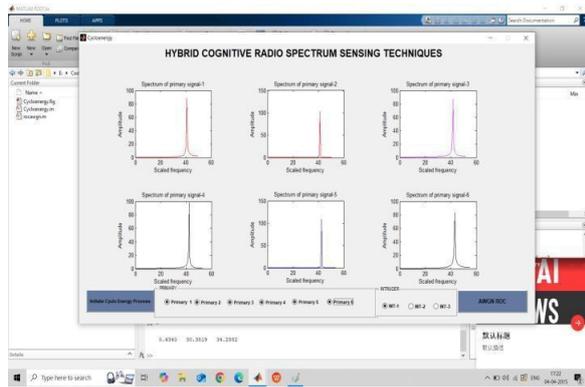


Fig.4. Signals

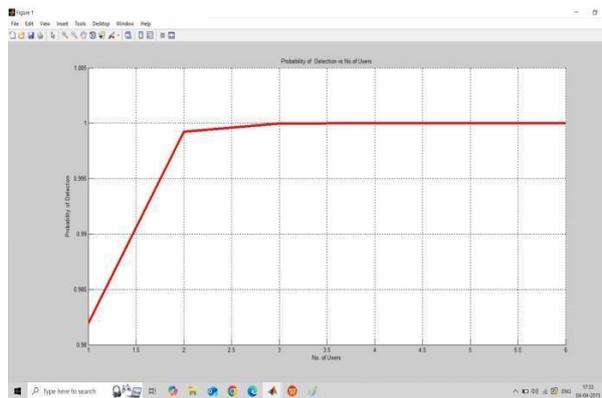


Fig 5. Probability of detection and No. of Users.

V. CONCLUSION

In summary, a review of current approaches highlights that cognitive radio systems incorporating ANN classification and cyclostationary detection represent major advances in wireless communication. Cognitive radios excel in dynamic spectrum management, making them highly adaptable in environments with dense frequency usage and critical applications, such as public safety and IoT. Hybrid systems that combine cyclostationary analysis with ANN classification provide enhanced detection accuracy, robustness to noise, and low false alarm rates, essential for reliable communication. While these approaches present operational and implementation complexities, the combined benefits make them promising solutions for creating efficient and resilient wireless networks, particularly as spectrum demand intensifies with the growth of device connectivity and data transfer needs.

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