IUST Iran University of Science and Technology

Iranian Journal of Electrical and Electronic Engineering

Journal Homepage: ijeee.iust.ac.ir

Research Paper

# Spectrum Sensing Optimization Using De-noising and Energy Detection

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**Abstract:** Cognitive radio (CR) is an effective technique for dealing with scarcity in spectrum resources and enhancing overall spectrum utilization. CR attempts to enhance spectrum sensing by detecting the primary user (PU) and allowing the secondary user (SU) to utilize the spectrum holes. The rapid growth of CR technology increases the required standards for Spectrum Sensing (SS) performance, especially in regions with low Signal-to-Noise Ratios (SNRs). In Cognitive Radio Networks (CRN), SS is an essential process for detecting the available spectrum. SS is divided into sensing time and transmission time; the more the sensing time, the higher the detection probability) and the lower the probability of a false alarm). So, this paper proposes a novel two-stage SS optimization model for CR systems. The proposed model consists of two techniques: Interval Dependent De-noising (IDD) and Energy Detection (ED), which achieve optimum sensing time, maximum throughput, lower and higher. The Simulation results demonstrated that the proposed model decreases the, achieves a higher especially at low SNRs ranging, and obtains the optimum sensing time, achieving maximum throughput at different numbers of sensing samples (N) and different SNRs from -10 to -20 dB in the case of N = 1000 to 10000 samples. The proposed model achieves a throughput of 5.418 and 1.98 Bits/Sec/HZ at an optimum sensing time of 0.5ms and 1.5ms respectively, when N increases from 10000 to 100000 samples. The proposed model yields an achievable throughput of 5.37 and 4.58 Bits/Sec/HZ at an optimum sensing time of 1.66ms and 13ms respectively. So, it enhances the SS process than previous related techniques.

**Keywords:** CR, IDD, Optimization, Optimum Sensing Time, Maximum Throughput

## 1 Introduction

WIRELESS networks and information traffic have risen at an exponential rate over the past decade, resulting in an overabundance of radio spectrum resources [1–2]. The radio spectrum is a restricted resource that is governed by rules and reputable organizations such as the United States Federal Communications Commission (FCC). The present radio spectrum allocation strategy assigns channels to specified users that have licences for certain wireless technologies and services. Certain licenced users have access to those spectrum sections to transmit and receive data, whereas others are not allowed to use them even when they are vacant [3]. According to recent research, spectrum usage in the United States ranges from 15% to 85% under the fixed spectrum allocation (FSA) regime [4]. According to FCC data, some channels are highly used while others are rarely used, as seen in Fig. 1 [5].

Iranian Journal of Electrical & Electronic Engineering, 2024
Paper first received 15 August 2023 and accepted 28 February 2024.
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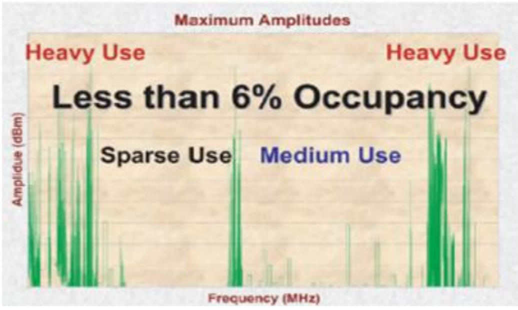

**Fig. 1** Radio spectrum occupancy [5].

The allocated spectrum regions are not always utilized by their owners, resulting in spectrum gaps. A spectrum hole, also known as white space, is a frequency band licensed to a PU but not used at a certain time or location. As a result, the radio spectrum is being used inefficiently [6–7]. As a result of the scarcity and inefficiency of spectrum management, an immediate method is required to improve radio spectrum access and achieve high network performance. A better technique to deal with spectrum scarcity is to manage it dynamically by sharing vacant channels with unlicensed users, known as Secondary Users (SUs), without interfering with PU transmissions. To overcome spectrum allocation issues, Opportunistic Spectrum Access (OSA), also known as Dynamic Spectrum Access (DSA), has been proposed. In contrast to the FSA, the DSA permits licensed and non-licensed users to share the spectrum, with the spectrum separated into several bandwidths allocated to one or more devoted users [8–9]. A CR system can learn from its surroundings, adapt to changing situations, and make judgements to make the best use of the radio spectrum. It enables SU to utilize the PU-assigned radio spectrum when it is not in use, as shown in Fig. 2 [1, 3].

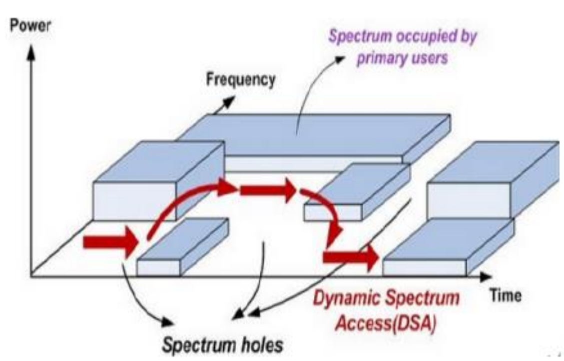

**Fig. 2** Dynamic spectrum access [3].

SS, spectrum sharing, spectrum mobility, and spectrum management are the four main objectives of a CR Network. SS scans the available spectrum for the presence of PUs. The spectrum management function manifests itself in the choice of the finest available channel that meets certain targets. Spectrum sharing tries to distribute spectrum gaps equally among SU. Spectrum mobility aims to maintain communication while transitioning to a better spectrum hole. Because interference with other users is forbidden, the primary task is SS. It is used to characterize the spectrum's occupancy conditions. It is often carried out in the frequency domain. To evaluate the performance of a spectrum sensor, two criteria are used: the sensor's capability to reliably locate unoccupied spectrum gaps without missing a PU and the sensor's capability to reduce the noise effect. SS is required for spectrum optimum use. ED is the easiest and simplest SS technique since it does not need information about the licenced user signal and has a short sensing time [10–11]. The frequency range under interest is sensed by the ED approach, and tests are performed to compare the energy obtained with a predefined threshold to detect the existence or absence of the PU [12]. Unfortunately, at low SNRs, the ED technique is not robust to noise, therefore impacting CR's performance and reliability [13–14]. Additionally, the ED SS approach is unable to separate noise from other signals.

A novel two-stage SS model for CR systems is introduced in this paper to overcome the problems of the single-stage ED SS approach and determine the optimum sensing time for achieving maximum throughput. It is formed by two stages: the first stage consists of an IDD detector, while the second stage consists of an ED. The IDD stage is used to detect the PU signal in the presence of noise by counteracting the noise effect. The proposed model significantly retains the needed $P_d$ and $P_f$ of the CR system at the appropriate levels. This paper is organized as follows. Section 2 presents a literature review regarding the SS. Section 3 shows the proposed model and model discussion, while Section 4 presents simulation results and related discussion. The conclusion and future work are provided in Section 5.

## 2. Related Works

The main advantage of having a multistage detector is to combine the benefits of each detector based on the received signal. The SNR is the initial driving characteristic for the multistage detector. The early stages of detection are characterized by simplicity. However, when the SNR decreases, this simplicity reduces sensor accuracy. To attain improved sensing accuracy, another stage is used. Multistage SS has been widely investigated in the literature, as summarized below. ED is a basic SS approach that measures and compares the received signal energy to the noise energy. As a result, the existence or absence of a signal is announced. ED is blind concerning the required knowledge of the signal properties. The sensing accuracy of ED is limited at low SNR regions, as the missed detection probability increases as the SNR decreases [15]. To transcend the constraints of the single-stage ED approach, multiple two-stage SS approaches were presented. These approaches have significant advantages over their single-stage counterparts, including increased $P_d$ and promising performance in low SNR conditions. The advantages of two-stage SS approaches can significantly increase CR performance. The majority of recent research works presume that ED is one of the adopted stages. Fast Fourier Transform (FFT), fuzzy logic, Maximum Minimal Eigenvalue (MME), Covariance Absolute Value (CAV), and waveform detection can be applied before or after the ED in the other stage [16–23].

The author's proposed in [16] two-stage SS approaches for CR with adjustable thresholds that combine two-well techniques: wavelet denoising and energy detection. An ED approach is employed in this work to identify the availability or existence of a PU signal in the case of a high SNR value by comparing the energy of the received signal with threshold values. In the case of low SNR values, however, a wavelet denoising (WD) stage is performed before ED to reduce the noise effect and detect the PU signal in noisy surroundings.

The authors of [17] developed a unique collaborative SS approach in CRN based on Estimated SNR with Adaptive Threshold (ESNR ADT). The proposed approach estimates SNR and selects either an ED with a fixed threshold or an ED with an adaptive threshold to increase detection performance at a fixed $P_f = 0.1$. The detector is chosen based on the estimated SNR value and the first threshold; if the estimated SNR value is higher or equal to this threshold then, an ED with a second threshold will be used; otherwise, an ED with an ADT will execute sensing operations.

In Ref. [18], a hybrid sensing model for spectrum detection in CR is executed. The first path is constructed from two sequential sensing stages; in the first stage, an ED is used to identify the presence of the PU signal when the signal has not been detected. The presence of the PU signal is detected using a second stage called Maximum-Minimum Eigenvalue (MME). The second path is composed of two parallel stage detectors employing separate ED and MME to detect the PU signal separately. The two results are brought together to form a decision, and the final decision is taken using the combined results of the two paths' detection. The suggested hybrid sensing method, used to improve sensing performance, is validated using traditional techniques, but it suffers from computational complexity.

The authors proposed an Improved-Two-Stage Detection (improved-TSD) approach for SS in [19]. There are two stages in the improved-TSD technique: the first stage contains two detectors, namely an ED using a single adaptive threshold (ED SAT) and an ED using two adaptive thresholds (ED TAT), organized in parallel, and the second stage contains a decision device (DD) that decides the final decision using the OR-rule. The proposed sensing method reduces sensing time, improves detection performance at $P_f = 0.1$, and performs well at low SNRs.

The authors illustrated in [20] an Improved Two-stage SS (ITSS) scheme, which consists of ED in the first stage and Maximum Eigenvalue Detection (MED) in the second stage. The ITSS algorithm framework includes an ED SS technique for the first stage because its average SS time is shorter. However, ED performs poorly in low SNR regions as compared to other SS approaches. To detect the presence of the PU in a specific PU channel, the ED SS approach first computes the received PU signal energy for that channel. If the calculated energy of the received PU signal exceeds the ED spectrum detection technique's pre-set threshold, the PU is considered to be occupying the channel otherwise, the PU is considered absent and the second stage is triggered. The second stage implements the MED technique to deliver better results than the ED SS approach.

In [21], the authors proposed a two-stage SS process: in the first stage (coarse sensing), ED is used to detect PU's signal; once the ED fails in detecting proceed to the second stage (fine sensing), where eigenvalues detection approach is performed. In this study, several eigenvalue methods performed well in the fine sensing stage. Furthermore, simulation results validate that this process leads to better detection performance than single stage ED at low SNR values and lower computational complexity than single stage eigenvalues detection.

Two-stage SS is proposed using ED as the coarse stage and Renyi entropy-based detection as the fine stage in [22] to enhance the performance of single-stage detection methods and to mitigate noise uncertainty. Tsallis, Kapur, Shannon, and Renyi entropy-based detection have been used, and their performances are compared to select the best performer. Although the performance comparison is executed among conventional ED, entropy-based detection, and the proposed two-stage techniques over the AWGN channel are performed. According to the comparison results, the Renyi entropy outperforms other entropy methods, which offer very good performance in the presence of noise uncertainty.

In [23], the author's presented a reciprocal two-stage SS approach to improve the efficiency of SS in the presence of noise uncertainty. The proposed method consists of two different stages: the first stage is wavelet denoising, and the second stage is an adaptive threshold ED, each has a certain rule. The first stage is used to gain detailed information about the noise to aid in adapting the threshold of the second stage. This demonstrates that the suggested model performs well in the presence of noise uncertainty since it increases the detection probability.

Anaand et al. [24] introduced a two-stage spectrum sensing method to improve the sensing performance of current single-stage spectrum detection approaches. In the first step, the ED detects the PU signal; if it is not detected, the MME is employed in the second stage.

Aparna Singh Kushwah et al. presented a two-spectrum sensing algorithm in [25] to improve the sensing performance of traditional single stage spectrum detection approaches. In the proposed scheme, ED is utilized in the first stage to identify the presence of a PU signal, and if it fails to detect the signal, MME detection is used in the second stage to determine the presence of a PU signal. The channel is sensed by using ED in the first sensing stage. If the decision metric exceeds the first threshold, the channel is considered to be occupied. Otherwise, the incoming signal is evaluated by a second sensing stage that includes MME detection. If the component detection metric exceeds a second threshold, the channel is considered occupied; otherwise, it is declared vacant.

Table [1] provides a summary of previous studies [16–25]. This table provides comprehensive details regarding prior two-stage work, including the PU SNRs (SNRp), $P_d$ , $P_f$ and the sensing samples number (N). According to prior research, It can be shown that the various two-stage SS approaches have a relatively high computing complexity, substantial sensing overheads, low and average sensing reliability, and poor efficiency under uncertain noise environments. Lastly, in the case of low SNRs, the step of differentiating between PU signals and noise is missing. This is a very important step for reliable SS. However, it can be concluded that for better sensing accuracy, the ED SS technique must be exerted in the sensing stage with another stage. In this paper, a novel two-stage SS model is provided to enhance the performance of the SS process to detect the PU signals at low SNRs efficiently. The presented work adopts a noise reduction technique IDD as a first stage before the ED stage.

The ED is used in the second stage for its efficiency at high SNRs and simplicity but the ED SS approach is unable to separate noise from other signals then the sensing accuracy of ED is limited at low SNR regions, as the detection probability decreases when the SNR decreases so the IDD stage is employed for noise elimination and for separating the licenced user signals from noise to accomplish accurate detection and efficient SS. In the IDD stage using Wavelet de-noising With the Wavelet transform, the received signal's time and frequency characteristics are presented, and the resulting approximation and detail coefficients reflect the low and high frequency components of the signal under analysis, respectively. As noise is mainly composed of high frequency components, noise reduction is accomplished by thresholding the detail coefficients using the interval thresholding technique, which first divides the coefficients at each level into blocks and then selects a local threshold for each interval. This signal division makes heteroscedastic noise almost homoscedastic inside each interval, improving the efficiency of de-noising, and then using the inverse wavelet transform, the signal is rebuilt using the modified coefficients.

## 3. Proposed Model

From the previously suggested approaches, it was noted that numerous two-stage spectrum sensing methods exhibit comparatively high computational complexity, increased sensing overheads, yield moderate sensing accuracy, and poor performance in the face of uncertainty noise conditions. Notably, in the case of low Signal-to-Noise Ratio (SNR), the step in differentiating between PU signals and noise is missed. The ability to differentiate PU activity from noise is deemed pivotal for ensuring accurate spectrum sensing. Additionally, these methods often require full or partial prior knowledge of the primary user signals or noise power. to address the challenges and problems associated with both one-stage and two-stage spectrum sensing techniques, we propose a solution that involves employing one of the noise reduction and cancellation techniques, this approach aims to extract signals from the noise and yields high $P_d$ and low $P_f$ at low SNR ratios, especially at -20 dB.

The proposed two-stage SS model is performed by using IDD in the first stage and followed by ED in the second stage. The proposed two-stage model is known as the IDD-ED detector, as displayed in Fig. 3. The objective of the proposed model is to obtain accurate detection and efficient SS and gain simplicity and reliability in finding the optimum sensing time and maximum throughput, especially in the case of low received SNRp for reliable SS performance.

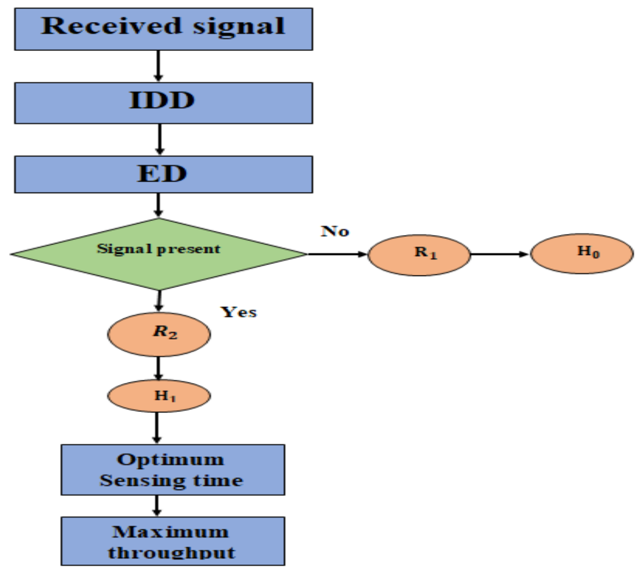


**Fig. 3** Two stages proposed IDD–ED model.

Noise randomly affects the received signal and can be caused by a variety of causes, including time-varying thermal noise at the communication system's receiver and noise interference from the surrounding atmosphere. Moreover, several factors, such as electromagnetic Interference influence the received signal. So Noise reduction is one of the most difficult challenges in communication systems, and it has received a great deal of attention in recent years. The need to reduce undesirable noise in desired signals has given rise to noise cancellation techniques and technology. Unfortunately, few articles on noise cancellation have been presented in the context of CR systems. Throughout the communication process, most communication systems use filters to cancel noise. Additionally, a CR system may also involve de-noising methods in the whole SS phase to improve sensing accuracy [26–33].

Therefore, it became very necessary to introduce an effective method to eliminate these undesirable noises from these signals of importance.

**Table 1** Summary of the prior two–stage techniques

| Two Stage Techniques | SNRp (dB) | $P_d$ | $P_F$ | $N_S$ | N | Two Stage Techniques | SNRp (dB) | $P_d$ | $P_F$ | $N_S$ | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **WD + ED [16]** | –10 | 0.90 | 0 | 1000 | **1000** | **ED + ED–ADT ESNR_ADT [17]** | –10 | 0.97 | 0.1 | 1000 | 100000 |
| | –15 | 0.90 | 0.04 | 1000 | **10000** | | –15 | 0.28 | 0.1 | 1000 | 100000 |
| | –15 | 0.92 | 0 | 1000 | **80000** | | –16 | 0.25 | 0.1 | 1000 | 100000 |
| | –15 | 0.90 | 0 | 1000 | **100000** | | –17 | 0.21 | 0.1 | 1000 | 100000 |
| | –20 | 0.90 | 0.60 | 1000 | **10000** | | –18 | 0.20 | 0.1 | 1000 | 100000 |
| | –20 | 0.90 | 0.18 | 1000 | **50000** | | –19 | 0.19 | 0.1 | 1000 | 100000 |
| | –20 | 0.91 | 0.04 | 1000 | **100000** | | –20 | 0.18 | 0.1 | 1000 | 100000 |
| **multi–path hybrid sensing model [18]** | –10 | 1 | 0.1 | – | **10,000** | **Improved TSD [(ED_SAT) + (ED_TAT)] [19]** | –10 | 0.96 | 0.1 | – | 1000 |
| | –15 | 0.88 | 0.1 | – | **10,000** | | –15 | 0.30 | 0.1 | – | 1000 |
| | –16 | 0.80 | 0.1 | – | **10,000** | | –16 | 0.26 | 0.1 | – | 1000 |
| | –17 | 0.67 | 0.1 | – | **10,000** | | –17 | 0.25 | 0.1 | – | 1000 |
| | –18 | 0.58 | 0.1 | – | **10,000** | | –18 | 0.20 | 0.1 | – | 1000 |
| | –19 | 0.52 | 0.1 | – | **10,000** | | –19 | 0.19 | 0.1 | – | 1000 |
| | –20 | 0.43 | 0.1 | – | **10,000** | | –20 | 0.18 | 0.1 | – | 1000 |
| **ITSS [ ED + MED ] [20]** | –10 | 0.99 | 0.2 | 2000 | **10^4-10^5** | **ITSS [ ED + MED ] [20]** | –10 | 0.99 | 0.01 | 2000 | 10^4–10^5 |
| | –15 | 0.85 | 0.2 | 2000 | **10^4–10^5** | | –15 | 0.85 | 0.01 | 2000 | 10^4–10^5 |
| | –16 | 0.82 | 0.2 | 2000 | **10^4–10^5** | | –16 | 0.82 | 0.01 | 2000 | 10^4–10^5 |
| | –17 | 0.80 | 0.2 | 2000 | **10^4–10^5** | | –17 | 0.80 | 0.01 | 2000 | 10^4–10^5 |
| | –18 | 0.79 | 0.2 | 2000 | **10^4–10^5** | | –18 | 0.79 | 0.01 | 2000 | 10^4–10^5 |
| | –19 | 0.77 | 0.2 | 2000 | **10^4–10^5** | | –19 | 0.77 | 0.01 | 2000 | 10^4–10^5 |
| | –20 | 0.75 | 0.2 | 2000 | **10^4–10^5** | | –20 | 0.75 | 0.01 | 2000 | 10^4–10^5 |
| **ED + MME [21]** | –10 | 1 | 0.1 | 2000 | **3000** | **ED + MMME [21]** | –10 | 1 | 0.1 | 2000 | 3000 |
| | –15 | 1 | 0.1 | 2000 | **3000** | | –15 | 1 | 0.1 | 2000 | 3000 |
| | –16 | 0.98 | 0.1 | 2000 | **3000** | | –16 | 0.99 | 0.1 | 2000 | 3000 |
| | –17 | 0.90 | 0.1 | 2000 | **3000** | | –17 | 0.95 | 0.1 | 2000 | 3000 |
| | –18 | 0.82 | 0.1 | 2000 | **3000** | | –18 | 0.86 | 0.1 | 2000 | 3000 |
| | –19 | 0.56 | 0.1 | 2000 | **3000** | | –19 | 0.70 | 0.1 | 2000 | 3000 |
| | –20 | 0.50 | 0.1 | 2000 | **3000** | | –20 | 0.53 | 0.1 | 2000 | 3000 |
| **ED + Renyi entropy [22]** | –10 | 1 | 0.05 | 10^4 | **1000** | **WD + AED [23]** | –10 | 0.2 | 0.1 | – | – |
| | –15 | 0.99 | 0.05 | 10^4 | **1000** | | –15 | 0.1 | 0.1 | – | – |
| | –16 | 0.98 | 0.05 | 10^4 | **1000** | | | | | | |
| | –17 | 0.97 | 0.05 | 10^4 | **1000** | | | | | | |
| | –18 | 0.93 | 0.05 | 10^4 | **1000** | | | | | | |
| | –19 | 0.86 | 0.05 | 10^4 | **1000** | | | | | | |
| | –20 | 0.72 | 0.05 | 10^4 | **1000** | | | | | | |
| **ED + MME [24]** | -10 | 1 | 0.1 | - | **100000** | **ED + MME [25]** | -10 | 1 | 0.1 | 1000 | 100000 |
| | -15 | 1 | 0.1 | - | **100000** | | -15 | 1 | 0.1 | 1000 | 100000 |
| | -20 | 0.89 | 0.1 | - | **100000** | | -16 | 1 | 0.1 | 1000 | 100000 |
| | | | | | | | -17 | 1 | 0.1 | 1000 | 100000 |
| | | | | | | | -18 | 0.99 | 0.1 | 1000 | 100000 |
| | | | | | | | -19 | 0.98 | 0.1 | 1000 | 100000 |
| | | | | | | | -20 | 0.89 | 0.1 | 1000 | 100000 |

Researchers have suggested a variety of signal de-noising approaches for this purpose, including linear methods (Fourier transform de-noising, Wiener filtering) and nonlinear methods (wavelet transform de-noising). Due to their relative simplicity, linear signal de-noising techniques were often utilized for noise removal up to 1990. These techniques are typically acceptable but have certain limitations since they assume that the signals are stationary. However, real-world signals frequently exhibit non-stationary statistical characteristics. Because they can reveal both the spectral and temporal information in a signal at once, nonlinear techniques like the wavelet transform have become an active topic of research over the last two decades [34].

De-noising technologies are classified into three types: time-frequency technologies, matrix-factorization technologies, and adaptive-filter de-noising technologies. Time-frequency de-noising methods allow for the study of noise-induced signals in both the frequency and time domains. WD, IDD, and decomposition de-noising are Samples of approaches that are related to this category the second type of de-noising approach is matrix-factorization de-noising, which is based on the examination of signal space. Singular value decomposition and nonnegative matrix factorization are two examples of matrix-factorization algorithms. Singular value decomposition and non-negative factorization may both factorize a large or scattered matrix into smaller knowledge sets that allow easier examination of a symbol. The third type of de-noising technology is adaptive filtering and de-noising, which uses adaptive algorithms to cancel noise. The Least-Mean-Square (LMS) and the Normalized Least-Mean-Square (NLMS) filters are Samples of the techniques that belong to adaptive filtering de-noising these filters can readjust their parameters to remove noise from a symbol.

In high-performance signal processing tool [35–37], Wavelet transform (WT) has been proven to be a very effective approach for de-noising signals when compared to traditional methods like the Fourier filter and Savitzky–Golay filter [38]. The accuracy of the reconstructed signal depends on both the thresholding method and the threshold values when a noisy signal is de–noised using the WT methodology. There are two basic ways for compressing wavelet coefficients hard thresholding and soft thresholding [39, 40]. About the selection of thresholds, several methods have been investigated [41]. The standard approaches include the level-dependent and interval-dependent threshold selections. The level thresholding approach, which chooses single universal threshold for each level and applies it to threshold all the coefficients at the level. In order to threshold the coefficients inside each interval, the interval thresholding technique first divides the coefficients at each level into blocks, and then selects a local threshold for each interval This signal division, make heteroscedastic noise be almost homoscedastic inside each interval, improving the efficiency of de-noising.

Wavelet de-noising with WT, the received signal's time and frequency characteristics are presented, and the resulting approximation and detail coefficients reflect the low and high frequency components of the signal under analysis, respectively. As noise is mainly composed of high frequency components, noise reduction is accomplished by thresholding the detail coefficients. The de-noising process typically consists of the following three steps:

- Decomposition: the noisy signal is converted into a collection of orthonormal wavelet basis functions, selecting a mother wavelet and a maximum decomposition level followed by computing the decomposition coefficients at each level.
- Thresholding: In this stage, the threshold values for each level are evaluated, and the coefficients at each level are applied to the threshold.
- Reconstruct: Using the inverse wavelet transform, the signal is rebuilt using the modified coefficients.

Hence the packet of wavelet technique is a generalization of wavelet decomposition that provides a wide variety of signal analysis scales. In packet wavelets analysis, the details as well as the approximations are divided into $\mathbf{2^n}$ different ways to represent the signal where the decomposition level is n. Several bases are produced by single wavelet packet decomposition, which provides a more complicated and adaptable analysis. The best level of signal decomposition is chosen using an entropy-based criterion. Fig. 4 displays the packet of wavelet decomposition and reconstruction trees.

The input signal $R$ is divided by using filters $G_o$ and $G_1$ into a low pass component $R_o$ and a high pass component $R_1$, which are decimated (down-sampled) by factor two. The low pass component is then divided more into $R_{00}$ and $R_{01}$, which are again decimated by factor two. This procedure is repeated as needed. The DWT outputs are the band pass coefficients $R_1$ ,$R_{01}$, $R_{001}$,……, and the last low pass coefficients $R_{000....0}$ The decimation ensures that the input sample rate and total output sample rate are identical, so there is no redundancy in the transform. The signal is reconstructed using a pair of reconstruction filters $H_o$ and $H_1$ are utilized in the configuration of Fig. 4 where $R_{000}$ may be reconstruction from $R_{0000}$ and $R_{0001}$; and then $R_{00}$

from $R_{000}$ and $R_{001}$; and so on back to $R$, using an inverse tree of $H$ filters.

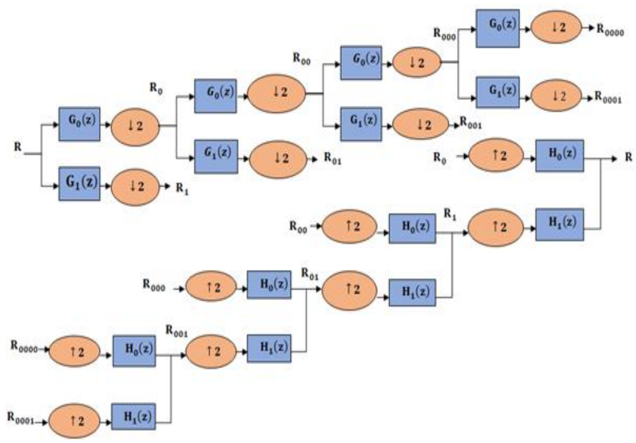


**Fig. 4** Packet of wavelet decomposition and reconstruction trees

The ED is used at the second stage for its efficiency and simplicity, so the IDD stage is employed for noise elimination and for separating the licenced user signals from noise to accomplish accurate detection and efficient SS. To calculate the energy of the received signal, the samples are squared and integrated across the observation period, and the integrator output is then compared to the threshold. If the integrator's output exceeds the threshold the assigned radio spectrum is then assumed to be occupied. Otherwise, it is regarded as empty.

### 3.1 The Proposed Two–Stage Model Analysis

The PU signal can be detected by using the following hypothesis for the received signal [42]:

$$\mathrm{R(n)} = \begin{cases} \mathrm{h(n)\,S(n) + w(n)} & \mathrm{H_P = H_1} \\ \mathrm{w(n)} & \mathrm{H_P = H_0} \end{cases} \tag{1}$$

Where $[R(n)]$ represents the received signal and $S(n)$ represents the PU signal of transmitted power $P_p$, $h(n)$ represents the channel gain, $w(n)$ represents the Additive White Gaussian Noise (AWGN) at the cognitive user receiver, which is considered to be a Circularly Symmetric Complex Gaussian (CSCG) random process with zero mean and one–sided power spectral density $N_o$ (i.e., $w(n) \sim \mathcal{CN}(0, N_o)$), and $n$ denotes the time index. $H_0$ is the null hypothesis, which denotes the absence of PU and $H_1$ is the alternative hypothesis, which denotes that PU is present.

By comparing the detectors decision parameter the probabilities of false alarm and detection can be determined, which determines under the hypothesis $H_P = H_0$ and $H_P = H_1$, respectively with a predefined threshold $\psi$. For ED, the decision parameter $Dp_{ED}$ is determined by the energy of the samples that were taken during the observation window duration τ, and it is represented by equations 2, and 3.

$$Dp_{ED} = \frac{1}{N}\sum_{n=1}^{N} |R(n)|^2 \tag{2}$$

$$Dp_{ED} \gtrless \psi \tag{3}$$

Where N denotes the number of sensing samples ($N = \tau\, f_s$); with $f_s$ indicating the sampling frequency under hypothesis $H_P = H_0$, we find

$$R_1 = w\,(n) \tag{4}$$

Then decision parameter will be:

$$Dp_{ED}|H_0 = \frac{1}{N}\sum_{n=1}^{N} |w(n)|^2 \tag{5}$$

Which is the squared sum of AWGN w (n). As a result of this a chi–square distribution of N degrees of freedom for real valued noise case, and 2N degrees of freedom for complex valued noise case.

In case of complex noise, and by using the application of the Central Limit Theorem (CLT), chi–square Probability Density Function (PDF) of huge N can be evaluated by a Gaussian distribution of mean $\mu_0 = N_o$, and variance $\sigma_0^2 = \frac{1}{N}N_o^2$. So, an approximated PDF can be indicated as follows:

$$\tilde{f}_{M[R(n)]|H_0}(\xi) = \frac{1}{\sqrt{2\pi}\sigma_0} e^{-(\xi-\mu_0)^2/2\sigma_0{}^2}, \quad \xi \geq 0 \tag{6}$$

Then,

$$P_f = \int_{\xi=\psi}^{\infty} \tilde{f}_{M|H_0}(\xi)d\xi$$

$$P_f = \int_{\xi=\psi}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_0} e^{-(\xi-\mu_0)^2/2\sigma_0{}^2} d\xi \tag{7}$$

Let $t = \frac{\xi-\mu_0}{\sigma_0}$ , Then, $\xi = \sigma_0 t + \mu_0$, , $d\xi = \sigma_0 dt$,

Equation (7) can be expressed as:

$$P_f = \frac{1}{\sqrt{2\pi}\sigma_0} \int_{t=\frac{\psi-\mu_0}{\sigma_0}}^{\infty} e^{-\frac{t}{2}}\, \sigma_0\, dt, \quad P_f = Q(\frac{\psi-\mu_0}{\sigma_0}) \tag{8}$$

Where $Q(.)$ represents the complementary distribution function of the standard Gaussian, i.e.,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{t}^{\infty} e^{-\frac{t}{2}}\ dt \tag{9}$$

Then Apply $\mu_0 = N_o$ , and $\sigma_0^2 = \frac{1}{N} N_o^2$ in to Equation (8), so the $P_f$ is defined as in equation (10):

$$P_f = Q\left(\left(\frac{\psi}{N_o} - 1\right)\sqrt{N}\right) \tag{10}$$

With $N = \tau\, fs$, then

$$P_f(\psi, \tau) = Q\left(\left(\frac{\psi}{N_o} - 1\right)\sqrt{\tau\, fs}\right) \tag{11}$$

Under the hypothesis $H_P = H_1$ , we find

$$R_2 = h(n) * S_p(n) + w(n) \tag{12}$$

The decision parameter $Dp_{ED}$ has a distributed PDF of non–central chi–square $f_{M[(R(n))]\,|H_1}(\xi)$ of 2N degrees of freedom and non–certainty parameter $2|h_{ps}|^2\gamma_P$ with $\gamma_P = \frac{P_P}{N_o}$ representing the PU SNR. For notational simplicity, let $\gamma = |h_{ps}|^2\gamma_P$ represent the SNR of the received signal.

Once again for huge N according to CLT, the decision parameter has a Gaussian PDF of mean $\mu_1 = |h_{ps}|^2 P_P + N_o = (\gamma + 1)N_o$ ,and variance $\sigma_1^2 = \frac{1}{N}(\gamma + 1)^2 N_o^2$ under the condition that $w(n)$ consider CSCG random processes as equation (10), the $P_d$ is evaluated by $P_d = Q(\frac{\psi - \mu_1}{\sigma_1})$, and after insertion of $\mu_1$ and $\sigma_1$ values, and then the $P_d$ represented as follows:

$$P_d(\psi, \tau) = Q\left(\left(\frac{\psi}{(\gamma + 1)N_o} - 1\right)\sqrt{\tau\, f_s}\right) \tag{13}$$

The core equations for evaluating both detection and false alarm probabilities for a pre–defined decision threshold $\psi$ are represented in Equations (11) and (13). It can rewrite them such that one is a function of the other the $P_d$ is related to the $P_f$ as follows:

$$P_d = Q\left(\frac{1}{(\gamma+1)}\left(Q^{-1}(P_f) - \gamma\sqrt{\tau\, f_s}\right)\right) \tag{14}$$

To guarantee effective protection for a PU network from harmful interference of a secondary network, a restriction of the target $P_d$ is typically adopted, especially in a low SNR environment. In IEEE 802.22 WRAN, the targeted probability of detection $\overline{P_d} = 0.9$ for the SNR of $-20$ dB then, for a target $\overline{P_d}$, the decision threshold can be obtained from Equation (13) as follows:

$$\psi = (\gamma + 1)N_o\left(\frac{1}{\sqrt{\tau\, f_s}} Q^{-1}(\overline{P_d}) + 1\right) \tag{15}$$

By substituting from Equation (15) into Equation (11), then $P_f$ for a target $P_d$ is expressed by:

$$P_f(\tau) = Q\left((\gamma + 1)Q^{-1}(\overline{P_d}) + \gamma\sqrt{\tau\, f_s}\right) \tag{16}$$

For noise reduction, the IDD technique is used as the first stage for an efficient SS process. Wavelet transformation is widely used in signal de–noising applications. Each time, the CR must process the sampled signal inside the licensed user's band. By measuring the energy of the signal R, which is determined by Equation 2, energy sensing aims to determine whether $H_0$ or $H_1$, is true. Equations (4) and (12) can be derived as follows:

$$R_1 = w(n) \tag{17}$$

$$R_2 = S_p(n) + w(n) \tag{18}$$

The received signal's wavelet transform is shown in the following way:

$$[a_R, d_R] = W_R = \mathrm{W}(s + w) = W_S + W_W \tag{19}$$

Where W stands for the DWT's left invertible transformation matrix. The details that represent the majority of the noise power in the wavelet transformation domain are contained in the detailed information $d_R$. The inverse wavelet transform can restore the required signal with reduced noise influence after thresholding the detailed information, which improves the ED process. The inverse wavelet transform can restore the required signal with reduced noise influence after thresholding the detailed information, which improves the ED process.

### 3.2 IDD-ED Maximum Throughput and Optimum Sensing Time Analysis

The frame duration, as represented in Fig.5, consists of one sensing slot $\tau$ and one data transmission slot $T - \tau$.The $P_d$ and $P_f$ are two parameters associated with SS the higher the $P_d$, the better the PU can be protected. However, from the point of view of the SUs the lower the $P_f$, the greater chance the spectrum holes can be exploited efficiently which leads to the higher the achievable throughput for the SUs. Thus, a fundamental choice for the secondary network between sensing capability and achievable throughput must be handled.

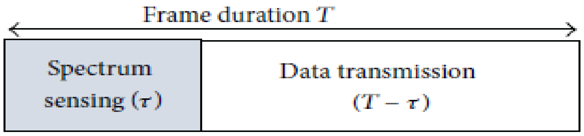


**Fig. 5** Frame duration of the conventional CR [43]

For a mathematical representation of this choice consider $C_0$, $C_1$ are the channel capacities of the secondary network when it operates in the absence or presence of the PU, respectively. Where the transmit power of SU is $P_s$ and the transmit power of PU is $P_P$ and $N_o$ is the spectral density of the AWGN noise so the signal–to–noise ratios of the PU and SU are $SNR_P = \frac{P_P}{N_o}$ and $SNR_S = \frac{P_S}{N_o}$, respectively Then,

$$C_0 = \log_2(1 + SNR_S)$$
$$C_1 = \log_2\left(1+\frac{P_s}{P_P+N_0}\right) = \log_2\left(1+\frac{SNR_s}{SNR_P+1}\right) \quad (20)$$

For a certain frequency band of interest, consider $P(H_1)$, $P(H_0)$ are the probabilities which represent the presence or absence of the PU, respectively. There are two scenarios for which the secondary network can operate at the PUs frequency band. When the PU is not active, and the SU produces no false alarm, the achievable throughput of the secondary network is represented by

$$Z_0(\tau) = \frac{T-\tau}{T}(1-P_f)P(H_0)C_0 \quad (21)$$

When the PU is active but is not identified by the SU, the achievable throughput of the secondary network is represented by

$$Z_1(\tau) = \frac{T-\tau}{T}(1-P_d)P(H_1)C_1 \quad (22)$$

Let the average achievable throughput is represented by:

$$Z(\tau) = Z_0(\tau) + Z_1(\tau) \quad (23)$$
$$\max_\tau \; Z(\tau) = Z_0(\tau) + Z_1(\tau)$$
Using
$$P_D(\tau) \geq \overline{P_d} \quad (24)$$

By applying the proposed sensing–through hput model for the ED scheme, then, from Eqs. (21) to (24) will be:

$$Z_0(\psi,\tau) = \frac{T-\tau}{T}\left(1-P_f(\psi,\tau)\right)P(H_0)C_0 \quad (25)$$
$$Z_1(\psi,\tau) = \frac{T-\tau}{T}\left(1-P_d(\psi,\tau)\right)P(H_1)C_1 \quad (26)$$

So, the average throughput is given by:

$$Z(\psi,\tau) = Z_0(\psi,\tau) + Z_1(\psi,\tau) \quad (27)$$

So, the optimum problem can be evaluated as:

$$\max_\tau \; Z(\psi,\tau) = Z_0(\psi,\tau) + Z_1(\psi,\tau)$$
Using $P_d(\psi,\tau) \geq \overline{P_d}$ (28)

The condition of the previous optimum problem can be met through choosing a detection threshold $\psi_o$ as $P_d(\psi_o,\tau) = \overline{P_d}$. If there is $\psi_1 < \psi_o$, then according to Eq. (13) $P_d(\psi_1,\tau) > P_d(\psi_o,\tau)$ as $Q(S)$ is decreases monotonically with $S$, which will satisfy the condition. Also, from Eq. (11), it can be shown that $P_f(\psi_1,\tau) > P_f(\psi_o,\tau)$. From Eq. (25) to Eq. (27), it can be obviously found that $Z(\psi_1,\tau) < Z(\psi_o,\tau)$. This means that the detection threshold $\psi = \psi_o$ satisfies the equality condition and allows maximum throughput Z ($\tau^*$). Thus, the optimum problem leads to the following:

$$\max_\tau \; Z(\tau) = Z_0(\tau) + Z_1(\tau)$$
With $0 < \tau < T$ and $\psi = \psi_o$ (29)

Where,

$$Z_0(\tau) = \frac{T-\tau}{T}\left(1 - Q\left((\gamma+1)Q^{-1}(\overline{P_d}) + \gamma\sqrt{\tau f_s}\right)\right)P(H_0)C_0 \quad (30)$$

$$Z_1(\tau) = \frac{T-\tau}{T}(1-\overline{P_d})P(H_1)C_1 \quad (31)$$

Mathematically, $Z(\tau)$ should be a unimodal function in the range $0 < \tau < T$ to solve this optimum problem. Denote $\tau^*$ as the optimum sensing time, so $z(\tau)$ is said to be a unimodal function if it is monotonically increasing for $0 < \tau < \tau^*$ and then monotonically decreasing for $\tau^* < \tau < T$, with a unique optimum point at $\tau = \tau^*$. This can be satisfied under the following three conditions:

$$\frac{dz(\tau)}{d\tau}\Big|_{\tau=0} > 0.$$

$$\frac{dz(\tau)}{d\tau}\Big|_{\tau=T} < 0.$$

There is a unique $\tau^*$, where $0 < \tau < T$, such that $\frac{dz(\tau)}{d\tau}\Big|_{\tau=\tau^*} = 0$.

The rest of this subsection verifies that $z(\tau)$ matches these previous conditions. For convenience, denote $\propto = (\gamma+1)Q^{-1}(\overline{P_d})$ and $\beta = \gamma\sqrt{f_s}$. It can be noticed that $\beta$ is always positive while $\propto$ is a negative value since $\overline{P_d}$ is above 0.5 for practical considerations. From Eq. (30) and (31):

$$\frac{dz_0(\tau)}{d\tau} = \frac{d}{d\tau}\left(P(H_0)C_0\frac{T-\tau}{T}\left(1-Q\left(\propto + \beta\sqrt{\tau}\right)\right)\right)$$

$$\frac{dz_0(\tau)}{d\tau} = P(H_0)C_0\left(\frac{-1}{T} + \frac{1}{T}\, Q\left(\propto + \beta\sqrt{\tau}\right) + \frac{T-\tau}{T}\frac{\beta}{\sqrt{8\pi\tau}}\exp\left(-\frac{\left(\propto+\beta\sqrt{\tau}\right)^2}{2}\right)\right) \quad (32)$$

, and $\frac{dz_1(\tau)}{d\tau} = \frac{-1}{T}\,(1 - \bar{P_d})P(H_1)C_1$ (33)

It can be clearly seen that $\frac{dz_1(\tau)}{d\tau}$ in Eq. (33) is a constant value. This means that $z_0(\tau)$ is responsible for satisfying the preceding conditions. To show this, firstly $\frac{dz_0(\tau)}{d\tau}|_{\tau=0} = \infty > 0$, and this matches the first condition.

Also, $\frac{dz_0(\tau)}{d\tau} = P(H_0)C_0\left(\frac{-1}{T} + \frac{1}{T}\, Q\left(\propto + \beta\sqrt{T}\right)\right) < 0$ since $Q(S) \leq 1$ for all $S$, and this satisfies the second condition. Finally, to prove that $z_0(\tau)$ satisfies the third condition, put $\frac{dz_0(\tau)}{d\tau} = 0$ in Eq. (32), this will result

$$\left(\propto + \beta\sqrt{\tau}\right)^2 = -2\ln\left(\left(\frac{\sqrt{8\pi\tau}}{\beta(T-\tau)}\right)\left(1 - Q\left(+\beta\sqrt{\tau}\right)\right)\right) \quad (34)$$

The desired optimum sensing time $\tau^*$ the time corresponds to the intersection of the two functions in the previous equation. So to prove that there is only one optimal point in the entire range $0 < \tau < T$, it should be verified that these functions intersect each other at only one point. The optimum sensing time $0 < \tau^* < T$ that matches this equality and the high performance of the proposed model will be obviously investigated in the simulation results in the following section.

## 4. Results OF Proposed Model

In this section, we describe the simulation results and analysis of the proposed two-stage model, which was executed in MATLAB. With a sampling frequency of 6 MHz and a zero–mean AWGN noise over 1000 Monte Carlo simulations with an SNR varying from −10 to –20 dB.

### 4.1 Result of the Proposed Model $P_d$, $P_f$ for Various Values of N and SNRp from −10 to −20 dB

The $P_f$ indicates how frequently PU is potentially subject to CR interference. Pd is one of the key parameters in CRN used to estimate system performance. The value of $P_d$ should be in accordance with IEEE 802.22 WRAN standard, as maximum as possible under the constraint of $P_f$. In Fig. 6, it is shown that when the number of samples increased the $P_f$ decreased. Further, the $P_d$ obtained from the simulation is shown in the figure. This demonstrates that the desired theoretical target $P_d$ has been attained.

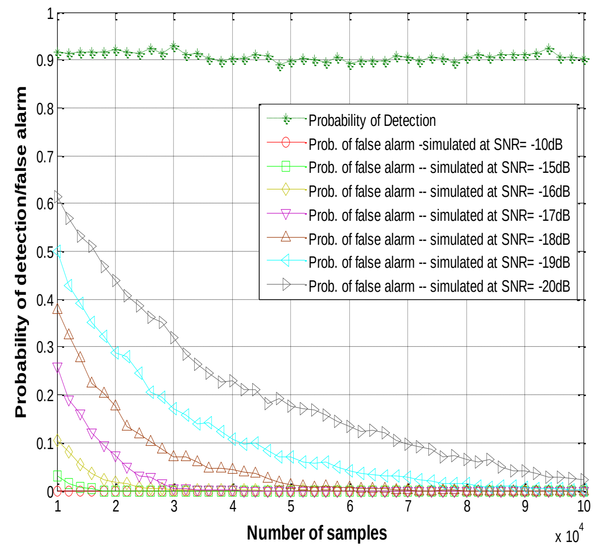


**Fig. 6** $P_d$ and $P_f$ Vs N from 10000 to 100000 at Different SNRp

Fig.6 shows the results of the proposed model $P_d$ and $P_f$ for different values of N and SNRp. In case of low SNRp and with the increase of N from 10,000 to 100,000, a very low value of $P_f$ can be obtained when the targeted $P_d$ is 0.90. As shown at SNRp from −10 to −19 dB and at N=100,000, the value of the $P_f$ equal 0 and when SNRp = −20 dB, the value of $P_f$ equal 0.03.

#### 4.1.1 Comparison between the Related Two Stage Methods and the Proposed Model $P_d$ and $P_f$

As shown in Fig.7 and Fig.8 the simulation results of the proposed model $P_d$ and $P_f$ for different values of SNRp and at N=100000 compared to prior relevant work, and it Validates that the proposed model improves the sensing Performance and helps to address the issues of high $P_f$ rates, poor detection accuracy at low SNRs level, and noise uncertainties because it obtains higher $P_d$ and lower $P_f$, even at low SNRs from −15 to −20 dB compared to prior two stage methods.

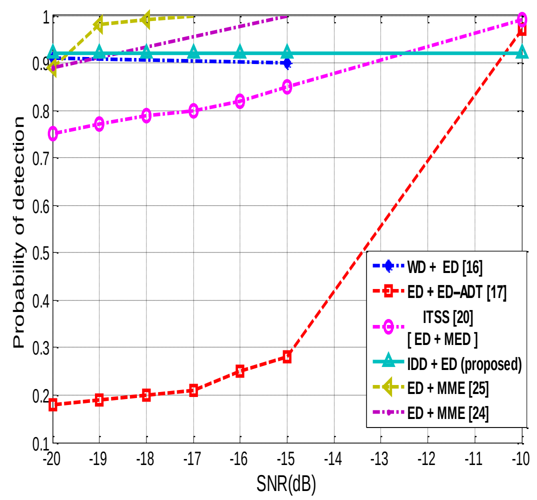


**Fig. 7** Comparison between $P_d$ of the related two stage methods and the proposed model at different SNR for N=100000

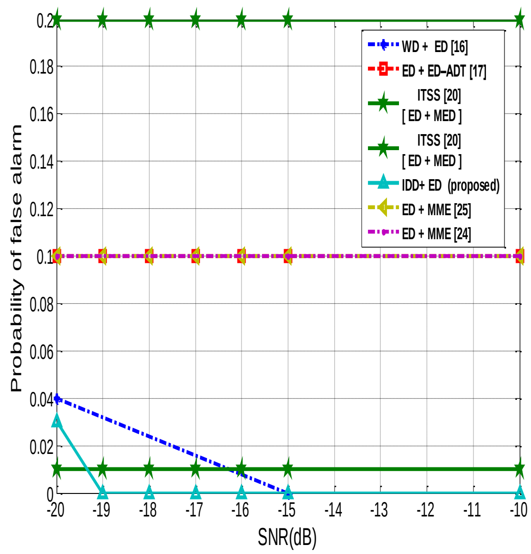


**Fig. 8:** Comparison between $P_f$ of the related two stage methods and the proposed model at different SNR for N=100000

### 4.2 Results of the Proposed Model Maximum Throughput and Optimum Sensing Time

Fig. 9 shows the Proposed model Achievable throughput Versus Sensing time from N = 1000–10,000 at different SNRp all the results are arranged in Table 2. It is seen that the maximum throughput is achieved at SNR = -10dB is 5.418 (bits/sec/HZ) at the optimum sensing time of 0.5ms and at SNR = -20dB is 1.98 (bits/sec/HZ) at the optimum sensing time of 1.5ms.

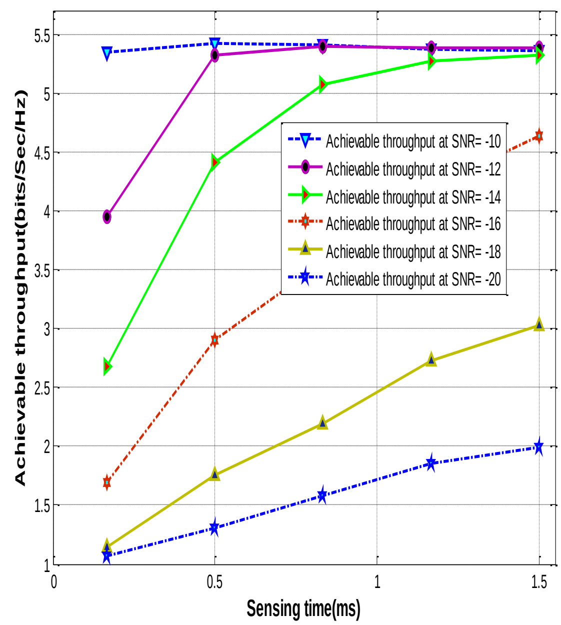


**Fig.9** The suggested model Achievable throughput Vs. Sensing time from N =1000–10000 at diff. SNRp.

**Table 2** The Proposed model Achievable throughput and its Optimum sensing time at N from 1000 to 10000 and SNRp from −10 to −20 dB

| Proposed model | SNRp dB | Achievable throughput Bits/Sec/HZ | Optimum sensing time (ms) | N |
|---|---|---|---|---|
| | **-10 dB** | 5.418 | 0.5 | 1000–10000 |
| | **-12 dB** | 5.38 | 0.833 | 1000–10000 |
| **(IDD+ED)** | **-14 dB** | 5.3 | 1.5 | 1000–10000 |
| | **-16 dB** | 4.7 | 1.5 | 1000–10000 |
| | **-18 dB** | 3.1 | 1.5 | 1000–10000 |
| | **-20 dB** | 1.98 | 1.5 | 1000–10000 |

Fig.10 shows the Proposed model Achievable throughput Versus Sensing time from N = 10,000–100,000 at different SNRp all the results are arranged in Table 3. It is seen that the maximum throughput is achieved at SNR = -10dB is 5.37 (bits/sec/HZ) at the optimum sensing time of 1.66ms and at SNR = -20 is 4.58 (bits/sec/HZ) at the optimum sensing time of 13ms.

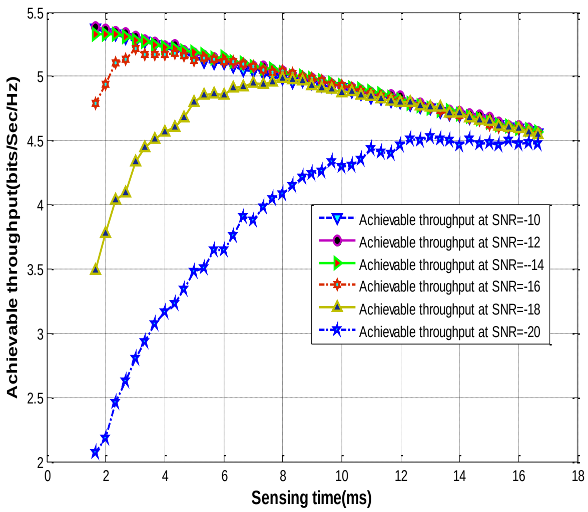


**Fig.10** The proposed model Achievable throughput Vs. Sensing time from N =100000–100000 at diff. SNRp.

## 5. Conclusion and Future Work

A novel two-stage SS model for CR systems that achieves optimum sensing time, maximum throughput, lower $P_f$ and higher $P_d$ and its performance evaluation are presented. In this paper, the proposed model provides a solution for detection, false alarm performance, and noise uncertainty at low values of SNR in CR systems. Therefore, the two-stage interval dependent de-noising and ED model is proposed to perfectly detect the PU signals at different low SNRs. At low SNRs, the ED method is ineffective in detecting the existence of the PU due to the noise issue in the received signals. So at low SNR, there is a need to use sequential detectors for accurate sensing detection results. Therefore, the interval dependent de-noising technique is used as the first detector for improving the signal reconstruction to further reduce the noise effect and accurately detect the PU signals. The results of the simulation show that the proposed model yields high $P_d$ and low $P_f$ at low SNR ratios from (-15 to -20) dB, and also shows that the suggested model enhances the rate of false alarm rather than the previous related two- stage methods in terms of sensing a spectrum in low SNR regions and achieves a very better optimum sensing time which achieves maximum throughput at different SNRs from -10 to -20 dB at different N .The obtained results indicated that the proposed model improves the sensing process for a better performance of the cognitive radio systems.

Future work can be done in this study by using another channel, like the fading channel (Rayleigh and Rician), which can be performed for detection instead of the AWGN channel, and it is recommended to analyse the impact of cooperative sensing case by employing the proposed model and evaluating its influence in the case of cooperative sensing performance. Another possibility is to modify the proposed model to analyze its behaviour in a MIMO sensing situation and evaluate its influence on sensing performance.

**Table 3** the proposed model Achievable throughput and its optimum Sensing time at N from 10,000 to 100,000 and SNRp from −10 to −20 dB

| Proposed model | SNRp dB | Achievable throughput Bits/Sec/HZ | Optimum sensing time (ms) | N |
|---|---|---|---|---|
| **(ED + IDD)** | **-10 dB** | 5.37 | 1.66 | 10000–100000 |
| | **-12 dB** | 5.38 | 1.66 | 10000–100000 |
| | **-14 dB** | 5.33 | 2 | 10000–100000 |
| | **-16 dB** | 5.22 | 3 | 10000–100000 |
| | **-18 dB** | 4.98 | 8 | 10000–100000 |
| | **-20 dB** | 4.58 | 13 | 10000–100000 |

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