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Analysis of Wideband spectrum sensing using Anderson darling test statistics in underlay cognitive microcell

Journal of Electrical Systems

Abstract: - The most widely used sensing technique for detecting energy is due to its ease of use and lack of need for signal information beforehand. Traditional methods often employ a two-threshold strategy in low signal-to-noise ratio scenarios, which can lead to temporary detection outcomes when the signal's energy is between the low and high threshold values. This subsequently results in inadequate detection accuracy, characterized by a reduced probability of detection, which ultimately results in an extended duration of the spectrum sensing. The paper suggests enhancing the efficiency of spectrum sensing through the utilization of a modified version of the Anderson-Darling test statistic, as opposed to other test statistics.To detect the presence of licensed users in each subchannel from the base station, the cognitive user implements the Anderson Darling test statistics as a sensing technique. The proposed work involves the mathematical derivation of the Anderson-Darling test statistics under a bandwidth of 6MHz.The simulation outcomes show that the sensing technique presented in this research study achieved a detection probability of 0.963 at a false alarm probability of 1%, using a small sample size of 20 at a signal-to-noise ratio of -20dB. This performance outperformed the other three detection algorithms.

Keywords: Spectrum sensing techniques, Cognitive microcell, Student's *t*- distribution, Anderson darling, Probability of detection, and False alarm.

I. INTRODUCTION

In the field of 5G cellular networks, cognitive radio technology integrated into microcell environments and utilizing subchannels is a rapidly developing area of interest. These advancements aim to optimize spectrum usage, enhance network efficiency, and meet the growing demands for high-speed data transmission [1]. The Institute of Electrical and Electronics Engineers (IEEE) plays a vital role in guiding the implementation of subchannel allocation strategies within cognitive microcells to support the evolution of 5G networks. The use of cognitive microcells in cellular networks with subchannel transmission aims to address spectrum scarcity and increasing data traffic demands. By employing cognitive radio technology, microcell base stations can dynamically [2] allocate subchannels to users, thereby improving spectrum utilization efficiency and overall network performance. However, a critical challenge in this context is seamlessly integrating cognitive microcells and subchannel transmission within 5G networks. To evaluate the effectiveness of subchannel transmission in cognitive microcells for 5G cellular networks, statistical tools such as the Anderson-Darling test statistics [3] can be used. This statistical method helps assess the goodness of fit of data distribution and provides insights [4] into the performance of subchannel allocation strategies within cognitive microcells. By leveraging the Anderson-Darling test statistics [9], network operators and researchers can analyze the efficiency and reliability of subchannel transmission in cognitive microcells, ultimately contributing to the development of 5G cellular networks. In this paper, we have implemented our proposed work by considering the entire spectrum divided into sub-channels. We employ a non-parametric GoF method, specifically the AD test, to quickly and reliably perform spectrum sensing.

II. RELATED WORKS

Due to the significance of spectrum sensing in the detection of wide-band signals in Cognitive radio (CR), it has been the subject of numerous research investigations. To enhance CR performance, suitable detection techniques for spectrum sensing have been proposed to improve the overall utility of CR systems. During the sensing process, the decision threshold plays a vital role in various spectrum sensing algorithms [10]. It establishes the differentiation point that determines when one should accept or discard the null hypothesis in favor of the alternative hypothesis. In recent literature, authors have introduced a spectrum sensing model that incorporates various threshold strategies, such as high and low thresholds [7], single and double thresholds [8], and consideration of data size. Each of these approaches offers a unique perspective and significance in the realm of CR systems. Nevertheless, techniques based on energy detection (ED) have gained considerable importance in diverse applications due to their simplicity and compatibility with different signals.

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Moreover, the ED technique has shown improved efficiency in noisy environments by using a double-threshold approach [11]. Their work involves comparing the energy level to two predefined thresholds. If the energy received by the signal is lower than the lower threshold, the spectrum is considered unoccupied. On the other hand, if the received energy signal surpasses the higher threshold, the presence of the PU signal is assumed. However, if the energy level falls between the higher and lower thresholds, a decision cannot be made at that time. This method has been expanded to include triple detection thresholds [12] and has been proposed for use in Vehicular Ad Hoc Networks (VANET) and small-scale primary user (PU) such as Wifi. To enhance the capabilities of ED technique, researchers have recommended the use of eigenvalue-based spectrum sensing methods to better detect signals in the presence of varying levels of noise [13].

Eigenvalue-based blind detection has been suggested as a potential solution to overcome the drawback of elevated detection error rates by analyzing the covariance matrix. This method capitalizes on corresponding eigenvalues to boost robustness against noise uncertainties. However, it necessitates an extensive number of samples to attain optimal performance and exhibits a relatively high level of complexity. Therefore, Zhao et.al [14] designed a combined energy detector as the initial stage and a mini-max eigen detector as the subsequent stage, achieving a detection probability of 0.6 at 0.9 false alarm. However, the high computational expenses associated with these methods limit their applicability to broader dimensional contexts. It is often impractical to require a large number of samples in certain spectrum sensing techniques, as it can lead to increased power consumption and processing time in real-world scenarios.

In [15], the authors explored the potential use of radial basis function SVM for spectrum sensing in scenarios with multiple-antenna secondary users (SUs). This approach involved incorporating the eigenvalue ratios from each sensor node into the decision vector. However, it is not practical to use supervised machine learning techniques in CR situations because the SU network lacks knowledge about the actual status of the PU. Researchers have suggested that analyzing the GoF may be a promising new approach to detecting issues, especially given the limitations of even the most advanced detection methods currently available. The authors have suggested numerous GoF tests in mathematical statistics literature, such as the Kolmogorov-Smirnov(KS), Cramer-Von Mises(CM), Shapiro-Wilk, and Anderson Darling(AD) tests [16][17], which are used to quantify the dissimilarity between two distribution functions during the presence and absence of a signal. In the study described in [18], the KS test, a non-parametric method for GoF analysis, was employed to rapidly and reliably sense spectral data. This approach is also resistant to non-Gaussian noise and channel variability. Furthermore, research conducted by Haiquan and colleagues [19] has suggested that the AD statistic is easier and more suitable than the KS test for reliable detection with fewer samples. To balance the trade-off between detection performance and sample size, the Student's *t*-distribution was used in the proposed work. Recent studies indicate that the cumulative function of the distribution of the Student's *t*-distribution [20] yields better results than non-central t-distributions.

To overcome the challenges outlined above, we propose a novel approach to spectrum sensing that is capable of providing a robust method to effectively operate with a reduced sample size. Our proposed method aims to enhance spectrum sensing performance under such constraints by reformulating the test statistics involving Student's t distribution, which is particularly effective when dealing with small sample sizes. This suggests that our proposed method is likely to perform better than existing methods, such as the ED and other goodness-of-fit (GoF)-based methods, in terms of detecting signals with greater sensitivity. To tackle the limitations of Gaussian approximation in AD, the AD test statistics has been reformulated using Student’s t distribution test, well-suited for situations with small sample sizes. Based on simulations, the proposed work demonstrates enhanced sensitivity in detecting signals compared to other GoF-based and ED methods. Moreover, it incorporates the DySTA algorithm, which enables multiple SUs to access the channel.

The paper is structured into various sections, each of which covers a specific aspect of the proposed research. In Section 3, we explain the sensing model, and in Section 4, we present a comprehensive analysis of the statistical model. In Section 5, we discuss theoretical findings related to false alarms and detection probabilities, which are relevant to the context. These findings are used to evaluate various GoF sensing methods in Section 6. In section 7, a flowchart is included to illustrate the algorithm’s process of dynamically allocating licensed band to SUs based on AD test statistics and other parameters. Finally, from Section 8, we present the findings of the proposed work, and in Section 9, we summarize our conclusions.

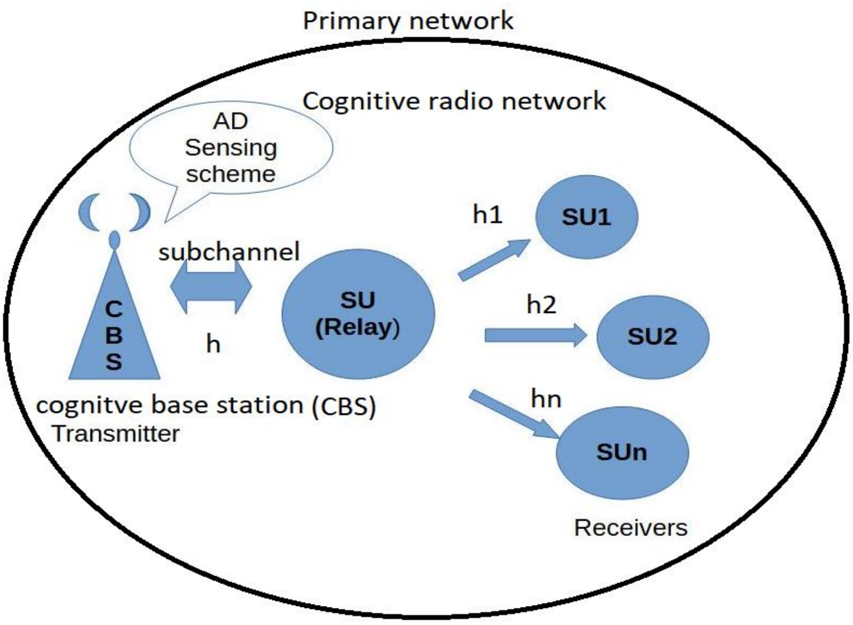

Figure.1 Spectrum sensing model of cognitive microcell

Table 1: Notations and descriptions for parameters

Notations	Definition
P_d	Detection probability
P_{fa}	False alarm probability
P_m	Missed detection probability
K	Number of subchannels
B_t	Total bandwidth
B_c	Channel bandwidth
n	Total number of samples
s	Samples size in each sub-channel
T_s	Sampling period
f_s	Sampling frequency
γ	Signal to noise ratio (SNR)
λ_0	Decision threshold
H_0	Absence of primary signal
H_1	Presence of primary signal
$F_0(x)$	Noise distribution of cumulative distribution function
$F_X(x)$	Empirical cumulative distribution function

III. PRINCIPLE OF SENSING MODEL

The paper focuses on the concept that wide-band signal detection is crucial. Let $'n'$ be the total number of samples through K sub-channels, where ‘s$'$ is the number of samples in each sub-channel. The Figure.1, illustrates the network model of cognitive microcell which covers a total bandwidth $B_t = KB_c$ of GHz spectrum, where the power spectral densities (PSDs) vary across different subchannels, resulting in a spectrum with heterogeneous power distribution characteristics. In each subchannel, a few of n-real-valued samples are taken at a sampling period T_s to ensure rapid detection. The Nyquist rate in each subchannel is $2B_c$, and the sampling period $T_s = {}^{1}/_{2QB_c}$, is set by the oversampling factor as Q. The GoF test proposed in this paper can be performed using the AD test statistics at CBS to detect the presence of PU using a small number of samples in Rayleigh channel. Initially, the hypothesis test is used to determine the status of the PU and is assumed to remain unchanged during the spectrum sensing process. Let y_k be the signal received by the CBS through kth subchannel. The spectrum sensing function accepts or rejects the hypothesis test as given as,

$$H_0 : y_k = w_k$$
$$H_1 : y_k = h_k n_k + w_k$$

(1)

where H_1 & H_0 represents the hypothesis of the existence and non-existence of PU in the kth subchannel.The presence of signal component in the subchannel is denoted as n_k having Rayleigh channel gain of $h_k$assumed to be unity with the subchannel index k= 1,2,..m.The Additive white Gaussian noise(AWGN), characterized as independent and identically distributed (i.i.d) random process with variance σ_k^2 and a zero mean represented as w_k.

IV. STATISTICAL MODEL OF PROPOSED WORK

Let X=$\{X_i\}_{i=1}^{n}$ represent the *n*- number of samples received by CBS through the sub-channel which are identically and independent and K-subchannels divided into each subchannels as 'k' and therefore *s*-samples in each subchannel which is indicated as, *s*= $\frac{n}{k}$.

We take into account that each of X_i, i=1,2,3....n has real-valued sequence. When primary signal transmission is absent in a subchannel, then X_1,X_2,.....X_n samples are typically regarded as noise and treated as an independently and identically distributed (i.i.d) sequence drawn with common cumulative distribution function (CDF) $F_0(x)$.Conversely, if primary signal transmission happens within the subchannel, then i.i.d sequence cannot be interpreted as $F_0(x)$.

As mentioned in the above, when there is no presence of primary signal in the subchannel, then X_i has Student's *t*-distribution with degree $s-1$. Thus, the Student's *t* distribution equation can be formulated from the equation (2) and (3), which can be used to calculate the average as well as the variance of the samples that were collected in the kth- subchannel.

$$\widetilde{Ex}_k \triangleq \sum_{j=0}^{s-1}\left(\frac{x_{sk-j}}{s}\right)$$

(2)

$$\sigma_k^2 \triangleq \sum_{j=0}^{s-1}\left[\frac{\left(x_{sk-j}-\widetilde{Ex}_k\right)^2}{s-1}\right] \text{ for } \quad k = 1,2,3......,m$$

(3)

where $\widetilde{Ex}_k$represents mean of the sample and σ_k^2 indicates the sample variance in the kth subchannel.

Therefore, the Student's t distribution equation can be formulated from the equation (2) and (3),

$$Y_k \triangleq \left(\frac{\widetilde{Ex}_k}{\sigma_k^2/\sqrt{s}}\right) \qquad (4)$$

Thus, in the above equation (4), the noise variance is unknown, obtained by dividing the equation (2) and (3) and follows H_0 hypothesis.

Consider the term $\mathrm{T}(s-1,\mathrm{t})$ used to define probability density function of Y_k under H_0 hypothesis [21] with $s-1$ degree of freedom which can denoted as,

$$\mathrm{T}(s-1,\mathrm{t}) = \frac{\Gamma\left(\frac{\mathrm{s}}{2}\right)}{\sqrt{\pi(\mathrm{s}-1)\Gamma\left(\frac{\mathrm{s}-1}{2}\right)}}\left(1+\frac{\mathrm{t}^2}{\mathrm{s}-1}\right)^{\frac{-\mathrm{S}}{2}}$$

(5)

where Γ denotes the Gamma function. Then the CDF of Y_k under H_0 using equation (5) as follow,

$$F_{0,s}(y) = \int_{-\infty}^{y} \mathrm{T}(s-1,\mathrm{t})\mathrm{dt}$$

(6)

Let the CDF sample collected at the subchannel as $\mathrm{Y} = \{\mathrm{Y}_k\}_{k=1}^{n}$ and it is denoted as empirical distribution of Y as $F_Y(x)$and the sequence Ysorted as $Y_1 \leq Y_2 \leq$........$\leq Y_k$. Then $F_Y(x)$ mathematically can be represented as

$$F_Y(x) = |\{k: Y_k \leq x, 1 \leq k \leq s\}|/s \qquad (7)$$

where for any set A,|A| denoted as cardinality of A.

The suggested GoF test is a non-parametric hypothesis examination that assesses whether received samples are derived from a distribution by identifying signals in noise.As in the absence of the PU, the received samples are likely to be noise and can be represented by an independently and identically distributed sequence with a known noise distribution as $F_0(x)$ .The hypothesis that aims to determine if a signal exists can be stated as follows.

$$H_0 : F_Y(x) = F_0(x)$$
$$H_1 : F_Y(x) \neq F_0(x)$$

(8)

where $F_0(x)$ denotes the hypothesized noise distribution of CDF and $F_Y(x)$ represent as empirical CDF of the received samples at the CBS. Taking into account as that there is no presence of primary signal, noise samples in terms of Gaussian distribution of Y_i can be mathematically expressed as,

$$F_0(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{0} e^{-\frac{-x^2}{2}} dx \quad (9)$$

Under the condition of H_0 hypothesis,the empirical distribution function $F_Y(x)$ converges with cumulative distribution function $F_0(x)$ under the condition i.e $F_Y(x) \geq F_0(x)$,CDF approaches to one as $s \to \infty$ for each x.On the other hand during presence of primary signal ,the function $F_Y(x)$ & $F_0(x)$ deviates each other during large value of 's''.

To measure the distance between $F_Y(x)$ & $F_0(x)$,AD test statistics [22] mathematically expressed as,

$$A_k^2 = n \int_{-\infty}^{+\infty} [F_Y(x) - F_0(x)]^2 \acute{\emptyset} \left(F_0(x)\right) dF_0(x) \quad (10)$$

where $\acute{\emptyset}(y)=(y(1-y))^{-1}$

let $z_s = F_0(x)$,therefore the above equation (12) can be simplified by solving the integral [22] and expressed as

$$A_k^2 = -n - \frac{\sum_{s=1}^{n} [(2s-1)(ln\, z_s + ln(1 - z_{n+1-s}))]}{n} \quad (11)$$

From the equation (11), the above AD test statistics can be modified and rewritten as follows,consider the second part from AD test statistics, defined as

$$\frac{\sum_{s=1}^{n} [(2s-1) log(1 - z_{n+1-s})]}{n} \quad (12)$$

We have assumed k sub-channel and s-number of samples in the AD test statistics, therefore by using the concept of change of variables in the above equation (12), then the expression can be derived as follows,

$$\text{At } n+1-s = k \text{ as if} \left\{ \begin{matrix} s = 1, \text{then } k = n \\ s = n, \text{then } k = 1 \end{matrix} \right\} \quad (13)$$

$$\sum_{k=1}^{n} \frac{\{2(n+1-k)-1\}}{n}\, ln\, (1 - z_k) \quad (14)$$

$$\sum_{k=1}^{n} \left\{2 + \frac{(1-2k)}{n}\right\} ln(1 - z_k) \quad (15)$$

Replacing the 'k'back with 's 'in (15), then the expression modified as

$$\sum_{s=1}^{n} \left\{2 + \frac{(1-2s)}{n}\right\} ln(1 - z_s) \quad (16)$$

substituting the equation (16) in (11), the expression can be written as,

$$\widetilde{A_k^2} = -n - \sum_{s=1}^{n} \left[\left(\frac{2s-1}{n}\right) \log\left(\frac{z_s}{1-z_s}\right) + 2\log(1 - z_s)\right] \quad (17)$$

We proposed a new mathematical expression for the spectrum sensing method as derived in the equation (17) based on GoF test , under the assumption H_0 , where the received energy tested with two degrees of freedom.Consequently, the revised spectrum sensing is represented using above equation as,

$$H_0 : \widetilde{A_k^2} \leq \lambda_0$$
$$H_1 : \widetilde{A_k^2} > \lambda_0 \tag{18}$$

where $\widetilde{A_k^2}$ is modified GoF test statistics of AD, and λ_0 is a threshold can calculate using [23] or by Monte Carlo simulation. The equation above implies that if the value of $\widetilde{A_k^2} > \lambda_0$, represents the presence of a primary signal in the subchannel is indicated by the rejection of the null hypothesis.

V. Performance analysis of modified AD sensing method

In the following section, we present the analytical findings for the proposed blind spectrum sensing's false alarm probability and detection probability.

The false alarm probability under H_0 for the proposed sensing by accepting the hypothesis which can be defined as

$$P_{fa} = Pr\{\widetilde{A_k^2} \geq \lambda_0 / H_0\} \tag{19}$$

where $Pr\{.\}$ denoted as probability operator.

According to the fundamental equation model [23], it can be inferred that when the null hypothesis is valid, the distribution of $\widetilde{A_k^2}$converges towards a particular limiting distribution.

$$\lim_{s\to\infty} Pr\{\widetilde{A_k^2} \leq \lambda_0 / H_0\} = \frac{\sqrt{2\pi}}{\lambda_0}\sum_{k=0}^{\infty} b_k(4k+1)\exp\left(-\frac{(4k+1)^2\pi^2}{8\lambda_0}\right)\int_0^{\infty}\exp\left(\left(\frac{\lambda_0}{8(\mathrm{n}^2+1)}-\frac{(4k+1)^2\pi^2\mathrm{n}^2}{8\lambda_0}\right)\right)\mathrm{d}\,n \tag{20}$$

where b_k=$(-1)^k\Gamma\,\frac{(k+0.5)}{(\Gamma(0.5)k!)}$ with Γ as Gamma function.

Then the probability of detection derived under the condition of H_1 can be expressed as,

$$P_d = Pr\{\widetilde{A_k^2} > \lambda_0 / H_1\} = 1 - \mathrm{F}_{\widetilde{A_k^2},\mathrm{H}_1}(\lambda_0) \tag{21}$$

where $\mathrm{F}_{A_k^{*2},\mathrm{H}_1}(\lambda_0)$ represents the CDF of the corresponding $\widetilde{A_k^2}$ under the condition of H_1.

To obtain the generalized mathematical expression for the upper bound on the detection probability based on the cumulative distribution of $\widetilde{A_k^2}$, we can employ equation (10) as follows,

$$\sqrt{\widetilde{A_k^2}} = \sqrt{n\int_{-\infty}^{+\infty}[F_Y(x)-F_0(x)]^2\acute{\emptyset}\left(F_0(x)\right)dF_0(x)}$$
$$\geq \sqrt{n\int_{-\infty}^{+\infty}[F_Y(x)-F_0(x)]^2\acute{\emptyset}\left(F_0(x)\right)dF_0(x)}$$
$$- \sqrt{n\int_{-\infty}^{+\infty}[F_Y(x)-F_1(x)]^2\acute{\emptyset}\left(F_0(x)\right)dF_0(x)} \tag{22}$$

Thus, the above equation can be approximated as,

$$\sqrt{\widetilde{A_k^2}} \geq \mathrm{C}\sqrt{n} - B_n \tag{23}$$

where

$$\mathrm{C}= \sqrt{\int_{-\infty}^{+\infty}[F_Y(x)-F_o(x)]^2\acute{\emptyset}}\,\left(F_0(x)\right)dF_o(x)$$

and

$$B_n = \sqrt{n\int_{-\infty}^{+\infty}[F_Y(x)-F_o(x)]^2\acute{\emptyset}}\,\left(F_0(x)\right)dF_o(x) \tag{24}$$

The equation (24) mentioned above can be expressed as the probability that a random variable $Y_k$underH_1 exceeds a specified threshold is limited by the upper bound on the probability of detection. This can be simplified as shown in reference [24].

$$F_{\widetilde{A_k^2},H_1}(\lambda) = \Pr\left\{\sqrt{\widetilde{A_k^2}} \le \sqrt{\lambda_0}\,/H_1\right\}$$
$$= \Pr\left\{e^{-\lambda\sqrt{\widetilde{A_k^2}}} \ge e^{-\lambda\sqrt{\lambda_0}/H_1}\right\}$$
$$\le \frac{\mathrm{E}\left[e^{-\lambda\sqrt{\widetilde{A_k^2}}}\right]}{e^{-\lambda\sqrt{\lambda_0}}}$$
$$\le \frac{e^{-\lambda C\sqrt{n}}\,\mathrm{E}\left[e^{-\lambda B_n}\right]}{e^{-\lambda\sqrt{\lambda_0}}} \quad (25)$$

To enhance the upper limit for specific values of λ_0 and n , the expression on the right side of equation (25) can be minimized with regard to λ. As per Markov's inequality, the value of $\lambda > 0$, which is positive and can be chosen as 1. Consequently, the aforementioned equation can be simplified as:

$$F_{\widetilde{A_k^2},H_1}(\lambda_0) \le \frac{e^{-C\sqrt{n}}\,\mathrm{E}\left[e^{-B_n}\right]}{e^{-\sqrt{\lambda_0}}} \quad (26)$$

Therefore, using the equation (26) in equation (21), the probability of detection can be written as,

$$P_d \ge 1 - \frac{e^{-C\sqrt{n}}\,\mathrm{E}\left[e^{-B_n}\right]}{e^{-\sqrt{\lambda_0}}} \quad (27)$$

As the value of n increases, the distribution B_n converges to a limiting distribution with the assumed constant value of C i.e., C >0. Similarly, as the value of $F_{\widetilde{A_k^2},H_1}(\lambda_0)$ approaches 0, the probability of detection becomes 1 when the expected value of B_n is bounded for any given λ_0. Finally, the probability of missed detection (P_m) can expressed from the probability of detection given as,

$$P_m = 1 - P_d \quad (28)$$

VI. OTHER GoF SENSING METHODS

A. Kolmogorov-Smirnov (KS) sensing

The Kolmogorov-Smirnov [25] statistic measures the distance between the empirical distribution functions of two samples or between a sample's empirical distribution function and the cumulative distribution function of the reference distribution. Under the assumption that the null hypothesis holds, which is that the sample is drawn from the reference distribution, the null distribution of this statistic is obtained. Therefore, this test statistic is expressed as,

$$D_Y^2 = \{sup|F_Y(x) - F_0(x)|\}^2 \quad (29)$$

where $sup\{\cdot\}$denote as supremum function represents the maximum value, therefore the equation (29) can be formulated as,

$$D_Y^2 = \left(max(D_Y^+, D_Y^-)\right)^2 \quad (30)$$

The equation (30) further simplified as follows,

$$D_Y^+ = \max_{1\le s\le n}\left\{\frac{s}{n} - F_0(x)\right\} \quad (31)$$

$$D_Y^- = \max_{1\le s\le n}\left\{F_0(x) - \frac{s-1}{n}\right\} \quad (32)$$

B. Cramer-Von Mises(CM) sensing methods

A useful method that is comparable to the chi-square test is the Cramer-Von Mises [26] an omnibus test. The CM test's test statistics represented as,

$$W_n^2 = n\int_{-\infty}^{+\infty}(F_Y(x) - F_0(x))^2 dF_0(x) \quad (33)$$

The integral function in the above equation can be simplified and be divided into m-parts. W_n^2 can be approximated as,

$$W_n^2 = \frac{1}{12s} + \sum_{s=1}^{n}\left(F_0(x) - \frac{(n-0.5)}{s}\right)^2 \quad (34)$$

VII. PROPOSED ALGORITHM

This paper introduces an algorithm to enhance the subchannel utilization of the primary user by the multiple SUs within the allocated time slot. The algorithm factors in the interference level of the PU and determines the permissible number of secondary users allowed to occupy the subchannel. In contrast, the traditional method allows one or two SUs to utilize the time slot based on the energy levels of the licensed user during the sensing duration. An alternative approach involves employing a statistical method based on the number of samples. The primary objective is to minimize false alarms and increase the probability of the secondary user accessing available frequency bands. Figure 3, illustrates a flowchart diagram that outlines the dynamic spectrum sensing and time slot adjustment for multiple SUs, considering the signal's energy is expected to remain relatively stable over a time frame.

Table 2. Simulation parameters

Parameters	Values
Transmit power	30dBm/1 Watt
Modulation	QAM
Total bandwidth	100MHz
Bandwidth of each subchannel(B_c)	6MHz
Number of subchannel(k)	10
Over sampling factor (Q)	100
Time slot length of primary users	100ms

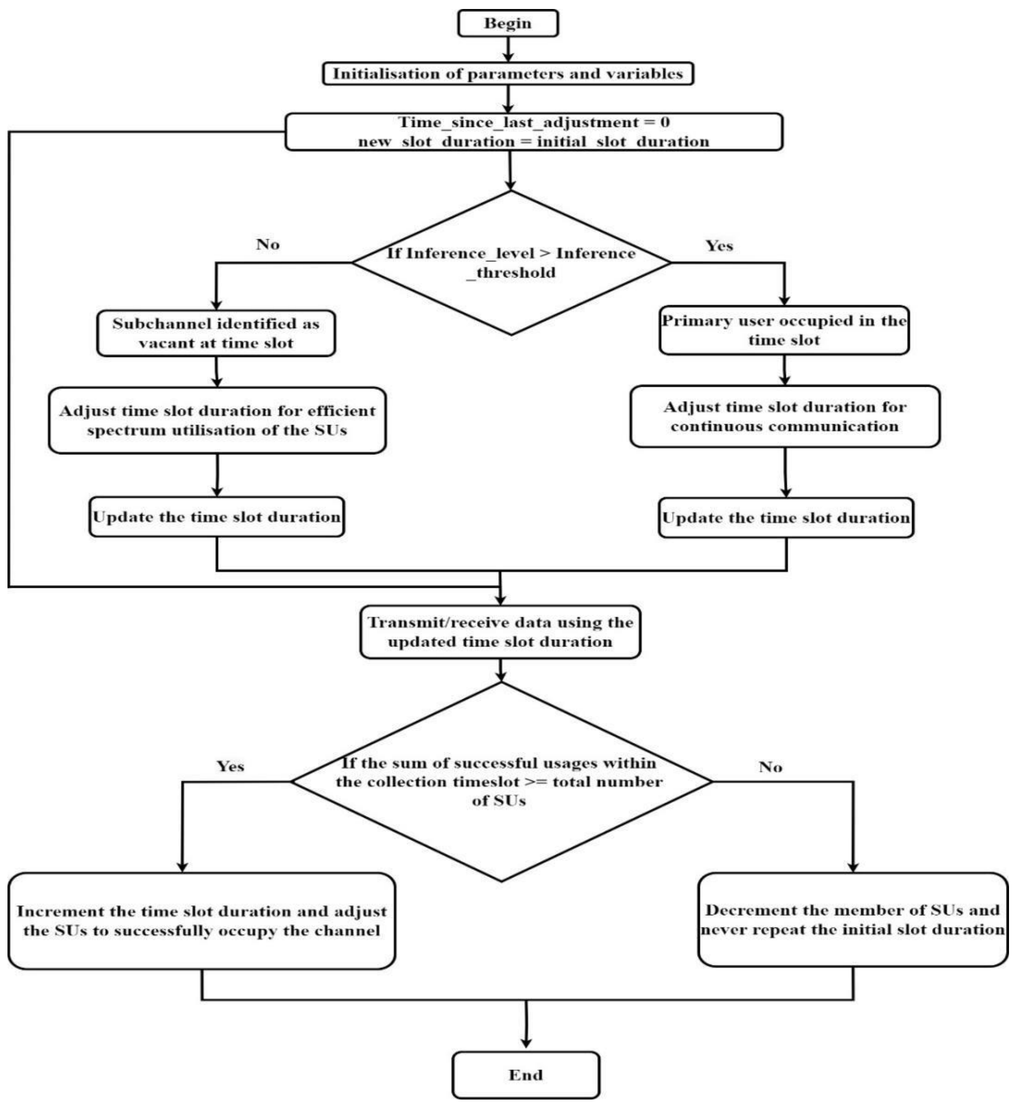

Figure 2. Flowchart of Dynamic Spectrum Sensing and Time Slot Adjustment (DySTA) Algorithm

VIII. RESUTLS AND DISCUSSION

The simulation outcomes obtained using the MATLAB tool (2023a version) under specific assumptions as per the Table 2. along with other specific assumptions are sampling frequency of 12MHz, and a received signal to noise ratio(SNR) ranging from -20 dB to 10 dB in Rayleigh channel with an AWGN noise. The network model covers a 500m radius and has ten SUs spaced equally apart.The threshold value measured for the proposed sensing algorithm was determined to be 2.96, utilizing the Monte-carol simulation at a given false alarm probability ,P_{fa}=0.01 and missed detection probability of P_m= 0.25.According to equation (17), the value of k ranged from 1 to 10 was utilized. Furthermore, equations (27) and (28) were useful in generation the simulation plot

To evaluate the effectiveness of the proposed spectrum sensing approach, we compared its outcomes with those of other detection algorithms, such as the three consecutive time double-threshold energy detection method (TCTDT-ED) [8], the history-based adaptive double-threshold energy detection algorithm (HBADT-ED) [7], and the conventional energy detection (ED) method [5]. We utilized a sample set of 20 for this comparison.

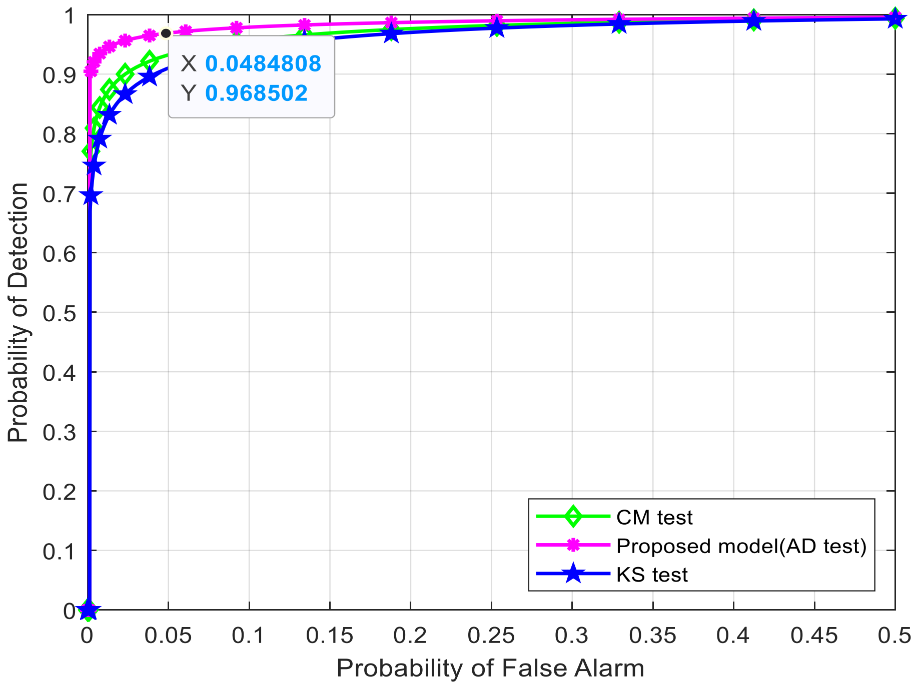

Figure.3 Detection probability versus the probability of false alarm for different GoF test-based spectrum sensing methods at SNR = -10 dB using 20 samples & 10 -SUs

The Figure 3 demonstrates the detection probability obtained using 20 samples and 10 subchannels for the proposed methods. The results show that the AD method, one of the proposed approaches, exhibits a significant improvement in detection, amounting to approximately 0.1dB, compared to other tests. Additionally, the proposed approach outperforms other sensing strategies when there are fewer than 20 samples. Conversely, the KS test displays inferior performance compared to the other two methods, while the CM test performs only 1% less than the proposed model. The results are both consistent and reliable, suggesting that the proposed approach is superior in terms of detection probability.

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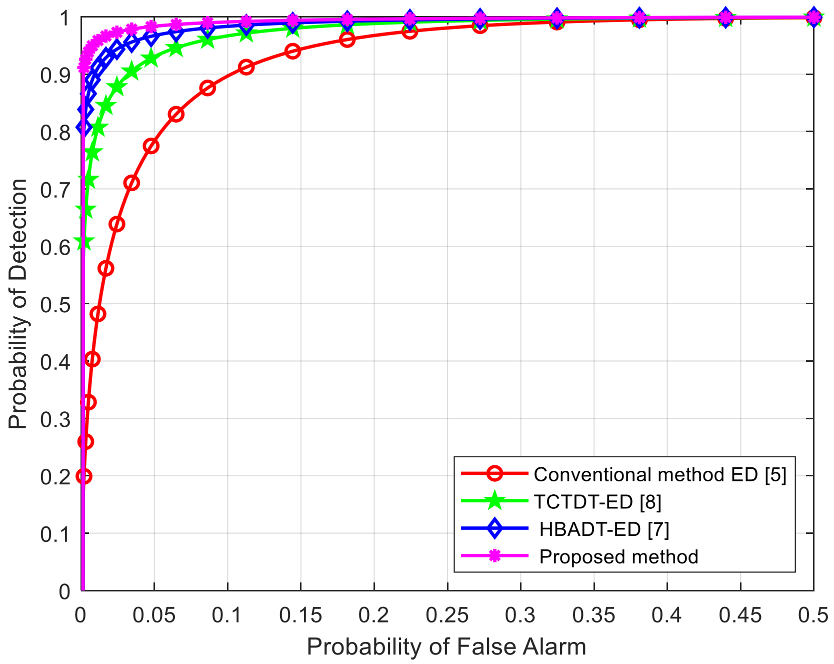

Figure.4 .False alarm probability versus detection probability for proposed Anderson darling at SNR=-10dB using 20 samples & 10 subchannel.

The Figures 4 and 5 depict the variations in detection with false alarm rates for different sensing algorithms at SNR levels of -10dB and -14dB, respectively.

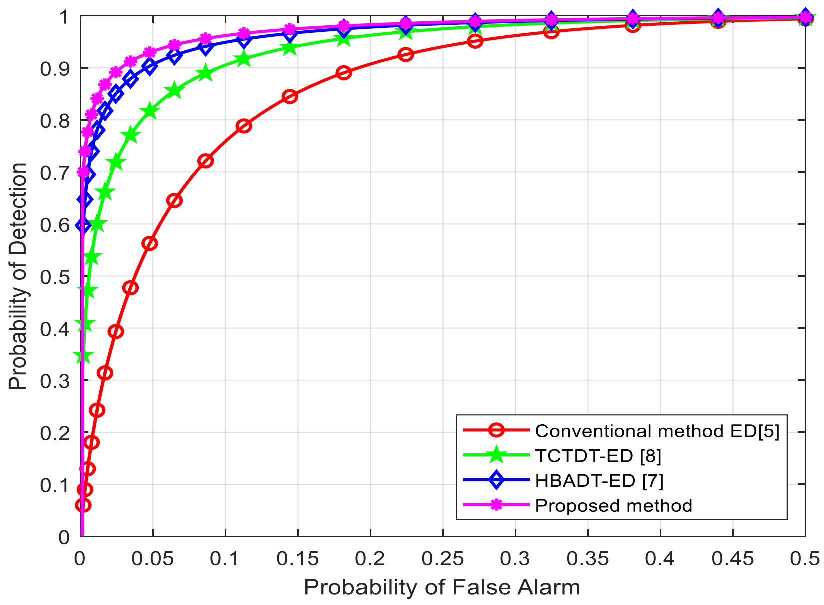

Figure.5 Probability of false alarm versus Probability of detection for proposed Anderson darling for SNR=-14dB using 20 samples &10 subchannels

The proposed method demonstrates superior performance with detection probabilities of 0.9 at low SNR and 0.7 at high SNR. Compared to other algorithms, the proposed method also exhibits a higher detection probability with a lower false alarm rate. Furthermore, when the false alarm rate is extremely low, the detection probability can approach the value 1.Subsequently, at -14dB of SNR, the detection probability increases as the false alarm probability rises. Moreover, in comparison to the other three methods, the proposed algorithm demonstrated superior performance at the same false alarm probability.

The algorithm ensures a higher detection probability, even when the false alarm probability is low. In fact, the detection probability reaches the value of 1, even at extremely low false alarm probabilities when using the HBADT-ED algorithm. The probability of detection continuously increases as the probability of missed detection decreases to 25%, regardless of the SNR value. In figure 6, the comparison of probability of detection and at different SNR with 0.5dB noise uncertainty. Further,it investigate the influence of different SNR received signal conditions on the detection probability (P_d).

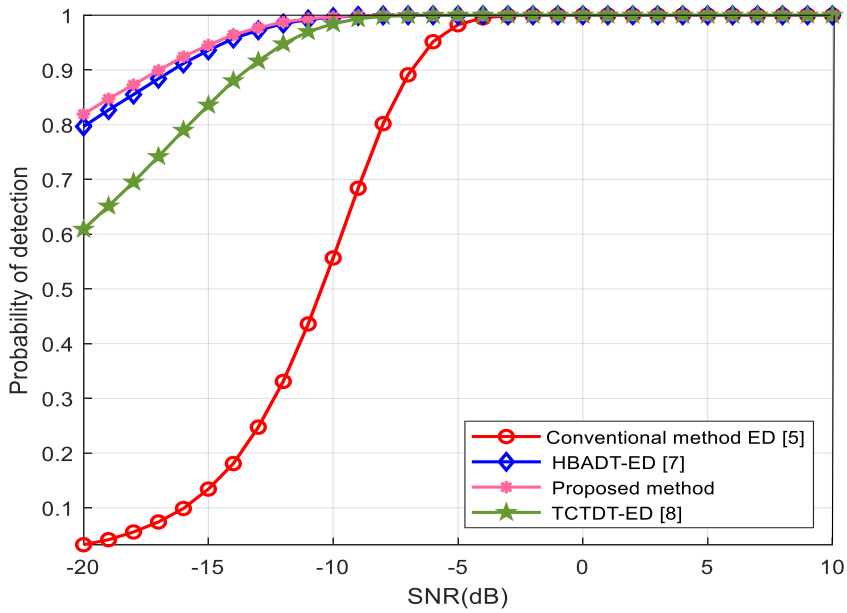

Figure.6. The relationship between detection probability and SNR when common false alarm probabilities P_{fa}=0.05 and P_m=0.25 using 10 subchannels

The proposed algorithm in Figure 6, has a significant advantage over other methods, as its detection probability approaches 1 when the SNR is at -9 dB. In contrast, TCTDT-ED methods require SNR values of -10 dB to achieve a similar level of detection probability. The conventional method using ED such as adaptive double threshold-ED (ADT-ED) [27] requires an SNR of more than -2dB before their detection probability approaches 1.The HBAT-ED also performs same as proposed algorithm and diminishes as the SNR value rises.

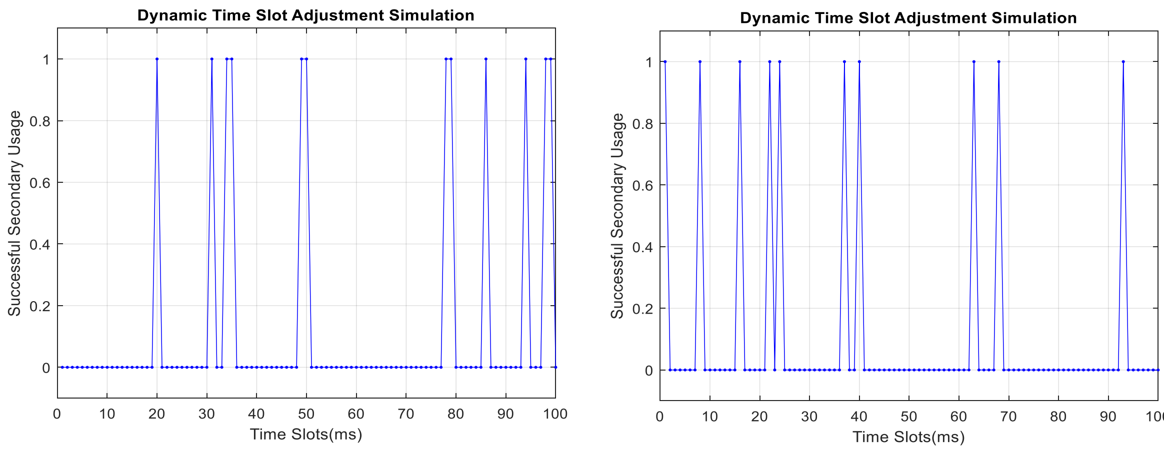

Figure.7. Successfully secondary usage versus Time slots (ms) (a) Interference threshold PU exceeds the AD statistics and (b) Interference threshold to PU below the AD statistics.

In Figure 7, the depiction illustrates available time slots for SUs to occupy the PU. The simulation plot indicates that if the interference threshold for the PU exceeds AD statistics, a limited number of time slots are adjusted, enabling secondary users to access the channel. Conversely, when the interference threshold to the PU is below AD statistics, multiple secondary users can utilize the time slots under the underlay model.

IX. CONCLUSION

In the proposed work, we provide a signal detection technique for cognitive microcell that needs a minimal amount of data. This technique is an improvement over traditional methods, as it makes more efficient use of the available samples through the use of Student's t-test, which is better suited for small sample sizes. The outcomes of the simulation show that the approach proposed can attain a higher detection probability of 0.963 than other methods, even when using a less sample size. The use of this method not only overcomes current limitations in sensing, such as time and energy consumption, but also lays the groundwork for compressed spectrum sensing applications. As a result, it has the potential to play a crucial role in the development of intelligent and environmentally conscious systems, solidifying its position as a foundational technology in this rapidly changing field.

ACKNOWLEDGMENT

The authors are thankful to the Department of Electronics and Communication Engineering, SRM Institute of Science and Technology for creating an environment that encourages research.

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