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SIMULATION AND ANALYSIS OF SPECTRUM SENSING IN COGNITIVE RADIO

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ABSTRACT

To satisfy future bandwidth demands, existing Cognitive Radio with Wireless Communication must be upgraded to make the best use of the bandwidth. The IEEE 802.22 standard's principal goal is to identify unoccupied spectrum bands in the Digital television channel (DTV) and use them for wireless rural broadband access. Cognitive Radio (CR) strives to maximise the use of limited radio bandwidth in wireless networks while accommodating an expanding number of services and applications. The secondary user (SU) should be able to use the radio spectrum not used by the essential network in the cognitive radio network to operate effectively. Sensing of spectrum is an important part of cognitive radio. Energy detection is one of the spectrum detection methods accessible in the literature and is widely used because it is easy to construct and does not need any information about the PU (primary user). In low SNR zones, however, the conventional energy detector's performance deteriorates. CSS (Cooperative Spectrum Sensing) with a double threshold was established to improve decision dependability, albeit at the sacrifice of some information. Extensive simulation utilising the MATLAB simulation programme is used to describe the detection performance.

KEYWORDS: Software Defined Radio, Cognitive Radio, Spectrum Allocation, Cooperative Spectrum Sensing (CSS), Spectrum Sharing, Spectrum Management, Energy Detection, Double Threshold CSS, MATLAB & SIMULINK

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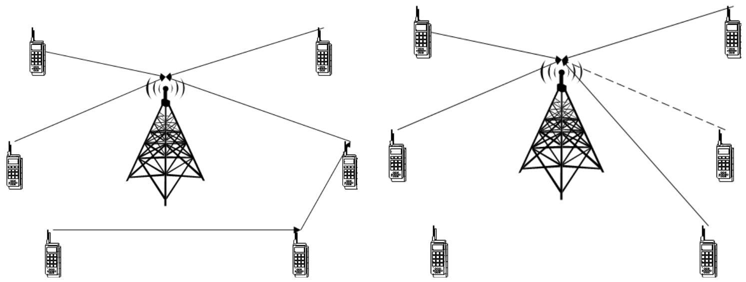
Original Article

1. INTRODUCTION

In the prosperous world that we live in right now, and communications enter our daily lives in manifold ways that it is easy to overlook the multitude of its facets. Mobile phones, radio broadcasting, TV towers, satellite antennas, and PCs with access to the Internet seem to rule the communications world. Data communication networks are crucial to any modern city because they are used extensively in numerous applications such as financial transactions, social interaction, education, national security, and more. Although passive optical networks (PONs) may be the best solution for a complex network that requires high-speed data communication, the system's design suffers from high costs and other fibre problems, thus wireless communications solve these troubles. However, there are some problems in wireless communications, such as frequency-dependent, relatively low bandwidth, and being tightly licensed by the government.

Only limited frequencies are authorised for mobile devices, which are becoming increasingly crowded. We can use all available frequencies, including those dedicated to television and satellites, with cognitive radio technology. The intelligent gadgets negotiate the most efficient use of the entire radio spectrum, allowing us to multiply the existing network requirements. The term "radio" refers to any wireless communication, nevertheless.

Currently, radios can only communicate with radios which are of the same type. Cognitive radio is a special type of radio which can understand any radio language. When combined with a new CR of radio present in any system, it can allow interaction with any physical object and provide a communication link over a large area of earth.

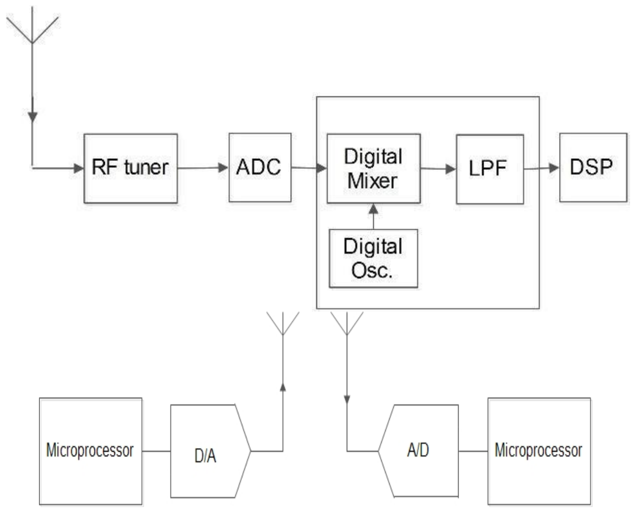


(a) Before Cognitive Radio (b) After Cognitive Radio

Figure 1.1: Radio Communications Systems before and after Cognitive Radio

1.1 Software Defined Radio (SDR)

Software-defined radio is a special radio with some or all of its physical layer functions that are software-defined. Figure 1.2 depicts the ideal (SDR). Within the microprocessor, the user data is mapped to the specified waveform. The signal is supplied directly to the antenna after being transformed into digital samples. The transmitted signal is sampled and digitised at the antenna before being processed in real-time by a general-purpose CPU.



(a) Ideal SDR (b) Non-Ideal SDR Receiver

Figure 1.2: Ideal SDR System Versus Non-Ideal SDR Receiver

1.2 Cognitive Radio (CR)

The modern technology that enables wireless terminals of the cognitive to dynamically access the available spectrum channels in cognitive radio. An SDR can take advantage of the underutilised spectrum for cognitive radio. Cognitive radio is defined by FCC is given as "a radio or system that senses its electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to switch system operation, such as maximise throughput, mitigate interference, facilitate interoperability, and access secondary markets," based on Mitola's definition.

Despite the discrepancies in the previous definitions, cognitive radio differs from traditional radio in two fundamental ways: cognition capability (intelligent adaptive behaviour) and reconfigurability.

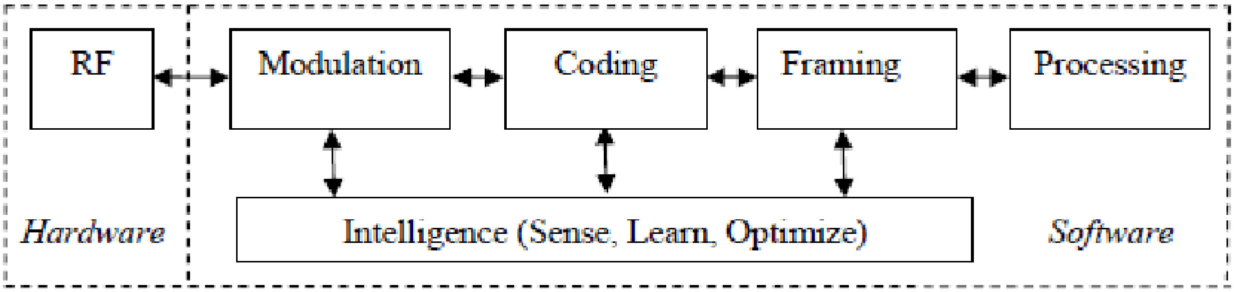


Figure 1.3: Scientific Block Diagram of Cognitive Radio.

1.3 Monte Carlo Simulation Technique

Simulation technique by Monte Carlo is a statistical-mathematical approach for generating random sample data for numerical experiments based on a given distribution. This strategy is used to solve problems with risk quantitative chemical analysis and decision-making. Professionals in various fields employ the approach, including large companies and among each team.

1.4 MATLAB

Matrix Laboratory, known as MATLAB, supports both aspect-oriented and object-oriented programming, a numerical computing environmentdeveloped by MathWorks. It integrates computing, visualization, and programming in a user-friendly environment using mathematical equations. MATLAB was first launched in 1984 and is compiled in C, C++, and Java. The most recent version was launched in March of this year.

The MATLAB scripting language is the foundation for MATLAB applications, which centeraround the following mathematical concepts:

- Variables
- Vectors and matrices
- Structures
- Functions
- Function handles
- Classes and object-oriented programming

2. SPECTRUM SENSING

The existence of a primary user on a band is determined in the first step of spectrum sensing. After scanning the spectrum, the cognitive radio will exchange its sensing results with other ones. Spectrum detection looks for the status and activities of the spectrum sensing by periodically detecting the target band. In particular, cognitive radio transmitter and receiver identify unused or unlicensed radio waves and determine the access method without interfering with the licensed transmission. Two types of spectrum sensing techniques are there; those arenon-Cooperative Spectrum Sensing and Cooperative Spectrum Sensing.

2.1 Non-Cooperative Spectrum Sensing Techniques

In real spectrum detection scenarios, sometimes only one detection terminal is available, or the detection terminals cannot cooperate due to lack of communication between them. In this topic, we will introduce the most common single-user perception systems, some of them can be used as the basis for collaborative perception. Due to the connection to signal detection, single user spectrum detection technology has become famous in the literature. Energy detector (ED), tailored filter detection, and cyclo-stationary detection are three traditional methods used for this purpose.

2.2Cooperative Spectrum Sensing Techniques

Cooperative spectrum detection can be:

- Centralized spectrum detection, in which a central system gather all information from all secondary CR receivers to decide on the state of confusion, and then sends it to the CR receiver
- In distribution phase, the recipients share Knowledge so that they can make their own decisions.

3. SINGLE THRESHOLD ENERGY DETECTION BASED NON-COOPERATIVE SPECTRUM SENSING TECHNIQUE FOR COGNITIVE RADIO

3.1 Energy Detection

It detects the initial signal supported by the observed energy in a non-coherent and non-cooperative manner. Energy sensing (ED) is the most widely used collaborative sensing method because it is simple and lacks the required knowledge of the primary user signal.

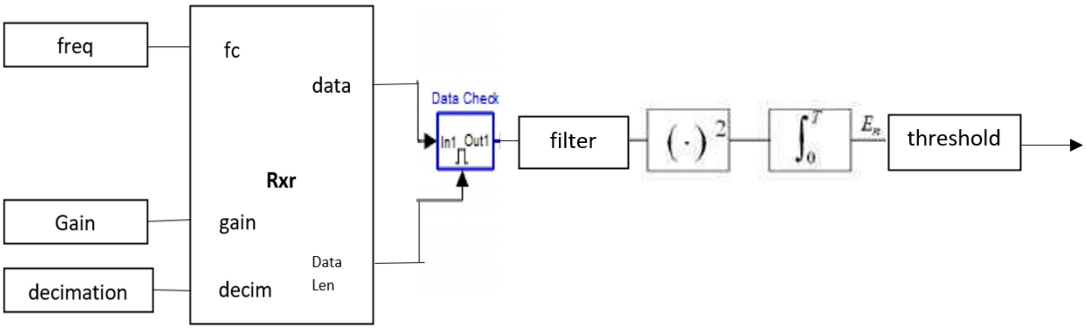


Figure 3.1: Block Diagram for ENERGY Detection Technique.

The above diagram represents the energy detection technique, as shown in **Figure 2.1**. It contains four main blocks:

- Multiple feedback filter(BPF)
- Square law demodulator
- Integrating device
- Threshold detection

3.2 Testing Binary Hypothesis

Signal detection at the secondary is generally represented as a Testing Binary Hypothesis, given as Depending on the sleep or active status of primary user and the noise, the signal detection at the secondary is often modelled as:

Hypothesis 0 (H_0): User is inactive

Hypothesis 1 (H_1): User is active

when signal is received, **Y,** is sampled by the n^{th}(n= 1, 2, 3____) sample, then y(n) is:

$y(n) = w(n)……H_0$

$y(n) = x(n) + w(n)……H_1$

x(n) is the PU's signal, x(n)=hs(n), h is a channel gain, and w(n) is the sample noise, it is considered as a Gaussian random variable of mean zero.

(IE[w(n)] = 0) and variance $2a$ i.e., w(n) - $N(O, 2a)$.

Then a **decision rule** can be given as:

$H_0 \; if \; \varepsilon < V_t$

$H_1 \; if \; \varepsilon > V_t$

E stands for the test statistic. By comparing E to the threshold voltage V_t, the two hypotheses H0 and H1 are found by energy detection.It is important to set an appropriate threshold. The main problem is shown in Figure 2, which provides the probability density function of signal received with and without PU.

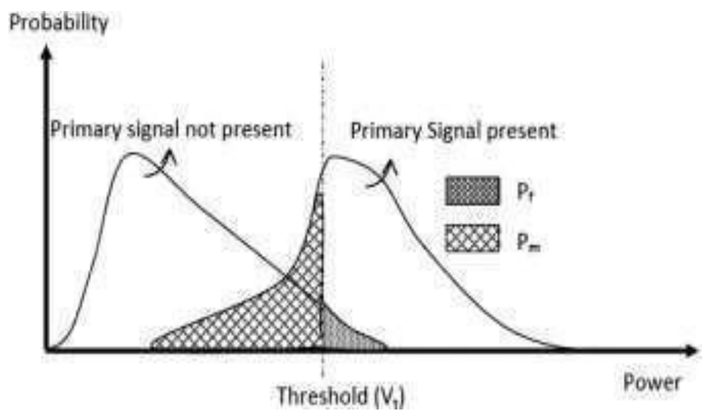


Figure 3.2: Adjusting of Threshold in CR, false Alarm and Missed Detection.

so if we select $V_t$is low, there is a chance for probability of false alarm, i.e.,

$P_f = Pr(\varepsilon > V_t \mid H_0)$ increases. As a result, the spectrum is underutilised. A high V_t, however, can result in missed detections, so the risk must not be overstated.

$Pm= Pr(\varepsilon < V_t \mid H_1)$ is increased. This may cause interference with active PU. Setting the threshold for ED requires careful consideration of trade-offs.

3.3 Test Statistic

The energy detector's test statistic is frequently presented as

$$\varepsilon = \frac{1}{2\sigma_w^2}\sum_{n=1}^{N}|y(n)|^2$$

Where 2σw2 is the variance of the noise and N is the number of samples, making N = 2TW, where TW is the product of the time bandwidth.

The following indicators are introduced to support the test statistics under the testing binary hypothesis to characterize the efficiency of the energy detector:

- **falsealarm Probability(P_f)** is defined as the probability of signal being present when the condition is true.

  $P_f \ = P_r \ (\varepsilon > V_t|H_0)$

  $V_t$is the threshold, and P_r[.] is an event probability.

- **Probability of missed-detection**(P_{md})is defined as the Probability of determining if the signal is not present.

  $P_{md} = P_r(\varepsilon < V_t|H_1)$

Detecting a spectrum hole is toidentify a spectrum hole where no one exists. As a result, huge P_{md} can interfere with primary users in unanticipated ways.

The **detection probability(Pd)** is defined as the probability of detecting when the signal is present and H1 is true.

$P_d = 1 - P_{md}$

Among the benefits of the spectrum sensing technology built into cognitive radio is both reliability and efficiency; it is preferred that P_d (or Pmd) is higher and Pf is lower.

4. DOUBLE THRESHOLD BASED COOPERATIVE SPECTRUM SENSING TECHNIQUE FOR COGNITIVE RADIO NETWORK USING MATLAB

4.1 Cooperative Spectrum Sensing (CSS)

CSS was previously used as a solution for the problem of node failure and fading. Figure 3.1 shows how CSS works. The FC receives local choices from each SU in this diagram. The outcome of each CR is then subjected to a fusion rule, such as the OR, AND, or Majority rule. The OR rule calculates the cumulative detection probability (Qd) and cumulative false alarm (Qf) of the cooperative arrangement as shown below.

$$Q_d = 1 - \prod_{i=1}^{M}(1 - P_{di})$$

$$Q_f = 1 - \prod_{i=1}^{M}(1 - P_{fi})$$

Pd and Pf respectively represent the false alarm probability and the probability of detection of each SU, and M represents the total number of CR’s included.

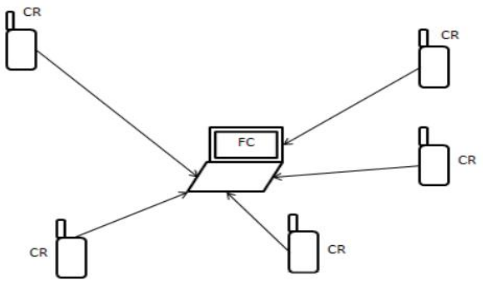


Figure 4.1: Cooperative Spectrum Sensing.

4.2 Double or Dual Threshold Cooperative Spectrum Sensing Technique

As mentioned earlier, each CR in a typical energy detector takes decisions based on a one threshold that is available in a single energy detector, as shown in Figure 3.2. (an example). Suppose X is the energy of the received signal Y.

If the calculated energy X is greater than the threshold, then suppose that H1 is correct; otherwise, assume H0. Figure 3.2 shows how to use the double threshold energy detection method (b). In this case, if X is greater than λ2, it is assumed that H1 is true, if X is less than λ1, it is assumed that H0 is true; however, if the detected energy X is in the middle of both thresholds, that is, λ1 <X <. λ2, no decision is taken, CR will keep on sensing.

Calculation of threshold λ is done by the given formula.

$$\lambda = Q^{-1}(P_{fa})\sqrt{2N\sigma_w^4} + N\sigma_w^2$$

And thresholds λ_1 and λ_2 can be found as:

$$\lambda_1 = (1-\rho)\lambda$$

$$\lambda_2 = (1+\rho)\lambda$$

Here ρ is the uncertainty parameter.

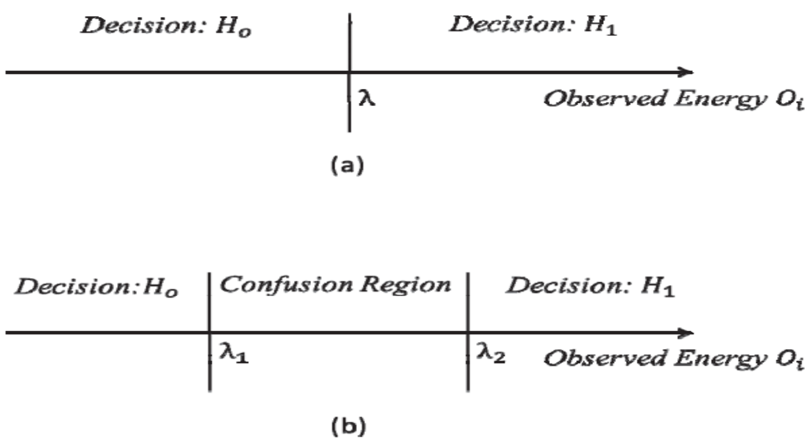


Figure 4.2: Comparison between Single and Double Threshold Detections.

In this survey, we established a dual-threshold CSS simulation model in this paper, and its operations are as follows:

- Every Secondary User will determine only if the measured energy Xi is greater than or equal to the value specified by
- X_i € H_0
- L_i = {
- X_i Σ H_1
- If X is in the middle of both thresholds λ1 and λ2, local CR does not make a decision, but sends to FC of the detected energy Xi.
- Assume FC is presented with L local decisions and M-L energy values. FC will average of all received energy values and compare with the threshold to determine for the best option(H_0 or H_1) as

$$X_{avg} = \frac{1}{M-K}\sum_{i=1}^{M-K} X_i$$

$$L_f = \begin{cases} 0 & X_{avg} < \lambda \\ 1 & X_{avg} > \lambda \end{cases}$$

- Then the FC will make its decision and consider it as L+1decision :L from the SU that made the decision, and additional decision from FC, based on the energy of the SU's which are in a confused state.
- From the above equations, FC will now use OR merge rules to combine these L + 1 decisions.
- In this method, no data loss is detected (each CR contributes to the FC decision) and the problem of false detection is also eliminated. The flowchart of the double-threshold CSS scheme is shown in Figure 3.3

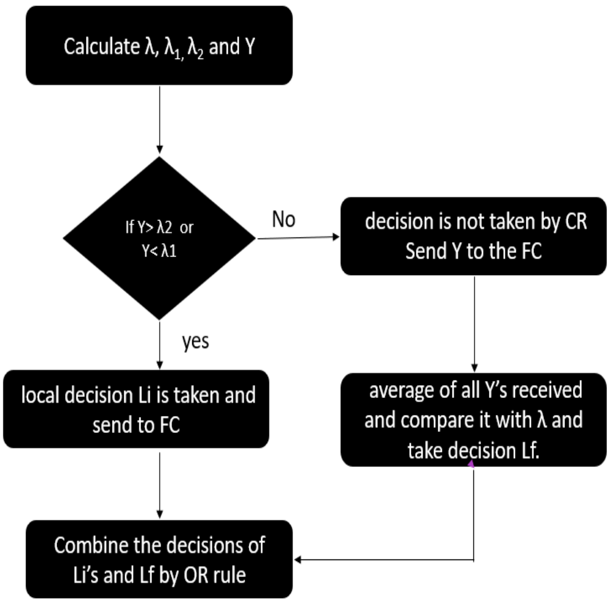


Figure 4.3: Flowchart of the Double Threshold Scheme.

5. SIMULATION ANALYSIS

We carry out a simulation study to evaluate the performance of the proposed solution. To test the simulation model, a simulation model of the single threshold energy detection method was done in MATLAB and compared outputswith the theoretical results. The theoretical and simulation results of N = 500 and 1000 ROC (Receiver Performance Characteristics) are compared and shown in figure 3.4. This shows that the generated simulation model is very much closer to the theoretical model. The performance of the suggested strategy is then evaluated using this simulation model. We've assumed that the signal is BPSK modulated.

With 200 samples, Figure 3.5 shows the curve between probability of detection and false alarm probability for single and dual thresholds at -5 dB Signal to Noise Ratio. In this case, the area of confusion is not considered. For simplicity, we assume each CR uses the similar threshold values and the same uncertainty parameter q = 0.1. The ROC for the conventional and Double Threshold CSS schemes is shown in figure 3.6. We hypothesised that the number of cooperative states would be five based on the number of participating states, M=5. The Double Threshold CSS system clearly outperforms the standard CSS, as shown in this graph. This curve is based on 100 samples at an SNR of -8dB. The graph shows that the Double Threshold CSS technique improves the chance of detection by over 10% at false alarm probability=0.1.

Figure 3.7 shows the relationship between Qd and SNR when false alarm probability = 0.1 It can be seen from the figure that the proposed system works better with a low SNR. The graph between the decision error probability (Pe) and Signal to Noise Ratio is shown in figure 3.8. It can be seen that the proposed technique minimizes the decision error in the low SNR region.

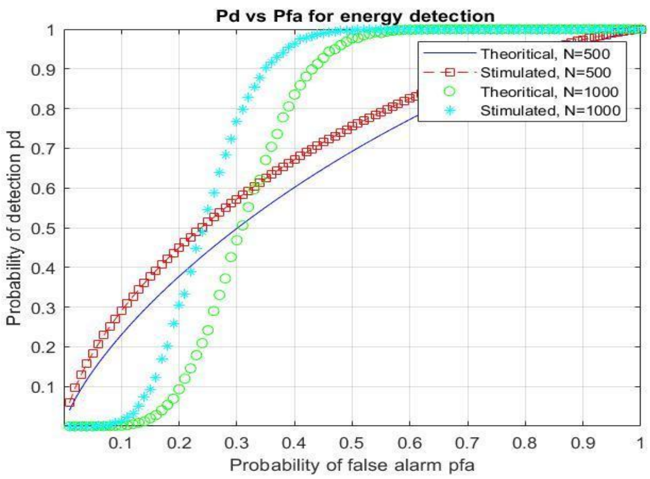


Figure. 5.1: Graph on Pd vsPfa for Energy Detection.

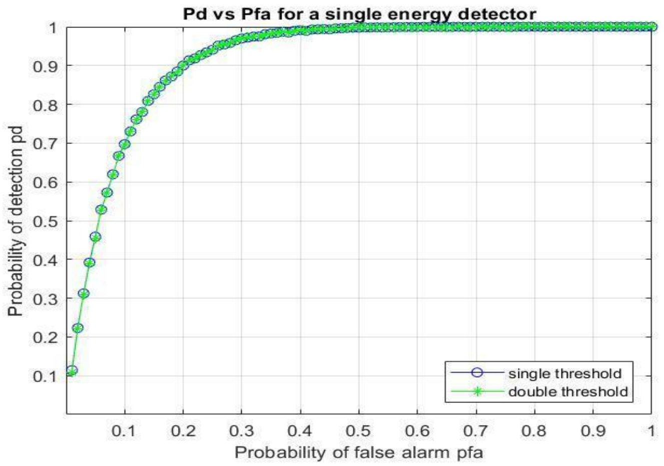


Figure 5.2: Graph on Single and Double Threshold Detection for Single Detector.

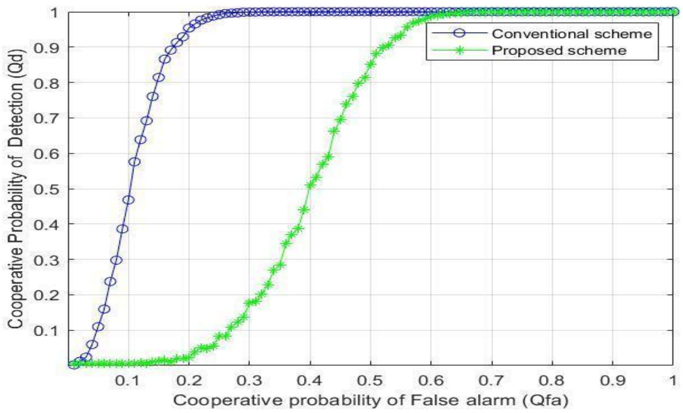


Figure 5.3: Graph on QdvsQfa for Single and Double Threshold Detection.

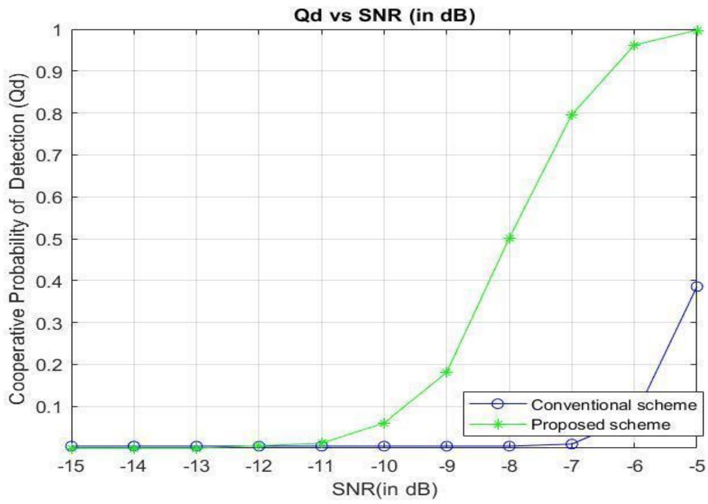


Figure 5.4: Graph on Qdvs Signal to Noise Ratio(in dB).

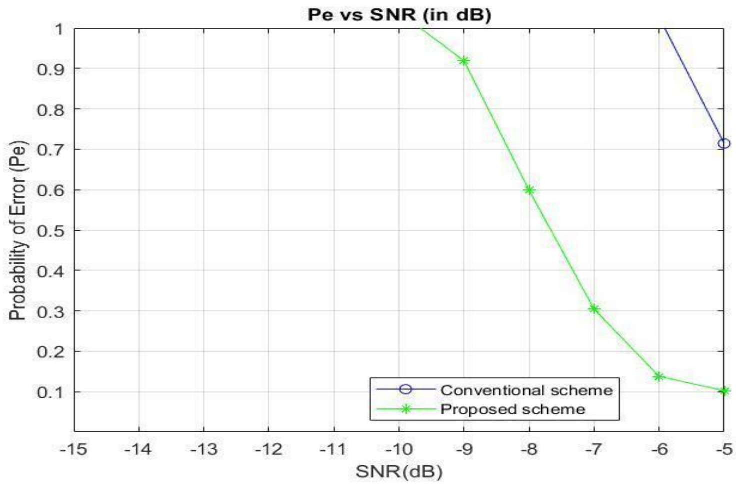


Figure 5.5: Graph on Error Probability vs Signal to Noise Ratio(in dB).

6. RESULT ANALYSIS

FC gets two types of decisions: simulated energy values and local decisions. We recommend a technique in which FC takes the average of the energy values which are observed during simulation and compares them with the threshold value of λ to make a local decision Lf. Then, using the OR rule of fusion, FC merges all of the local decisions obtained from SUs and decision Lf to form a global decision. When the Double Threshold CSS approach was used, detection performance improved significantly. Additionally, the issue of sensing failure has been resolved. Since the energy value is transmitted to FC, optimization of spectrum detection performance and overload load can be explored in the future.

7. CONCLUSIONS

Energy detection based sensing has been studied in cognitive radio networks. By running simulations, view and analyze graphs of detection probability and false alarm probability. The Probability of detection increases as an increase in the number of false alarms. The simulation results show that this sensing technology has a significant reduction in the chance of missed detection. The detection probability is also influenced by SNR. SNR has a significant impact on detection likelihood. As the SNR rises, the likelihood of detection rises as well. As a result, we are on the verge of obtaining the final energy detection result that we had hoped for. We developed the notion of cooperative spectrum sensing for greater performance by employing the prior Energy detector. As we all know, the performance of the energy detector is affected by the uncertainty of the noise power. In such instances, different detection strategies such as Cyclic feature detection are used.

Through this article, we have concluded that double or dual threshold cooperative spectrum detection is based on conventional threshold technology and is the best technology to reduce the total error rate by finding two thresholds in the detection.

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