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# A Study on Twin fold Power Identification Technique for Cognitive Radio Networks

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## ABSTRACT

Cognitive Radio (CR) is an innovative model for wireless communication that addresses the issue of spectrum inadequate utilization. Spectrum sensing is one of cognitive radio's key tasks. Power identification is a popular spectrum sensing methodology due to its simplicity and lack of need for preexisting knowledge of the primary user (PU). However, traditional energy detectors function poorly in low SNR regions. The CSS (Cooperative Spectrum Sensing) with double thresholds improved decision-making validity, but resulted in some loss of sensing knowledge. In this study, we have projected a dual threshold Cooperative Spectrum Sensing approach where every CR (Cognitive Radio) communicates local resolution or perceived power to the FC (Fusion Center) based on the region where the perceived power is located. FC then renders an ultimate judgment based on local decisions and measured power values. Our simulation framework demonstrates that the suggested technique surpasses standard CSS in low SNR regions. The proposed method *Twin fold Power Identification Technique for Cognitive Radio Networks* (TFPIT) is better than conventional CSS methods in context of energy detection.

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## INTRODUCTION

Wireless technology for communication has advanced rapidly, resulting in an increasing number of wireless network amenities. The radio spectrum, the most precious resource in wireless networks, cannot meet current and anticipated wireless service needs [1]. The current static allocated spectrum mechanism reduces spectrum consumption and causes significant disparities. Depending on the analysis, the average spectrum use is under five percent at all times and locations [2]. Dynamic spectrum access (DSA) is widely regarded as the primary technical answer to the supply-demand imbalance [3]. Cognitive radio (CR) technologies, which serves as the foundation for DSA, has emerged as one of the most advanced research subjects in the area of wireless networking.

CR may communicate with its communication context and alter its transmission variables based on the results. The cognitive radio network (CRN) [4] is a network that uses CR as its service terminal. In the CRN, both licensed and unlicensed consumers coexist, with the licensed user referred to as the (PU) and the unlicensed user referred to as the secondary user (SU). CR users with CR can detect idle spectrum resources and enhance their utilization while avoiding interference with PU. The CRN's research focuses primarily on spectrum sensing (SS), spectrum communication, spectrum access, and spectrum movement [5].

The fundamental goal of cooperative spectrum sensing (CSS) is to assess whether a specific frequency has been utilized by a licensed user or not, allowing unlicensed users known as secondary users (SUs) to access that spectrum if it is not owned. A secondary user who cannot be served by his band may be granted entry into a spectrum hole at the appropriate time and location in order to increase the efficiency of spectrum use. The "Cognitive Radio," which makes use of a Software Defined Radio (SDR) to efficiently allocate spectrum by using the spectrum holes in one band to offset the congestion of another band, is capable of performing this kind of dynamic allocation.

## LITREATURE REVIEW

The primary job of SS is to discover spectrum holes accessible to SU and to observe the PU's signal activity so that when the PU utilizes the spectrum subsequently [6] [7], SU may swiftly vacate the relevant frequency region. Two factors affect the efficiency of SS: false alarm likelihood and detection likelihood. The false alarm likelihood is negatively connected with the CR's throughput, but the detection probability represents the protective capacity of the PU. Conventional SS methods include single node-based SS and cooperative spectrum sensing (CSS). The single node-based SS includes matched filter detection [8], energy detection (ED) [9], Cyclostationary feature detection [10], and covariance matrix detection[11], among others. Still, single-node-based SS either performs poorly or is very complex [7]. When dealing with the concealed terminal difficulty (the shadow and deep fading), the sensing results of a single node-based SS are unreliable, thus it is important to incorporate the sensing outcomes of several nodes to increase detection dependability, called CSS.

Traditional CSS schemes combine centralized and distributed CSS [12]. Centralized CSS means that each node sends local sensing information to the fusion Module, which makes a decision based on the fusion rules. Finally, the FM communicates the decision outcome to each local node. Centralized CSS, as defined by the FM's fusion rule, includes AND rule-based CSS, OR rule-based CSS, and majority voting (MV)-based CSS, among others. There is no fusion center for distributed CSS [13], thus each local node trades detection findings with the others before combining their local fusion decision. The sensing precision of the CR system is significantly increased for dispersed CSS. Yet this comes at the cost of network load and system complexity.

This research focuses on double-threshold energy detection techniques. The typical double-threshold spectrum sensing approach matches the energy value to two predetermined decision thresholds. If the energy exceeds the higher level, it means that the PU existed. If it is below the lower criterion, it is assumed that the PU is not present. And if it falls between the high and low limits, the decision is not temporary. To increase energy detection efficiency, [14] proposes a weighted-cooperative double-threshold spectrum sensing system as well as two adaptive double-threshold energy methods. When the energy lies between the high and low thresholds, all of the above-mentioned double-threshold approaches yield no conclusion. To address this issue, [15] presents a memory-based energy detection system that uses memory sticks to boost speed at the expense of secondary device connection delays. Furthermore, in [16], the correlation coefficient of received signals, the two-state Markov chain model, and historical sensing data are used, accordingly, to decide a result when the energy falls between two thresholds. The most basic approach for spectrum sensing is energy detection (ED), as illustrated in Fig.1. This function detects the principal user's energy and compares it to a predetermined threshold value $\lambda$ . If this energy is under the threshold value, it is determined that the licensed user does not exist and the spectrum is available; alternatively, the spectrum is considered to not be free.

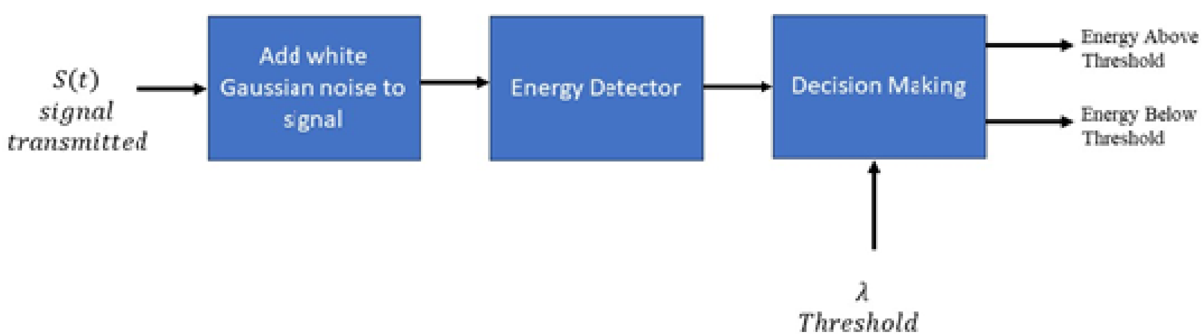


**Figure 1: Energy Detector in CRN**

The signal to be discovered is deterministic but has an uncertain form. Noise is believed to be an additive white Gaussian with zero mean. To calculate the electrical energy of an input signal, it is first sent through an analog to digital converter, squared, and then accumulated over time. The existence or absent of PU is determined by comparing the estimated or measured energy to a threshold. The literature considers two hypotheses of the received signal: hypothesis $H_o$ when PU does not exist and hypothesis $H_1$ when PU exists. These are as follows:

$$H_1: y(n) = s(n) + u(n) \quad (1)$$

$$H_0: y(n) = u(n) \quad (2)$$

Here, y(n): Received Signal, u(n): AWGN noise with zero mean, s(n): primary User signal with zero mean. For N, number of samples, the received energy is given by:

$$X = \sum_{n=1}^{N} |y(n)|2 \quad (3)$$

Probability of false alarm is given by:

$$PROB_{false\_alaram} = P(X < \lambda) = Q(\frac{\lambda - N\sigma^2{}_w}{\sqrt{2N(\sigma_w)^4}}) \quad (4)$$

Probability of detection is given by:

$$PROB_{detection} = P(X > \lambda) = Q(\frac{\lambda - N(\sigma^2{}_w + \sigma^2{}_s)}{\sqrt{2N(\sigma^2{}_w + \sigma^2{}_s)^2}}) \quad (5)$$

Miss Detection Probability is given by:

$$PROB_{miss-detection} = 1 - PROB_{detection} \quad (6)$$

Decision Error probability is given by:

$$PROB_{error = prob_{false-alaram} + prob_{miss-detection}} \quad (7)$$

Here noise variance is given by: $\sigma^2{}_w$ and Signal variance is given by: $\sigma^2{}_s$.

**COOPERATIVE SPECTRUM SENSING (CSS)**

CSS is demonstrated in figure 2. In this model, each SU communicates its local decision to the FC. FC merges the results of each CR using fusion rules such as OR, AND, and Majority. Under OR rule, the probability of detection and Probability of false alarm is given by:

$$Q_{detection} = 1 - \prod_{i=1}^{M}(1 - P_{detection_i}) \quad (8)$$

$$Q_{false-alarm} - 1 - \prod_{i=1}^{M}(1 - P_{false-alarm_i}) \quad (9)$$

Here, M is the number of CR participating in CSS.

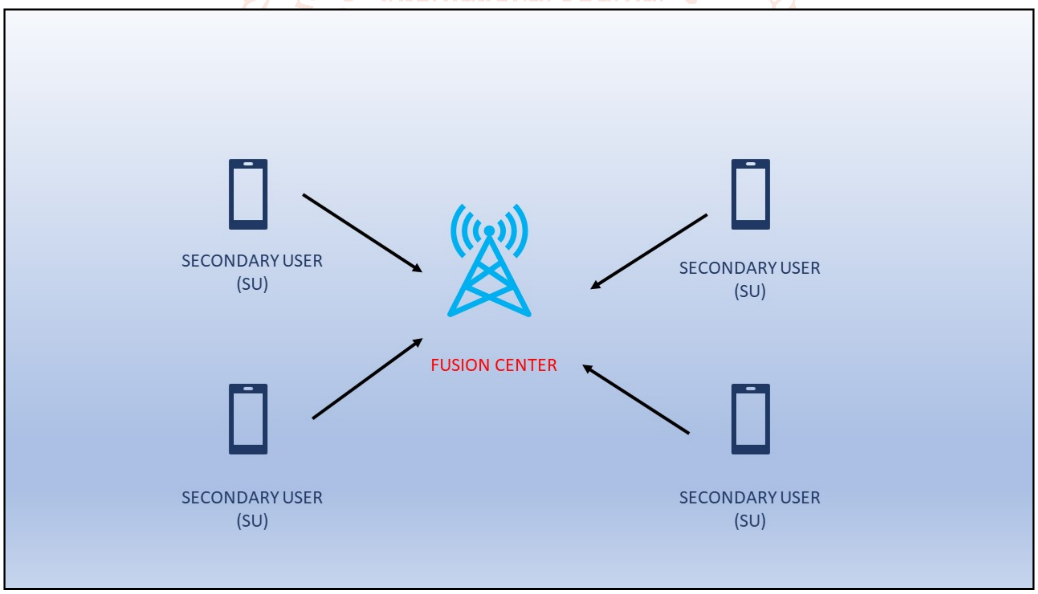


**Figure 2: Fusion Center and SU**

**TWIN FOLD POWER IDENTIFICATION TECHNIQUE FOR COGNITIVE RADIO NETWORKS (TFPIT)**

In typical energy detectors, each CR makes local judgments based on a single threshold, as illustrated in Figure 3(a). If the estimated energy X (or measured energy Oe) exceeds the threshold $\lambda$, hypothesis $H_1$is valid; otherwise $H_0$.

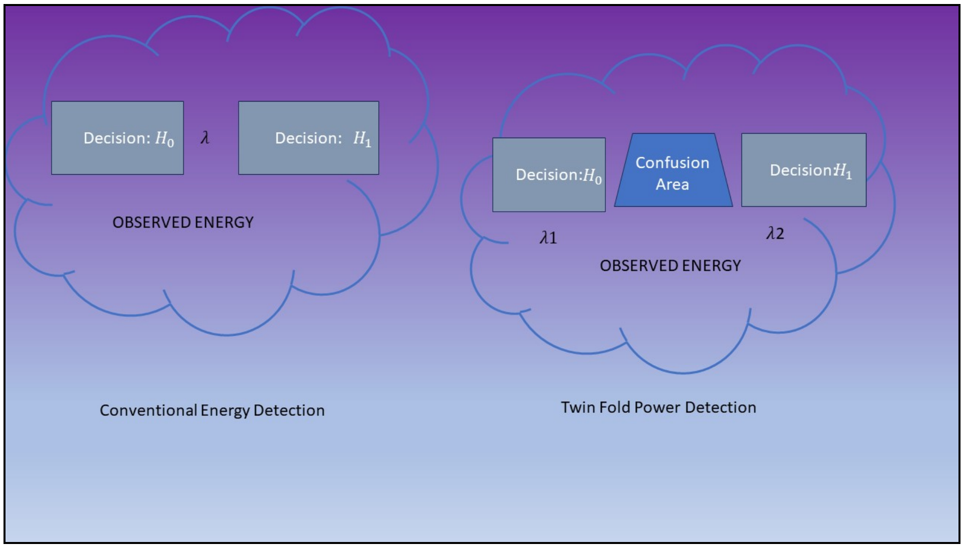


**Figure 3: Energy Detection**

Figure 3(b) illustrates the Twin Fold threshold method for detecting energy. Hypothesis $H_1$ is true when X is greater than $\lambda_2$, while hypothesis $H_0$ is true when X is less than $\lambda_1$ . If the detected energy X falls between the two thresholds, no choice is made and the CR will continue sensing. Each SU makes a decision if measured energy Oe lies above or below threshold values, otherwise it does not make any decision. The FC take the average of local decisions and energy values and compare it with threshold value lambda and select between $H_1$ and $H_0$. Now FC will receive decisions from Sus and one decision from the confused area. Next, using equation (8) and (9) FC can combine all decisions. So, problem of sensing information failure or lost is eliminated.

## ANALYSIS OF SIMULATION RESULTS

In this section, we have simulated the cognitive radio environment for the proposed method and results are as follows. Number of samples range from 500 to 1000. We have modulated the communicating signals using Binary phase shift key method. The proposed method is very close to conventional method. The graph shows that the proposed technique operates better with low SNR. The suggested technique minimizes decision errors in low SNR regions. The graph clearly shows that the proposed technique improves detection probability.

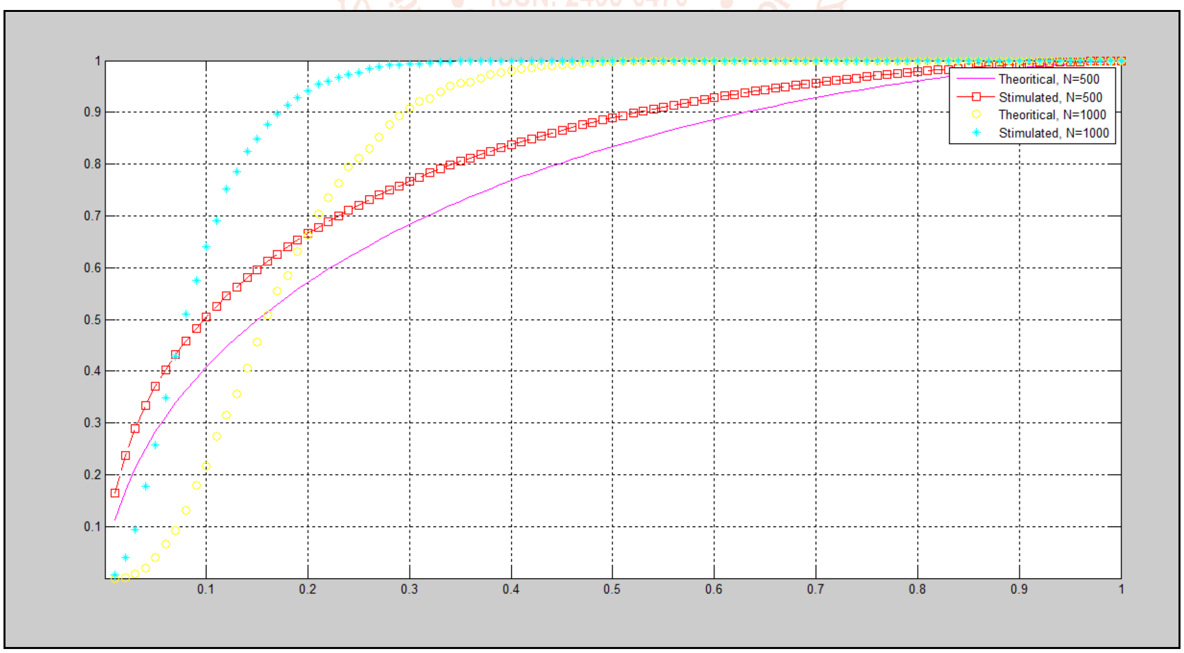


**Figure 1: Comparison Between Theoretical and Simulated models**

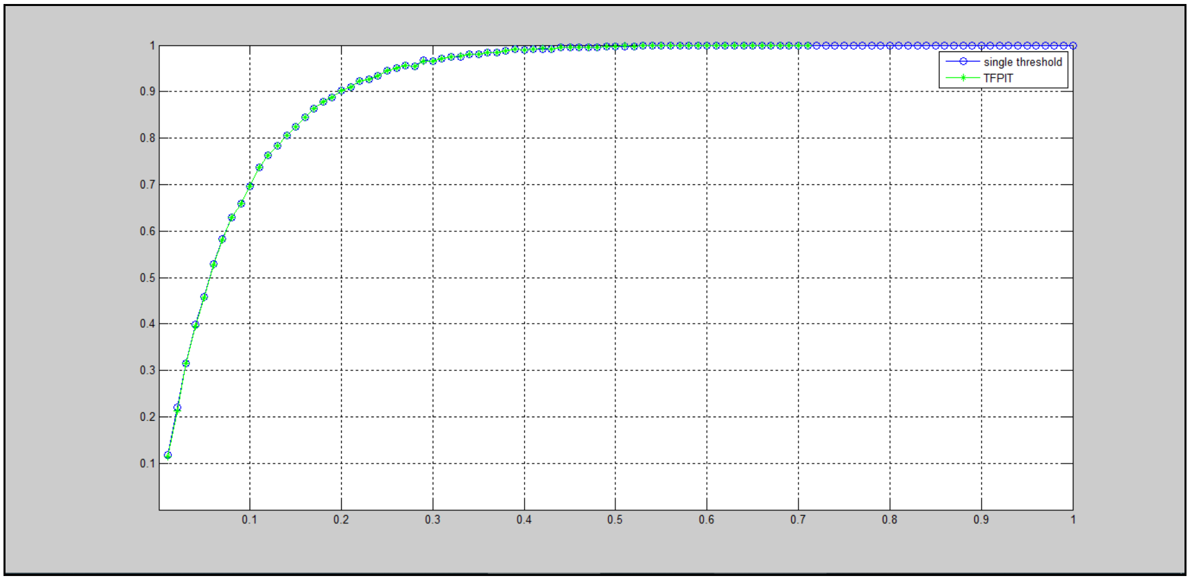


**Figure 2: Comparative Energy detection**

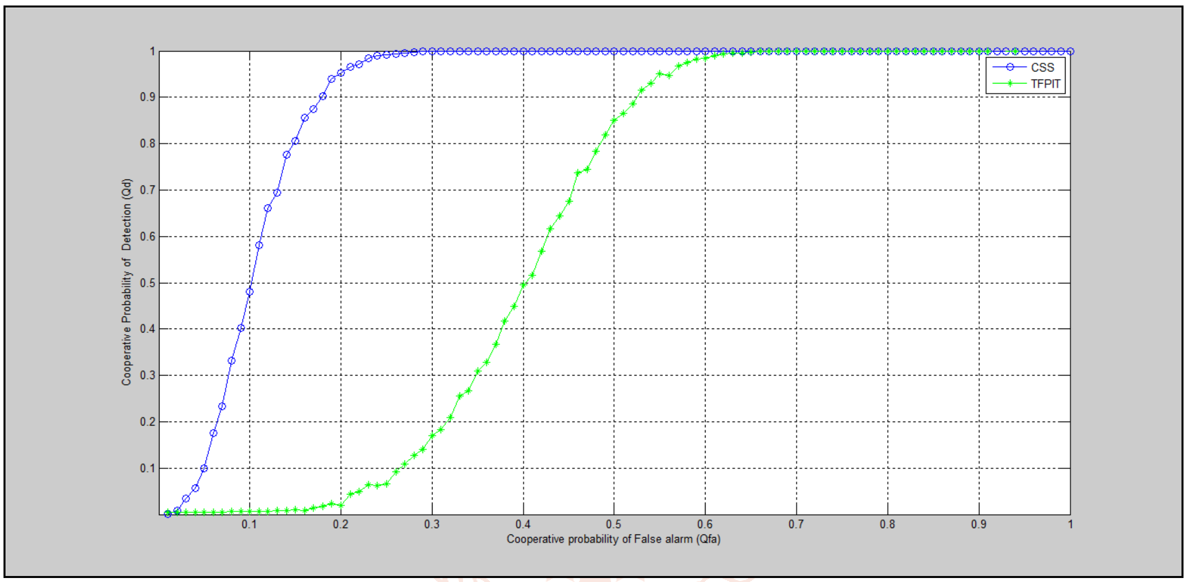


**Figure 3: Comparative Probability of detection**

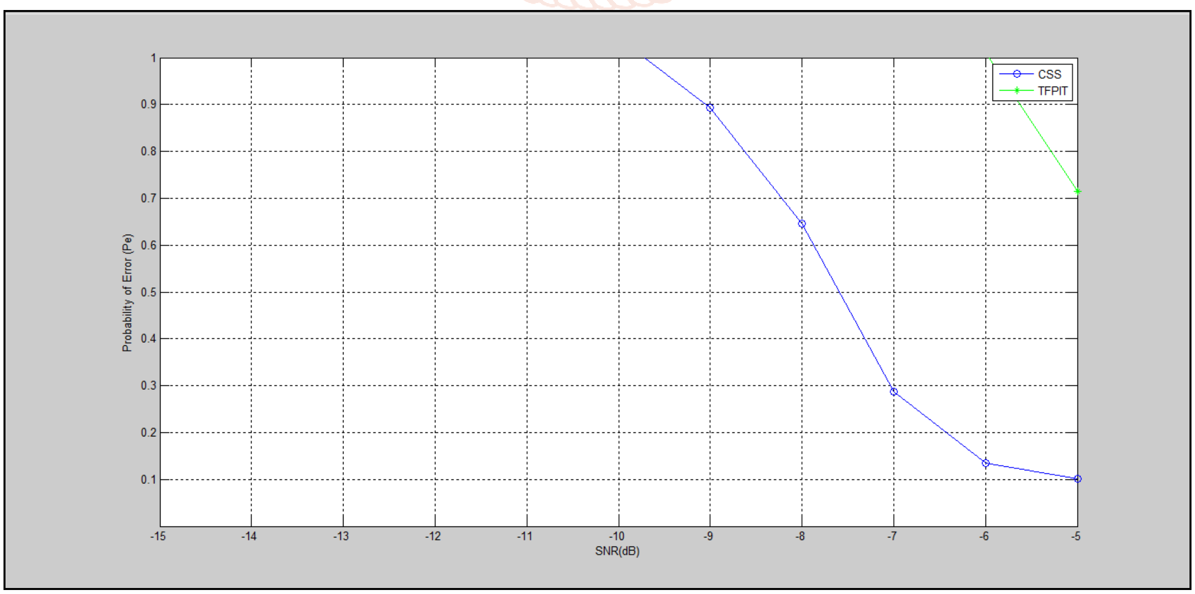


**Figure 4: Error of Probability**

## CONCLUSIONS

This paper discusses cooperative spectrum sensing with Twin fold thresholds for each CR. FC processes two sorts of decisions: local decisions and observable energy levels. We suggest a technique in which FC averages perceived energy values and compares them to a threshold value to make decisions. FC merges local judgments from SUs into a global decision using the OR rule of fusion. The suggested strategy significantly improves detection performance. Furthermore, the issue of sensing failure has been resolved.

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