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Performance Comparison of Energy Detection Based non – Cooperative Spectrum Sensing Techniques in Cognitive Radio

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Abstract

Cognitive radio is a ground-breaking software-defined radio paradigm that offers Dynamic spectrum access, allowing secondary users to use the frequency band allotted to the principal user when it is not in use and vacate when the prime application returns. The ability to sense the spectrum is critical to cognitive radio's efficiency. Energy detection sensing is the simplest and most often used spectrum sensing approach, owing to its ease of implementation in cognitive radio applications. The three-energy detection-based algorithms adopted for different scenarios have been compared in this study. The algorithms include the double-threshold energy detection, adaptive single threshold energy detection, and the adaptive double threshold spectrum sensing algorithm. Since the noise prediction in the practical situation is difficult, the necessity is to find the best algorithm in this condition. The other equally important parameters for efficiently sensing the spectrum are spectrum efficiency and less interference to the primary user. Simulation findings show that the adaptive double threshold approach outperforms the other two algorithms in all respect. The detection probability of the method is typically found to be substantially greater as compared to other two techniques. In addition, the likelihood of a false alarm is significantly reduced. Furthermore, when the signal-to-noise ratio value is low, often below -5dB, the performance of this approach is poor. MATLAB is used to run all of the simulations.

Keywords: Cognitive radio, Dynamic spectrum access, Energy detection algorithm, Receiver operating characteristics, Spectrum sensing.

1. Introduction:

The booming wireless communications industry with the demand for high data transmission rates has increased a variety of wireless standards for various applications. However, these upcoming wireless networks have to be licensed by a fixed spectrum allocation policy which is almost impossible because wider ranges of the available spectrum have been already allotted to the different services. On the other hand, a larger fraction of the previously allotted spectrum is used infrequently, with temporal and geographical fluctuations ranging from 15% to 85% in the usage of the assigned spectrum [1]. Dynamic spectrum access (DSA) is a suggested approach to alleviate spectrum scarcity and inefficiency issues by allowing underutilized spectrums to be used in a shared manner [2]. The new paradigm that makes DSA possible is cognitive radio (CR). The cognitive radio is a technique based on software-defined radio (SDR) which helps the secondary user to opportunistically and dynamically use the unused spectrums given to the primary user (PU) [3]. The secondary users are called the cognitive radios and the mostly vacant spectrums or the underutilized spectrums are called spectrum holes. IEEE 802.22, a cognitive radio-based IEEE standard, was presented and demonstrated to be a solution to the current underutilization of the radio spectrum by TV services, which are referred to as spectrum holes [4]. So, the major challenge for the cognitive radio network is to sense the vacant spectrum or the spectrum holes. The intelligence of identifying the spectrum holes in the vicinity of the cognitive receiver and vacating those when the primary users return for the quality communication is termed spectrum sensing [5], [6]. The important task for cognitive radio is the best detection of the presence of the primary user to lower the interference in a negligible amount. There have been different detection schemes proposed in the context of cognitive radio applications including Energy Detection (ED) [7], Matched Filtering [8], feature-based sensing [9][10], and other sensing techniques (covariance-based methods[11] and Eigen - value-based methods [12]). Based on their benefits and drawbacks, different strategies are used for different reasons. The energy detector is the best spectrum sensing system for detecting the PU signal without knowing its position, structure, or strength because it is based solely on the received signal's power [13]. It is widely used due to its ease of implementation. Furthermore, in CR, energy detection-based spectrum sensing can be done independently or collaboratively. The effectiveness of cooperative spectrum sensing has recently received a lot of attention. Even though cooperative spectrum sensing has significantly increased the sensing performance, it has drawbacks over non-cooperative spectrum sensing like difficulty to create a rapid and smooth spectrum transition due to the randomness of PU appearance- resulting in limited PU interference and performance loss [14] and increasing the communication and computing load of the secondary [15].

In this study, energy detection-based non-cooperative spectrum sensing has been explored. Since its performance is governed by the choice of the threshold. Threshold optimizing is a challenging task. Based on how the threshold is calculated, the different algorithms are adopted for energy detection-based spectrum sensing. The algorithms ultimately desire to improve the efficiency of energy detector-based spectrums sensing. A single threshold energy detection algorithm (STEDA) has been proposed when noise is uncertain and the signal is unknown deterministic[16]. To increase the performance of the detector, a double threshold energy detection algorithm (DTEDA) has been reported by [17], [18] where two other parameters: collision probability and spectrum unavailable probability were numerically calculated and illustrated that collision probability decreases from 32.31% to 8.914% and spectrum unavailable probability increases from 2.331% to 3.57% at a threshold voltage of 10 dB. This finding suggests that the configuration reduces cognitive radio and primary user interference while compromising a little amount of spectrum efficiency. Another algorithm, under the same scenario of noise uncertainty, an adaptive single threshold energy detection algorithm (ASTEDA), is proposed and simulated showing that it is more robust than the single threshold algorithm [19]–[21]. Moreover, by combining the strong points of adaptive threshold algorithm and double threshold algorithm, an adaptive double threshold energy detection algorithm (ADTEDA) to overcome sensing failure at very low signal to noise ratio (SNR) with uncertain noise power has been reported and numerically analyzed which enhances detection probability and lowers the error rate and shows robustness to noise uncertainty [22], [23]. Having surveyed the results of these algorithms, it is found that their performances have been presented for different scenarios. This study creates a common platform and compares the performances of the last three algorithm for SNR greater than − 5 dB, based on the performance parameters like the probability of detection, probability of false alarm, probability of spectrum unavailability, and the likelihood of collision at noise uncertain condition. we believe that the comparison based on these fours parameters is the novel work. The results of the simulations reveal that an adaptive double threshold technique is resistant to noise uncertainty for SNR greater than -5dB, however, the other two algorithms are not resistant to the noise uncertainty for the same range.

2. Simulation Method and Models:

2.1. The system model:

The constructed system model, on which the three algorithms are implemented, is depicted in Fig. 1. At the secondary receiver, the primary signal energy from the AWGN channel is received. As shown in Fig. 2, the received signal is subsequently supplied into the energy detector [24], wherein four algorithms were implemented.

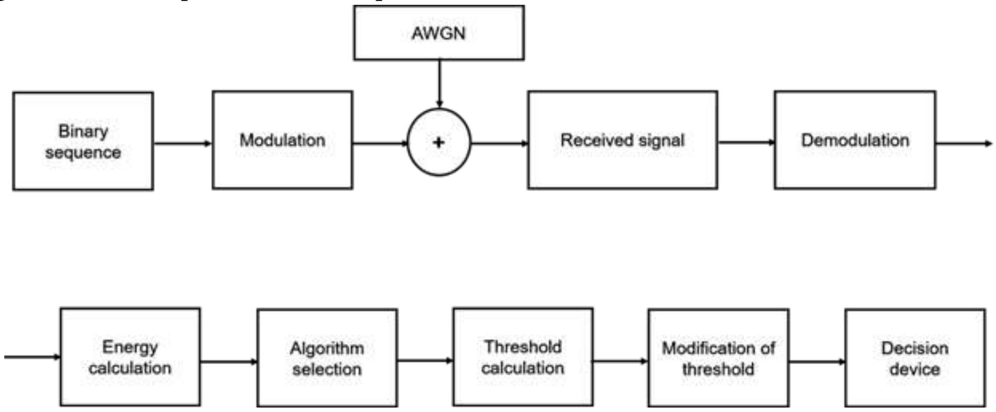

Fig. 1: Schematic diagram of overall system model

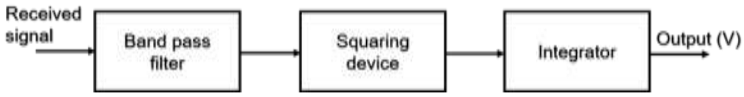

Fig. 2: Energy detector block schematic [19]

At the secondary receiver, the primary signal energy from the AWGN channel is received. As shown in Fig. 2, the received signal is subsequently supplied into the energy detector [24], wherein four algorithms were implemented.

After filtering, the energy of the incoming signal is computed and averaged over the appropriate sample size. Different threshold calculation connections are shown by these algorithms. Probability of detection, probability of false alarm, collision probability, and spectrum unavailability probability are the performance metrics. The probability of detection, on the other hand, is the most important consideration since it indicates the likelihood of precisely sensing the occupancy of PUs in the frequency band. The likelihood of miss detection is equal to the chance of detection multiplied by the probability of miss detection. The goal of detection methods should be to optimize detection likelihood while minimizing false alarm risk. However, there is a cost to this probability.

2.2. Analytical Frameworks for Different Algorithms:

2.2.1. Energy Detection Technique with a Threshold:

There is only one detection threshold, as the name implies. When the obtained wave energy V exceeds the sensing gate V_{th}, the detector determines that the PU is present in the band of interest, and H_1 is shown. The primary user, on the other hand, is not shown and is represented by H_0. The detection probability, false alarm probability, and miss probability can all be estimated using the following formulas [17].

$$P_D = Pr\{V > V_{th}|H_1\} = Q_u\left(\sqrt{2\gamma}, \sqrt{V_{th}}\right) \quad (1)$$

$$P_{FA} = Pr\{V > V_{th}|H_0\} = \frac{\Gamma\left(u, {}^{V_{th}}/_{2}\right)}{\Gamma(u)} \quad (2)$$

$$P_M = Pr\{V \leq V_{th}|H_1\} \quad (3)$$

where γ is the *SNR* obtained by SU, Q_u(a,b) is the normalized Marcum function with order u, and monotonically increasing with u and a, decreasing with b; Γ(a,b) is a non-complete gamma function which is monotonically decreasing with b and Γ(a) is a complete gamma function.

2.2.2. Energy Detection Technique with Dual Thresholds:

Within the traditional single-threshold ED approach, this algorithm adds another detection threshold. The two thresholds are defined as V_{th0} and V_{th1}. If and only if, $V > V_{th1}$, the PU will be discovered and if and only if $V < V_{th0}$, the PU will not be detected. The decisions correspond to H_1 and H_0 respectively. There is a high possibility of deciding if and only if V lies in anywhere in between the thresholds i.e., V is in $(V_{th0}, V_{th1}]$. It is necessary to re-detect the detector for it to operate better. We can calculate the performance indicators of the double threshold ED method, such as detection probability, false alarm probability, and missing probability, using the typical single-threshold ED technique. They can be calculated as [17]:

$$\boldsymbol{P'_D = P_r(V' > V_{th1}|H_1) = Q'_u\left(\sqrt{2\gamma}, \sqrt{V_{th1}}\right)} \tag{4}$$

$$\boldsymbol{P'_{FA} = P_r(V' > V_{th1}|H_0) = \frac{\Gamma\left(u', {}^{V_{th1}}/_{2}\right)}{\Gamma(u')}} \tag{5}$$

$$\boldsymbol{P'_M = P_r(V' \leq V_{th1}|H_1) = 1 - P_D} \tag{4}$$

where P'_D is the probability of correctly detecting PU when it is present, P'_{FA} is the probability of the PU being identified now if it is not present, and P'_M is the probability that PU may not be detected if it is present. Two new performance indicators for analysis have been added to the dual-threshold ED technique. They are the probability of a collision between the SU and the PU, as well as the probability of the cognitive user's spectrum being unavailable. These two parameters are defined and calculated as follows: The probability of collision between the cognitive user and the primary user: $p_c = p\{V' < V_{th0} |H_1\}$ It is the possibility that the PU is not recognized, but that it exists, and that the SU will be assigned to the unoccupied spectrum. Because of the ambiguity of spectrum detection, it suggests that the cognitive user is interfering with the primary user. The greater the likelihood of a collision between primary users and cognitive users, the more serious the cognitive user's interference with the primary user; on the other hand, there is less interference. The probability of restricting the cognitive user to the spectrum, i.e., the likelihood of the spectrum being unavailable: $p_{na} = p\{V' > V_{th0} |H_0\}$. It is the possibility that the primary user will be detected even if it is not present, and this "busy" spectrum should not be assigned to the SU to prevent interference with the PU. It shows whether the spectrum utilization is efficient, i.e., whether there are enough spectrums for the CR to access the system promptly. The lower the efficiency of spectrum consumption, the higher the probability of spectrum being unavailable.

2.2.3. Algorithm for Adaptive Single-Threshold Energy Detection:

The likelihood of detection and the probability of false alarm for a large number of samples is given by [19]

$$P_D = P_r\{D(Y) > \lambda | H_1\} \tag{7}$$

$$P_{FA} = P_r\{D(Y) > \lambda | H_0\} \tag{8}$$

To adapt to noise fluctuation, an adaptive decision threshold is set for the energy decision threshold (λ). This threshold is determined by the noise power and signal power. The likelihood of detection and the likelihood of a false alarm is determined by [19]:

$$P_{d1} = Q\left(\frac{\lambda - (\sigma_n{}^2 + \sigma_s{}^2)}{(\sigma_n{}^2 + \sigma_s{}^2)\Big/\sqrt{{}^{N}/_{2}}}\right) \tag{9}$$

$$P_{f1} = Q\left(\frac{\lambda - \sigma_n{}^2}{\sigma_n{}^2\Big/\sqrt{{}^{N}/_{2}}}\right) \tag{10}$$

where σ_n^2 denotes noise power and σ_s^2 denotes signal power. The noise power and signal power determine the appropriate threshold, which is used to adapt noise fluctuation. P_{d1} and P_{f1} are higher when λ is smaller. The higher the P_{d1} value, the less interference to PU, but the lower the P_{f1} value, the less likely the channel will be reused when it is accessible and useable. As a result, the secondary network's possible throughput is reduced. As a result, $P_{d1}$and P_{f1} are mutually exclusive. The key difficulty in spectrum sensing is how to set the judgment threshold in a robust manner to signal and noise power change. If λ is less than the noise power σ_n^2, numerous samples of the noise will be identified as PU signals, resulting in a significant probability of false alarm. Furthermore, if the decision threshold λ is less than the signal power σ_s^2 many samples of the PU signal will be miss detected, with a very low likelihood of detection. As a result, we'd set λ as follows:

$$\sigma_n{}^2 \leq \lambda \leq \sigma_s{}^2 \quad (11)$$

For the well-known two primary characteristics connected with spectrum sensing performance, i.e., the tradeoff between the probability of detection and the likelihood of false alarm, the weighted tradeoff principle is applied. P_{f1}'s weight factor is denoted by α and P_{d1}'s weight factor is denoted by 1- α. P_{m1} is the weighted probability of missing a target and it is expressed as:

$$P_{m1}(\lambda) = \alpha P_{f1} + (1-\alpha)P_{d1} = \alpha Q\left(\frac{\lambda-\sigma_n{}^2}{\sigma_n{}^2 \big/ \sqrt{N/2}}\right) + (1-\alpha)Q\left(\frac{\lambda-(\sigma_n{}^2+\sigma_s{}^2)}{(\sigma_n{}^2+\sigma_s{}^2) \big/ \sqrt{N/2}}\right) \quad (12)$$

For a given value of α, the weighted probability miss detection is strictly a convex function of λ, so the optimal threshold is given by

$$\lambda^* = \frac{1+\sqrt{1+\dfrac{4(2\sigma_n{}^2+\sigma_s{}^2)}{N\sigma_s{}^2} ln\left[\dfrac{\alpha(\sigma_n{}^2+\sigma_s{}^2)}{(1-\alpha)\sigma_n{}^2}\right]}}{\dfrac{2\sigma_n{}^2+\sigma_s{}^2}{\sigma_n{}^2(\sigma_n{}^2+\sigma_s{}^2)}} \quad (13)$$

We can simply obtain the best decision threshold if we know the noise power and the signal power or SNR of the received signal. This threshold can be used to make a good detection judgment, resulting in the best performance.

2.2.4. Algorithm for Adaptive Double-threshold Energy Detection:

This algorithm has two thresholds (λ_1,λ_2) and they are based on the searching threshold adaptively which is obtained by estimating the noise power and the signal power. The PU will be detected if the received signal power denoted as $D(Y)$ is greater than the upper threshold denoted by λ_2. It will not be detected if $D(Y)<\lambda_1$, where λ_1 is a lower threshold. When the received power is in the range (λ_1, λ_2], it is prone to mistakes. It needs detection again. This region is called an uncertain region. The optimal detection threshold is obtained as that before as given in Eq. (13).

The question now is which of the two thresholds to use. Based on the best threshold, we may automatically set the double thresholds λ_1 and λ_2 based on noise fluctuation. In most cases, λ_1 and λ_2 are fixed by the following relations.

$$\lambda_1 = \alpha\lambda' \quad (14)$$

$$\lambda_2 = \beta\lambda' \quad (15)$$

where α and β are constants. If the received power $D(Y)$, and the SNR is γ, the probability of detection PD and the probability of false alarm P_{FA} are [22], [25][26] respectively:

$$P_D = P\{D(Y) > \lambda_2|H_1\} = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda_2}\right) \quad (16)$$

$$P_{FA} = P\{D(Y) > \lambda_2|H_0\} = \frac{\Gamma\left(u, {}^{\lambda_2}/_2\right)}{\Gamma(u)} \quad (17)$$

And the probability of miss detection P_M is given by

$$P_M = P\{D(Y) < \lambda_1|H_1\} = 1 - \Delta_1 - P_D = 1 - Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda_1}\right) \quad (18)$$

Since the lowest value of the double thresholds λ_1 is lower than the single threshold λ', the probability of miss detection PM would be lower then P'_M as provided by Eq. (18). The chance of detection, on the other hand, can be improved in Eq. (16). We can deduct from these two facts that the probability of a collision between the PU and the cognitive user can be reduced, improving spectrum utilization efficiency. Certain modification is done on the calculated threshold for getting its optimal version depending upon the algorithms chosen. At last, the decision device decides for and against the primary user.

2.3. Simulation Process:

To verify the predicted performance based on these aforementioned analytical frameworks, different parameters at different conditions are simulated based on the concept described by Fig.1. All the simulations are done using MATLAB Simulator.

Each simulation run, in particular, is carried out in the following manner:

- Decision thresholds (λ_1,λ_2) are generated for constant false alarm rate criteria in case of double threshold algorithm. The optimum threshold is generated in the case when the noise is uncertain (particularly in low SNR) for implementing an adaptive spectrum sensing algorithm as given in Eq. (13). The two thresholds (λ_1,λ_2) are generated based on the optimum threshold as given by the relation Eq. (14) and (15) respectively in implementing an adaptive double threshold algorithm.
- Equally likely hypothesis $H \in \{H_0, H_1\}$ is generated.
- The received signal from the primary transmitter $y(t)=s(t)+n(t)$ is generated under the Additive White Gaussian noise (AWGN) channel.
- Next, the received energy i.e., square of $y(t)$ of step 3, at the CR receiver is compared with the respective threshold voltage and respective hypothesis.
- Steps 1 to 4 are repeated a large number of times (particularly 10000) to reliably estimate the results.

In the later part, we consider SNR and simulate the model as follows

- Steps 1 to 2 are repeated.
- CR sensor SNR is generated.
- The received signal of the CR receiver is generated.
- Step 4 is repeated.
- To correctly estimate the probability detection (P_D), probability of false alarm (P_{FA}), spectrum unavailable probability (P_{na}) and collision probability (P_c), steps 5 to 8 are repeated a large number of times.
- The plot of these parameters versus SNR is generated.

Table 1: Simulation Parameters

Simulation Parameters	Values
Sample Size (N)	10000
Run time or Monte Carlo simulation time	10000
Channel Used	AWGN
Modulation Type	QPSK with a modulation index of 4
Number of primary transmitters	1
Signal type	Additive White Gaussian Signal with unity power
Noise type	Additive White Gaussian Noise with random noise power
Constants	$\alpha = 0.8$ and $\beta = 1.2$

3. Result and Discussion:

3.1. Receiver Operating Characteristics (ROC) Plot for Spectrum Sensing Using an Energy Detector:

For different amounts of the chance of false alarm, probability of detection, and signal to noise ratio, this study describes the receiver using ROC and complementary ROC curves, as described in [27]. The effect of sample size is also analyzed. The important parameters considered are as follows:

- P_D= Chance of detection
- P_{FA}= chance of false alarm
- P_C= Probability of collision
- P_{na} = Probability of spectrum unavailability

The major measuring criteria used to evaluate the performance of spectrum sensing systems are P_D and P_{FA}. The ROC curve, which is a plot of P_D vs P_{FA}, illustrates the execution of spectrum sensing technology

3.2. Simulation of a Single-threshold Energy Detection Algorithm:

The channel used is AWGN. Real valued Gaussian PU's signal is transmitted through the AWGN channel. The sample size taken is 2000 and the SNR (dB) is -12, -11, and -10. By adjusting the likelihood of false alarm from 0 to 1 with the stepping of 0.1 and computing the probability of detection using Monte-Carlo simulation for each example, the detection performance can be observed. It has been discovered that increasing the SNR value improves detection performance. This also shows the ROC curves for spectrum sensing utilizing the energy detection approach, i.e., P_D versus P_{FA}. The graph displays the likelihood of detection for various SNR values over the AWGN channel, and it also demonstrates that as SNR grows, the P_D increases. This increment is quantified in Table 2. Fig. 3 shows the plot of P_D for different values of SNR.

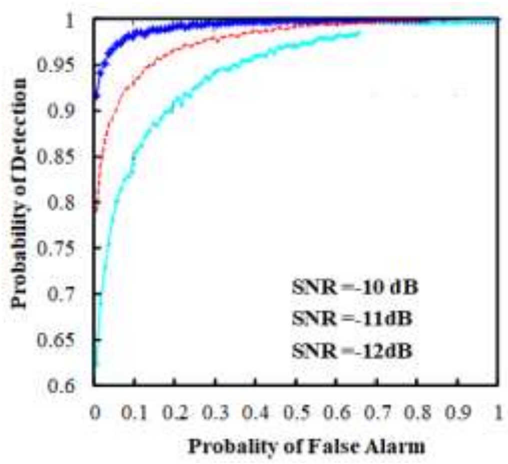

Fig. 3: ROC curves plot for different values of SNR

It shows the P_D is low in the lower values of SNR and its value goes on increasing with increasing values of SNR. This concludes that the ED performance is better only for larger values of SNR.

Table 2: Improvement in P_D when SNR is increased in the Energy detector

P_{FA}	P_D (SNR = -12dB)	P_D (SNR = -11dB)	Enhancement (in times)
0.01	0.6358	0.7850	0.23
0.1	0.8427	0.9304	0.10
0.2	0.9066	0.9661	0.065
0.3	0.9379	0.9820	0.047
0.5	0.9724	0.9893	0.0173

Table 2 shows that increasing the SNR by 1 dB increases the chance of detection at (SNR = -12 dB) by 0.23 times when compared to the likelihood of detection for the AWGN channel (at SNR = -11 dB). As a result, for low SNR levels, traditional energy-based detection performs poorly. Even for low values of SNR, the performance of this detector can be improved by increasing the number of sample points for a given value of chance of false alarm, as shown in Fig. 4 and summarized values in Table 3.

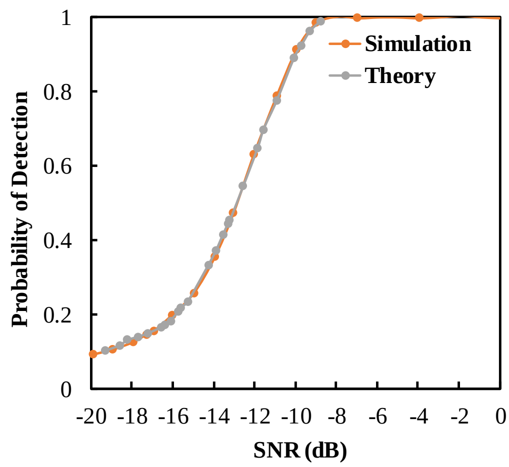

Fig. 4: Detection probability plot for various SNR values.

Table 3: Improvement of the probability of detection for a low value of SNR in energy-based detection by increasing sample size

Samples (N)	P_D (SNR = -14dB)	P_D (SNR = -10dB)	Enhancement (in times)
600	0.1747	0.5214	1.89
700	0.1901	0.5792	2.04
900	0.2149	0.6570	2.05
1200	0.2523	0.7667	2.03
2000	0.3508	0.9184	1.61

3.3. Double Threshold Energy Detection Algorithm, Adaptive Spectrum Sensing Algorithm, and Adaptive Double Threshold Energy Detection Algorithm:

When the noise is certain, the noise variance is assumed to be unity to accommodate the DTED. Thus, in this case, the SNR is 10dB. The signal variance for all cases is assumed unity. The modulation scheme used is QPSK. This modulated signal is then passed through the AWGN channel before reaching the receiver. The sample size taken is 10000.

The likelihood of detection for various SNR levels is shown in Fig. 5, demonstrating that the

ADTSSA outperforms the other two algorithms. It also demonstrates that, as compared to the DTED approach, the detection probability for low SNR values is significantly increased. The adaptive double threshold technique outperforms the traditional double threshold algorithm in both low and high SNR cases. Because the P_D is high at low SNR values, the secondary user's interference with the primary user is considerably reduced. As a result, we can conclude that employing the adaptive double threshold technique in energy-based spectrum sensing can reduce interference generated by the secondary to the first user.

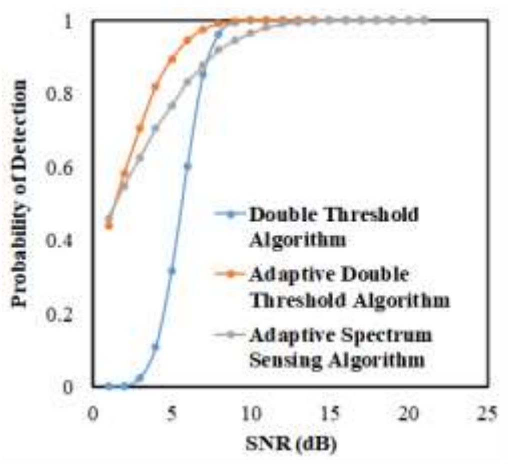

Fig. 5: Probability of detection plotted against SNR levels.

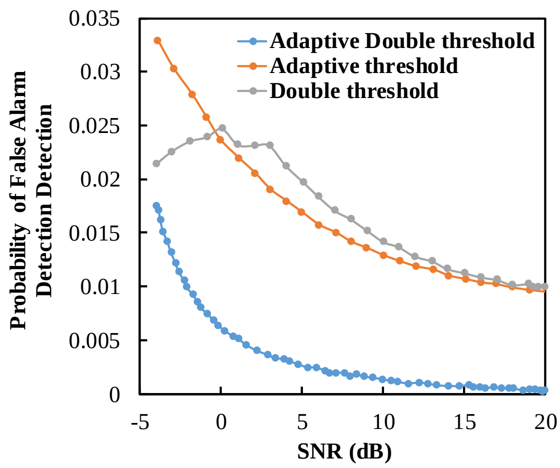

Fig. 6: Probability of false alarm plotted for various SNR values.

The P_{FA} values are plotted and compared to each other for the three different algorithms in Fig. 6. In comparison to other methods, P_{FA} with dynamic dual gate-based band sensing is low across a broad scale of SNR values. The channel is best used by the SU because it has a low P_{FA}. This improves the secondary user network's throughput or boosts spectrum efficiency. As a result, it is noted that the dynamic dual-threshold spectrum recognition technique outperforms the next two algorithms in terms of secondary user network throughput.

The comparison of spectrum unavailability for three strategies is shown in Fig. 7. It demonstrates that for low SNR values, the spectrum unavailability problem is best observed when using Double Threshold Spectrum Sensing. This issue is significantly reduced when using adaptive frequency spread sensing and even further reduced when using commutative dual gate-based Spectrum Sensing. This means that the secondary user's execution can be enhanced while the intrusion it can cause to the primary user at lower SNR values is reduced.

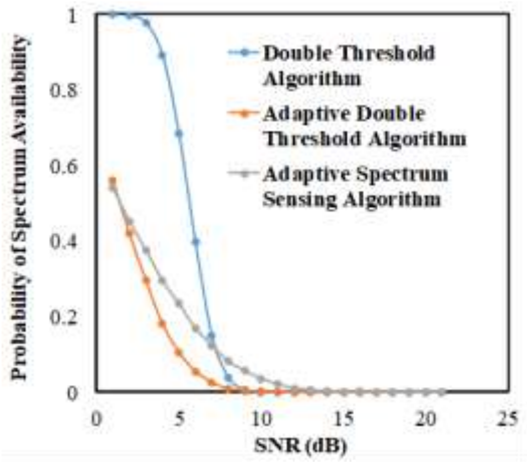

Fig. 7: Spectrum Unavailability plotted for various SNR values

The odds of collision between the cognitive user and the primary user change with varying values of SNR across the three algorithms, as shown in Fig. 8. The following are the simulation parameters: The signal variance power is one, the SNR values vary from -20dB to 20dB, the channel is AWGN, the modulation order is four, the sample size is ten thousand, and the simulation run time is ten thousand. It also shows that the collision probability is higher and reaches up to unity for low SNR values (below -20dB, the case is worst) for both customizable frequency band recognition algorithm and adaptive dual-gate algorithm. The rate of decrement is sharp for increasing SNR. At the same time, it is better in the case of the Double Threshold Algorithm, however, its rate of decrement is slow for increasing SNR. For the higher values of SNR and above 10 dB, the collision probability is decreasing and reaching almost zero. In the case of the Double Threshold Algorithm, its value is seen to be slowly declining. For higher SNR levels, the Adaptive Double Threshold technique is the best of the three (typically above -5dB). From the result, we can conclude that the noise is uncertain in low SNR, and this causes to increase in the collision probability.

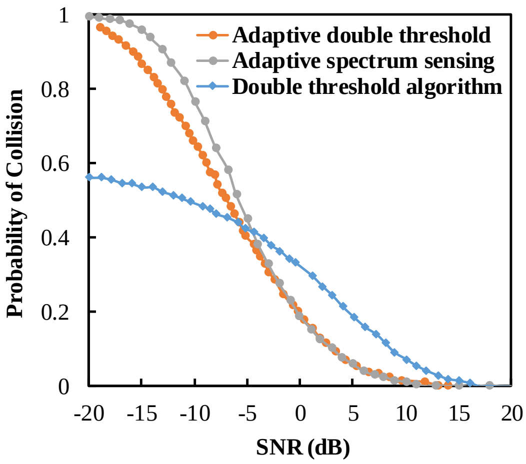

Fig. 8: Plot of Probability of Collision for different values of SNR

Table 4: Comparative results of three Algorithms for SNR greater than -5dB

Energy Detection Algorithms	P_D	P_{FA}	P_{na}	P_C
Double Threshold Algorithm	Low	Medium	High	High
Adaptive Spectrum Sensing Algorithm	Medium	High	Medium	Medium
Adaptive Double Threshold Algorithm	High	Low	Low	Low

Different SNR levels were used in the simulations. The performance metrics and their dependencies on SNR for different algorithms were evaluated through simulations. The simulations were run to improve the performance of spectrum sensing based on energy detection. The simulation findings' final remarks are reported in Table 5. However, using the adaptive double threshold approach, the collision probability is often below -5dB. This shows that for lower SNR values, the performance of energy detection-based spectrum sensing based on an adaptive double threshold technique is poor.

4. Conclusion:

The execution of energy-based non-cooperative frequency band detecting is assessed using a variety of techniques, including single threshold energy detection, double threshold energy detection, adaptive spectrum sensing, and commutative dual-threshold frequency range sensing. The major conclusions drawn from the simulations are pointed out as:

- When noise is unpredictable, dual-threshold energy recognition performs poorly.
- While noise is unpredictable, the adaptive spectrum sensing method optimizes the energy detector's detection threshold.
- In the scenario of detection probability declining as SNR lowers below noise unpredictability, a commutable dual-threshold spectrum recognition technique outperforms the other two algorithms.

Finally, the adaptive double threshold algorithm's performance is found to be poor at extremely low SNR levels, often below -5dB.

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