ABSTRACT

As the demand for wireless communication grows, optimizing spectrum utilization becomes imperative. This project focuses on improving efficiency through "Cooperative Spectrum Sensing using ANFIS" within a Cognitive Radio framework. The first phase involves Software-Defined Radio (SDR) implementation, specifically using the ADALM PLUTO device, for energy detection in various frequency ranges. This cooperative sensing approach aims to identify vacant spectrum holes to be allocated to secondary users, mitigating the inefficiencies caused by underutilized spectrum allocated to primary users. The second phase employs Adaptive Neuro-Fuzzy Inference System (ANFIS) for decision-making based on the collected sensing data.

The literature review delves into the foundations of cognitive radio, spectrum sensing techniques, and the application of ANFIS in decision-making. The implementation section details the setup using GNU Radio, energy detection in MATLAB, and the utilization of ANFIS for modeling and decision-making. The results highlight the success of cooperative sensing in accurately identifying available spectrum channels and the efficacy of ANFIS in making informed decisions.

This project contributes to the field by offering a comprehensive solution to the spectrum utilization problem, leveraging cooperative sensing and intelligent decision-making. The findings demonstrate the potential of this approach in enhancing communication systems, paving the way for more adaptive and efficient utilization of the radio frequency spectrum.

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

Radio is a fundamental medium of communication that plays a pivotal role in connecting and sharing information in societies. Till the present day, it has undergone remarkable transformations and evolved into a versatile medium of communication. The entire range of frequencies of electromagnetic radiation, each corresponding to a different type of electromagnetic wave is known as the spectrum. Radio waves are used for communication. One significant drawback of traditional radio communication systems, especially in the context of increasing demand for wireless services, is the efficient use of the radio frequency(RF) spectrum. Cognitive radio refers to a type of intelligent wireless communication system that is designed to autonomously and dynamically adapt its parameters and behaviour based on real-time analysis of its operating environment. Cognitive radios exhibit adaptability by adjusting transmission parameters based on real-time spectrum sensing. This adaptability ensures that communication systems can respond dynamically to changes in the RF environment, optimising performance and reliability. Spectrum sensing is a critical aspect of cognitive radio, allowing the system to intelligently adapt to the RF environment. Cognitive radios employ various sensing methods to detect and analyse the occupancy of different frequency bands.

1.1. Spectrum Sensing.

Energy detection is a basic spectrum sensing method used in cognitive radio systems to determine whether signals are present in particular frequency bands or not. Cognitive radios constantly measure the energy levels within a frequency range and compare them to a predetermined threshold based on the theory that the existence of a signal increases the energy within it. When wideband sensing is needed or when the properties of the signals are unknown, this approach is adaptable and efficient. Energy detection, despite its simplicity, is essential for dynamic spectrum access since it helps to locate accessible spectrum opportunities. Its shortcomings include being blind to signal structure and sensitive to noise. Energy detection is a useful tool in optimizing coexistence and interference mitigation due to its versatility. However, Energy detection lacks signal structure information and is noise-sensitive. By Cooperative sensing, radios can reduce the impacts of noise, integrate signal information, adjust to changing conditions and take advantage of geographical variety in cooperative spectrum sensing.

A key idea in cognitive radio networks is cooperative sensing, in which several radio devices work together to share and aggregate data about the radio frequencies they have observed locally to jointly contribute to spectrum sensing. The main goal is to improve spectrum sensing's accuracy and dependability, especially in demanding and dynamic conditions. In contrast to individual radios operating independently, cooperative sensing makes use of the network's collective intelligence, which has numerous advantages.

1.2. ANFIS

With the characteristics of fuzzy logic systems and artificial neural networks combined, the Adaptive Neuro-Fuzzy Inference System(ANFIS) is a potent hybrid computational model. Specifically, ANFIS excels in predicting outcomes from input data and modelling intricate linkages. Fuzzy logic, which is based on rules and neural networks' learning capabilities, is combined to create an autonomous learning process that allows it to automatically modify its parameters. As a result of its superior ability to handle uncertainties and capture non-linear patterns, ANFIS is extensively used in domains like data analysis, pattern recognition and control systems. Given the dynamic and uncertain situations, the model's capacity for self-adjustment and data-driven learning makes it a flexible tool for a wide range of jobs requiring intelligent and adaptable decision-making.

1.3 SDR

Software-Defined Radio(SDR) is a transformative technology in wireless communication systems that replaces traditional hardware-based radio components with software-based solutions. With SDR, radio frequency signals are first received using the general-purpose antenna to start the data collection process. An analog-to-digital converter(ADC) is then used to transform these analog signals into digital signals. Digital signal processing(DSP) using software is applied to the digital signal, encompassing modulation, demodulation and additional manipulations. The signal is simplified for additional analysis through baseband processing. Software control, which enables users to dynamically configure parameters like frequency, bandwidth and modulation schemes, makes SDR unique. Because of its versatility, SDR can support a wide range of communication protocols, which makes it appropriate for a variety of users.

1.5 Evaluation matrix

An evaluation matrix is integral to the process of evaluating the accuracy and performance of the model in Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The matrix is useful for comparing the actual observed values from a dataset with the predicted outputs produced by ANFIS. Metrics like correlation coefficients, Mean Squared Error(MSE) and Root Mean Squared Error(RMSE) are commonly included in this matrix. These metrics provide a quantitative assessment of ANFIS's predictive power by quantifying the degree of agreement between expected and actual outcomes. To optimize the performance of the model and adjust its parameters, the evaluation matrix is a useful tool. It helps practitioners to continuously improve the accuracy of the ANFIS model, guaranteeing that it successfully captures the underlying patterns in the data and generates trustworthy predictions for real-world applications.

CHAPTER 2

PROBLEM STATEMENT

Efficient use of spectrum is needed in th represent generation as the number of users are increasing. So in this project, **‘SDR Implementation of Cooperative Spectrum Sensing using ANFIS’** the aim is to increase the efficiency of spectrum usage by allocating vacant spectrum holes to secondary users. Primary users are known as authorised users in the given spectrum and the unauthorized users in the given spectrum are known as secondary users. The spectrum is allocated to the secondary users where the primary users is not present, due to it even if the allocated spectrum to the primary users is not being used by them cannot be reallocated to secondary users which leads to inefficient use of spectrum. So to overcome this Cognitive radio is used. Cognitive radio is an intelligent and adaptive radio technology that allows devices to sense, learn and make decisions about the radio environment in real-time. Cognitive radio allocates the unused spectrum by primary users to secondary users. It can be achieved by spectrum sensing and decision making in cognitive radio.

For the first half as mentioned above spectrum sensing is done in cognitive radio. Spectrum sensing is a crucial function in cognitive radio networks because it enables the dynamic and opportunistic utilization of available radio frequency(RF) spectrum. The spectrum sensing technique used in this project is cooperative sensing . The data needed for this is collected through the sdr device. The sdr device used is ADALM PLUTO (AD9363), where the SDR device acts as a secondary user. The data consists of energy values for the respective frequencies in the respective frequency range. The predefined threshold is set for the energy values and the maximum active channels in the spectrum is observed. The data is then collected on the number of maximum active channels in the spectrum of the respective frequency ranges and is used for the next half of this project for decision-making in cognitive radio.

For the second half as mentioned above the decision-making in cognitive radio takes place by using the prior data gained after the spectrum sensing. This data is then simulated in the ANFIS toolbox in Matlab. The data is trained and tested for decision-making. It is then given to the fuzzy logic toolbox for certain defined rules for decision making and then the evaluation matrix is generated for accuracy.

CHAPTER 3

LITERATURE REVIEW

3.1 Cognitive radio: Brain-empowered wireless communications.

A cognitive radio that operates in a spectrum hole while staying within an interference power cap is the recommended method in this paper. When the primary user shows up, cognitive radio is regarded as noise, it can simply move to a different spectrum hole. This integrates the cognitive radio techniques of overlay and underlay.

MAC layer protocols, MIMO techniques and other measures, however, will be necessary to make it possible for cognitive radios to share the same spectrum. The method is non-centralized since it doesn't assume the existence of a base station, a mechanism must be in place to modify each cognitive radio's transmit power level in accordance with predetermined protocols. It is advised to use dynamic spectrum management.

3.2 Novel Adaptive non-uniform Sub-Nyquist Sampling Technique for Cooperative Wideband Spectrum Sensing

This work proposes a modified sub-Nyquist sampling technique with fewer branches than needed in traditional non-blind multi-coset sampling. The technique is based on an adaptive multi-coset sampling technique with blind input signal. Through the suggested method, a number of(Y) cognitive radio users collaborate to achieve cooperative sensing based on the majority decision rule.

The performance of a cluster of 4 CRs is simulated using Matlab 16 and Simulink. Assuming that each cluster of cooperative CRs receives a sparse input signal x(t) that varies in terms of noise level and kind. Thus, if the channel bandwidth is 20MHz for a sparse wideband input signal in the frequency range of [0:500]MHz, then L=25 segments. By employing an adaptive multi-coset sampling algorithm on a shared sparse input signal x(t) with different noise types that impact each cognitive radio user based on their locations and fading issues. Assuming, Srxx is a vector of the estimated active bands at the CR0 receiver, Srxx1 is related to CR1 , Srxx2 for CR2 and Srxx3 for CR3. After simulation, using the majority decision rule of cooperative sensing where, the final decision is based on selecting the repeated bands at most of CR users.

The results of the simulation demonstrated that by resolving the fading and shadowing issues, the suggested strategy improved the likelihood of detection when compared to individual sensing. Furthermore, the CR user can increase the system complexity and power consumption by depending on other cooperative nodes when its own node is not sensing.

3.3 Artificial Intelligence-Based Cooperative Spectrum Sensing Algorithm for Cognitive Radio Networks.

Techniques for sensing the wide spectrum have become very important in cognitive radio networks. Thus, the wide-spectrum sensing technique used in this paper is based on adaptive blind Multi-coset sampling. A centralized cooperative sensing scheme is created to combat the effects of noise and fading issues. The five SUs in the suggested system use the adaptive MC algorithm to find free channels. Afterwards, each user's detection results are gathered using a centralized cooperative sensing scheme. Following that, a fifteen-rule set of inputs and an AI-detecting technique based on the ANFIS structure are put into practice. When compared to other channels with five senders, the channel power levels PMU for ANFIS-detected channels was the highest. Although the theoretical error was estimated to be roughly 10%, in actuality it was 1% after 300epoch of training. Hence the simulation results of this work prove that the proposed cooperative model based on ANFIS detection is better than the common conventional detection rules.

The simulation process and the output results demonstrated that, in terms of the probability of false alarms, probability of false alarms occurring, and other factors, the suggested technique performs better than both standalone sensing techniques and other cooperative sensing with conventional decision-making algorithms.

3.4 Cooperative spectrum sensing optimization based adaptive neuro-fuzzy inference system (ANFIS) in cognitive radio networks.

This paper proposes an Adaptive Blind Multi-Coset (ABMC) sampler for wideband spectrum sensing in cognitive radio networks by obtaining the vacant channels. A centralized cooperative spectrum sensing scheme is designed to address issues with channel noise, fading and shadowing that interfere with the sensing process. Next, in order to arrive at the best choices, the ANFIS model is applied to the sensed results that were obtained from all of the cooperative users at the fusion centre. The proposed ANFIS model is composed of fifteen rules that are based on the power values of the detected channels from the secondary users and it uses five secondary users as input senders. The error is theoretically adjusted to be roughly 10%, but after 300 training epochs, it's actually reached about 1%.

The proposed ANFIS model's simulation results demonstrated that, in comparison to the standalone model of using ABMC on an individual basis, it provides a higher probability of detection(Pd), a lower probability of missed detection(Pmd), lower probability of false alarms(PFA). Other conventional (AND, OR) detection rules were outperformed by the proposed cooperative wideband sensing-based ANFIS detection technique. The ideal number of cooperative users is provided by the ANFIS model's second stage. As a result , the suggested system has excellent performance and theoretical dependability

CHAPTER 4

Project Requirements and Specifications

4.1 Objective

The primary objective of this project is to implement a Software-Defined Radio (SDR) based system employing Cooperative Spectrum Sensing using Adaptive Neuro-Fuzzy Inference System (ANFIS). This system aims to enhance the efficiency of spectrum utilization by facilitating the allocation of vacant spectrum bands to secondary users, thereby maximizing spectrum utilization in dynamic and challenging RF environments.

4.2 Functional Requirements

Spectrum Sensing

- Implement cooperative spectrum sensing techniques to detect available spectrum bands.
- Collect data using SDR devices, specifically utilizing the ADALM PLUTO (AD9363) SDR as a secondary user.
- Employ energy detection methods to identify occupied and vacant spectrum bands.
- Define and set a predefined threshold for energy values.
- Capture data on maximum active channels in respective frequency ranges for decision-making.

Decision-Making with ANFIS

- Utilize the collected data from spectrum sensing for decision-making using ANFIS in MATLAB.
- Train and test the ANFIS model for intelligent decision-making in allocating spectrum to secondary users.
- Create evaluation matrices using metrics like correlation coefficients, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to assess the accuracy and performance of the ANFIS model.

4.3 Technical Requirements

Hardware

- SDR Devices: ADALM PLUTO (AD9363) and RTL-SDR for spectrum data collection.
- General-purpose antenna for receiving radio frequency signals.
- Analog-to-Digital Converter (ADC) for transforming analog signals to digital signals.

Software

- MATLAB with ANFIS toolbox for modeling and training ANFIS.
- GNU Radio for spectrum detection and signal processing.
- Simulink for simulating and analyzing cooperative spectrum sensing techniques.

4.4 Constraints

Bandwidth and Frequency

- Spectrum sensing within defined bandwidths and frequency ranges.
- Limitations on the number of channels that can be simultaneously sensed.

Processing and Computational Resources

- Consideration of computational resources required for ANFIS training and decision-making.

4.5 Non-functional Requirements

Accuracy and Reliability

- Ensure high accuracy in spectrum sensing and decision-making.
- Reliable functioning of SDR devices and software tools.

Scalability and Adaptability

- Ability to scale the system for handling varying numbers of primary and secondary users.
- Adaptability to changing RF environments and spectrum availability.

CHAPTER 5

PROPOSED METHODOLOGY

5.1 Overview of Design

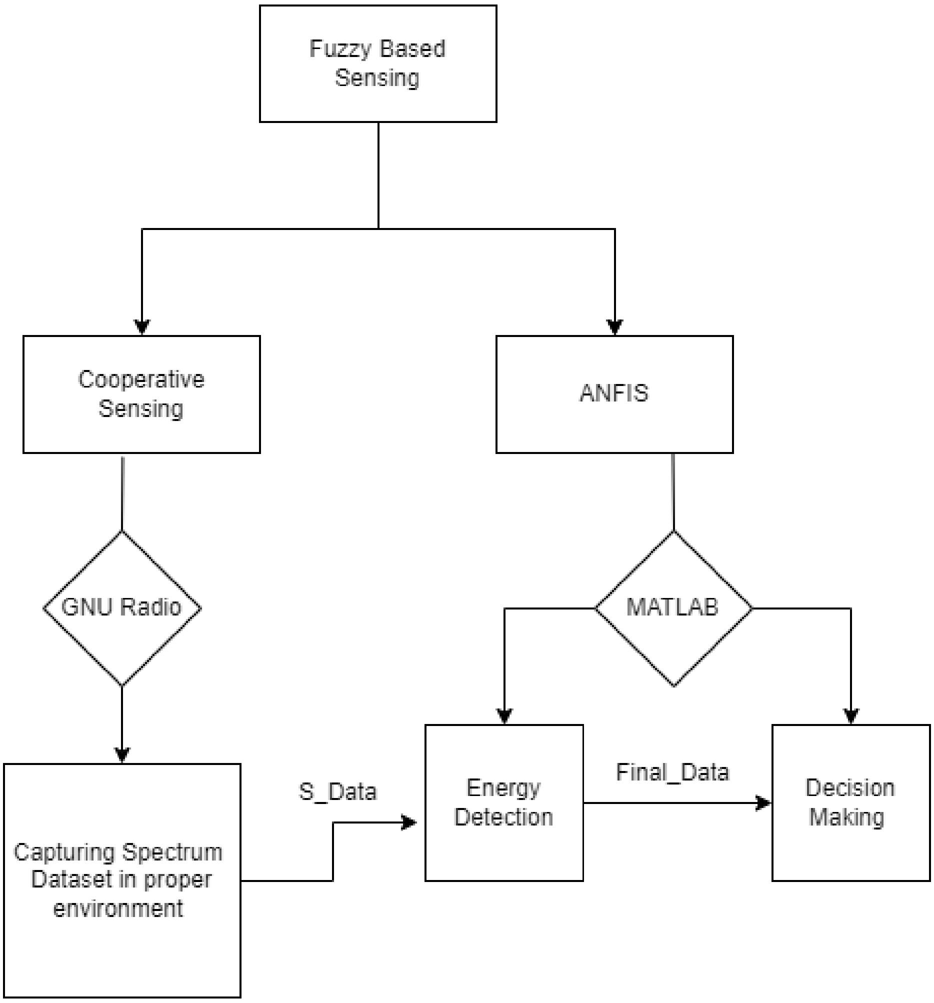
In this section, we present a detailed description and overview of the system design and proposed methodology employed in our project. A cognitive radio mainly consist of the following part:

Spectrum sensing method

Detection method

Decision method

The following block diagram outlines the key components of the proposed methodology.



5.2 Spectrum Detection

Spectral detection is a crucial process in the cognitive radio system. This enables the identification and analysis of signals present in the radio frequency spectrum. The primary goal of spectrum detection is to sense the environment efficiently to detect the presence of

Primary and secondary users in the spectrum. We accomplish this by using a RTL SDR which is interfaced through GNU radio. [what is RTL SDR how is it useful, which sdr we are using] The process begins with the collection of data from the spectrum at a particular centre frequency, Bandwidth and sampling rate.

The collected data undergoes pre-processing to filter out the noise and unwanted signals. The data is also aligned with the corresponding frequency in a single CSV file. These steps simplify the process and improve the accuracy of subsequent processes. This is followed by energy which is discussed in the next section

5.3 Energy Detection

In order to detect the presence of primary and secondary user we are using energy detection methodology. Energy detection is simple yet effective spectrum detection method. Its is chosen for its ease of implementation and it is independent from any requirement of prior knowledge about the primary signal. [state some research paper]. The working principle of the model assumes that the received signal Y is the sum of primary user signal X, and Gaussian noise N along with the channel gain H. Equation [ ]

$Y = HX + N$

Null hypothesis is as the statistical method for detection. Two hypotheses are considered. H0 (null hypothesis) denotes the absence of primary user in the band, while H1 [Alternate Hypothesis] signifies the presence of the primary user. The detection statistics involves calculations of the average energy of the observed samples, The decision regrading the spectrum occupancy is made by comparing the detection statistic { above equation } with pre computed threshold value [T]. The threshold is play a crucial role in determining the between the probability of false alarm and probability of detection.

Efficient energy detection involves optimizing the threshold calculation. In our proposed system, proposed method, practical parameters are measured and threshold values are decided. The energy. The implementation details of this are discussed in the following implementation section.

5.3 ANFIS

Using ANFIS (Adaptive Neuro-Fuzzy Inference Systems), we start a crucial phase of decision-making. Using datasets from two distinct devices, we hope to integrate membership functions and fuzzy rules to train and test the ANFIS model. The membership functions have a significant impact on the model's understanding of the underlying data patterns; in this case, the Gaussian membership function was chosen since it explains the symmetry found in the majority of the dataset. Fascinatingly, the ANFIS model automatically creates fuzzy rules based on the learned membership functions. This automated rule-generating procedure adds flexibility to the model, enabling it to identify complex relationships in the energy detection dataset. Our study attempts to increase decision-making systems' precision and effectiveness in the area of energy detection.

CHAPTER 6

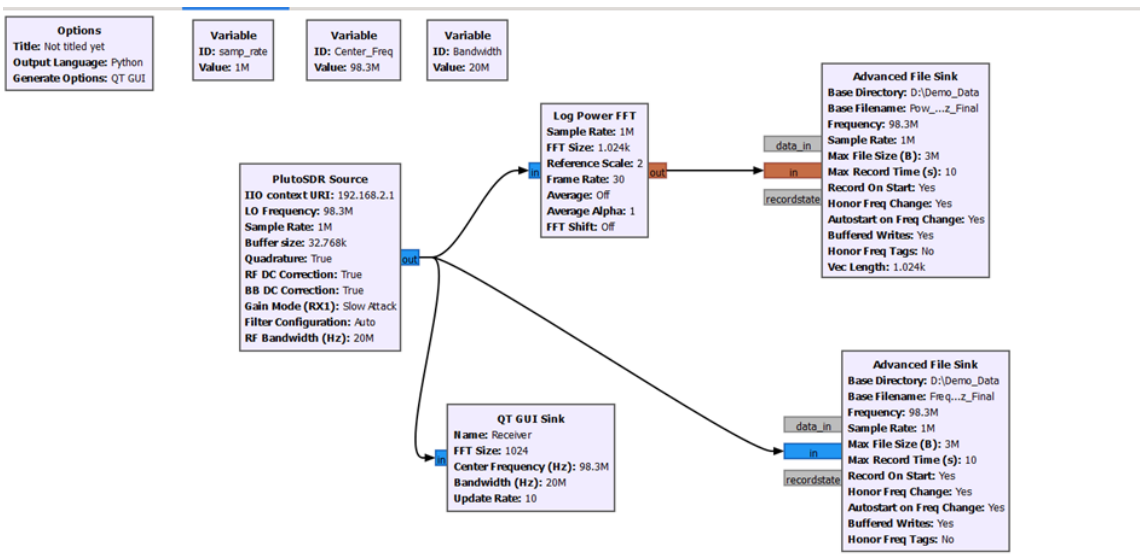
IMPLEMENTATION

6.1 Cooperative Sensing with GNU Radio

Understanding the hardware specifications and preparing our system by installing the necessary drivers and libraries are the first steps in the implementation process. Multiple blocks are present for different SDRs, and since we are using the Pluto SDR, the source block is selected as the Pluto SDR source. Modify the block's parameters in accordance with the specifications. The Advance File Sink block is selected to capture the spectrum dataset, modify the file size and recording duration in accordance with the needs, and link this block to the source block, which provides us with the frequency values from the spectrum in the form of.IQ files, which will subsequently be converted to the proper format. Only the power values of the spectrum are obtained by using the log power FFT between the source and the sink. The spectrum is analyzed using the QT GUI Sink. After doing several tests with different bandwidths, sampling rates, and centre frequencies, we selected a value that works for both FM and Wi-Fi-ranging signals. The tool's dataset will undergo additional processing in order to facilitate signal processing.

6.2 Energy Detection using Matlab

We used MATLAB to perform energy detection on datasets from many channels, such as FM channels from 88 to 108 GHz and Wi-Fi operating at 2.4 GHz and 5 GHz. After loading the datasets into MATLAB, the minimum and maximum values of the frequency dataset were aligned to guarantee compatibility. One of the most important preprocessing steps to enable proper comparison and analysis was to normalize the datasets.



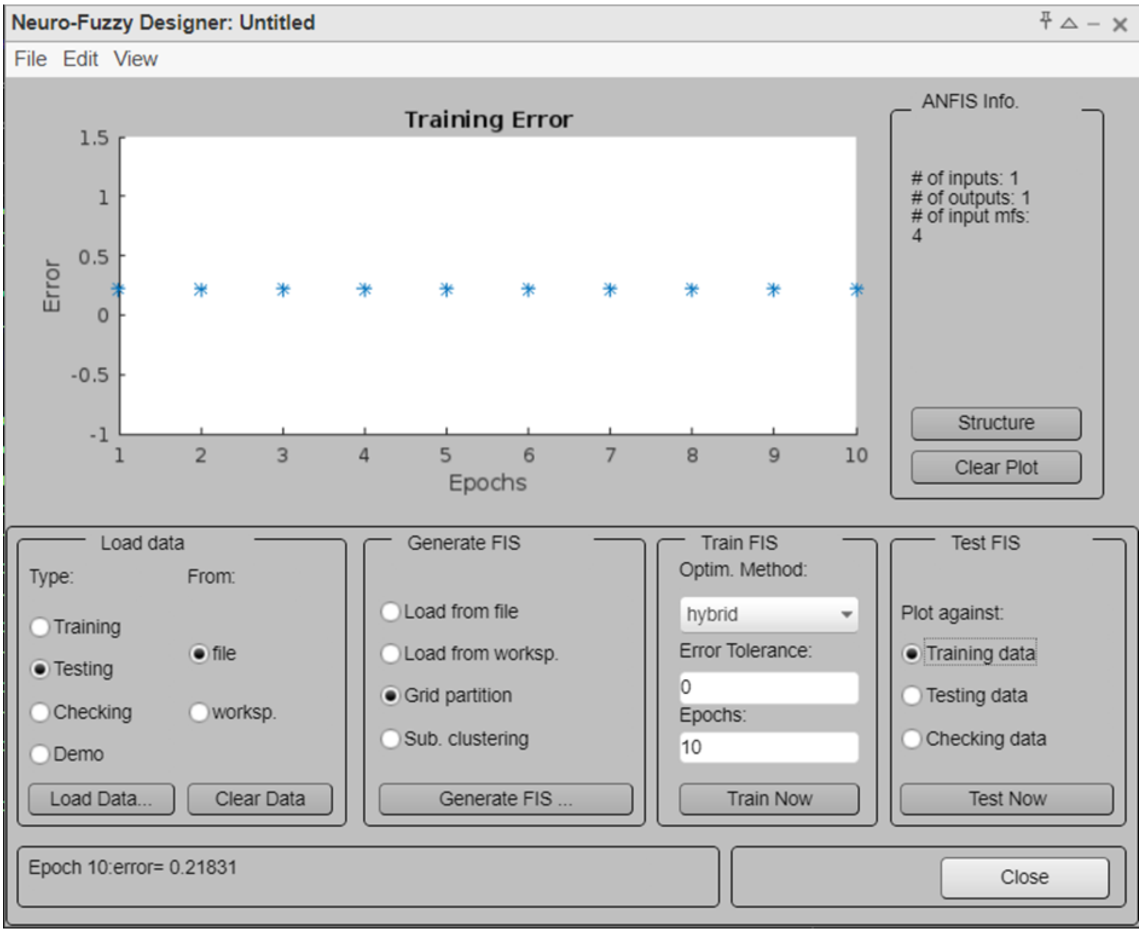
The threshold parameter (th) was adjusted after normalization to better fit the unique features of the datasets. The power levels were compared to the threshold to initiate the energy detection procedure. If the power value was higher than the threshold, the hypothesis (Ho) was set to 1; if the power value was lower than the threshold, Ho was set to 0. This binary decision system successfully identified whether a signal was present in the specified channels.

A new dataset with the Ho column containing the detection results was developed in order to aid in additional analysis and interpretation. The power values in this dataset were presented in conjunction with the matching Ho values, offering a thorough depiction of the energy detection outcomes.

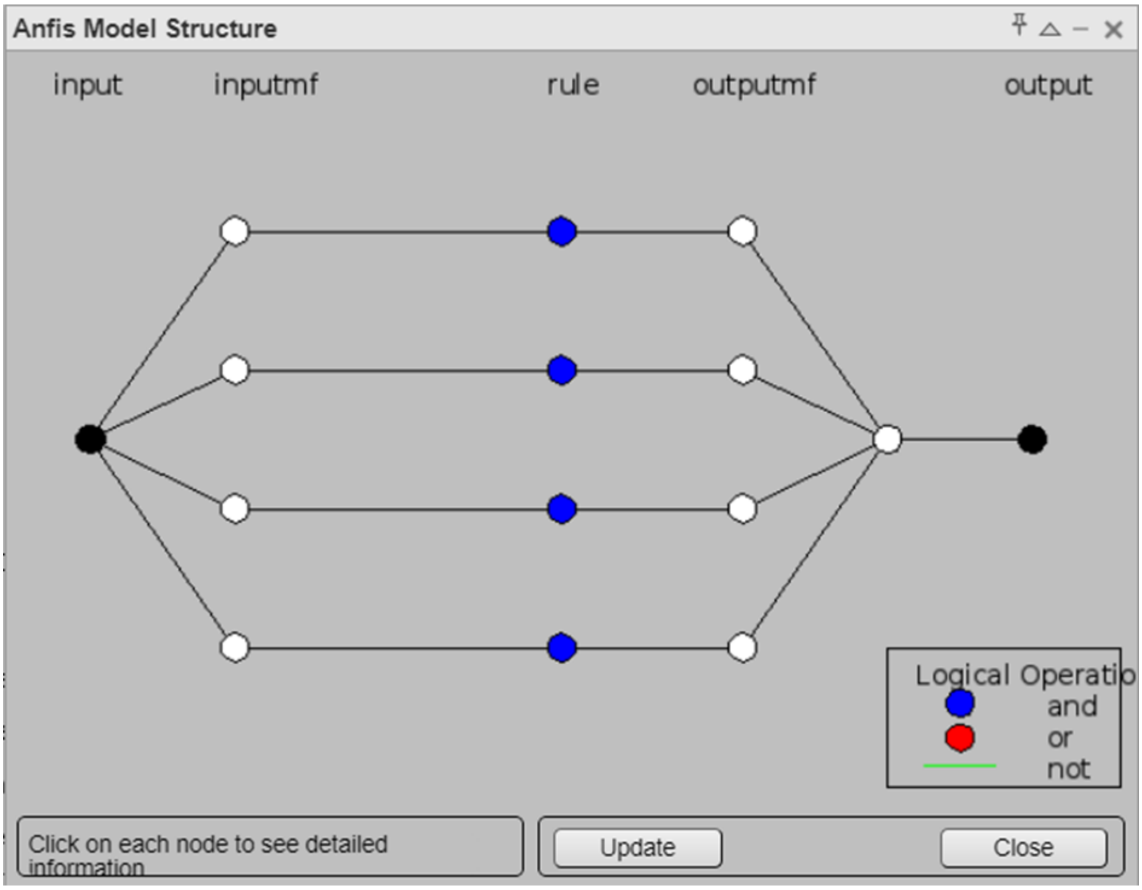
The Pluto SDR gear, which guarantees accurate and dependable signal capture within the necessary frequency bands, was used to collect the data.

6.3 Decision Making

In order to solve a challenging problem utilizing fuzzy logic, this study made use of MATLAB's Anfis package for modelling fuzzy inference systems (FIS). Installing the required tools and running "ANFIS edit" to launch Anfis was the first step, and it opened an interface that was easy to use for the other activities. After being suitably divided into training segments to enable efficient model training, the dataset was then put into the Anfis block.



After that, the FIS was developed, carefully choosing membership functions that were most appropriate for the current situation. The FIS was then trained further, honing its membership functions and rule base to improve its predictive power. The application of fuzzy logic and rule-based generation for the FIS, which enabled a flexible and nuanced modeling approach, was a crucial component of the project.



A testing dataset was loaded, and the outcomes were plotted to evaluate the performance of the trained model. Evaluation criteria, including the chance of detection, false alarm rate, and confusion matrix, were used to thoroughly examine the accuracy and efficacy of the model. This thorough technique made it possible to examine training and testing errors in great detail, which shed light on the FIS's generalization abilities.

The use of fuzzy logic and the evaluation matrix contributes to a robust assessment of the model's performance, making this project valuable for applications that require nuanced and adaptive modelling in complex scenarios.

6.4 Pseudocode

GNU radio:

Step 1: Install Pluto SDR's necessary drivers and packages, then verify that the connection is working.

Step 2: Select the Pluto SDR Source Block (Receiver) and enter the desired specifications, such as centre frequency and bandwidth.

Step 3: To capture the frequency dataset, use the file sink block.

Step 4: To record the spectrum power in the DBM, use the Log fft block along with the File Sink block.

Step 5: Join the blocks, extract the dataset, and save it in a .mat or.csv file format.

Energy Detection:

Step 1: Open MATLAB and load the datasets.

Step 2: Set the frequency dataset's minimum and maximum values in alignment.

Step 3: After normalizing the datasets, modify the threshold (th) as necessary.

Step 4: If Power Val > Th, then Ho = 1; if Power Val < Th, then Ho = 0.

Step 5: Make a new dataset with the Ho (output) column having power values in it.

ANFIS:

Step 1: Install the necessary toolbox and use "anfisedit" to open Anfis.

Step 2: Load the dataset into the Anfis block after splitting it into training segments.

Step 3: Create a FIS, select the membership function suitably, and begin training.

Step 4: Load the testing dataset, plot the results, and look for errors in the testing and training.

CHAPTER 7

RESULTS AND DISCUSSION

7.1 Results of Co-operative Sensing

In this research endeavour, a hypothesis-driven process was employed to locate energy through cooperative sensing. The main hypothesis states that if the Power Value exceeds a threshold (Th), the null hypothesis (Ho) is assigned a value of 1; if the Power Value is less than Th, the null hypothesis is assigned a value of 0. To facilitate the training and testing of an Adaptive Neuro-Fuzzy Inference System (ANFIS) model, a meticulous dataset was created. Two Pluto Software Defined Radios (SDRs), each operating at a bandwidth of 20 MHz and a sampling frequency of 1 MHz, were employed to obtain the finest feasible spectrum resolution.

The threshold was established by means of a thorough examination of differences in active bands. Taking advantage of the Pluto SDRs' capabilities, datasets were obtained and then exposed to energy detection. The datasets were then processed and analysed using the ANFIS model, a potent computational tool for system identification and control.

Thorough testing and experimentation were used to further evaluate the resilience of the process. Utilizing a 20 MHz bandwidth and a 1 MHz sample frequency allowed for a more detailed spectrum analysis, which improved the precision and dependability of the findings. By offering a methodical and hypothesis-driven approach, backed by a carefully selected dataset and sophisticated computational modelling, this research advances the fields of cooperative sensing and energy detection and paves the way for improved spectrum sensing and utilization in communication systems.

7.2 Evaluation of ANFIS model

Following several trials of the Adaptive Neuro-Fuzzy Inference System (ANFIS), our study yielded exceptional performance metrics. The confusion matrices generated by contrasting the ANFIS model's output with the test data provided a comprehensive insight of classification effectiveness.

Matrix

	Pred Neg	Pred Pos
Actual Neg	65012	61343
Actual Pos	299	144603

With notable overall accuracy, precision, recall, F1 score, and efficient handling of false alarms and miss detection rates, the ANFIS model demonstrates robustness in decision-making. These outcomes show how useful the model is and offer useful details for real-world scenarios where accuracy and sensitivity are crucial. This work contributes to our understanding of the applicability and performance characteristics of ANFIS under various trial scenarios and emphasizes the technology's promise for accurate prediction in difficult situations.

CHAPTER 8

Conclusion and Future Work

Cooperative sensing and energy detection play a crucial role in communication systems, especially in the context of spectrum sensing and utilization. Accurate detection of energy levels in the spectrum is essential for efficient allocation and utilization of available frequencies. Additionally, cooperative sensing, which involves the collaboration of multiple devices to sense and analyze the spectrum, can enhance the reliability and robustness of spectrum sensing. By improving our understanding of the applicability and performance characteristics of techniques like ANFIS in cooperative sensing and energy detection, this research has the potential to contribute to the development of more accurate and efficient communication systems.

Adaptive sampling techniques will be incorporated into the planned future work to improve cooperative sensing and energy detection capabilities. We expect a more dynamic and responsive system that can adjust to changing environmental conditions by enhancing the sampling strategies, which will raise the cooperative sensing framework's overall efficiency. Furthermore, the training and testing dataset will be strengthened by extending beyond conventional channels like WiFi and FM. By adding a variety of channels, the dataset will be larger and the model's range of applicability will be increased. In addition, the direction of future study is adding more environmental interferences to create a scenario for cooperative sensing that is more difficult and realistic. This strategy supports the goal of creating.

REFERENCES

[1] T. Rasheed, A. Rashdi and A. N. Akhtar, "Cooperative spectrum sensing using fuzzy logic for cognitive radio network," 2018 Advances in Science and Engineering Technology International Conferences (ASET), Dubai, Sharjah, Abu Dhabi, United Arab Emirates, 2018, pp. 1-6, doi: 10.1109/ICASET.2018.8376914.

[2] M. Sani, J. Tsado, S. Thomas, H. Suleiman, I. M. Shehu and M. G. Shan'una, "A Survey on Spectrum Sensing Techniques for Cognitive Radio Networks," 2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS), Abuja, Nigeria, 2021, pp. 1-5, doi: 10.1109/ICMEAS52683.2021.9692412.

[3] Javed, Farrukh & Mahmood, Asad & Shafi, Imran & Ali, Saqib. (2012). Open Research Areas in Cognitive Radios. Proceedings of International Conference on Computational Intelligence, Modelling and Simulation. 375-380. doi: 10.1109/CIMSim.2012.40.

[4] Y. Mimbeu , J. Matanga , Y. Malong , A. Ngalle, J. T Tasona Doko, J. F. Essiben, N. Severin, O. Raphael, I. Breunon, 2022, Optimization Of Spectrum Management in A Cognitive Radio Network using Fuzzy Logic, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 11, Issue 09 (September 2022),

[5] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in IEEE Personal Communications, vol. 6, no. 4, pp. 13-18, Aug. 1999, doi: 10.1109/98.788210.

[6] Al khayyat A, Abedi F, Bagwari A, et al. Fuzzy logic, genetic algorithms, and artificial neural networks applied to cognitive radio networks: A review. International Journal of Distributed Sensor Networks. 2022;18(7). doi:10.1177/15501329221113508

[7] N. Gupta, S. K. Dhurandher and B. Kumar, "Contract Theory Based Incentive Mechanism Design Approaches in Cognitive Radio Networks: A Survey," 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), Ghaziabad, India, 2019, pp. 1-6, doi: 10.1109/IoT-SIU.2019.8777498.

[8] A. Bdrany and S. B. Sadkhan, "Decision Making Approaches in Cognitive Radio-Status, Challenges and Future Trends," 2020 International Conference on Advanced Science and Engineering (ICOASE), Duhok, Iraq, 2020, pp. 195-198, doi: 10.1109/ICOASE51841.2020.9436597.

[9] R. K. Prasad and T. Jaya, "Decision Making Method ETOP for Handoff in Cognitive Radio Network," 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2020, pp. 774-779, doi: 10.1109/ICECA49313.2020.9297548.

[10] Masonta, Moshe & Mzyece, Mjumo & Ntlatlapa, Ntsibane. (2013). Spectrum Decision in Cognitive Radio Networks: A Survey. IEEE Communications Surveys &amp Tutorials. 15. 1088-1107. doi: 10.1109/SURV.2012.111412.00160.

[11] A. Borany and S. B. Sadkhan, "Decision-making approach in Cognitive Radio using Tsukamoto and Mamdani FIS," 2021 1st Babylon International Conference on Information Technology and Science (BICITS), Babil, Iraq, 2021, pp. 144-148, doi: 10.1109/BICITS51482.2021.9509910.

[12] Obite, F., Usman, A. D., & Okafor, E. (2021). An overview of deep reinforcement learning for spectrum sensing in cognitive radio networks. Digital Signal Processing, 113, 103014. doi:10.1016/j.dsp.2021.103014.

[13] A. F. Tayel, S. I. Rabia, A. H. Abd El-Malek and A. M. Abdelrazek, "Spectrum Access Management of Multi-class Secondary Users in Hybrid Cognitive Radio Networks," 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Helsinki, Finland, 2021, pp. 1-6, doi: 10.1109/VTC2021-Spring51267.2021.9448748.

[14] J. Xie, J. Fang, C. Liu and X. Li, "Deep Learning-Based Spectrum Sensing in Cognitive Radio: A CNN-LSTM Approach," in IEEE Communications Letters, vol. 24, no. 10, pp. 2196-2200, Oct. 2020, doi: 10.1109/LCOMM.2020.3002073.

[15] C. Clancy, J. Hecker, E. Stuntebeck and T. O'Shea, "Applications of Machine Learning to Cognitive Radio Networks," in IEEE Wireless Communications, vol. 14, no. 4, pp. 47-52, August 2007, doi: 10.1109/MWC.2007.4300983.

[16] Ghosh, Goutam & Das, Prasun & Chatterjee, Subhajit. (2014). Simulation and Analysis of Cognitive Radio System Using Matlab. International Journal of Next-Generation Networks. 6. 31-45. 10.5121/ijngn.2014.6203.

[17] G. M. Salama and S. A. Taha, "Cooperative Spectrum Sensing and Hard Decision Rules for Cognitive Radio Network," 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia, 2020, pp. 1-6, doi: 10.1109/ICCAIS48893.2020.9096740.

[18] M. Mourad Mabrook, Hussein A. Khalil, Aziza I. Hussein,"Artificial Intelligence Based Cooperative Spectrum Sensing Algorithm for Cognitive Radio Networks",Procedia Computer Science,Volume 163,2019,Pages 19-29,ISSN https://doi.org/10.1016/j.procs.2019.12.081.

[19] M. M. Mabrook, G. A. Fahmy, A. I. Hussein and M. A. Abdelghany, "Novel adaptive non-uniform sub-Nyquist sampling technique for cooperative wideband spectrum sensing," 2016 12th International Computer Engineering Conference (ICENCO), Cairo, 2016, pp. 20-25, doi: 10.1109/ICENCO.2016.7856439.