A STUDY OF COOPERATIVE AND NON-COOPERATIVE WIDEBAND SPECTRUM SENSING RADIO NETWORKS IN THE COGNITIVE RADIO 5G ERA

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ABSTRACT

The advent of 5G technologies has ushered in unprecedented demands for efficient spectrum utilization to accommodate a surge in data traffic and diverse communication services. In this context, accurate and reliable spectrum sensing is crucial. We investigated wideband spectrum sensing strategies by comparing non-cooperative cognitive radio (CR) approaches with cooperative methods across multiple sub-bands. Our research led to the development of a sophisticated cooperative wideband spectrum sensing framework that incorporates a K-out-of-N fusion rule at the fusion center to make optimal decisions, selecting an appropriate K for a given number of cooperating CRs. This method aims to combat the noise uncertainty typically affecting traditional non-cooperative energy detection methods in 5G environments under Additive White Gaussian Noise (AWGN) conditions, assumed to be identically and independently distributed (i.i.d). However, our findings indicate that while cooperative sensing significantly improves detection in scenarios with poor signal-to-noise ratios (SNRs) and higher false alarm rates (between 0.5 and 1), it does not consistently outperform non-cooperative methods at very low false alarm rates (0.01 and 0.1). This finding suggests the limited effectiveness of the cooperative sensing method under certain conditions, underscoring the need for further research to optimize these strategies for diverse operational environments

KEYWORDS

Cooperative Wideband Spectrum Sensing, Non-Cooperative Wideband Spectrum Sensing, Energy Detection, Additive White Gaussian Noise, K-out-of-N Fusion Rule.

1. INTRODUCTION

The Federal Communications Commission (FCC) plays an important role in managing the radio frequency spectrum in the United States, overseeing a dynamic regulatory framework for spectrum sensing, sharing, and management. This framework allocates spectrum to fixed licensed owners - primary users (PUs) and flexible, unlicensed secondary users (SUs). While the fixed spectrum often remains underutilized, the unfixed spectrum faces congestion challenges exacerbated by the burgeoning proliferation of Internet of Things (IoT) devices. The limited spectrum available struggles to accommodate these emerging technologies, necessitating innovative solutions.

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Cognitive radio (CR) technology enhances spectrum utilization [1]. It dynamically detects underutilized bands within the wireless spectrum and adapts its transmission parameters accordingly, ensuring a seamless flow of information. The core functions of cognitive radio are spectrum sensing and adaptation [2]. This adaptability includes modifications to transmission power, modulation, and frequency bands to minimize interference with PUs and adjust for the possible re-emergence of PUs during SU transmissions. SUs initially perform spectrum sensing to identify frequencies not occupied by PUs. Post-detection, SUs adjusts their transmission characteristics to exploit these 'spectrum holes' effectively as seen in figure 1, while ensuring minimal interference with existing PUs. This process requires reliable detection metrics, notably the probability of detection (PD) and the probability of false alarm (PFA). PD measures the accuracy of detecting PUs' presence or absence, while PFA indicates the erroneous reporting of PUs' presence.

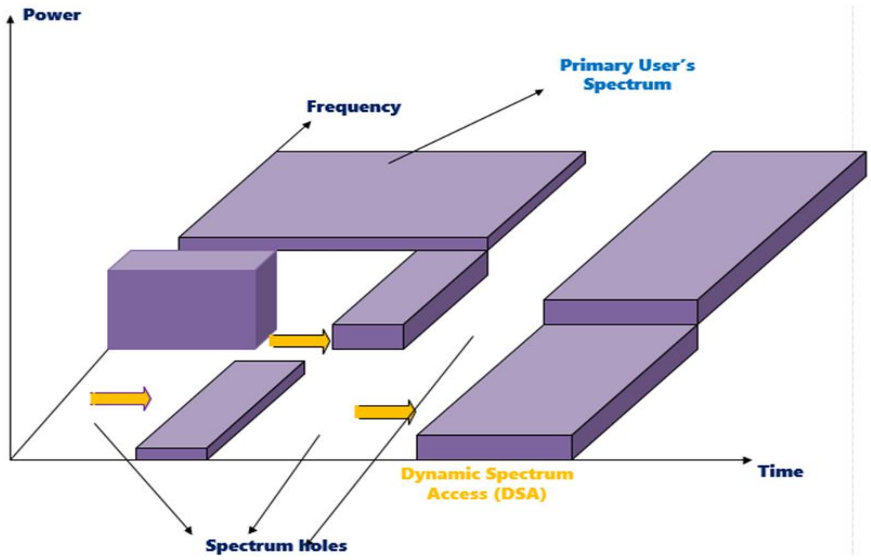

Figure 1: Underutilized Spectrum Hole

However, the performance of these detection mechanisms can be significantly compromised by factors such as multipath effects, hidden node issues and shadowing, particularly in non-cooperative spectrum sensing contexts [3]. Cooperative spectrum sensing was introduced to address these challenges and is gaining traction among researchers. This method enhances sensing accuracy by enabling SUs to share sensed information with a centralized fusion center, leveraging collective data to improve decision-making processes under diverse environmental conditions [3,4]. Integrating K-out-of-N decision rules at the fusion center enhances this approach, which is particularly crucial in 5G environments where efficient and reliable spectrum management is paramount. This paper investigates the performance of non-cooperative and cooperative spectrum sensing techniques tailored for energy detection (ED) in 5G environments, specifically within Additive White Gaussian Noise (AWGN) and individually and identically distributed (i.i.d) contexts. We developed a simulation to determine the optimal average proportion of decisions required by CRs with an optimal k in the K-out-of-N rule under differing false alarm rates. This systematic approach maximizes PD while maintaining PFA within acceptable limits.

The authors in [5] researched an algorithm for sensing node reliability in CRNs. They confirmed that the secondary users (SUs) may have several sensing nodes that are uniformly distributed, and each node utilizes the energy of the primary user (PU) individually to confirm the availability of the spectrum. From path loss theory, the PU signal energy is individually sensed by each node, although operating within the same condition. More so, from energy detection theory, incorrect decisions will be made by nodes that receive less energy, and these nodes will interfere with the global decision. The authors in [6] believe that the fusion centers' reliability helps maintain optimal detection in low SNR conditions.

The authors in [7] researched cooperative sensing and investigated the effect of shadowing among cognitive radios. They inferred that correlated shadowing limits the cognitive node's performance and suggested that few independent users can perform better than many correlated users. This assumption is correct since a narrowband sensing node performs sensing at a particular spectrum band and may be significantly affected by deep fade. This problem can be solved by independent multiple radio sensing at individual spectrum bands, which explains the concept of wideband spectrum sensing

The authors in [8] proposed an efficient sequential decision fusion (SDF) scheme based on the k-out-of-N rule. They believed that the fusion center (FC) might achieve a global decision by fusing the received decisions sequentially before receiving all individual choices. They assume that the fusion center may decide that the PU is occupying the spectrum if there is a continuous sequential result of ‘1’ from at least five individual SU. This may not apply in real life due to unstable environmental conditions. Based on their proposed scheme, they investigated the average proportion of decisions required based on three fusion rules, AND, OR, and Majority rule, when there are different numbers of SUs in cognitive radio networks. They observed that the average decision percentage required at the fusion center is significantly large when the AND fusion rule is implemented, especially at low SNR. This is because, under the AND rule, the gap between the PD and PFA is minimal in low SNR, necessitating high individual detection probability for all SUs. However, at a high SNR, the average number of decisions decreases for AND rule implementation, making AND rule outperform the OR and Majority rule in terms of the probability of detection.

In [9], while considering the TV spectrum, the authors believe that a detector can minimize detection error probability by implementing the k-out-f-N rule while maintaining an optimal number of Sus for cooperative sensing. The authors in [10] worked on a wideband spectrum considering the energy measurement of different subbands. Their observation is based on a simulation that the wideband sensing subbands algorithm detects PU’s signal up to -8dB with a sample size of 256 for eight nodes in a corporation considering DVB-T signal under AWGN and Rayleigh fading channels. They affirm that the CR senses the signals in wideband to improve the opportunistic throughput.

In this paper, we developed a simulation to determine the optimal average proportion of decisions required by CRs with an optimal k in the K-out-of-N rule under differing false alarm rates. This systematic approach maximizes PD while maintaining PFA within acceptable limits. We designed an architecture with six cognitive radios (6CRs) and implemented an optimal value of k=2 to detect the signal accurately in a wideband spectrum sensing scenario. The fusion center activity is detailed, illustrating how local decisions collected from different cognitive radios (CRs) are aggregated to determine the optimal K value, thereby providing practical insights into the fusion center's operation in real-world settings. The efficacy of the K-out-of-N fusion rule is visualized through the fusion center's rapid and accurate decision-making process, which facilitates timely spectrum sharing among CRs for efficient transmission without interfering with primary users (PUs).

The cooperative spectrum sensing aims to combat the noise uncertainty typically affecting traditional non-cooperative energy detection methods in 5G environments under Additive White Gaussian Noise (AWGN) conditions, assumed to be identically and independently distributed (i.i.d). However, our findings indicate that while cooperative sensing significantly improves detection in scenarios with poor signal-to-noise ratios (SNRs) and higher false alarm rates (between 0.5 and 1), it does not consistently outperform non-cooperative methods at very low false alarm rates (0.01 and 0.1).

We organize the rest of the papers as follows: Section II presents the concept of non-cooperative spectrum sensing and clearly explains the energy detection (ED) technique and non-cooperative wideband spectrum sensing with subbands. In section III, we described the concept of cooperative sensing techniques where we explored the overview of cooperative spectrum sensing as well as the cooperative wideband spectrum sensing with subbands, with the implementation of an optimal value for k needed for 6CRs in k-out-of-N rule algorithm to solve the problem of noise uncertainty in ED in practical scenarios. The simulation results in section IV compare the results of non-cooperative and cooperative spectrum sensing and verify that the detection performance of the cooperative sensing strategy improves across all the poor SNR at higher false alarm rate but has a lower performance at very low SNR and very low false alarm rate. We concluded the paper in Section V.

2. NON – COOPERATIVE SPECTRUM SENSING METHODS

The following< Different detectors' spectrum sensing decisions are based on a binary hypothesis model whereby the signal received might be noise or signal with some noise components.

$$R(t) = \begin{cases} w(t), \; H_0 \\ x(t) + w(t), \; H_1 \end{cases} \qquad 1$$

Where R(t) is the SU's received signal, x(t) is the transmitted signal of the PU observed by the SU, and w(t) is the additive white Gaussian noise (AWGN). The two hypotheses, H_0 and H_1, assume that the PU is absent or present, respectively.

Non-cooperative sensing is regarded as narrow-band spectrum sensing. This is because the detectors individually sensed the spectrum. The non-cooperative spectrum sensing techniques are energy detectors, matched filter Detectors, cyclostationary feature detectors, eigenvalue detectors, and preamble detectors [11]. This section explains the energy detection technique and demonstrates the workings of non-cooperative wideband spectrum sensing.

2.1. Energy Detection

An energy detector is a non-coherent detector that measures the signal energy received from a particular frequency band by measuring the received signal energy and comparing it with an established threshold. The threshold is set considering the value of the noise power. If the signal energy of the received signal lies above a set threshold, the band is declared busy; otherwise, the band is idle and can be accessed by a cognitive user [12]. The architecture of the Energy detector is shown in Figure 2 below:

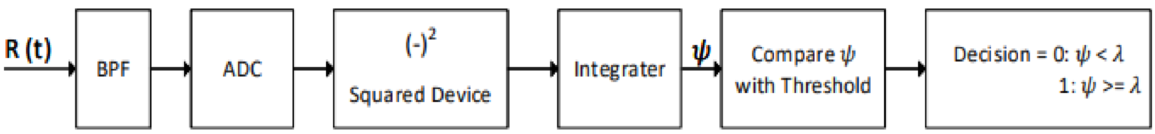

Figure 2: Conventional Energy Detector

The decision statistics, ψ, for energy detection in the time domain are based on the Neyman-Pearson criterion and are given as follows:

$$\psi = \frac{1}{N} \sum_{n=0}^{N-1} |x[n]|^2 \qquad 2$$

Where x[n] represents the sampled signal, and N is the number of samples. A decision for the presence of the primary user is made if ψ exceeds a threshold, λ, which is calculated based on the noise floor to maintain a specific false alarm rate. In the frequency domain, energy detection measures the power P(f) of the received signal at the output of a bandpass filter with bandwidth by the method of periodogram [13].

2.2. Non-Cooperative Wideband Spectrum Sensing

Non-Cooperative Wideband Spectrum Sensing is the process by which a cognitive radio (CR) autonomously identifies and detects signals across a wide range of frequencies [10]. For a wideband non-cooperative sensing, the received signal of a CR is shown to be divided into subbands to emulate the PU subbands as shown in Figure 3:

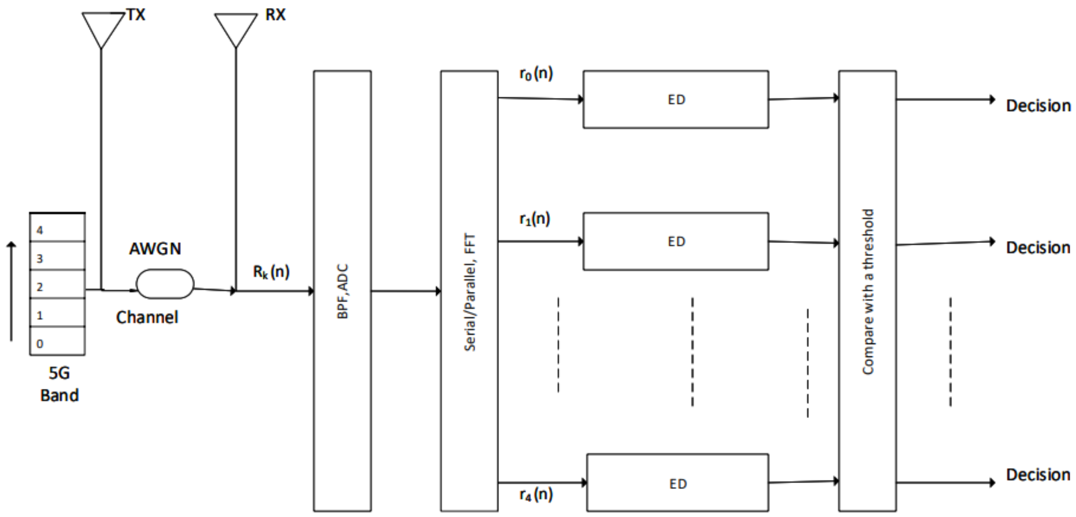

Figure 3: Architecture of Non-cooperative Wideband Spectrum Sensing

The signal from the PU is corrupted by the additive white Gaussian noise (AWGN) and is received by the receiving antenna. Under the null hypothesis (H_0), the received signal $R_m(n)$ for subband m at n is equal to $W_m(n)$

Under the alternate hypothesis (H_1), the received signal, $R_m(n)$ for subband m at n is equal to the transmitted signal $X_m(n)$, scaled by the channel gain and the added noise, $W_m(n)$.
Where each subband m of a single CR with one antenna is defined as:

$$H_o^m : R_m(n) = w_m(n) \qquad 3$$
$$H_1^m : R_m(n) = h_m s_m(n) + w_m(n), \quad n = 0,1,2,\ldots,N-1 \qquad 4$$

$R_m(n)$, $w_m(n)$, $x_m(n)$ is modelled in matrix form as:

$R_m(n)$ = [r (0), r (1), r (2), ……………… ,r_{m-1}(n)]

$w_m(n)$= [w (0), w (1), w (2), ……………,w_{m-1}(n)] 5

$x_m\ (n)$= [x (0), x (1), x (2), …………….., x_{m-1}(n)]

Where $r_i\ (n) = [\ r_i\ (0), r_i\ (1), r_i\ (2), \dots \dots \dots \dots \dots\ ,\ r_i\ (N-1)$ and is the received signal in the i-th subband. , $n = 0,1,2, \dots, N-1$ is the observational sample sequence in the i-th subband, (i Є {0,1,2,…, M-1} and N is the total number of samples used for sensing.

Considering Figure 3, the received signals, $R_m\ (n)$ are filtered and conditioned with BPF, ADC and FFT, to remove noise and interference, ensuring the signals are suitable for further processing.

The energy, Yn is computed for each of the subband and given as:

$$Yn = \sum_{n=0}^{N-1} |R_m\ (n)|^2 \qquad 6$$

The computed energy is compared with a threshold λ, to decide if some of the PU channels are occupied. The threshold λ is calculated in Equation 7 and used for energy detection (ED) under the assumption of complex additive white gaussian noise (AWGN).

$$\lambda = Q^{-1}(Pf).\sqrt{2\left(Ps + \sigma^{2} N\right)} \qquad 7$$

Where Pf is the desired probability of false alarm and Q^{-1} is the inverse Q function. The threshold is correctly set to maintain a specific probability of false alarm, Pf, considering noise power per sample, σ^2 , $\sigma^2 N$ is the total noise power, and Ps being the signal power. Q is the Q-function describing the tail probabilities of the Gaussian distribution, σ^2 is the noise power and the variance of AWGN, N is the number of samples per cognitive user per subband and λ is the detection threshold.

3. COOPERATIVE SPECTRUM SENSING METHOD

3.1. Cooperative Sensing Overview

Cooperative sensing improves detection accuracy through the cooperation of individual detection and by having the benefit of spatial diversity, thereby combating some spectrum sensing problems such as shadowing, fading, and receiver uncertainty issues. All the secondary users are distributed over the entire cognitive radio network (CRN) over a specified distance from the PU transmitter. Each SU senses the whole band and sends its local binary decisions (“1” or “0”) to the fusion center, which makes the final decision. The model architecture of the cooperative spectrum sensing is shown in Figure 4 below:

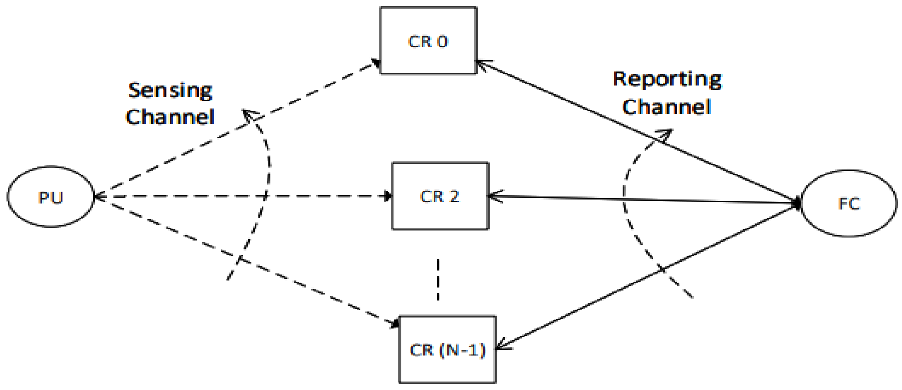

Figure 4: Cooperative Spectrum Sensing System Model

The three steps in the cooperative sensing process are [14]:

1. A particular band of interest is individually sensed by cooperating cognitive radios (CRs)
2. All cooperating CRs' sensing results are sent to the fusion center via a control channel.
3. The fusion center combines all the received sensed information, makes decisions for the presence or absence of a primary user (PU), and reports to the CRs.

By actively utilizing the benefit of spatial diversity, the problems of shadowing fading and noise uncertainty are solved by the CR's cooperation in sharing their individual information at the fusion center, which makes a final binary decision of the presence or absence of the primary user. The cooperative sensing's two primary schemes are soft fusion and hard fusion schemes. In soft-data fusion schemes, all CRs send their sensing data as received energies or soft values to the fusion center without making a local binary decision. Soft-data fusion schemes that different researchers have reviewed are square law selection (SLS), maximal ratio combining (MRC), and selection Combining (SC). In the hard-decision fusion rule, different CR users sense the spectrum and report their local binary decision to the fusion center. Different hard-decision fusion schemes such as OR-rule, AND-rule, Majority rule, and K-out-of-N rule are employed to make a binary decision by each CR user. [15]

Logical OR Rule

The logical OR rules establish the presence of a PU if at least one SU detects it. Therefore, the cooperative probability of detection and the probability of false alarm for this rule is evaluated by setting k=1 in [15]

$$P_D^{OR} = 1 - \prod_{k=1}^{K}(1 - P_D,\ k) \quad 8$$
$$P_{FA}^{OR} = 1 - \prod_{k=1}^{K}(1 - P_{FA},\ k) \quad 9$$

The OR rule, which by implication is the 1-out-of-N rule, has the fastest detection performance since its detection happens if at least one of the SUs detects the PU signal. The problem with its reliability is that it has a high probability of false alarm, as noise in any single SU can trigger a false detection

Logical AND Rule

The logical AND rule only decides if all the SUs detect the signal. The cooperative probability of detection and the probability of false alarm for this rule is evaluated by setting k=M in [15]

$$P_D^{AND} = \prod_{k=1}^{K} P_D, k \quad 10$$
$$P_{FA}^{AND} = \prod_{k=1}^{K} P_{FA}, k \quad 11$$

The AND rule requires all SUs to detect the signal before the detector declares the presence of the signal. Although the AND rule can minimize Pfa, it also reduces the probability of detection, especially in noisy environments and where the CRs are spatially diverse

Logical MAJORITY Rule

For the Logical Majority rule, a consensus is made if half or more of the SUs detect the presence of the PU. The cooperative probability of detection and the probability of false alarm for this rule is evaluated by setting k=M/2 in [15]

$$P_D^{MAJ} = \sum_{i=[K/2]}^{K} \binom{K}{i} P_D{}^i (1 - P_D)^{K-i} \quad 12$$
$$P_{FA}^{MAJ} = \sum_{i=[K/2]}^{K} \binom{K}{i} P_{FA}{}^i (1 - P_{FA})^{K-i} \quad 13$$

The MAJORITY rule maintains that at least half of the CR users will detect the signal before the signal's presence is declared. It balances between the OR and AND rules and requires an odd number to declare a clear majority, but it is still not robust in highly heterogeneous networks.
Logical K-out-of-N Rule

A decision is made on whether K out of N SUs correctly detect the PU signal. K- out-of- N rule is adopted in this research and represented by binomial distribution theorem, based on Bernoulli trials, and each trial represents the decision process of each SU [15]; the probability of detection and probability of false alarm, respectively, at the fusion center is given as M=

M/k$P_D^{K-out-of-N} = \sum_{i=K}^{N} \binom{N}{i} P_D{}^i (1 - P_D)^{N-i}$
14

$$P_{FA}^{K-out-of-N} = \sum_{i=K}^{N} \binom{N}{i} P_{FA}{}^i (1 - P_{FA})^{N-i} \quad 15$$

The K-out-of-N rule allows for customization of K and declares the presence of a signal if at least K out of the CR users detects it. It is highly flexible and can be adjusted to specific environmental conditions and network states without system reconfigurations. The main concern is that it requires a careful selection of K, which can balance between detection and false alarm. It can be turned to find the best balance between the PD and PFA based on the environmental conditions, especially as the noise environment changes. Wrongfully selecting K can lead to high false alarms or missed detection.

4. COOPERATIVE WIDEBAND SPECTRUM SENSING

4.1. Architecture Design

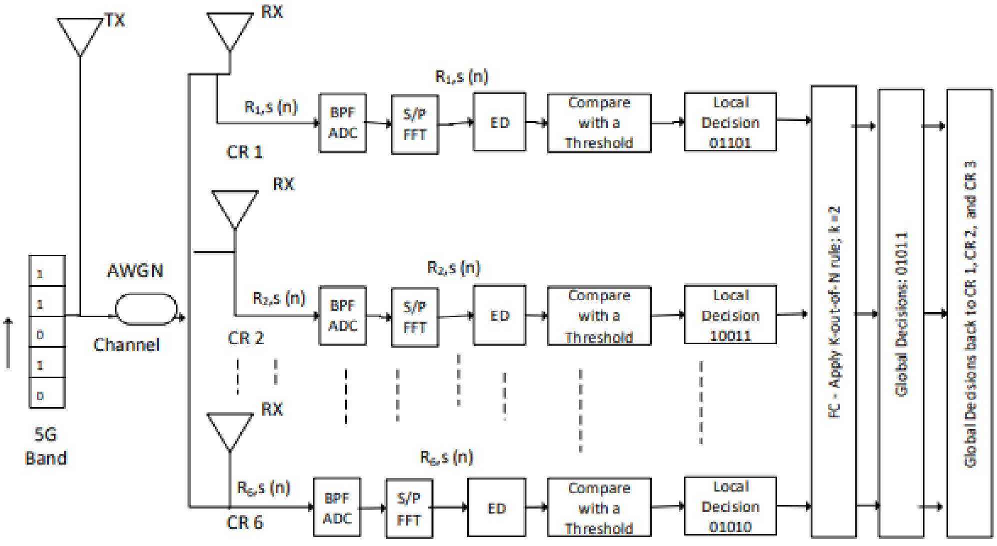

Figure 5: Cooperative Wideband Spectrum Sensing for 6 Cognitive Radio (6CRs)

Here, we partitioned the received signal into five subbands for a channel bandwidth of 100 MHz, giving a total bandwidth of 500 MHz from 3.3 GHz to 3.5 GH to reduce the design's complexity. We implemented the energy detection (ED) technique because of its non-coherency and simplicity, and we proffered a solution to the issue of noise uncertainty by implementing cooperative sensing.

Each cognitive radio (CR1-CR6) receives an analog serial signal through its antenna and contains a wide range of frequency components from various primary user (PU) subbands. The bandpass filter (BPF) is applied to the analog signal to remove frequencies outside the desired bandwidth to prevent aliasing in subsequent stages. The analog-to-digital converter (ADC) converts the filtered analog signal into a digital signal. This process involves sampling the continuous-time analog signal at discrete intervals and quantizing these samples into digital values. The serial digital output of the ADC is converted into multiple parallel streams, and each stream is dedicated to a specific subband to facilitate simultaneous processing of different segments of the signal. This process is essential in 5G networks as it increases throughput and decreases processing time. The fast Fourier transform (FFT) is applied to each parallel stream or subband. FFT is a computational algorithm that converts a time-domain signal into its frequency-domain representation, and it is beneficial in spectrum sensing as it identifies and analyzes specific frequencies within each subband. After FFT, each frequency component or subband has its energy calculated by summing the squares of the magnitude of the FFT output component, representing the power at each frequency. Energy detection is crucial in spectrum sensing as it determines the presence of a signal in a frequency band based on the energy content within that
The local binary decision output from each subband from each CR is sent to the fusion center, which aggregates these decisions using k-out -of-N to make a global decision. A soft optimal k, which in this case is “2,” is implemented for six CRs, and the fusion center makes a global decision on the state of the spectrum. This decision is sent back to each cognitive radio, which can transmit utilizing the free PU’s band.

4.2. The Model

The system is modelled as a binary hypothesis which can be either null, H_o^k or true, H_1^k hypothesis at a given state. [10]

$$H_o^k : S_m^k(n) = W_m^k(n), \; m = 0,1,2,3,\dots,M-1 \quad 16$$
$$H_1^k : S_m^k(n) = X_m^k(n) + W_m^k(n), \; n = 0,1,2,3,\dots,N-1 \quad 17$$

Where $S_m^k(n)$, $X_m^k(n)$, and $W_m^k(n)$ are the received, primary user, and the noise signals, respectively. The matrix representation of the model is given as:

$$\begin{aligned} S_m^k(n) &= [s_m^0, s_m^1, s_m^2, \dots, s_m^{(k-1)}], \\ W_m^k(n) &= [w_m^0, w_m^1, w_m^2, \dots, w_m^{(k-1)}] \\ X_m^k(n) &= [x_m^0, x_m^1, x_m^2, \dots, x_m^{(k-1)}] \end{aligned} \quad 18$$

Model Assumptions:

1. At each cognitive radio (CR), we assume that the noise $W_m^k(n)$, is an Additive White Gaussian noise, which is complex and individually and identically distributed (i.i.d) across all CRs.
2. All CRs are also assumed to be synchronized during the sensing and reporting period.
3. The reporting channel through which the local decisions are communicated to the fusion center is assumed to be error-free.

The model involves multiple cognitive radios working together to determine the presence or absence of a primary user (PU) within a frequency band of 3.5GHz, characterized as a 5G mid-band. The 3.5 GHz band is mainly used in urban and sub-urban coverage as it balances coverage and capacity with better penetration and higher speeds than other higher bands. The received signal is passed through the band pass filter, allowing the specific chosen band to pass through while rejecting other frequencies. This helps to filter out noise, and the detection process is the same as in the non -non-cooperative spectrum sensing described above, Each CR performs local spectrum sensing using an energy detector defined as:

$$Y_m = \sum_{n=0}^{N-1} \left|S_m^k(n)\right|^2 \quad 19$$

The decision at each CR is based on comparing Y_m with a threshold, λ_m

$$D_m = \begin{cases} 1, \; if \; Y_m \geq \lambda_m \\ 0 \quad if \; Y_m < \lambda_m \end{cases} \quad 20$$

The threshold λ for the energy detector is computed using the noise floor and the desired probability of false alarm. The threshold is calculated following the distribution of the noise; in our case, we are working with AWGN. The assumption of AWGN follows a Chi-square distribution when squared values are summed up. Alternately, given N samples and assuming the noise variance, σ^2 is normalized, where σ^2 = 1, the threshold λ for a given PFA can be computed using inverse Chi-square distribution [16].

For a real AWGN channel, the threshold is calculated using the inverse Q-function and the chosen PFA and is given as:

$$\lambda = Q^{-1}(Pf).\sqrt{2\left(Ps + \sigma^{2} N\right)} \qquad 21$$

Where Q^{-1} is the inverse Q-function for the chi-square distribution, PFA is the desired false alarm probability, and 2N is the degree of freedom in the chi-squared distribution for N complex samples. Note, each complex sample contributes to two degrees of freedom, one for the real part and the other for the imaginary part. The σ is the standard deviation of noise, N is the number of samples.

The decision, D_m from all the CRs are sent to a centralized fusion center to perform a global decision. The fusion center aggregates the local binary decision using a fusion rule. In this paper, we implemented a hard decision rule, k-out-of-N, and we performed soft decision by manually selecting the optimal k based on the number of CRs performing spectrum sensing. The final decision, D by the fusion center is as follows:

$$D = \begin{cases} 1, \ if \ \sum_{n=1}^{M} D_m \geq K \\ 0 \quad if \ \sum_{n=1}^{M} D_m < k \end{cases} \qquad 22$$

Where D is the final decision on the presence or absence of the primary user, D_m is the local binary decision from the m-th CR. The decision is “1” if PU is present and “0” if otherwise. M is the total number of CRs involve in the sensing and k is the threshold number of accurate decisions required to declare the presence of the primary user. The performance matrix is based on the probability of detection and the probability of false alarm.

The probability of detection depends on the signal power μ, the noise power σ^2 and the number of samples N. If the signal power is higher than the noise power, the probability of detection can be calculated assuming a non-central Chi square distribution of the test statistics under Hi, which signifies that the signal is present and the PD is given as:

$$P_D = Q\left(\frac{\lambda - \left(Ps + N\sigma^{2}\right)}{\sqrt{2N\sigma^{2}}}\right) \qquad 23$$

Where the signal power is Ps, and 2N is the degree of freedom that accounts for the real and imaginary components of the complex samples.

The PFA is formed under the noise-only signal and given by:

$$P_{FA} = Q\left(\frac{\lambda - N\sigma^2}{\sqrt{2N\sigma^{2}}}\right) \qquad 24$$

Q is the Q-function describing the tail probabilities of the Gaussian distribution, which is the noise power and the variance of AWGN. N is the number of samples per cognitive user per subband and is the detection threshold. Note that the above probabilities apply to a single sensor using an energy detector in noise-only and signal environments.

The K-out-of-N data-fusion rule is best for scenarios where resources are limited or when reducing the system’s complexity and power consumption since not all N cognitive users are involved in the decision process. The probability of detection and false alarm are computed based on binomial distribution and a single sensor’s PD and PFA.

$$.P_D^{K-out-of-N} = \sum_{i=K}^{N} \binom{N}{i} P_D{}^{i}(1-P_D)^{N-i} \tag{25}$$

Where $P_D = Q\left(\frac{\lambda-(Ps+N\sigma^2)}{\sqrt{2N\sigma^2}}\right)$

$$P_{FA}^{K-out-of-N} = \sum_{i=K}^{N} \binom{N}{i} P_{FA}{}^{i}(1-P_{FA})^{N-i} \tag{26}$$

Where $P_{FA} = Q\left(\frac{\lambda-\mathrm{N}\sigma^2}{\sqrt{2N\sigma^2}}\right)$

Algorithm Comparison Between Single CR and Cooperative wideband Spectrum Sensing with multiple CRs (3CR) with K-out-0f-N Data-Fusion Rule

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Input: numCRs, SNR_range, Pfa, MaxPfa, Thresholds, Noise Power
Output: NonCoopPd, CoopPd, OptimalK – Optimal Num. of CRs required to declare detection

```
Initialize: comparison arrays for nonCoopPd and CoopPd across SNR_range
For each SNR in SNR_range do:
Compute detection thresholds for each CR base on noise power and pfa
    If numCRs == 1:
        Compute NonCoopPd using the threshold for a single CR
    Else:
        Initialize local decisions for each CR
        For each CR compute local Pd using the threshold and current SNR
        Initialize maxPd to 0 and optimal k to 1
        For K =1 to numCRs
            Calculate global decisions by applying k-out-of-N rule across CR local decision
        compute CoopPd and pfa for global decisions
        If pfa <= Maxpfa and pd > maxpd then
            optimal k = k
            maxPd = CoopPd
        End if
    End for k
    Store the optimal k for the current SNR
End for each SNR
Return NonCoopPd, CoopPd, and the arrays of values of optimal k corresponding to each SNR
End Algorithm
```

The algorithm shows steps involved in comparing non-cooperative and cooperative detection probabilities in cognitive radio spectrum sensing. Each CR computes its detection threshold based on its noise power and false alarm probability. From the algorithm, we can observe that before cooperative decision-making, an individual probability of detection is calculated to establish a baseline, which in this case is the NonCoopPd. The k-out-of-N rule is applied where the presence of a signal is declared if at least 'k' out of 'numCRs' CRs detect the signal. The algorithm iterates over possible values of k to find an optimal number that maximizes the probability of detection without exceeding the maximum acceptable PFA. We soft-coded 'k =2' for 6CRs to understand the actual implementation of 'k' out of many cognitive radio users in the network. Once a "k" success is made, the fusion center takes a global decision. It simultaneously communicates the result to each CR in the process to enable them to access the available spectrum band.

5. Simulation and Result

All simulations were performed in MATLAB R2023b to evaluate the performance of cooperative and non-cooperative sensing techniques under complex AWGN, which is independently and identically distributed in a 5G wireless network environment. Parameters such as signal-to-noise ratio (SNR), number of CRs, and PFA are varied to determine the probability of detection (PD). We implemented a maximum of 6CRs with k=2 for the cognitive radio network at a 3.5 GHz frequency, and the threshold was set based on the noise floor and acceptable false alarm limit.

The graph of Figure 6 shows a plot of the probability of detection versus the probability of false alarms for non-cooperative sensing under varying SNRs. We observed that poor SNR affects a single CR even with subbands, as some subbands may have occluded signals and, therefore, are unsuitable for 5G networks. From the plot, subband 5 of 0dB had a better detection at 0.01 PFA and might be positioned in the part of the spectrum with less environmental noise.

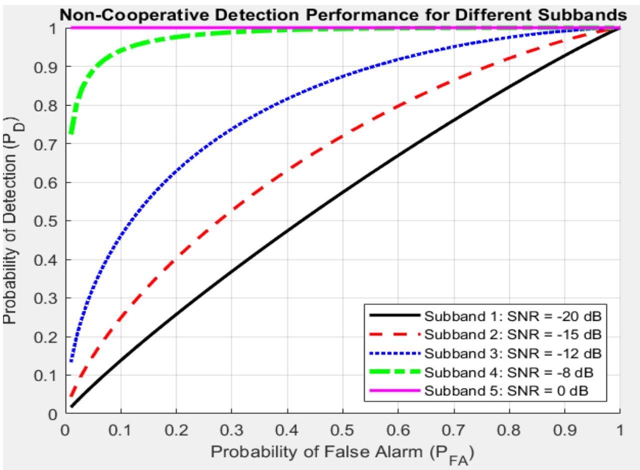

Figure 6: Plot of ROC for Non-Cooperative Spectrum Sensing under varying SNR

In addition, the range of false alarms is chosen from 0.01 to 1, and at 0.1 PFA, the 4th subband of -8dB was able to show an improved detection. As the PFA values increase, the subbands with poor SNR try to detect the PU's signal, which by implication is erroneous as noise can be interpreted as signal. The inability to accurately detect signals at different SNR levels leads to underutilization of spectrum and interference.

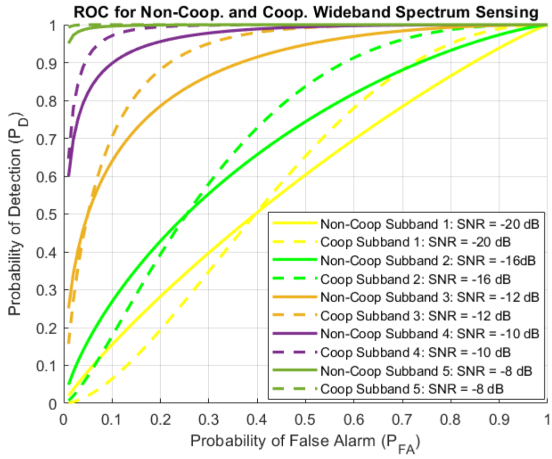

Figure 7: Plot of PD versus PFA for 1 CR and 3CRs at K =2 under varying SNR.

Considering Figure 7, with only three cognitive radios (3CRs), with k= 2, the cooperative sensing is less effective in performance at low SNR compared to the single cognitive radio (1CR). The reason is that with fewer cognitive radios, the noise in individual measurements might not be well averaged out, leading to poor performance, especially at lower PFA and very low SNR, as seen in the plot. There is a tendency that the 2 out of 3 CRs might be affected by noise and hence cannot perform well at a very poor SNR, which may lead to increased vulnerability to false positives. Both cooperative and non-cooperative show progressive improvement as SNR improves as well as an increase in PFA, although the rise in PFA should be avoided to reduce interference.

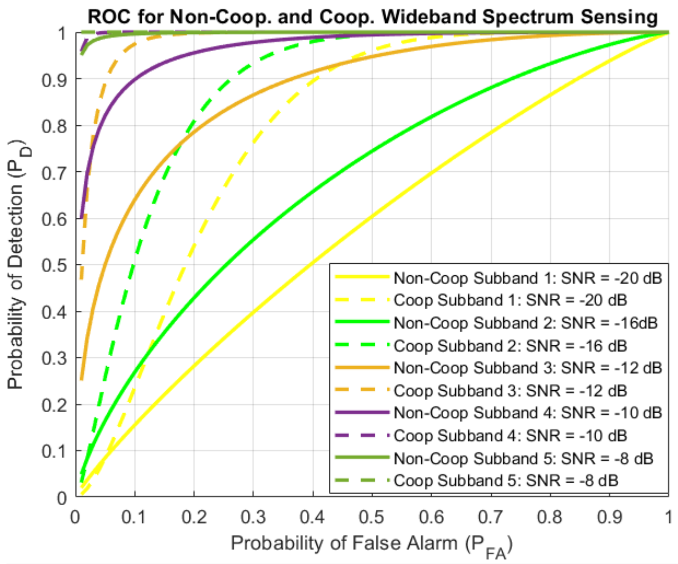

Figure 8: Plot of PD versus PFA for 1 CR and 6 CRs at K =2 under varying SNR

The receiver operating characteristics for 6CRs at k=2 and a single CR show that cooperative sensing only performs better than single cooperative sensing, especially at an improved SNR and higher PFA. It can be observed from the plot that non -cooperative sensing tends to have an initial detection than cooperative sensing, mainly at a very poor SNR and very low PFA of 0,01. We observed that 6CRs with k=2 provide better detection and robustness to the system, as against 3CRs with k =2.

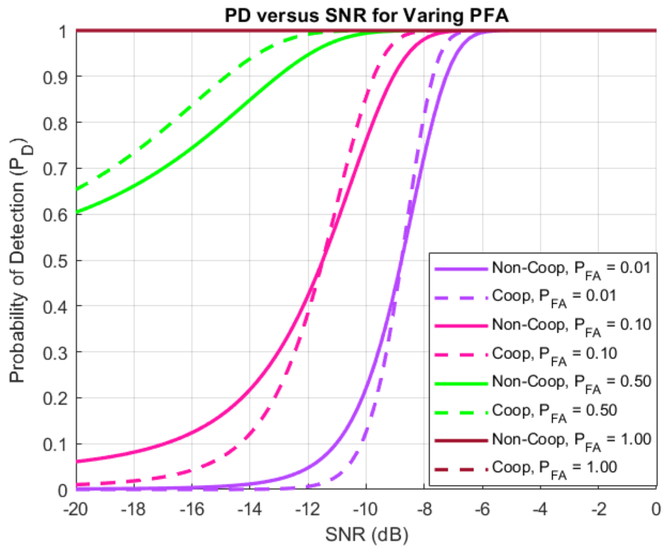

Figure 9: Plot of PD versus SNR for 1CR and 3CRs at k=2 across varying PFA

In Figure 9, non-cooperative sensing shows a higher PD than cooperative sensing, especially at lower PFA values of 0.1 and 0,01 in the scenario of 1CR against k = 2. The cooperative mechanism might not optimally handle information fusion due to the combination of suboptimal data. So, the choice of k=2 for 3CRs might be sub-optimal, especially at an increased poor SNR. In addition, at very low SNRs (-20, -16 dB), all curves start near zero, indicating that cooperative and non-cooperative methods struggle to detect signals under deplorable noise conditions. As SNR approaches 0dB, both methods of detection probabilities increase as the noise level becomes negligible with the signal strength.

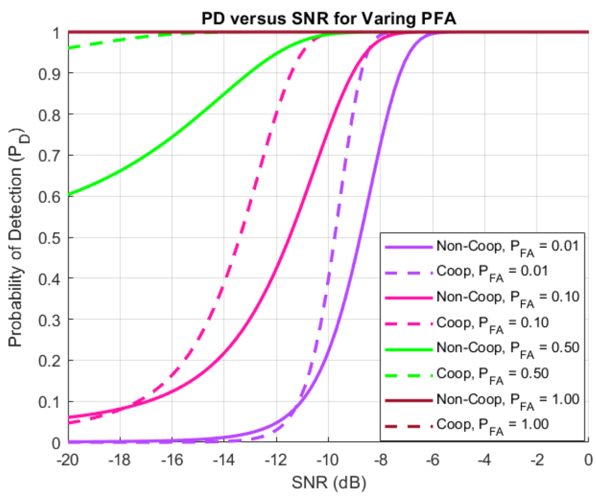

Figure 10: Plot of PD versus SNR for 1CR and 6CRs at k=2 across varying PFA

In Figure 10, with 6CRs and k=2, PD showed a little improvement than the 3CRs with k=2. The low SNR ratio affected the performance of cooperating sensing especially at very low false alarm probability. The cooperative sensing showed an enhanced PD at very low SNR and higher false alarm rate of 0.5 and 1. However, as SNR improves at 0dB, both sensing strategies increase their detection performance. Increasing the number of CRs provides more diversity and redundancy, as it reduces the impact of individual noise and the likelihood of error propagation. The result visualizes how SNR impacts detection performance in spectrum sensing applications especially in cooperative wideband spectrum sensing under complex AWGN channel and 5G environment scenarios, critical for cognitive radio functionality in next-generation networks.

6. CONCLUSION

The study underscores the benefit of energy detectors in enhancing wideband spectrum sensing within cognitive radio networks, which is crucial for achieving optimal spectrum utilization amidst the complexities of the 5G era. Our investigation, focusing on both non-cooperative and cooperative spectrum sensing strategies using energy detection (ED) methods in an Additive White Gaussian Noise (AWGN) channel, which is assumed to be identically and independently distributed (i.i.d), reveals nuanced outcomes. While ROC curve analysis delineates the advantages of cooperative sensing in significantly elevating detection performance in scenarios with extremely low Signal-to-Noise Ratios (SNRs) and higher false alarm rates (ranging from 0.5 to 1), the results were less consistent at very low false alarm rates (0.01 and 0.1). This inconsistency suggests that despite its benefits in specific settings, cooperative sensing does not uniformly surpass the performance of non-cooperative methods under all conditions, especially at a very low SNR.

Implementing the K-out-of-N rule within cooperative strategies effectively enhances the accuracy and reliability of detecting spectrum states under challenging conditions prevalent in dense 5G networks. These networks are characterized by higher traffic and a diverse array of IoT applications, where efficient and reliable spectrum management is indispensable. To our knowledge, the architectures and simulations used in this work is novel and the findings of the performance of cooperative sensing technique across deplorable signal conditions in a complex AWGN channel and different false alarm rates underscores the need for further refinement of this technique to address the diverse operational environments within 5G networks.

Future research will aim to optimize cooperative wideband spectrum sensing strategies further, including integrating a diversity scheme in the energy detection circuitry to enhance SNR and improve the detection capabilities of cooperative sensing techniques within 5G networks. Incorporating machine learning algorithms to dynamically determine the optimal 'k' value with minimal human intervention could significantly propel the autonomous capabilities of cognitive radio networks. These enhancements are crucial for effectively managing the radio spectrum and facilitating dynamic spectrum access in increasingly complex 5G and beyond environments, especially where traditional methods face limitations.

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REFERENCES

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in IEEE Personal Communications, vol. 6, no. 4, pp. 13-18, Aug. 1999, doi: 10.1109/98.788210

[2] Prof. Abhijeet A. Chincholkar, Ms. Chactali H. Thakare,'Matlab Implementation of Spectrum Sensing Methods in Cognitive Radio', Global Journal of Engineering, Science and Research Management, June 2014.

[3] E. Kasem, D. Lekomtcev and R. Marsalek, "Cooperative spectrum sensing in real channel conditions," 2015 13th International Conference on Telecommunications (ConTEL), Graz, Austria, 2015, pp. 1-6, doi: 10.1109/ConTEL.2015.7231192

[4] G. Xiong, S. Kishore and A. Yener, "On performance evaluation of cooperative spectrum sensing in cognitive radio networks," 2010 44th Annual Conference on Information Sciences and Systems (CISS), Princeton, NJ, USA, 2010, pp. 1-6, doi: 10.1109/CISS.2010.5464933

[5] H. Tangsen, L. Xiaowu and C. Qingjiao, "Research on an Evaluation Algorithm of Sensing Node Reliability in Cognitive Networks," in IEEE Access, vol. 8, pp. 11848-11855, 2020, doi: 10.1109/ACCESS.2020.2965292.

[6] Z. Wang, D. Wei and Z. Chen, "Cooperative spectrum sensing over imperfect reporting channels in cognitive radio for Wi-Fi networks," 2013 3rd International Conference on Consumer Electronics, Communications and Networks, Xianning, China, 2013, pp. 203-208, doi: 10.1109/CECNet.2013.6703307.

[7] S. M. Mishra, A. Sahai and R. W. Brodersen, "Cooperative Sensing among Cognitive Radios," 2006 IEEE International Conference on Communications, Istanbul, Turkey, 2006, pp. 1658-1663, doi: 10.1109/ICC.2006.254957.

[8] H. Luan, O. Li and X. Zhang, "Cooperative Spectrum Sensing with energy-efficient Sequential Decision Fusion rule," 2014 23rd Wireless and Optical Communication Conference (WOCC), Newark, NJ, USA, 2014, pp. 1-4, doi: 10.1109/WOCC.2014.6839957.

[9] C. You, H. Kwon and J. Heo, "Cooperative TV spectrum sensing in cognitive radio for Wi-Fi networks," in IEEE Transactions on Consumer Electronics, vol. 57, no. 1, pp. 62-67, February 2011, doi: 10.1109/TCE.2011.5735482

[10] S. Srinu, S. L. Sabat and S. K. Udgata, "Wideband spectrum sensing based on energy detection for Cognitive Radio network," 2011 World Congress on Information and Communication Technologies, Mumbai, India, 2011, pp. 651-656, doi: 10.1109/WICT.2011.6141322.

[11] B. Suseela and D. Sivakumar, "Non-cooperative spectrum sensing techniques in cognitive radio-a survey," 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR), Chennai, India, 2015, pp. 127-133, doi: 10.1109/TIAR.2015.7358544.

[12] P. Semba Yawada, An Jian Wei and M. Mbyamm Kiki, "Performance evaluation of energy detection based on non-cooperative spectrum sensing in cognitive radio network," 2015 4th International Conference on Computer Science and Network Technology (ICCSNT), Harbin, China, 2015, pp. 1036-1040, doi: 10.1109/ICCSNT.2015.7490914.

[13] C. Bin Ali Wael, N. Armi and R. Sariningrum, "Wideband spectrum sensing using Welch periodogram in cognitive radio," 2015 International Conference on Radar, Antenna, Microwave, Electronics and Telecommunications (ICRAMET), Bandung, Indonesia, 2015, pp. 104-108, doi: 10.1109/ICRAMET.2015.7380783

[14] D. Teguig, B. Scheers and V. Le Nir, "Data fusion schemes for cooperative spectrum sensing in cognitive radio networks," 2012 Military Communications and Information Systems Conference (MCC), Gdansk, Poland, 2012, pp. 1-7.

[15] S. Nallagonda, Y. R. Kumar and P. Shilpa, "Analysis of Hard-Decision and Soft-Data Fusion Schemes for Cooperative Spectrum Sensing in Rayleigh Fading Channel," 2017 IEEE 7th International Advance Computing Conference (IACC), Hyderabad, India, 2017, pp. 220-225, doi: 10.1109/IACC.2017.0057.

[16] B. Adhikari and Jamadagni H. S., "Wideband spectrum sensing receiver for cognitive radio application," 2015 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2015, pp. 1-6,

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