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(Research Article)

Implementation of Monte Carlo and ANFIS techniques for detection threshold estimation in cognitive radio

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Abstract

This research explores the implementation of Monte Carlo and Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques for detection threshold estimation in cognitive radio networks. Accurate detection threshold estimation is essential for effective spectrum sensing, minimizing false alarms, and optimizing spectrum utilization. The study first outlines conventional spectrum sensing methods and their limitations, particularly in dealing with noise uncertainty and dynamic spectral environments. Monte Carlo simulations are employed to statistically model detection scenarios and derive optimal threshold values, while ANFIS leverages machine learning and fuzzy logic to adaptively adjust thresholds in real time. A comparative analysis of both techniques is conducted, evaluating their efficiency, computational complexity, and adaptability in cognitive radio applications. The findings demonstrate that Monte Carlo offers a robust probabilistic approach suitable for static environments, while ANFIS enhances real-time adaptability, making it more effective for dynamic spectrum sensing. This research significantly contributes to improving cognitive radio performance, ensuring reliable spectrum access, and reducing interference in wireless communication networks.

Keywords: Cognitive Radio; Detection Threshold Estimation; Monte Carlo Simulation; Adaptive Neuro-Fuzzy Inference System (ANFIS); Cooperative Spectrum Sensing.

1. Introduction

The rapid growth of wireless communication technologies has led to an increasing demand for efficient spectrum utilization, necessitating the development of cognitive radio (CR) systems that can dynamically adapt to varying spectral conditions[1]. Spectrum sensing, a crucial function of CR, enables secondary users to detect and utilize unused frequency bands while ensuring minimal interference with primary users[2]. Accurate detection of spectrum availability is highly dependent on the estimation of detection thresholds, which determine whether a signal is present or absent. Traditional threshold estimation methods are often challenged by noise uncertainty, environmental variations, and dynamic interference conditions[3]. To address these challenges, advanced techniques such as Monte Carlo simulations and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been employed to enhance detection threshold estimation. Monte Carlo methods provide statistical insights by simulating multiple random scenarios to determine optimal thresholds, whereas ANFIS integrates fuzzy logic and neural networks to adaptively adjust thresholds based on real-time conditions[4]. The combination of these techniques offers a robust approach to improving spectrum sensing accuracy, reducing false alarms, and optimizing cognitive radio performance. This study explores the implementation of Monte Carlo and ANFIS techniques for detection threshold estimation in cognitive radio, providing a comprehensive evaluation of their methodologies, effectiveness, and impact on spectrum sensing efficiency[5]. Cognitive Radio (CR) has emerged as a promising solution to enhance spectrum utilization by allowing secondary users

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to dynamically access underutilized frequency bands. A critical component of CR is spectrum sensing, which ensures that secondary users can detect the presence of primary users to avoid interference[6]. One key parameter in spectrum sensing is the detection threshold, which determines the ability of the CR system to accurately differentiate between occupied and unoccupied spectrum bands.

1.1. Overview of Spectrum Sensing in Cognitive Radio

Spectrum sensing is a fundamental aspect of cognitive radio that enables the efficient utilization of available spectrum by dynamically detecting vacant frequency bands. The primary goal of spectrum sensing is to ensure that secondary users (unlicensed users) can opportunistically access underutilized spectrum without causing harmful interference to primary users (licensed users). Several spectrum sensing techniques exist, including energy detection, matched filtering, and Cyclostationary feature detection. Energy detection is the most commonly used due to its low computational complexity and implementation simplicity. It involves measuring the received signal energy and comparing it with a predefined threshold to determine the presence of a primary user. However, energy detection is highly susceptible to noise uncertainty and requires accurate threshold estimation to maintain an optimal balance between false alarms and missed detections.

Matched filtering, on the other hand, is a coherent detection technique that provides optimal detection performance when the primary user's signal characteristics are known. While this method offers higher accuracy, it requires prior knowledge of the primary user's signal, which may not always be available. Cyclostationary feature detection exploits the inherent periodicity in modulated signals to distinguish between primary user signals and noise. This method is highly robust against noise uncertainties but demands higher computational resources.

Several spectrum sensing techniques exist, including energy detection, matched filtering, and Cyclostationary feature detection. Energy detection is the most commonly used due to its low computational complexity and implementation simplicity. It involves measuring the received signal energy and comparing it with a predefined threshold to determine the presence of a primary user. The test statistic for energy detection is given by[7]

$$T = \sum_{n=1}^{N} |y(n)|^2 \dots\dots\dots\dots\dots\dots\dots\dots. (1.1)$$

Where $y(n)$ is the received signal and N is the number of samples.

Matched filtering, on the other hand, is a coherent detection technique that provides optimal detection performance when the primary user's signal characteristics are known. The decision statistic is given by[7]

$$T = \sum_{n=1}^{N} y(n)h(n) \dots\dots\dots\dots\dots\dots\dots. (1.2)$$

where $h(n)$ is the matched filter impulse response.

Cyclostationary feature detection exploits the inherent periodicity in modulated signals to distinguish between primary user signals and noise. The spectral correlation function used in this technique is given by[8]

$$S_x(f, \alpha) = \int x(t)e^{-j2\pi ft} x * (t + a)dt \qquad (1.3)$$

To enhance detection reliability and minimize sensing errors, cooperative spectrum sensing has been introduced, where multiple CR nodes collaborate to improve sensing accuracy. By sharing sensing information, cooperative sensing mitigates the effects of multipath fading and shadowing, leading to a more robust spectrum sensing framework.

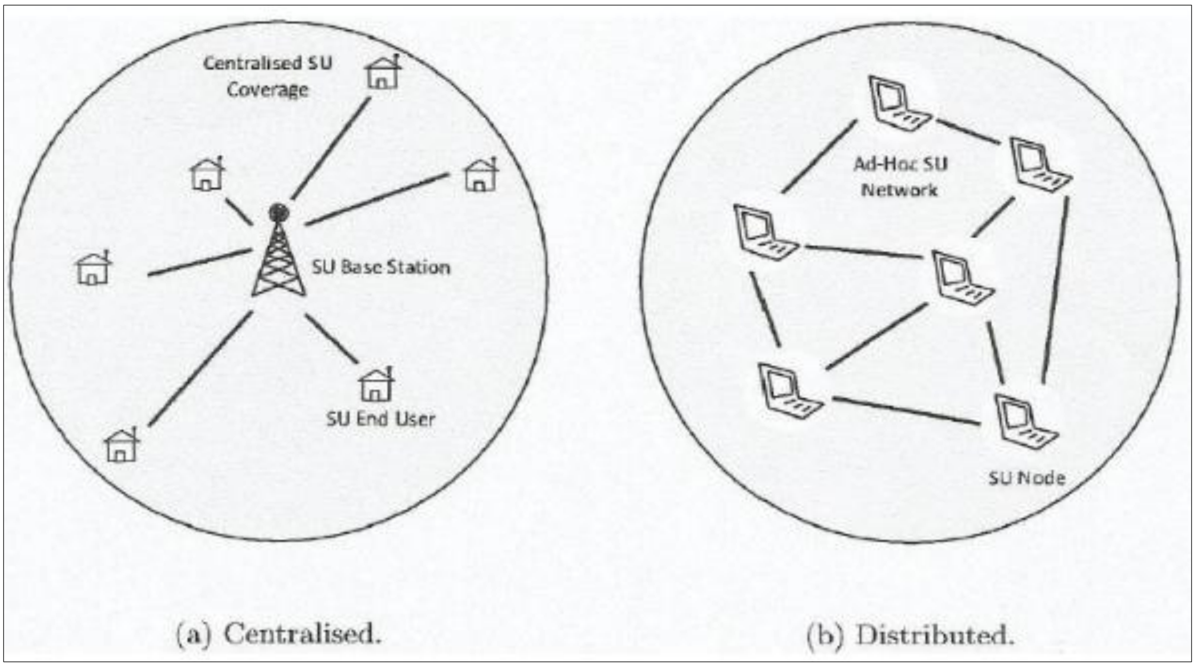

Figure 1 Architecture of Centralized vs. Distributed Cognitive Radio Network

Detection threshold estimation plays a crucial role in minimizing false alarms and missed detections, ultimately improving the efficiency of CR networks. Traditional methods of estimating detection thresholds often struggle with noise uncertainty and environmental variations, necessitating more advanced techniques such as the Monte Carlo simulation and Adaptive Neuro-Fuzzy Inference System (ANFIS). These techniques offer robust approaches for estimating optimal detection thresholds by leveraging probabilistic modeling and machine learning capabilities.

This review article explores the implementation of Monte Carlo and ANFIS techniques for detection threshold estimation in cognitive radio. It provides an in-depth analysis of their methodologies, compares their effectiveness, and discusses their impact on spectrum sensing performance. The findings aim to contribute to the development of more reliable and adaptive spectrum sensing mechanisms in cognitive radio networks.

1.2. Importance of Detection Threshold Estimation

Detection threshold estimation is crucial in cognitive radio networks as it directly influences the accuracy and efficiency of spectrum sensing. The detection threshold serves as the decision boundary that distinguishes between the presence and absence of a primary user signal[9]. An improperly set threshold can lead to two significant issues: false alarms and missed detections. A high detection threshold increases the likelihood of missed detections, where the secondary user fails to recognize an active primary user and inadvertently causes interference. On the other hand, a low detection threshold results in an increased false alarm rate, where the secondary user incorrectly identifies an empty spectrum as occupied, leading to inefficient spectrum utilization. To optimize the detection threshold, techniques such as Monte Carlo simulations and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are employed. Monte Carlo simulations provide a statistical approach by running multiple iterations of spectrum sensing scenarios to derive an optimal threshold value. ANFIS, on the other hand, integrates fuzzy logic and neural networks to adaptively determine the best detection threshold based on dynamic environmental conditions[4]. Accurate detection threshold estimation enhances spectrum efficiency, minimizes interference, and ensures reliable communication in cognitive radio networks. By implementing advanced threshold estimation techniques, cognitive radios can operate more effectively, making intelligent decisions about spectrum access while maintaining compliance with regulatory constraints[10]. Detection threshold estimation plays a crucial role in minimizing false alarms and missed detections, ultimately improving the efficiency of CR networks. Traditional methods of estimating detection thresholds often struggle with noise uncertainty and environmental variations, necessitating more advanced techniques such as the Monte Carlo simulation and Adaptive Neuro-Fuzzy Inference System (ANFIS)[4]. These techniques offer robust approaches for estimating optimal detection thresholds by leveraging probabilistic modeling and machine learning capabilities. This review article explores the implementation of Monte Carlo and ANFIS techniques for detection threshold estimation in cognitive radio. It provides an in-depth analysis of their methodologies, compares their effectiveness, and discusses their impact on spectrum sensing performance. The findings aim to contribute to the development of more reliable and adaptive spectrum sensing mechanisms in cognitive radio networks.

1.3. Spectrum Sensing Techniques

Spectrum sensing plays a crucial role in cognitive radio communications, as it must be conducted before granting unlicensed users the ability to utilize available licensed spectrum. The fundamental aspects of spectrum sensing are two-fold: first, to guarantee that cognitive radio or secondary users do not interfere with primary users, and second, to help cognitive radio or secondary users discover and take advantage of spectrum gaps to ensure the necessary quality of service [11]. This spectrum sensing operation involves a binary hypothesis-testing scenario. The objective of spectrum sensing is to determine which of the two hypotheses is true:

- H0: x(t) = n(t) (1.4)
- H1: x(t) = s(t) + n(t) (1.5)

where, H0denotes the absence of the primary user, H1denotes the presence of the primary user, x(t) is the received signal at the cognitive radio, s(t) is the transmitted signal from the primary transmitter and n(t) is the Additive White Gaussian Noise (AWGN). The determination of the two hypotheses is called spectrum sensing.

Typically, spectrum sensing methods are divided into two main categories: non-cooperative and cooperative. Nevertheless, when considering signal detection, sensing techniques can be categorized into four general types [12]. The initial two main categories consist of coherent and non-coherent detection methods. Coherent detection necessitates prior knowledge of the primary users' signals, which will be used to compare against the received signal to achieve coherent detection of the primary signal. Conversely, non-coherent detection does not require prior knowledge of the primary users' signals for detection. The final two main categories are determined by the bandwidth of the spectrum being observed and include narrowband and wideband detection methods. The classification of sensing techniques is shown in Figure 2.4.

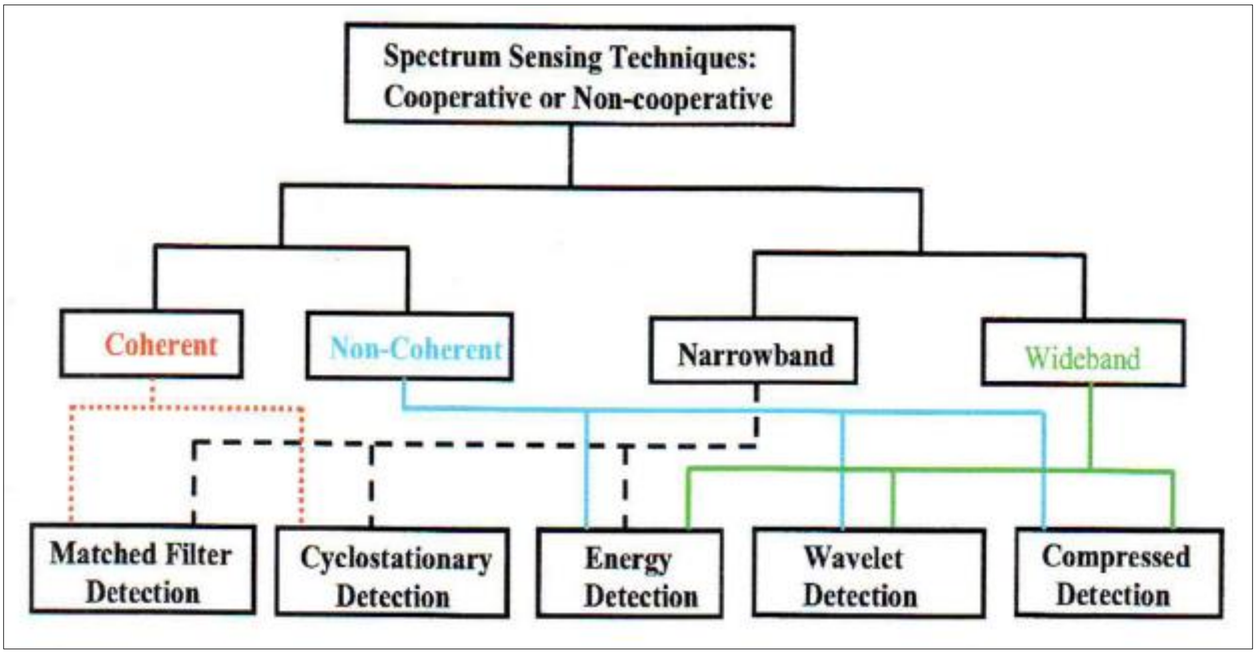

Figure 2 Classification of Spectrum Sensing Techniques [12]

Parameter Definition for Spectrum Sensing

- H0: hypothesis that PU is absent and only noise present
- H1: hypothesis that PU is present plus noise present
- Y[n]: the received signal
- W[n]: the received noise energy
- X[n]: received energy of primary user

- P_md: probability of missed detection
- P_d: probability of detection
- P_fa: probability of false alarm
- T_i: test statistic
- Λ: threshold setting

The spectrum sensing issue can be mathematically represented as a Binary Hypothesis Testing (BHT) problem characterized by the two aforementioned hypotheses[12]

$$H_0: y[n] = w[n] n = 1,2,\dots,N \dots\dots (1.6)$$

$$H_1: y[n] = x[n] + w[n] n = 1,2,\dots,N \; (1.7)$$

Where H0 is a null hypothesis which states that the received signal y[n] corresponds to noise samples w[n] only; meaning no PU signal in the sensed spectrum band.

H1 indicates the contrary; that a licensed user is present, making the received signal

$$y[n] = x[n] + w[n] \dots\dots\dots\dots\dots\dots\dots (1.8)$$

In an ideal scenario, spectrum detection would involve hypothesis H1 indicating the presence of the primary user (PU) and hypothesis H0 suggesting its absence. However, due to errors in spectrum sensing and the random nature of spectrum usage in real-world situations, we need to introduce some new terms to address the challenges posed by incorrect detections. These terms include missed detection (md) and false alarms (fa). With these definitions in place, the effectiveness of any spectrum algorithms can be represented by means of two probabilities.[12]:

Probability of missed detection given by

$$P_{md} = P(H_0|H_1) \dots\dots\dots\dots\dots\dots\dots\dots\dots (1.9)$$

or complimentarily, the probability of detection

$$P_d = P(H_0|H_1) = 1 - P_{md} \dots\dots\dots\dots (1.10)$$

And probability of false alarm

$$P\_fa=P(H\_0 \mid H\_1) \cdots\cdots\cdots\cdots\cdots\cdots..(1.11)$$

In practice, it is preferable to have high Pd and low Pfa values, though some compromises are necessary. There are two approaches to spectrum sensing

- Non-cooperative Spectrum Sensing Method
- Cooperative Spectrum Sensing Method

In the non-cooperative spectrum sensing method, a single cognitive radio device or secondary user performs local spectrum sensing. Each secondary user will monitor the spectrum channel to determine whether a primary user is present or absent. Because this sensing technique does not involve sharing results or decision-making processes, its energy consumption is significantly lower compared to cooperative spectrum sensing, which requires considerable energy due to extensive communication. However, the accuracy of detection in this method is lower than that of the cooperative method. This is primarily due to the adverse effects of poor channel conditions on the results of single-user spectrum sensing [13]. In contrast to non-cooperative spectrum sensing techniques, where a single cognitive radio assesses the spectrum to collect data, the cooperative spectrum sensing approach typically entails two or more cognitive radios collaborating.[14]. In this spectrum sensing approach, each cognitive radio or secondary user conducts local spectrum sensing on their own and then reaches a conclusion. After that, all cognitive users will send their decisions to a centralized receiver or Master Node (MN). The centralized receiver will aggregate these decisions and come to a final conclusion regarding the presence or absence of the primary user within the monitored frequency band.

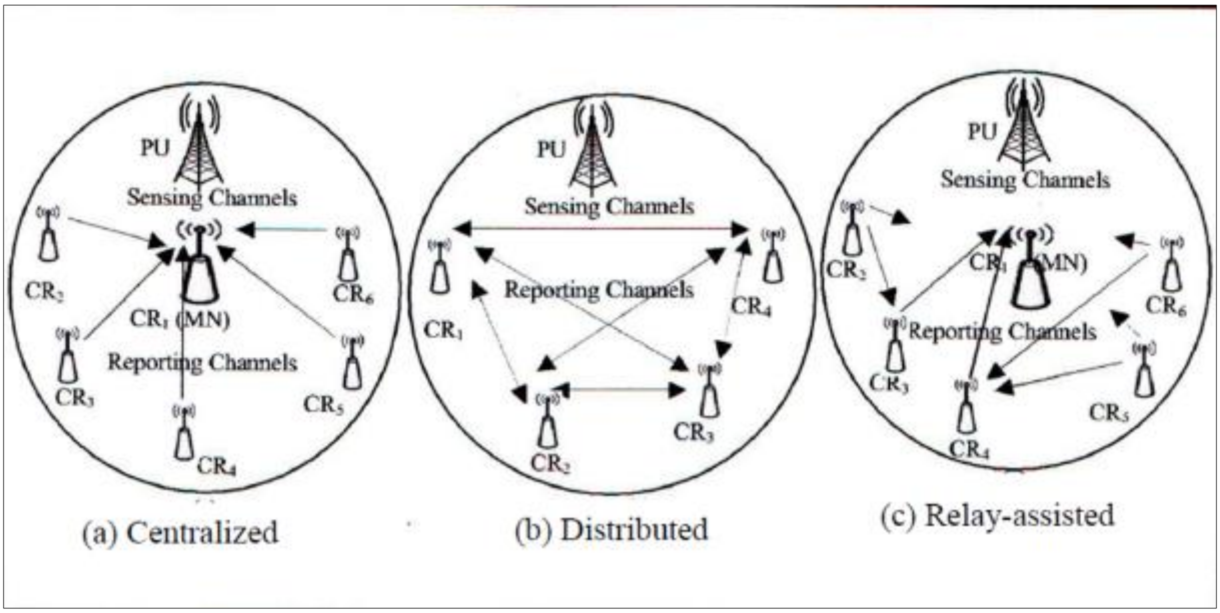

Figure 3 Classification of Cooperative Sensing [11]

1.4. Role of Monte Carlo and ANFIS Techniques in Spectrum Sensing

Monte Carlo and ANFIS techniques play a crucial role in enhancing the accuracy and adaptability of spectrum sensing in cognitive radio networks. Monte Carlo simulation is a statistical approach that relies on repeated random sampling to compute results, making it highly effective for estimating detection thresholds under varying environmental conditions[15]. By running multiple iterations of spectrum sensing scenarios, Monte Carlo simulations provide insights into the probabilistic distribution of signal detection, allowing for the derivation of optimal threshold values. ANFIS, on the other hand, combines the capabilities of fuzzy logic and artificial neural networks to create an adaptive model that learns from input data. In spectrum sensing, ANFIS can dynamically adjust detection thresholds based on real-time conditions, improving the accuracy and robustness of the sensing process[15]. The integration of fuzzy logic enables ANFIS to handle uncertainties and noise in the radio environment, while the neural network component allows for pattern recognition and continuous learning. By leveraging Monte Carlo simulations and ANFIS, cognitive radios can achieve more precise and adaptive spectrum sensing, reducing false alarms and missed detections. These techniques contribute to the overall efficiency of cognitive radio networks by ensuring that secondary users can reliably detect available spectrum opportunities without causing interference to primary users.

2. Research methodology

The system considerations for the non-cooperative and cooperative spectrum sensing techniques comprise combination of different elements working together to produce a cognitive radio network.

2.1. Cognitive Radio System

The cognitive radio system consists of three main components: spectrum sensing, spectrum predicting, and spectrum management modules. This study primarily centers on the functions of spectrum sensing and spectrum predicting within cognitive radio. As illustrated in Figure 4 , the block diagram represents a cognitive radio system. The operational components of the cognitive radio system include a Primary User generator, a transmission channel for signal propagation, a spectrum sensing subsystem, a Secondary User Generator, and a spectrum management or allocation subsystem.

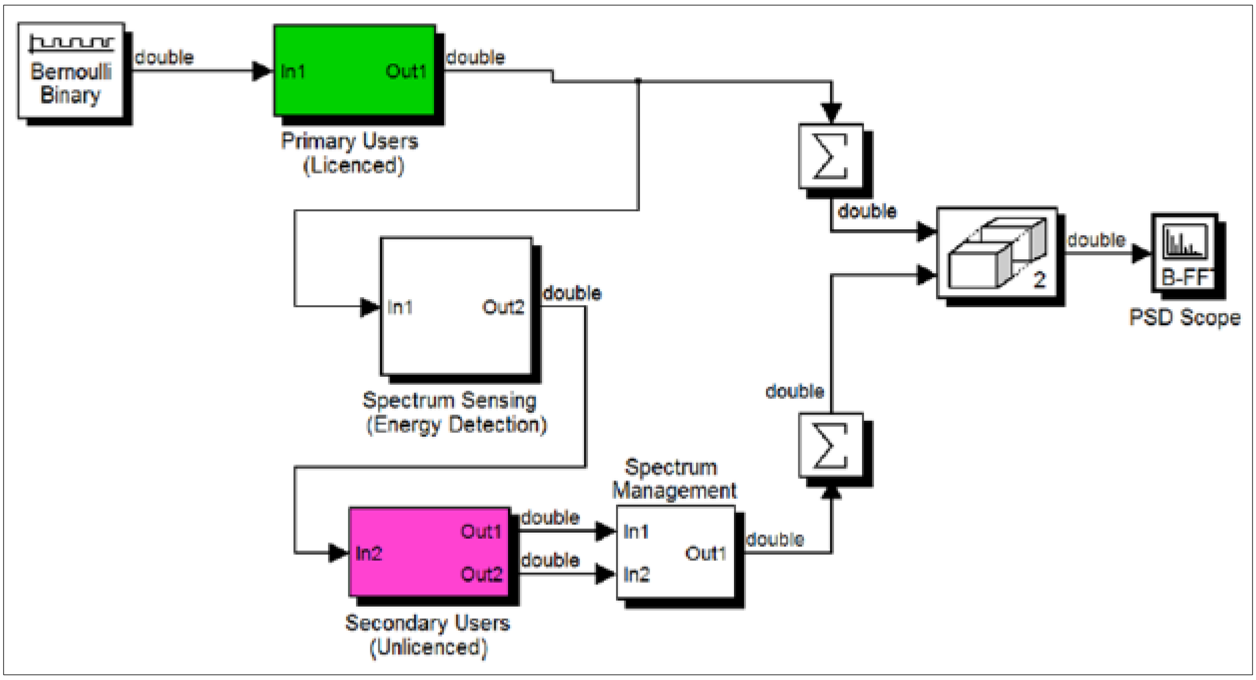

Figure 4 Cognitive Radio Systems

The cognitive radio's spectrum sensing module utilizes an energy detection algorithm. The system process of the energy detector is illustrated in the block diagram presented in Figure 5. In this block diagram, the key functional subsystems comprise a prefilter for the incoming signal, along with a squarer and an integrator, which together provide the magnitude of the detected energy signal.

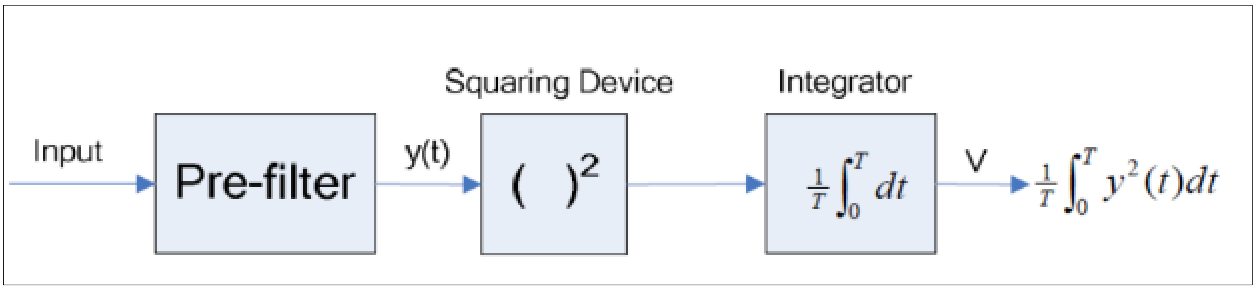

Figure 5 Block Diagram of the Energy Detector

The energy detector was employed to accomplish the following objectives

- Sampling through an Analog to Digital Converter (ADC) and applying filtering techniques
- Calculating the covariance or magnitude squared of the energy signal, also known as power spectral density.
- Evaluating this energy output against a test statistic represented by a threshold to determine the existence of a Primary User signal.

In the function of spectrum prediction, a detection threshold needs to be established, which is influenced by noise levels. Typically, the maximum noise energy value is designated as the starting detection threshold. However, since noise is inherently random and there is an uncertainty region (a mixture of noise and signals) during the spectrum sensing phase, the detection threshold will inevitably reside within this uncertainty region.

2.2. Non-cooperative System Development

In a non-cooperative spectrum sensing approach, individual cognitive radio devices or secondary users perform the spectrum sensing locally. Each secondary user monitors the spectrum channel to determine whether a primary user is present or not. Since this sensing technique does not involve sharing the results of spectrum sensing or making final decisions, it has a lower energy consumption compared to cooperative spectrum sensing, where users require significant energy due to extensive communication. Nonetheless, the detection accuracy of this method is considerably lower than that of the cooperative method. This is primarily due to the impact of poor channel conditions on the results obtained from single-user spectrum sensing. Figure 6 illustrates the flowchart for the non-cooperative spectrum sensing process.

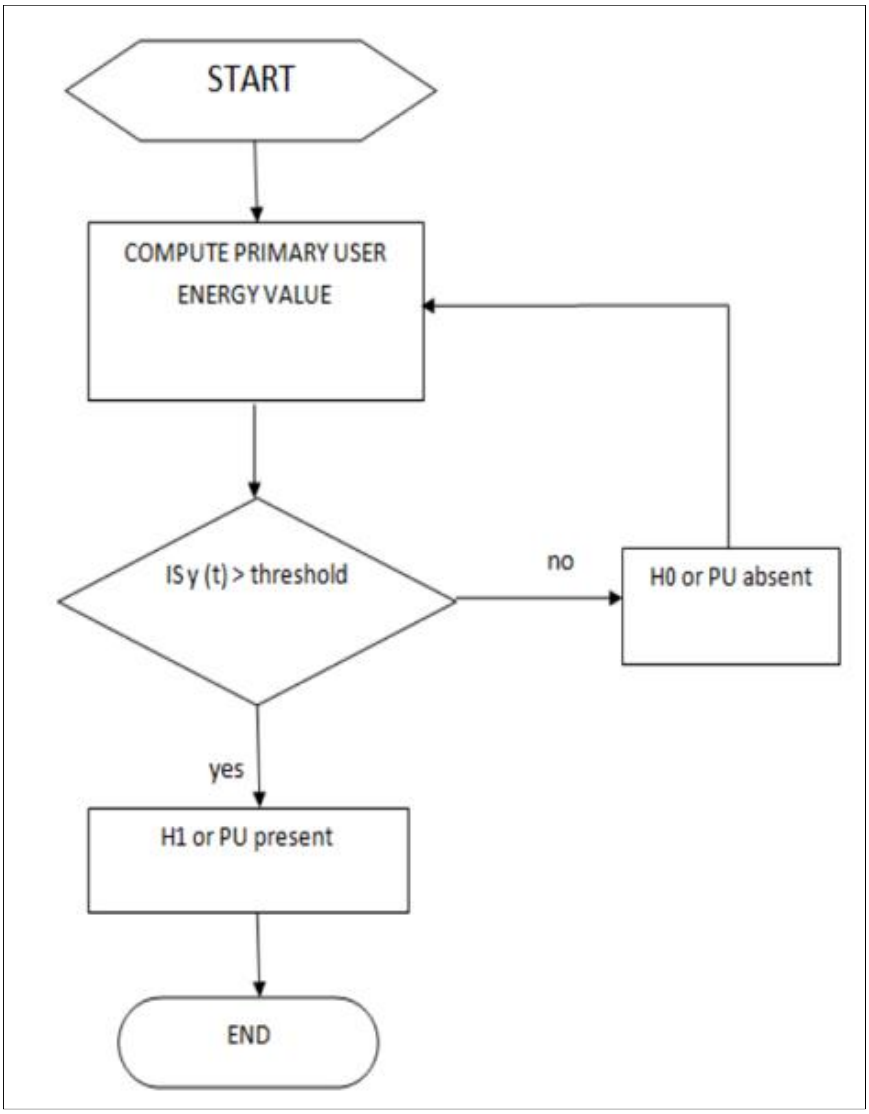

Figure 6 Program Flow chart for non-cooperative spectrum sensing

2.3. Cooperative System Development

The model for cooperative spectrum sensing necessitates a framework that incorporates the exchange of information and decisions among individual cognitive users alongside a central fusion decision center, as illustrated in Figure 7. A fundamental cognitive radio system is composed of five subsystems

A Cognitive Radio Network with N Secondary Users, which includes a Primary User Generator, a transmission channel, a spectrum sensing subsystem or energy detection system, and a Secondary User Generator, among others.

- A Fusion Center Subsystem.
- A Voting Subsystem.
- An Allocation or Spectrum Management Subsystem.

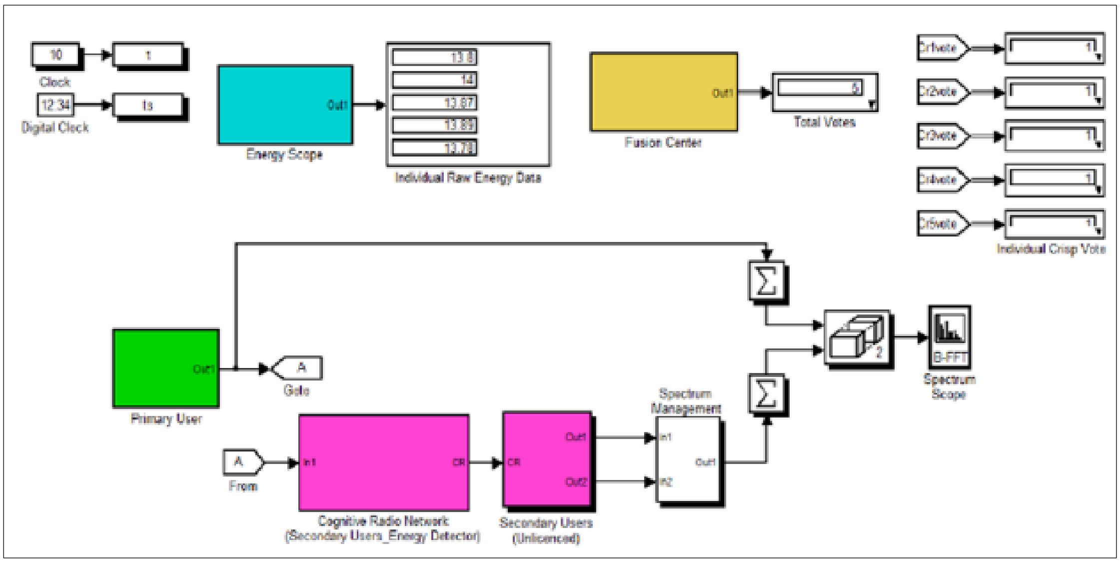

Figure 7 Cooperative Sensing Spectrum Model

These four subsystems integrate to form an effective cooperative spectrum sensing model. The subsystem governing primary user behavior remains unchanged from the non-cooperative model. This is due to the fact that the cooperative spectrum sensing method solely varies in the number of secondary users and the approach taken to determine the presence of the primary user. The subsystem consists of a Bernoulli Binary Generator, a Sine Wave Generator, a Gaussian Noise Generator, and a Modulated Sine Wave Signal Product.

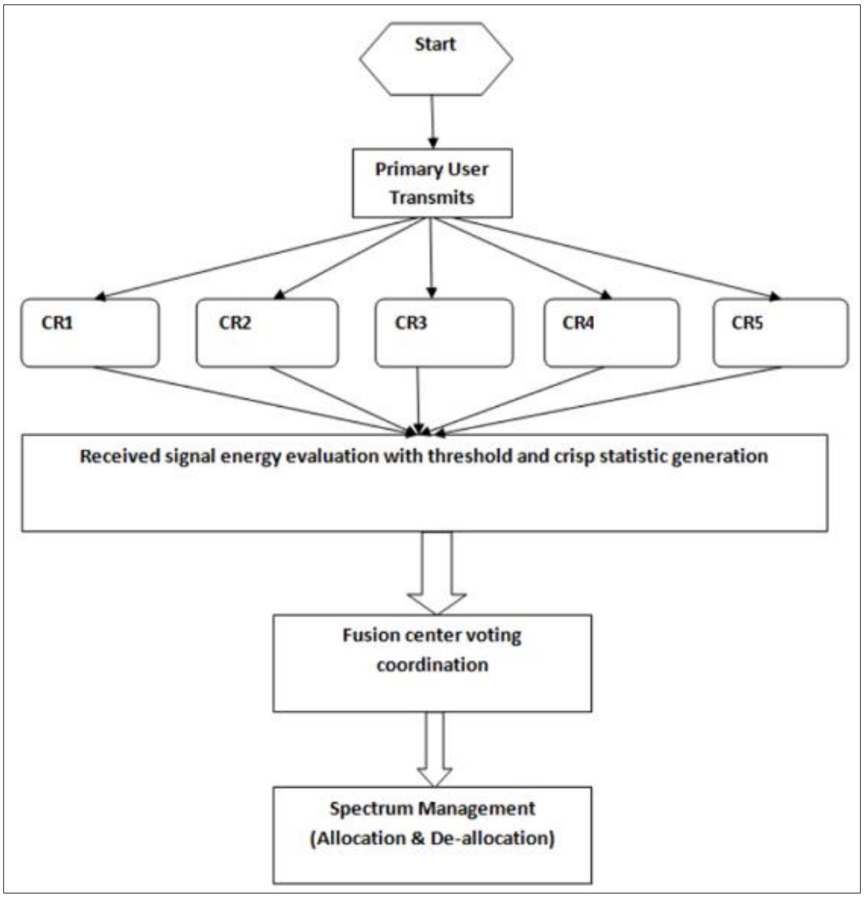

Figure 8 Cooperative Spectrum Sensing Flowchart

Although there is one main user, the secondary users can be generalized to be more than two, extending up to N users. The assessment of energy and statistical analysis is facilitated through the comparison of energy thresholds. The fusion center is responsible for gathering all individual results from cognitive radios and counting the votes regarding the availability of the primary user. This functionality is crucial in the cooperative spectrum sensing model of cognitive radio, as it manages the cooperation among the cooperative cognitive radios.

2.4. Determination of Detection Threshold

Determining the correct threshold in real-time is extremely important. The approach used integrates two estimation techniques: Monte Carlo and ANFIS, to identify primary users through the selection of an estimated threshold. The threshold value for each cognitive radio was established to facilitate local sensing and detection decisions. This is necessary as each radio experiences varying types and intensities of interference from noise sources. The requirement for accurate threshold selection, along with a cooperative spectrum sensing approach, becomes essential due to the inherent limitations of Cognitive Radio Networks, such as

- Noisy channels
- Fading effects or fluctuating signal strength at the receiver in contrast to that at the transmitter
- Diverse operational environments for radios

These elements together render a single threshold value ineffective for sensing within a Cooperative Cognitive Radio model utilizing an Energy Detector as the sensing methodology. To address this limitation, the threshold is determined based on the knowledge of received signal energies and their probability distribution in real-time while the cognitive radio is in operation.

2.5. Monte Carlo Analysis

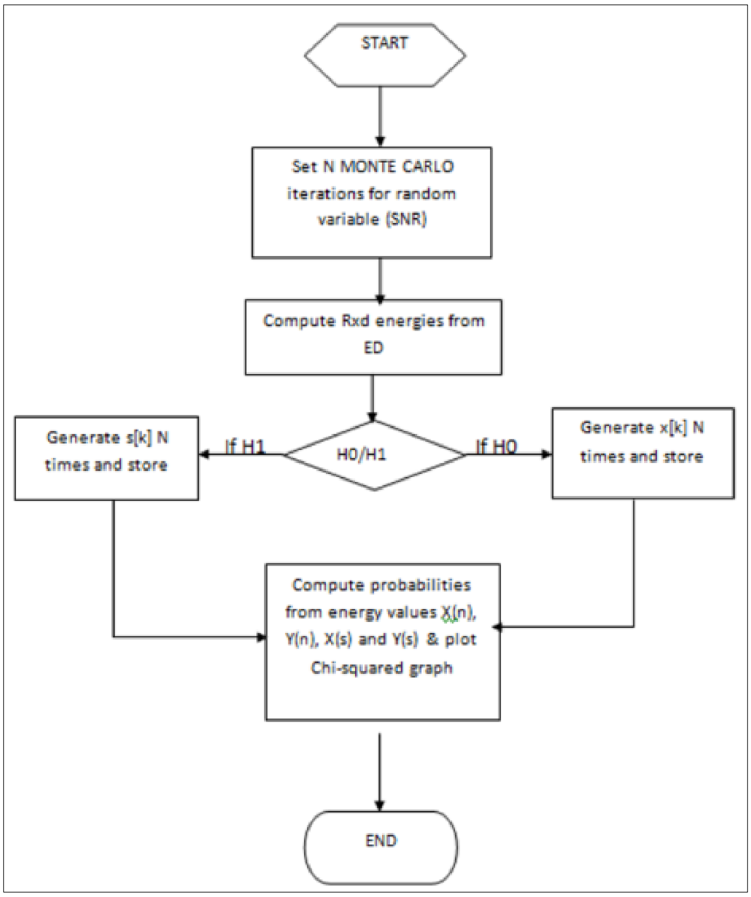

Figure 9 Flowchart of Monte-Carlo Estimation

The Monte Carlo analysis applied in threshold estimation acts as a statistical method for determining the ideal threshold for energy detection, using SNR as a variable in the estimation process. Figure 9 presents a flow chart illustrating the

Monte Carlo Algorithm. The Monte Carlo estimator takes in a random variable, with two potential candidates in the cognitive radio model: the signal to noise ratio (SNR) or degree of freedom (DOF), both of which influence the PDF curve of the Primary User signal, as depicted in the uncertainty graph of PDF versus energy. The output consists of the calculated probabilities of detection and false alarms. Conducting a Monte Carlo analysis requires utilizing a substantial number of samples during the simulations to obtain a reliable estimate, ensuring a large dataset for analysis. In summary, the greater the volume of data, the closer the results will be to an optimal value.

It is important to note that as the number of data points increases, this will lead to longer simulation run times, and typically, the standard processors found in our laptops are too slow for conducting these data-intensive computations. The Monte Carlo model is embedded within a portion of the Cognitive Radio model, as will be demonstrated in the script examples found in Appendix A2. Given that the Monte Carlo analysis is designed to select an appropriate threshold value for effective detection, the algorithm for the Monte Carlo section operates within the sensing component of the model. It functions by recalculating the SNR for each iteration of the Cognitive Radio model and employs the newly calculated SNR to capture the variations in radio characteristics encountered by the Primary User signal. This information is subsequently utilized to determine an appropriate threshold based on the observed SNR in the transmission channel.

2.6. ANFIS Analysis

The ANFIS analysis conducted aims to calculate the probabilities expressed by the probability distribution function (PDF) that describes Pd, Pm, and Pfa. A flowchart illustrating the algorithm utilized is shown in Figure 3.9. These PDFs will act as outputs, while the known inputs consist of the SNR and the signal energy. The specified ranges for the inputs and outputs were determined based on insights gained from conducting several simulations and iterations in the previously completed Monte Carlo analysis. According to existing literature, a SNR value around 15dB has been used in experimental studies utilizing a Matlab/Simulink system for cognitive radio applications; hence, we chose a starting SNR range of 10 to 15dB. This value was deemed appropriate for this study and is a suitable range for the "universe of discourse" concerning the SNR input variable. The universe of discourse for a fuzzy variable denotes the realistic range of values that variable can assume. Given that energy cannot be negative, we selected an energy range from 0 to 100, which effectively represents the energy values observed during the Monte Carlo simulation. This approach to defining variable values is a distinctive aspect of fuzzy analysis, and establishing representative values is crucial for obtaining accurate fuzzy estimates.

2.6.1. Fuzzy Variables

The variables used in the fuzzy decision engine are

- Inputs: SNR and Energy
- Output: PDF

2.6.2. Universe of Discourse

The range of values for the selected variables has been determined based on established understanding of their value space. The specified ranges are as follows:

- SNR will range from 10 to 15dB.
- Energy will vary between 0 and 130dB.
- Probabilities will naturally lie between 0 and 1.

2.6.3. Linguistic Terms

The values of these variables will now be assigned linguistic terms that define their level of belonging within the specified ranges. These linguistic terms are referred to as fuzzy sets, and in this context, they are expressed as:

- Very Low (VL) or Low (L)
- Medium (M)
- Very High (VH) or High (H)

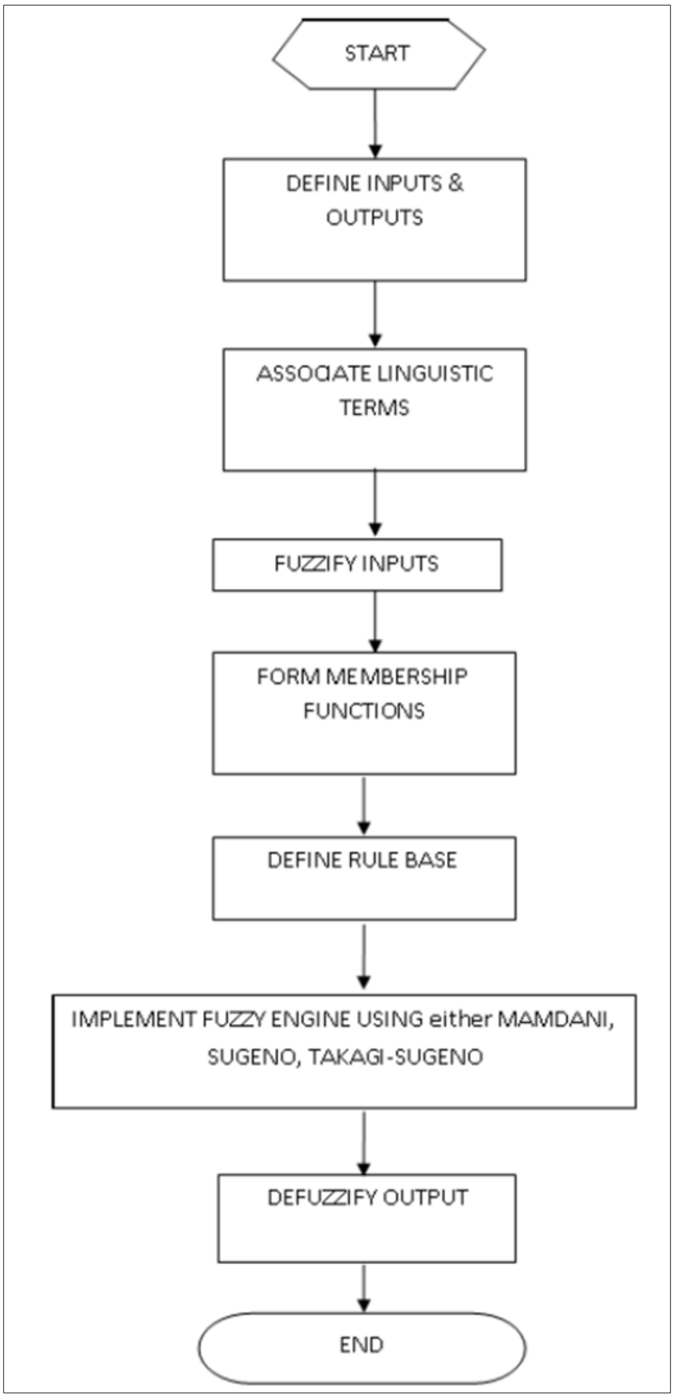

Figure 10 Flowchart for ANFIS Algorithm

3. Results and discussions

3.1. Introduction

The results of the various experimental analyses carried out in this work include the results of various Monte Carlo and Adaptive Neural Fuzzy Inference Systems simulations obtained from the developed spectrum sensing models, the comparative analyses on the performance of the techniques were highlighted and the results of the experimental validation for the detection threshold using the commercially acquired hardware energy detector were presented.

3.2. Monte Carlo Experiments and Analyses

250 iterations of the Monte Carlo were made in this experiment. The parameter values used for the plot of Figure 4.1 are for 3 different points within the total Monte Carlo iterations. The results for only three simulations is here shown because of the computational power involved in plotting more and also for clarity sake in rendering the uncertainty region to be analyzed. The three samples used for the plots shown in Figure 11 are at 80,160 and 240 extracted from the total of 250 iterations. The uncertainty regions are represented by approximate triangles called delta1, delta2 and delta3.

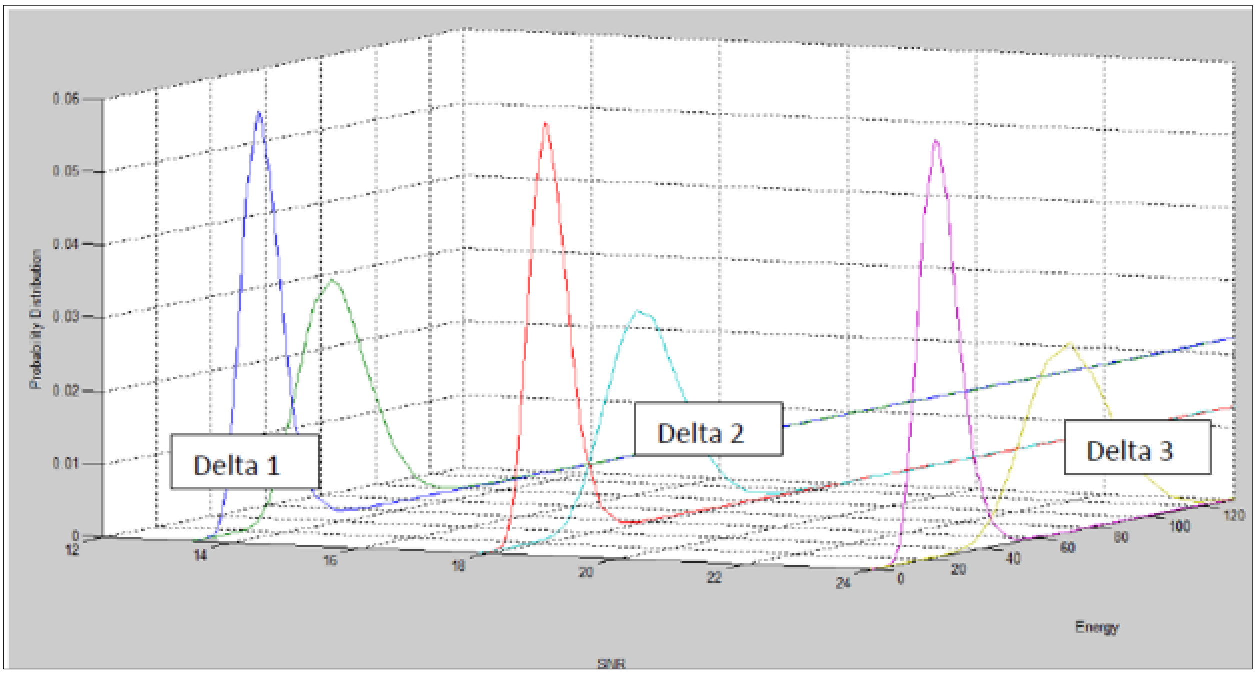

Figure 11 Chi-square Plot Showing Uncertainty Region as Triangles

Each of the points of the triangle is described using a coordinate triple i.e. (x, y, and z)

- Delta1: peak (13.4,37.15,0.01508),left(13.4,23.43,0.00095),right(13.4,51.42,0.00059)
- Delta2: peak(17.86,38.8,0.01115),left(17.86,27.85,0.0006334),right(17.86,52.93,0.0003958)
- Delta3: peak(23.94,44.53,0.003317),left(23.94,37.76,0.000996),right(23.94,52.89,0.0003998)

The areas are now computed for each of the triangles using the parameters highlighted

- Delta1 area: ½ *27.99*0.01449=0.202
- Delta 2 area: ½ *25.08*0.01075=0.1348
- Delta 3 area: 1/2 *15.13*0.00292=0.022

Reduction in uncertainty is given by

$$\%reduction = \frac{area\ difference}{original\ area} * 100 \ldots (3.1)$$

- delta1 and delta 2: (0.202-0.1348)/0.202 *100 =33.27%
- delta2 and delta 3: (0.1348-0.022)/0.1348 *100 =83.7%
- delta1 and delta 3: (0.202-0.022)/0.202 *100 =89.1%

A look at the values obtained for the areas of the uncertainty triangles shows that there is a remarkable reduction in the uncertainty region as SNR increases; which is a very significant result considering the fact that a good SNR value enhances the detection capability of the energy detector.

The results shown in Figures 4.3-4.7 show some of the deductions already referred to above

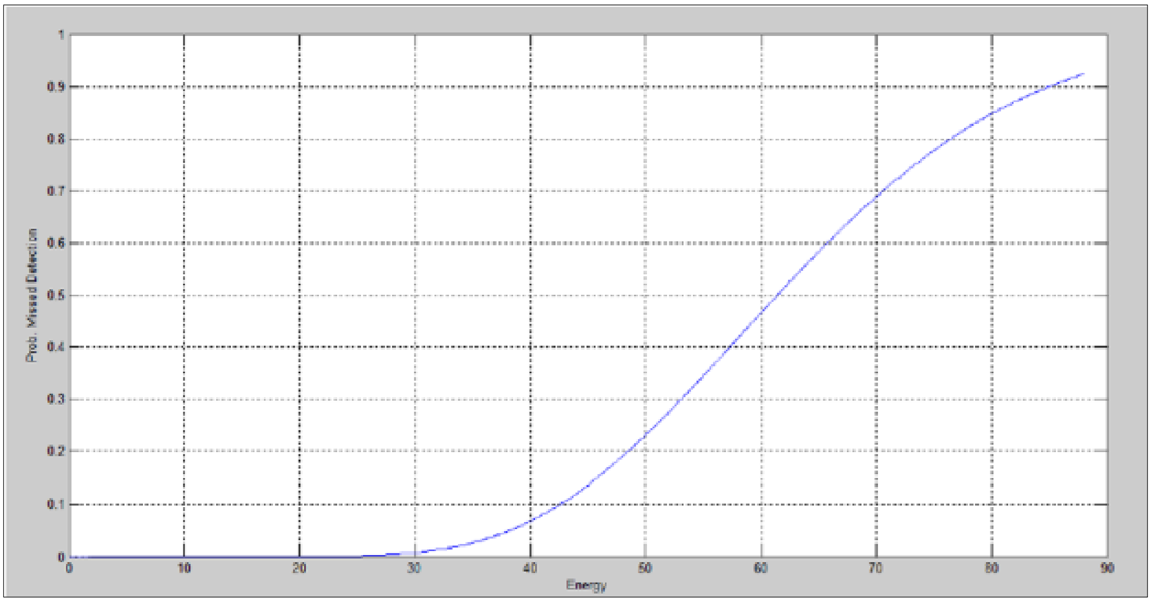

Figure 12 Pmd vs. Energy Plot

From a single iteration of the Monte Carlo model, an array of values is obtained for the Pd, Pm, Pfa. The average of these values is computed and this value is subsequently mapped to the energy axis of the PDF vs. Energy plot to obtain an optimal threshold value. For an average probability of Missed detection of about 0.395 computed by the Monte Carlo model, have an equivalent energy threshold value of about 51dB/Watt from the plot above. Looking at the equivalent plot as shown in Figure 12, the PDF value can be traced at 0.395 on the first set of plots to obtain a close result to what is obtained here. Subsequent simulations done showed that a large Pd value and a small Pfa value to meaning that a good detection threshold is feasible.

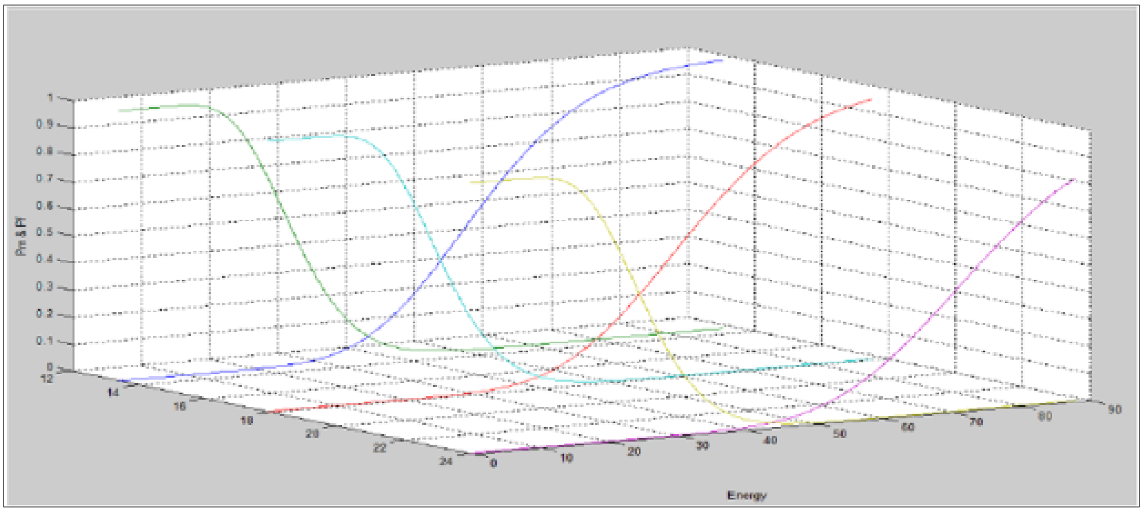

Figure 13 Pmd and Pfa vs. Energy Plot

Figure 13 show the result from plotting probabilities of false alarm and missed detection against SNR and energy. This plot is used to obtain a threshold on the energy axis corresponding to an optimal value of either probability of false alarm or probability of missed detection but not both simultaneously. This is because optimization of one item means sacrificing optimality in the other. The method used in this work to determine the threshold also employed the convergence point of the two plots to decide the optimal threshold by computing the values of probabilities at the index at which the two plots intersect and further reading the corresponding energy value.

The Monte Carlo analyses show an estimated energy detection system. This estimation is dependent on the number of iterations made. More iterations result in a quicker convergence to the optimal value and a corresponding reduction in the uncertainty region which is a major objective of this work. Figure 14 to 18 are results that show the changing uncertainty region for 250 Monte Carlo iterations. It can be seen that as the number of iterations increase and with corresponding increase in SNR, the size of the uncertainty region diminishes. Further estimation studies are performed using ANFIS as discussed in section 3.3.7.

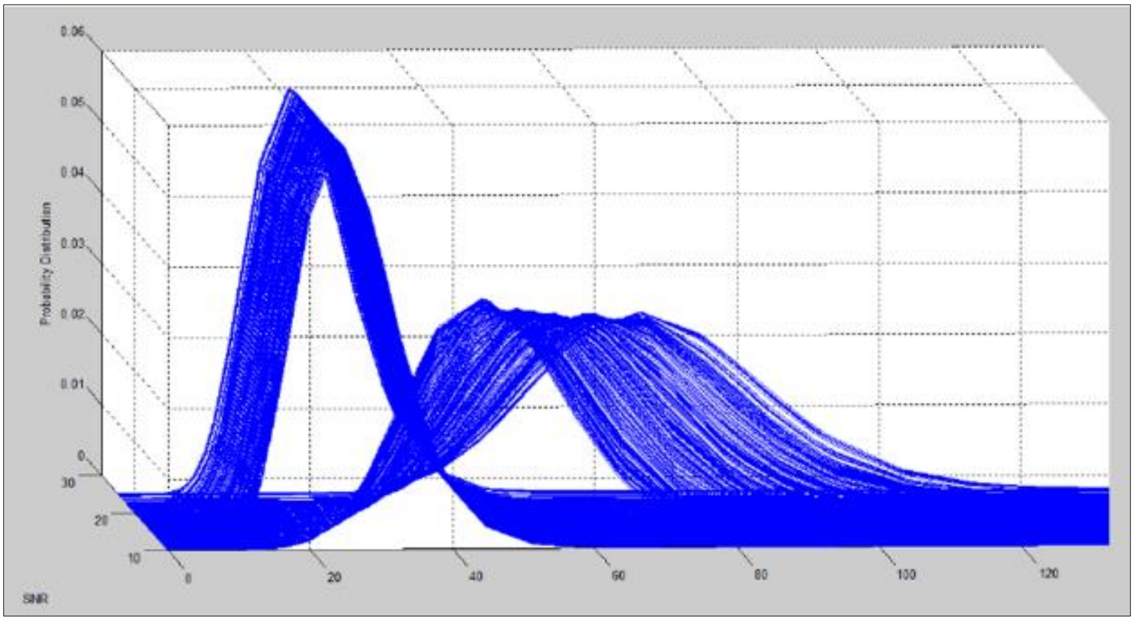

Figure 14 PDF vs. Energy for 250 Monte Carlo Iterations

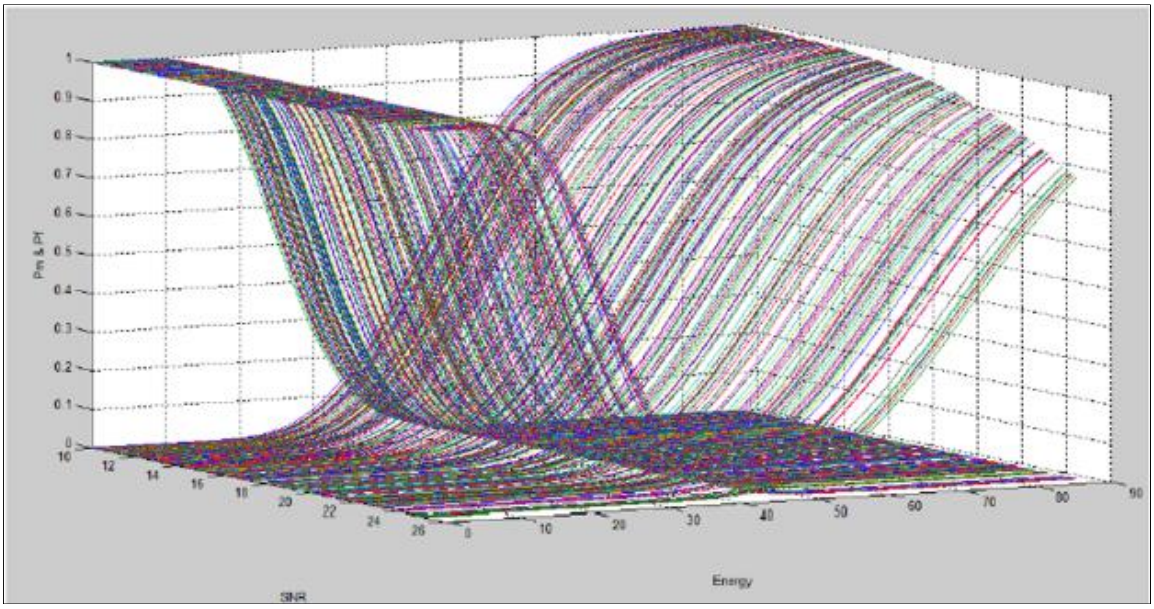

Figure 15 Pm and Pf vs. Energy for 250 Monte Carlo Iterations

3.3. Threshold Estimation using Monte Carlo (MC) Statistical analysis

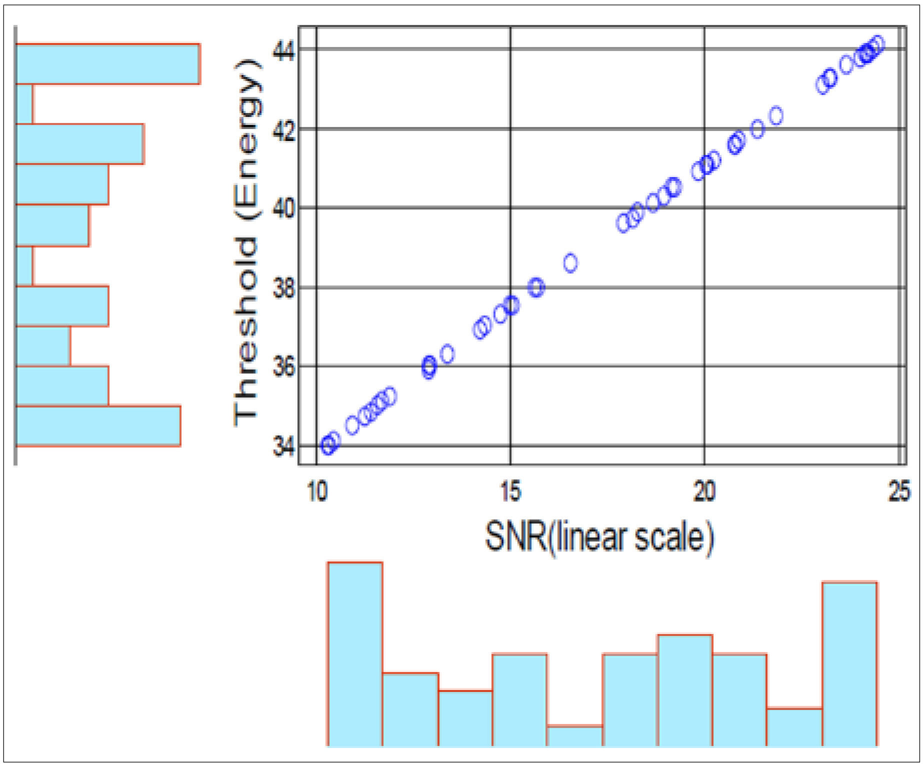

Figure 16 50 Monte Carlo Iterations

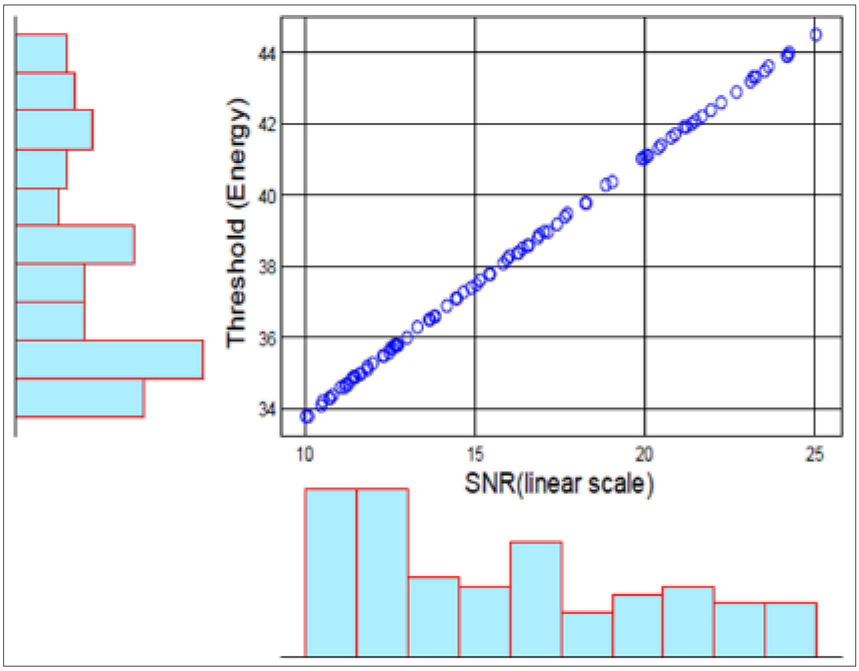

Figure 17 100 Monte Carlo Iterations

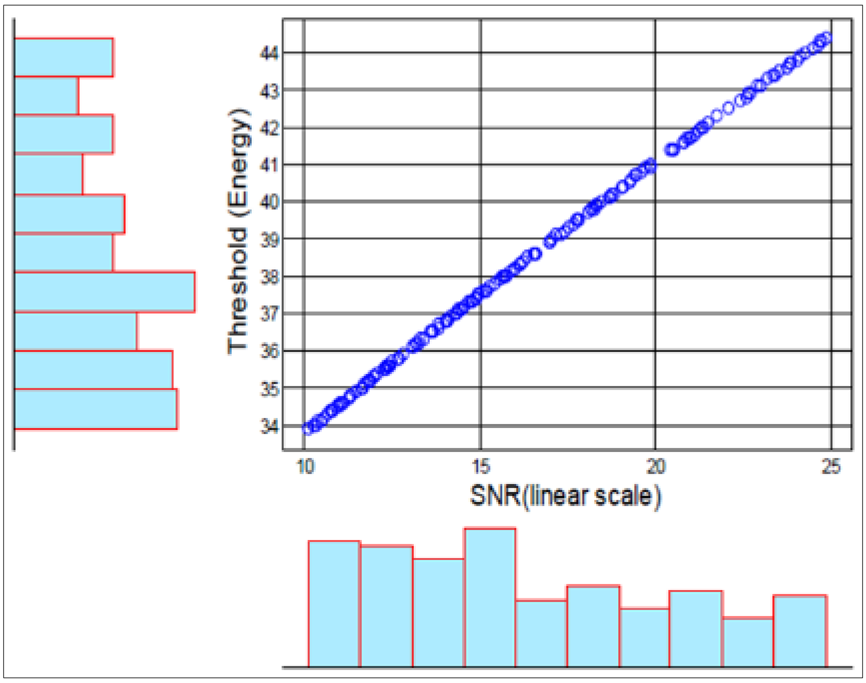

Figure 18 250 Monte Carlo Iterations

Different iterations were made in the Monte Carlo experiment to study the convergence rate to an optimal energy threshold value and the magnitude of deviation between the starting seed threshold and the final computed optimal value. In particular, the Monte Carlo simulation were iterated for 50,100,150,200,500 and 1000 times for the optimization of the detection threshold and all results obtained are logged and displayed for analyses. The increasing number of iterations made is necessary because the Monte Carlo technique which simulates random or chance occurrence of events will perform better with a large sample space. Larger number of iterations bringing correct convergence to a single optimal value.

3.4. Presentation of Results from Monte Carlo and ANFIS Estimation Experiments

Plots from the Monte Carlo and ANFIS Experiments are shown in Figures 19-24. Using similar experimental parameters for reason of visualization and setting a good basis for comparison. The parameters used for the experiments include the same threshold value for individual cognitive radio sensing, the same number of iterations and same set of input energy values sensed by secondary users.

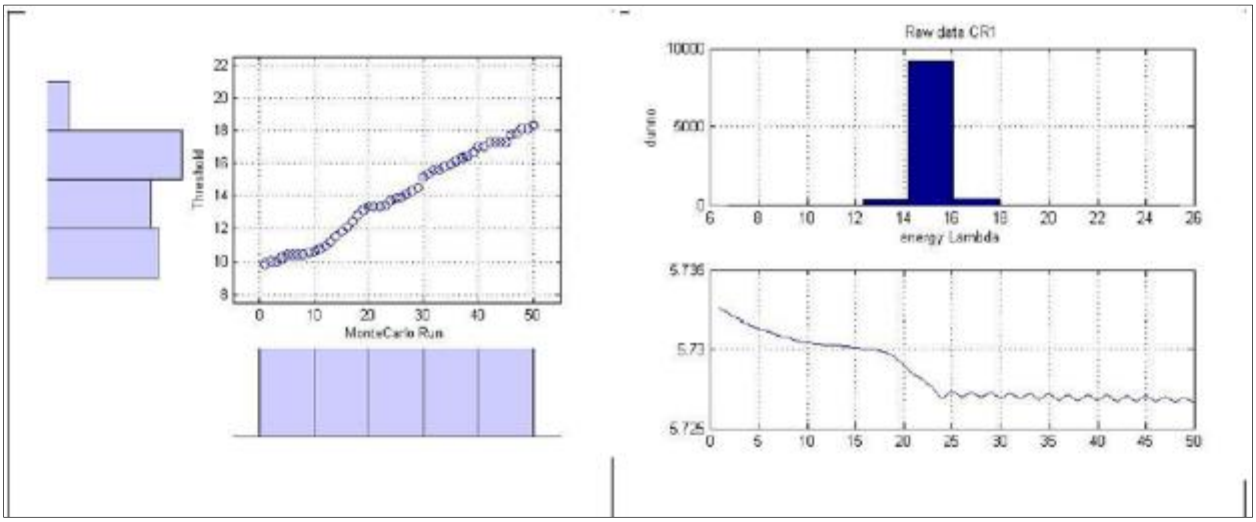

Figure 19 Monte Carlo and Fuzzy Results for 50 Iterations on CR1

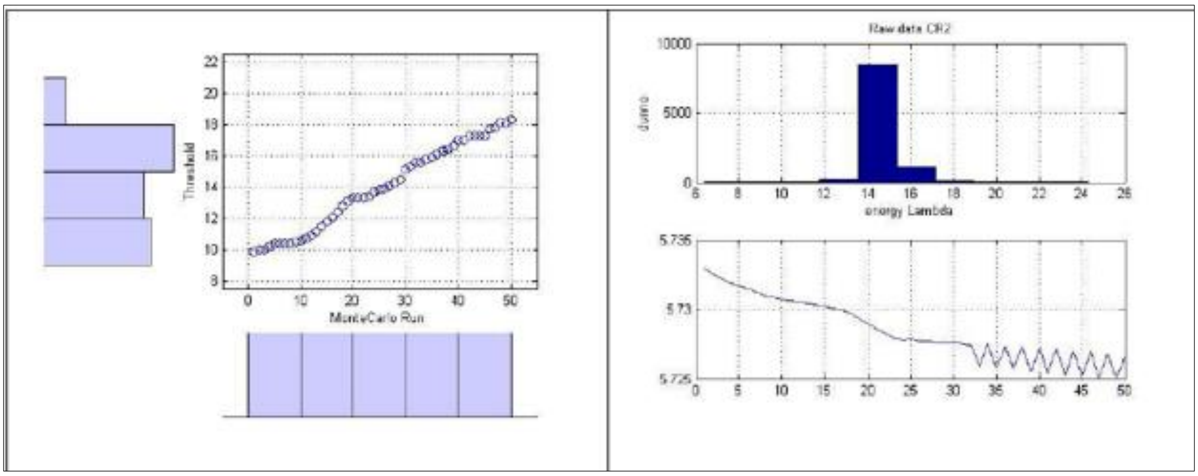

Figure 20 Monte Carlo and Fuzzy Results for 50 Iterations on CR2

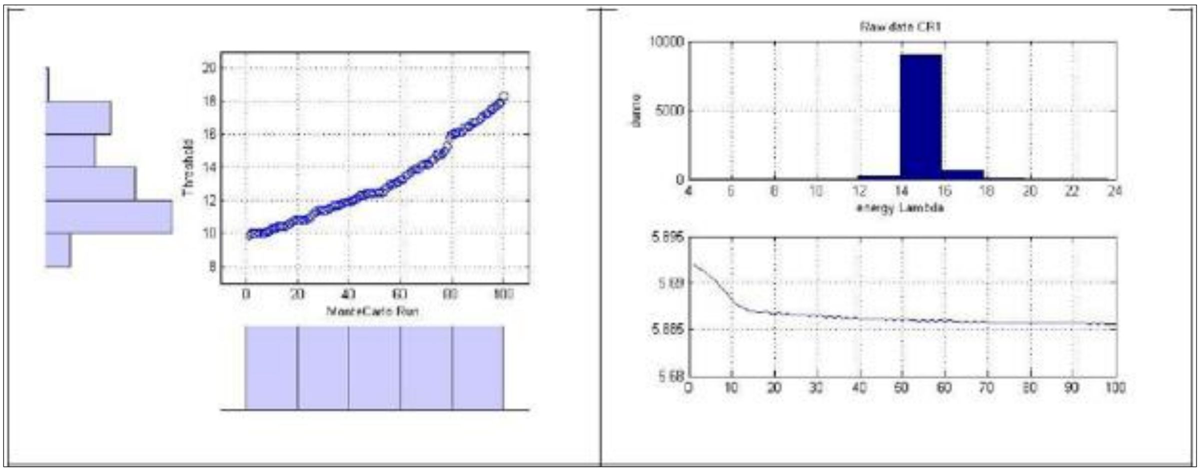

Figure 21 Monte Carlo and Fuzzy Results for 100 Iterations on CR1

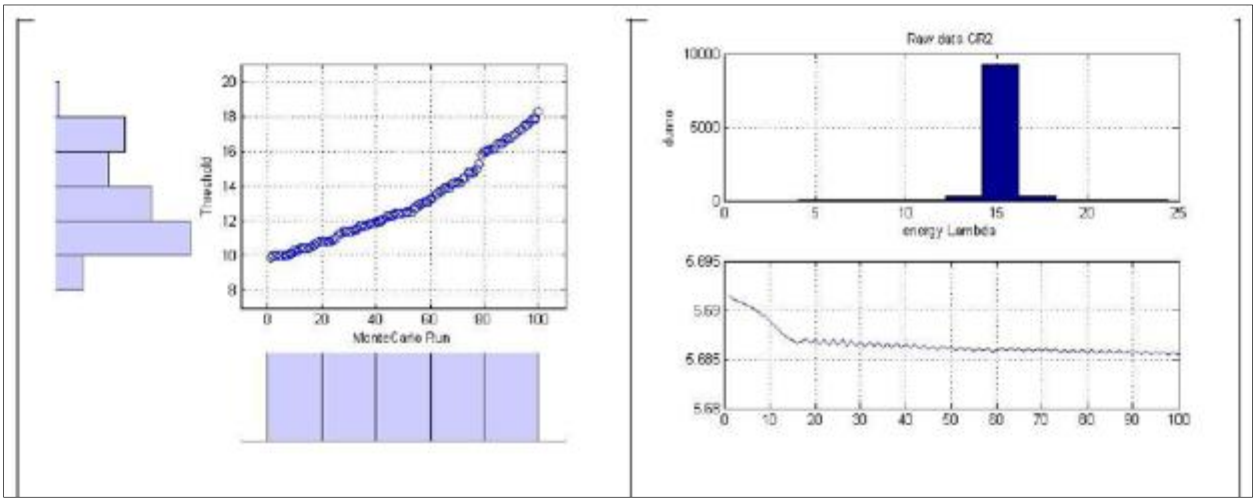

Figure 22 Monte Carlo and Fuzzy Results for 100 Iterations on CR2

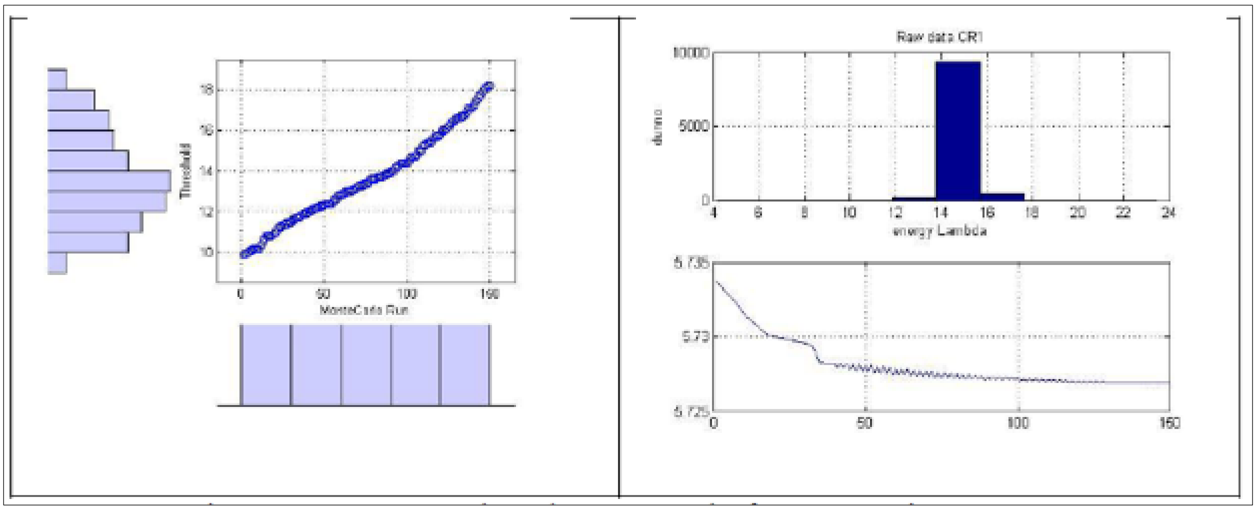

Figure 23 Monte Carlo and Fuzzy Results for 150 Iterations on CR1

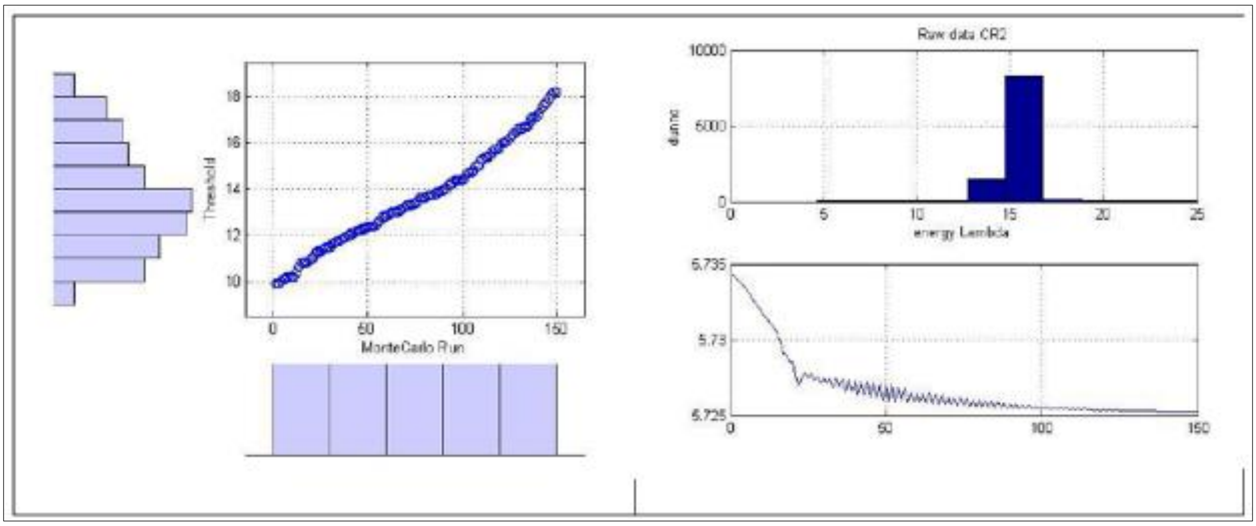

Figure 24 Monte Carlo and Fuzzy Results for 150 Iterations on CR2

Observing the results from the Monte Carlo and ANFIS experiments show a very close concurrence in the detection output threshold value obtained. The basis for the comparison rests on the selection of similar parameters for both experiments. It is also of note that both estimation methods employ the model directly in their analysis. Table 4.1 shows some relevant parameters used in the experiments. The start threshold parameter is carefully selected to have a value approximately equal to the signal to noise ratio value used for the simulation. This is because using this value is a good estimate of the energy to be sensed. This experiment uses two variants of the start threshold value; firstly, a fixed threshold value is used and later the same experiment is performed with a randomly generated threshold.

Table 1 Performance Comparison between Monte Carlo and Fuzzy Logic

Experiment type	No. of Iterations	Seed threshold/SNR	Estimated threshold	% Estimation	Elapsed time(s)
Monte Carlo	50	25	15.0	60.0	333.649
Monte Carlo	100	25	11.5	46.0	626.445
Monte Carlo	150	25	13.0	52.0	945.2198
Monte Carlo	200	25	12.0	48.0	1284.56
ANFIS	50	25	14.5	58.0	587.9206
ANFIS	100	25	14.0	56.0	1171.0
ANFIS	150	25	13.7	54.5	1807.1
ANFIS	200	25	15.0	60.0	2360.99

3.5. Comparative Analysis of Monte Carlo and ANFIS Estimation Results

Comparative analysis of results from Monte Carlo and ANFIS simulations showed that the estimated threshold in all iterations remained within the observed uncertainty region. Comparison includes

- Monte Carlo simulations showed a dependence on the number of iterations used unlike the ANFIS simulations which do not depend on the number of iterations.
- The computation time for the Monte Carlo analysis as compared to ANFIS was shorter. This can be explained by the type of fuzzy inference engine used which is adaptive and requires continuous recalculations.
- Monte Carlo analysis is suitable in non-cooperative cognitive sensing where static allocation is being used. This is so as user diversity is not an issue in the static case. On the hand ANFIS will work better in cooperative spectrum sensing scheme as against non-cooperative.
- The role of ANFIS is found to be more useful in cooperative sensing as against non-cooperative spectrum sensing. Especially as it is used to overcome the presence of noise power uncertainty which is the major drawback in cooperative spectrum sensing.

4. Conclusion

The implementation of Monte Carlo and ANFIS techniques for detection threshold estimation in cognitive radio networks provides an effective solution for improving spectrum sensing accuracy. Monte Carlo simulations offer reliable statistical insights, especially in static environments, while ANFIS enhances adaptive threshold estimation in dynamic and uncertain conditions. The comparative analysis highlights that ANFIS is particularly beneficial in cooperative spectrum sensing, where real-time adaptability is crucial. Overall, the integration of these advanced techniques enhances cognitive radio performance, minimizes detection errors, and optimizes spectrum utilization. Future research could explore hybrid models combining both approaches to further improve detection accuracy and computational efficiency.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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