Cooperative Fusion Architecture-based Distributed Spectrum Sensing Under Rayleigh Fading Channel

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Abstract
Cognitive radio is one of the most promising technologies due to the spectrum scarcity, especially in the microwave band. Spectrum sensing forms an essential functionality for CR systems. However, such detection performance is usually compromised by shadowing and fading channel conditions. Cooperative sensing is one of the crucial solutions to overcome degraded detection performance. A distributed architecture for the processing and fusion of sensing information is proposed to improve sensing performance and reduce reporting error. The decision fusion for cooperated users could be complex in dense network scenarios and reported sensing traffic may require significant bandwidth. The paper presents a new cooperative distributed PUs detection and proposes dynamic threshold based on controlled probability of false alarm to enhance sensing efficiency and reliability in a Rayleigh fading environments. A cooperative distributed PUs detection is realized by fusion node (FNs) that dynamically selected from the group members. The adaptive detection threshold is computed dynamically using the link quality indicators (LQIs) of the sensing channels. Moreover, the proposed scheme can significantly minimize the typically transmitted bits in the reporting channels. This work also deliberated the design parameters of the CR on the performance of fusion values. The simulation evaluation presents that the adapted threshold considerably improves the performance of the distributed cooperative sensing (DCS) process. The simulation results verified that the error was minimized remarkably. The ROC graph is notably enhanced for the sensing process in term of probability of detection and probability of false alarm. Finally, it was presented that with the proposed scheme the sensitivity requirements could be significantly enhanced up to 0.95.

Keywords
Energy detection · Cognitive radio network; receiver operating characteristic (ROC) · Spectrum sensing; distributed cooperative sensing (DCS) · Detection probability and false alarm probability
1 Introduction

Radio spectrum has become one of the international wealth that creates research and academia attention since early this century. Spectrum bands, especially those between 300 MHz and 10 GHz, become crowded with many wireless technologies, services, and devices. The wireless industry and vendors are looking eagerly for new opportunities for the highly demanded wireless communication market. The industry is now looking forward to a more freely available or unutilized spectrum—for example, 700 MHz for broadband services, auctioned in many countries. As the new spectrum, some state-of-the-art technologies recently have been innovated at Terahertz (THz) and visible light (VL) bands.

The Federal Communications Commission (FCC) report [1] indicates that: some frequency bands in the spectrum are primarily unoccupied most of the time, some other frequency bands are only partially occupied, and the remaining frequency bands are heavily used. Cognitive Radio (CR) is currently considered one of the most promising solutions to the spectrum above scarcity problem and efficient usage of many underutilization licensed frequency bands [2, 3].

Cooperative Cognitive Radio has been introduced to improve the spectrum sharing efficiency, improve the capacity and avoid interference between various radios that work in the same frequency [4–7]. Wireless communications have many impairments, problematic issues, and challenges; these become severe and critical in the cognitive radio arena due to collisions and conflict in the Radio Access Network (RAN). Hidden node problems and synchronization are examples, in addition to many problems that Rayleigh fading may cause. Therefore, one of the critical functions that CR needs to be aware of is detection reliability. Many research and studies have been proposed to increase the detection and sensing reliability to ensure no disturbance can be caused due to coexistence and spectrum sharing. The industry could not reach a consensus for cognitive radio standards due to the high probability of disturbance for the primary users [8].

The cognitive radio may not be able to detect a Primary User (PU) reliably. This is due to the PU signal’s signal-to-noise ratio (SNR) being meager due to Rayleigh fading and shadowing. Weak SNR with high probability can lead to hidden node problems that can cause severe interference problems to the PUs [9–12]. A shadow may hide the Secondary Users (Sus) from the PU transmitter. The PUs receiver may be close enough to the SU not hidden by a shadow from the PU transmitter. Therefore, it may start sending although the PU uses the same frequency, interfering and hence interfering with the intended receiver. Also, [13] shows that when the number of cognitive users increases, the probability of bit error also increases, dramatically reducing spectrum agility.

Due to these problematic issues, cooperative spectrum sensing in cognitive radio has been proposed recently to support the sensing/detection decision and improve the probabilities of false alarm and detection [14–17]. Rayleigh fading channel is the leading cause of low SNR in practice, so many related works have been suggested for the obligation of users’ cooperation to cope with cognitive radio detection. Cooperative sensing achieves diversity gain and can reduce the detection time and thus increase the overall spectrum agility [18]. However, the cooperative sensing performance can be severely degraded due to fading reporting/control channel [19], where the low SNR is commonly used. Also, with a large number of cognitive users, the decision fusion for cooperated users could be complex, and the reporting sensing result may require a large bandwidth [20].

A hard decision auto-correction reporting system is proposed in [21]. An auto-correction scheme is introduced for the reported bit error which then reduces and minimizes the
number of bits in the reporting channels by letting the user with detected information. Even though this method reduced the required bandwidth and energy in the reporting channel due to only a few SUs reporting their observations without hearing from the other users, the spectrum agility can be degraded dramatically with the number of users in the network.

One possible approach to increase spectral agility and decrease the probability of interference of cognitive radios to the existing radio systems is proposed by [22], in which distributed spectrum sensing has been used. In [23], a cluster-based cooperative spectrum sensing method is proposed by separating the secondary users into a few clusters and selecting the most favorable user in each cluster. Another kind of cooperative spectrum sensing was proposed in [2, 24], and [25], where a power-constrained cooperation scheme is discussed. The cognitive user near the PU is regarded as a relay to forward its sensing data to the receiver that receives a weak signal due to fading and shadowing. However, when the number of cognitive users increases, this requires a high bandwidth reporting channel. The probability of error becomes higher, leading to the wrong decision at the fusion point.

The rest of this paper is organized as follows: Sect. 2 presents the system model of the local sensing based on the energy detection and network architecture based on the distributed cooperative sensing (DCS), and cooperation behaviors of the system. Section 3 shows the analytical and simulation results. Finally, Sect. 4 concludes the paper.

2 Main Aim and Contribution

This paper introduces cooperative cognitive radio detection to utilize spatial and temporal diversity for multiuser detection reliability [26–31]. Cooperative spectrum sensing is proposed to overcome the fading, shadowing, and noise uncertainty problems. Cooperating is quite successful in dense urban and urban scenarios due to the number of participated nodes in the cooperative process. Cooperative can also work for broad coverage areas with a reliable answer to the hidden-terminal issue since SUs are apart more than the correlated (shadow, fading) distance, making it unlikely for two SUs to be shadowed instantaneously from the PUs. Related works on cooperative cognitive radio sensing among users [32, 33] have investigated methods where cooperative detection has exploited all users in the cognitive radio network (CRN). Literature proved that this scheme vitally enhanced the detection of reliability of PU activity. The problem statement we are addressing in this paper is as follows:

- Unreliable ED (energy detection) monitoring in local users sensing addition to deficient (faded) reported detection by reporting channel with limited bandwidth under the hypothesis of a large number with long-distance of cognitive users.
- Decision fusion procedure complexity; fusion is a centralized-based idea with many problems such as computation complexity, single point of failure, and energy consumption.

This paper proposes a distributed sensing where the Cognitive Radios (CR) are divided into subgroups. The users perform sensing using ED and then report their observation utilizing auto-correction based on the best SNR reporting channels. Each group does the processing and fusion of spectrum observations by electing one fusion node (FN); fusion node
is selected based on the best signal-to-noise ratio, which we will express here with $\gamma$. the procedure would be like follows:

- The group is collaboratively making the sensing decision,
- FC (fusion center) receives the group decision using the reporting channels.
- The FC calculates the final decisions and final spectrum usage map.

Furthermore, an adaptive medium access control protocol is proposed for data exchange. The noise estimation is also used for the nodes reporting scheduling; the proposed scheme increases sensing time for the delayed scheduled CR nodes. The paper proposed a distributed cooperative sensing (DCS) technique to overcome low SNR caused by the Rayleigh fading report channel, which significantly enhances detection readability in the simulation results and numerical analysis. The detection probability, false alarm probability, and reported bit error rate were examined in the proposed model. As performance metrics to validate and verify the proposed distributed decision fusion architecture for the cooperative spectrum sensing for direct cognitive radio-distributed decision fusion architecture under Rayleigh fading channel and non-cooperative detection. Also, an investigation and optimization of the distributed cooperative gain and an analytical formulation with probable candidate node selection criteria are used.

3 System Model

In the CR network, to recognize white space channels available for transmission, the CR nodes accomplish active detection of the surrounding through (passive) for frequency time and space degrees of freedom [34]. Then, nodes send their local sensing -under a maintained probability of false alarm- to fusion node (FN) users. The fusion user decides the group and forwards the reporting bits to the fusion center (FC). Consequently, the fusion center produces the final decision and final spectrum usage map. The network scenario is shown in Fig. 1. An AWGN channel with squared power path loss is assumed for CR-to-CR & CR-to-FN transmission.

Assuming communication from FN-to-FC faded by Rayleigh characteristics. Moreover, in the network for the cooperative nodes, the distance between any two nodes compared with the wavelength leads to independent fading coefficients [35]. The rationale behind such channel assumptions is that the fusion node (FN)-to-fusion center transmission

![Fig. 1 Network architecture](image-url)
distance is much more considerable than the CR-to-FN and FN-to-FN transmission range when the communication environments are more complex.

3.1 System Design

The system design discusses the distributed cooperative sensing (DCS) methodology, which shows in Fig. 2 that the sensors sense the local environment. The sensing process depends on a threshold to improve the receiver operating characteristic (ROC) and detection efficiency. Each node forwards the sensing information to the group’s fusion node. The fusion nodes in the groups are selected based on a specific criterion. The fusion nodes receive sensing data from all group members then create a fusion database using OR-rule. Then decide which information needs to be forwarded to a fusion center that took the most acceptable decision.

3.2 Distributed Spectrum Sensing

The distributed cooperation architecture is known to have the potential to increase spectral estimation reliability and decrease the probability of interference of cognitive radios to existing radio systems. The Network architecture consists of two essential elements: the sensing group and the Sensing Coordinator (SC) [36–38]. The sensing group is divided into G sensing subgroups which each subgroup performed by n secondary users.

The secondary cognitive radio operates in a distributed cooperative group manner, where the fusion processing of local spectrum sensing for each group [39]. The detection decision at the group level is made to be sent through the best SNR reporting channel. These processes span through both y using PHY parameters. While choosing the group head GH is done through PHY and MAC, based on the best SNR, the groups elect their GH using MAC messaging. This can be performed by using a self-organizing algorithm.

The GH communicates with SC (i.e., a base station (BS)) via the best SNR. The BS uses the Radio Resource Management (RRM) features in the medium access control (MAC) sublayer to generate the spectrum decisions. The flow chart of the decision stages is described in Fig. 3. Algorithm 1 shows the details of the distributed cooperative sensing (DCS) pseudo-code. Figure 4 shows the Distributed sensing stages.

Assume that all channels are to be modeled as Rayleigh fading. Moreover, channels corresponding to different cognitive users are assumed to be independent. Thereby, the signal received at the SU’s antenna can be expressed as follows [40]:

$$s[n] = hx[n] + w[n]$$

where $w[n]$ is the noise which is here we consider it as AWGN, $x[n]$ is the detected signal, $n$ is an indication of many samples for the discrete channel’s index, and $h$ is the impulse response the of fading channels. Here we considered that $x[n]=0$ in the case of no PU signals [41]. We assumed the noise is additive white Gaussian (AWGN) with zero mean and variance $\sigma_w^2$ i.e., $w[n] = N(0, \sigma_w^2)$. In our proposed scheme the noise at the fusion node needs to be calculated to compute the SNR for the channel. Which is proportionally related to $P_e$ a.k.a. BER. The BER for BPSK can be written as $P_b = Q\left(\sqrt{\frac{2\gamma_b}{N_0}}\right)$. $\gamma_b$ is defined as $E_b/N_0$ and sometimes it is called SNR per bit. $\gamma_b = \frac{E_b}{N_0}$. We also, assumed that Rayleigh fading between the nodes in the same group. As shown, in Algorithm 1, the fusion node is computing the gain of all nodes’ channels under the same group.
detection of the primary user signal existence can be generated by comparing the decision metric $M$ against a fixed threshold.
Algorithm 1: The proposed distributed cooperative sensing (DCS) pseudo-code

1. Apply distributed architecture procedure in CRN
2. Apply k-mean method for node grouping
3. Give ID (identification) to all groups
4. For all groups, select the best reporting channel associated with a node and assign it as fusion/relay node
5. Compute gain of channels at the fusion center
6. Announce the fusion/relay nodes for each group
7. For all groups, define the threshold for PU detection
8. Calculate the noise at the fusion/relay node
    compute the $P_f$
9. // Noise calculation is out of this work scope
10. Probability of false alarm is selected as $P_f = 0.1$
11. // Sensing Data collection
12. Compute the detection threshold for $P_f = 0.1$
13. Apply ED in each node in the group given the calculated threshold $P_{received} \leq$ threshold
14. Send ED result to the fusion/relay node
15. // Detection Results
16. Run the decision procedure in the fusion/relay node
17. Run OR_rule for received reports
18. Send the OR_rule results to the fusion center
19. Run the ultimate detection decision procedure at fusion center
20. //Performance evaluation
21. Assess the parameters for the system performance
22. Evaluate ROC parameter
23. Save results’ history and evaluate it with the on/off mode
24. Calculate the $P_e$ for reporting channel
25. Calculate sensitivity level
26. // Feedback for adaptivity
27. Use node_selection procedure to decrease the bandwidth
28. Let nodes with detection information send their decision
29. Modify any no_detection status to detection status
30. Re-calculate the parameters for system performance
31. Store all evaluated performance parameters and bandwidth values


Fig. 3  The decision stages for the distributed cooperative spectrum sensing

![Diagram](image)

To distinguish between the hypothesis testing busy channel, \( H_1 \), and idle channel, \( H_0 \), can be stated as [10]:

\[
H_0 : s[n] = w[n]
\]

\[
H_1 : s[n] = hx[n] + w[n] \quad H_0 : s[n] = w[n]
\]

\[
H_1 : s[n] = hx[n] + w[n]
\]

(2)
Energy detection (ED) is one of the most used techniques to detect and estimate spectrum sensing for unknown signals. The detection of unknown signals using ED the mathematical expression can be modeled as \[42\],

\[
M = \sum_{n=0}^{2N-1} s[n]
\]

(3)

The AWGD is modeled analytically as a random variable with normal distribution with the variance is \(\sigma_w^2\) and mean \(\mu=0\) i.e.

\[
w[n] = N(0, \sigma_w^2)
\]

\[
w[n] = \frac{1}{\sigma_w \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{n}{\sigma_w} \right)^2}
\]

(4)

The decision statistics I is a probability density function which presumed to be chi-square distribution, \(\chi^2\), with a degree of freedom \(k=2N\), in case of the true hypothesis \(H_0\); else, it would be as non-central with (mean \(\mu=0\)) chi-square distribution \(\chi^2\). This is can be represented as:

\[
M \sim \{\chi^2_{2N} \chi^2_{2N(v)}\} H_0 H_1
\]

(5)

If we assumed that the samples are quite large, then the distribution can be approximated as central limit theorem with Gaussian normal distribution using the, so Eq. (5) of the Chi-square distribution \(M\) can be rewritten in the following format \[43\],

\[
M|H_0 \approx N\left(N\sigma_x^2, 2N\sigma_w^2\right)
\]

\[
M|H_1 \approx N\left(N\left(\sigma_x^2 + \sigma_w^2\right), 2N\left(2\sigma_x^2 + \sigma_w^2\right)\right)
\]

(6)

where \(N(\sigma_x^2 + \sigma_w^2)\) a.k.a central limit theorem with Gaussian normal distribution with mean \(\sigma_x^2\) and variance \(b\). The detection threshold \(\lambda\) for a given \(P_f\) can be estimated as \[44\]:

Fig. 4 Distributed sensing stages
\[ \lambda = \sqrt{2N\sigma_x^2Q^{-1}(P_f)} + N\sigma_w^2 \] (7)

where \( Q(a) = \int_{a}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{a^2}{2}} da, \)

Undertake that \( k \) cognitive users are contained in a group of \( G_j \) where \( (K \in K_i) \), where \( K_i \) is the cognitive user’s number in the network which comprises of some number of groups. So, the decision statistics \( M \) for group \( M_j \) that collaboratively sense the PUs can be expressed as

\[
M_j = \sum_{K=0}^{K-1} \sum_{n=0}^{2N-1} s_j[n] \quad (8)
\]

The distribution probability of the cooperative sensing group \( M_j \) approximated as the central limit theorem with chi-square random distribution. The decision statistics \( M \) for group \( M_j \) that collaboratively sense the PUs can be expressed:

\[
M_j|H_1 \sim N\left[N\left(\sum_{K=0}^{K-1} \sigma_{x,j}^2 + J\sigma_{w,j}^2\right), 2N\left(\sum_{K=1}^{K-1} \sigma_{x,j}^2 + J\sigma_{w,j}^2\right)\right] \]

\[
M_j|H_0 \sim N\left(NK\sigma_x^2, 2NK\sigma_w^2\right) \quad (9)
\]

then the detection threshold \( \lambda_j \) for a given \( P_f \) can be estimated as:

\[
\lambda_j = \sqrt{2NK\sigma_x^2Q^{-1}(P_f)} + NK\sigma_w^2 \quad (10)
\]

From (7) and (8) and following the exact derivation in [45–47], then the probability of detection \( P_d \) for the local nodes and sensing group can be written as \( k \) total number of cognitive nodes and \( j \) is the total number of sensing groups as:

\[
P_{d,k} = Q\left(\frac{\lambda - N\left(\sigma_{x,j}^2 + \sigma_{w,j}^2\right)}{\sqrt{2N\left(2\sigma_{x,j}^2 + \sigma_{w,j}^2\right)}}\right) \quad (11)
\]

\[
P_{d,j} = Q\left(\frac{\lambda_j - N\left(\sum_{K=0}^{K-1} \sigma_{x,j}^2 + K\sigma_{w,j}^2\right)}{\sqrt{2N\left(2\sum_{K=0}^{K-1} \sigma_{x,j}^2 + K\sigma_{w,j}^2\right)}}\right) \quad (12)
\]

3.3 Auto-correction

In the cooperative sensing and the ED level, the SUs have to decide that if the PUs signal is detected or not [48]. For that, the integrator output \( Q \) is associated with the threshold \( \lambda \). If the value of \( Q \) is exceeded \( \lambda_2 \), the threshold \( 2\lambda_2 \), a report of the decision \( H_1 \) is taken. The decision of binary 1 is sent to group head GH. If \( Q \) is lower than \( \lambda_1, \lambda_2 \), the threshold two a report the
decision $H_0$ is also taken and the decision of binary 0 1 is sent to fusion node (FN) else “no decision” is considered. This concept can be summarized and calculated as:

$$H_0 | Q < \lambda_1 H_1 | Q > \lambda_2 \text{ no decision } \lambda_2 > Q > \lambda_1$$

(13)

Equation (11) is illustrated in Fig. 5a. To reduce the number of reporter bits, in this paper, we proposed a single reporting bit using the auto-correction technique, where a single threshold $\lambda$ is introduced. If the value of $Q$ is exceeded $\lambda$, a report of the decision $R$ is considered, and the decision of binary one is sent to Fusion nodes (FNs); otherwise, “no decision” decision $R'$ is taken. This is given by:

$$R = \{ 1 | Q > \lambda \text{ no decision } Q < \lambda \}$$

(14)

This can be illustrated as shown in Fig. 5b.

Assume that the group head GH receiver receives $k$ (out of $K$, where $K$ is the cognitive user’s number in the whole network, while $k$ is the number of users per group) local decision by the cooperative cognitive users. Suppose the FN receives locally the decision 0 instead of 1. Here, it’s taken as an error due to the faded and attenuated channel. The decision to be auto-corrected to decision 1 [43].

Under these circumstances, the network efficiency would be high irrespective of the channels conditions. The ultimate sensing decision $H$ is taken based on the coefficient $k'$ at the FN server. If the FN server obtains any local sensing decision 0 or 1, a final decision $H = 1$ is considered. If no local sensing decision is received to the FN server, then a final sensing decision $H = 0$ is considered. This can be illustrated as:

$$H = \{ \text{10k local decisions k} \leq K \text{ no local decision k} = 0 \}$$

(15)

Let $\bar{k}$ denote as normalize a mean number of bits reporting; then:

$$\bar{k} = \frac{k_{\text{avg}}}{K}$$

(16)

$k_{\text{avg}}$ denotes as mean bits number in reporting phase. assume that $R_k$ is the state of $k$ reporting from users, and $R_{k-k}$ is the state of $K-k$ not reporting of cognitive users, from (12), we can write:

$$P\{R_k\} = (P\{Q > \lambda\})^k = (1 - P\{Q < \lambda\})^k$$

(17)

Fig. 5  a A local user using a cooperation sensing detection scheme with double thresholds  b Auto-correction scheme with a single threshold
where \( P \) is the probability. Further, suppose \( P_0 = P\{H_0\} \) and \( P_1 = P\{H_1\} \). So, the mean reporting number of bit is expressed as:

\[
k_{\text{avg}} = P_0 \sum_{k=0}^{K-1} k(Kk)P\{\bar{R}_{K-k}\vert H_0\} + P_1 \sum_{k=0}^{K-1} k\left(\begin{array}{c} K \\ k \end{array}\right)P\{R_k\vert H_1\}
\]

(19)

If \( R'_0 \) and \( R'_1 \) represent the probability of “No report” under the hypothesis \( H_0 \) and \( H_1 \) respectively. Then by using (14), we can write:

\[
\bar{k} = 1 - P_0 R'_0 - P_1 R'_1
\]

(20)

where

\[
R'_0 = P\{Q < \lambda \vert H_0\}, \quad R'_1 = P\{Q < \lambda \vert H_1\}
\]

(21)

Equation (20), indicates that the normalized mean reporting number of bits is continuously \( \bar{k} < 1 \).

### 3.4 Fusion decision (F)

Assume that the SC receivers receive \( j \) group head (GH) decisions where \( j \) is the total number of groups in the network, i.e., \( j = \text{from}0\text{to}J \), which is computed based on \( G_j \) decision reported locally from the cognitive nodes for each group. Then the last detection fusion decision \( F \), is calculated in the FC [49]:

\[
F = \begin{cases} 
1 \sum_{j=1}^{J-1} f_j \geq 1 & \text{0 otherwise} \\
\end{cases}
\]

(22)

\( J \) is denoted as the active group’s number in the cooperative network. These groups can be recognized based on antenna beamforming (BF) in the BS or self-initiation by the users themselves, i.e., utilizing self-healing (-organizing) protocols. Let \( P_{e,j} \) denote the error probability in reporting the group \( j \) ’s sensing decision and let \( \gamma'_j \) denote the SNR for the reporting channel in group \( j \). \( \gamma'_j \) is considered as the reporting channels in the group that has the best SNR (with high channel quality indicators (CQIs)) [50]. If we use Binary PSK for the reporting channels, then the error probability can be written as:

\[
P_{e,j}\gamma'_j = Q\left(\sqrt{2\gamma'_j}\right)
\]

(23)

Therefore, the average probability of error over the Rayleigh fading channels could be expressed as follows [51–53]:

\[
\]
where $Q(.)$ is the Q-Function a.k.a. Marcum function [31] and $J$ is the total cognitive number groups. Then by substituting Eq. (10) in Eq. (23), the network detection probability could be derived in Eq. (25) [54]:

$$P_d = \prod_{j=1}^{J} (1 - P_{d,j}(1 - P_{e,j}) + P_{d,j}P_{e,j})$$

(25)

For analyzing and characterizing our cooperative sensing approach, the main performance parameter and coefficient are detection probability, $P_d$, and false Alarm probability, $P_f$, both $P_f$ and $P_d$ are considered as design parameters for the two performance parameters, received SNR and the threshold of cooperative distributed detection [55, 56]. The proposed method assumes ED, the adaptive threshold of distributed detection is attained by defining the higher allowable probability of false alarm $P_f$. Our technique is assessed and analyzed for detection probability $P_d$ of for a certainly allowed $P_f$ [57].

Let $\gamma'_j$ denote the reporting channel SNR from fusion node $j$ where $\gamma'_j$ is selected as the best SNR channel among all reporting channels in the group, that is $\gamma'_j = \max \{ \gamma_{j,1}, \gamma_{j,2}, \ldots, \gamma_{j,G_j} \}$, where $\gamma_{r,s}$ denotes the channel SNR from the user $g$ in the group $j$ to the fusion center which is exponentially distributed with the same mean value $\gamma'_j$ because they are close to each other [58]. The probability density function $\gamma'_j$ is

$$f(x) = \frac{G_j}{\gamma'_j} e^{-\frac{x}{\gamma'_j}} \left(1 - e^{-\frac{x}{\gamma'_j}}\right)^{G_j - 1}$$

(26)

Typically, the ultimate value for both $P_f$ and $P_d$ are 0 and 1, respectively. However, in practice the $P_f$ and $P_d$ probabilities are required to be more realistic where $P_f$ need to be more relaxed with a range of 0.01–0.5 and $P_d$ with range of 0.1–0.99 [44]. A high probability of false alarm $P_f$ could be set with a low probability of detection $P_d$ to protect the PUs from co-channel interference by SUs. So, to realize that the ROC for the sensing coordinators (i.e., BSs receivers) is computed as:

$$P_d = Q\left(\sqrt{2\beta(\gamma)}, \sqrt{-2 \ln \ln P_f}\right)$$

(27)

where $Q$ is the Marcum’s (a.k.a. Q-) function and $\beta$ is a coefficient depending on the type of modulation, i.e., BPSK $\beta = 1$.

### 3.5 Sensitivity as Gain of Cooperative Sensing

Secondary users should consider to do not surpass the interference harmful probability at the PUs radios, $P_i$. Assume that we have $X$ non-cooperative users which raise the interference level in the network, so all nodes in the network need to make sure that its detection probability is maximum as $P_{d,net} \approx 1 - P_i/X$. If the cooperative radios number ($K$) for
cognitive networks grow, the essential individual node detection probability $P_d$ is enhanced as [12]: $P_d = 1 - \sqrt{1 - P_{d,\text{net}}} = 1 - \sqrt{P_i/X}$ [2]. Looking to the formula one can notice that $K$ related to $X$ in logarithmic format which means as $K$ exceeds $\log X - \log P_i$, the needed $P_d$ dramatically goes to 0.

4 Simulation Design and Architecture

Distributed cooperative cognitive radio (CR) divides radios into groups, fusion node (FN) is elected from each group among all nodes, which should have the most robust SNR channel reporting [59]. The cognitive radio nodes perform local sensing based on ED (energy detection) and send their binary decision to the FN. Figure 6 shows the simulation modeling and DCS architecture. The fusion nodes FNS selection was performed based on the best SNR channel reporting based on the reporting channel SNR to FC (fusion center). The flow chart in Fig. 7 also shows an approach of dealing with new nodes joining or existing nodes leaving the CR network, though, in our simulation, we assumed that no leaving/joining nodes in the fixed architecture scenario.

The simulation architecture of the proposed method, as shown in Fig. 8, considers sensing groups ($J$) with a different number of nodes per group. The user that has the best SNR is selected as the group head (reporter node). Figure 9 shows 30 distributed cognitive radios with different reporting SNR (fusion node (FN) to the fusion center (FC)) where the cognitive nodes are considered an independent and identically distributed, i.i.d with a random and same probability distribution, and all are mutually independent. This scatters distribution setup is used throughout the simulation. The detection thresholds are set without a maintained probability of false alarm.

Reporting SNR, $\gamma'$, is randomly generated for all nodes. Node grouping is performed based on distance metric; we linked our simulation with the routines in the C clustering

![Fig. 6 Simulation design and the DCS architecture](image)
library to perform grouping with the modified K-Means method where $K$ (or $J$) is several groups set to 4 [60]. However, the number of groups considered is changed corresponding to the case. Figures 9 and 10 illustrate the dendrogram and architecture of node grouping, respectively. This method is selected because it performs non-hierarchical and not overlaps groups. Several simulations have been performed, and the simulation settings are changed corresponding to the cases under consideration.

5 Simulation Setup and Performance Evaluation

5.1 Simulation Setup

A simulation environment is utilized to evaluate the proposed DCS scheme, in which we explore the application of DCS on a simulated network. Various scenarios were
examined and simulated; the main idea is illustrated in Fig. 11. The simulation comprises three sections: PUs while representing the primary spectrum nodes with two modes on/off. SUs represent the CR users that intend to share the spectrum. The
SUs are stated and distributed for various groups, as shown in Fig. 10. The proposed scheme is simulated using MATLAB 9.11 [61] with release name R2021b. The simulation parameters are stated in Table 1.

Fig. 10 The simulation scatter distribution setup for i.i.d. 30 distributed cognitive radios with different reporting groups

Fig. 11 Simulation architecture
5.2 Simulation Result

Figure 12 shows the probability of detection $P_{d,j}$ vs. probability of false alarm $P_{f,j}$ for group $G_j$ with $K = 128$ users with different SNR channels for the control/reporting to the coordinator node of cooperative sensing (FN) from the group head (GH). Figure 12 also illustrates the process of selecting the best SNR channel for decision (minor fading and shadowing effects) to improve the spectrum sensing performance. The detection probability per group $P_{d,j}$ increases to near 1 while the probability of false alarm $P_{f,j}$ decreases. This is shown in the SNR = 30 dB, where the values ($P_{f,j}, P_{d,j}$) were $(3.4 \times 10^{-7}, 0.97)$, which is too difficult to implement in real situations.

Figure 13 shows the probability of error for the proposed distributed cooperative spectrum sensing (DCS) approach that derived for each group with a different number of users {$K = 64, 128, 256, \text{ and } 512$}. Figure 13 also shows that the error probability ($P_e$) for fixed

| Parameter                           | Setup                                      |
|-------------------------------------|--------------------------------------------|
| Modulation Method                   | BPSK/QPSK                                  |
| No. of users                        | 64/128                                     |
| No. of created groups               | 4                                          |
| Noise                               | white noise (AWGN)                         |
| PUs Tx power                        | 25 dBm                                     |
| Path loss                           | Free space                                 |
| Channel Model                       | Rayleigh Fading Channel                    |
| Frequency                           | ISM band 2.4 GHz                           |
| $P_f$ (false alarm)                 | 0.1                                        |

Table 1  The parameters set up in the MATLAB simulation
SNR has been enhanced and increased for the reporting phase when the cognitive user’s number increased within the groups.

Figure 14 shows that the direct cooperative spectrum sensing can be degraded when the number of users $K$ increases. Generally, the more concave the ROC curve [62], the better

![Graph showing the relationship between SNR (dB) and Probability of error ($P_e$).](image)

**Fig. 13** Probability of error for sensing groups allocated with a different number of users $K = 64, 128, 256, 512; J = 4$)

![Graph showing the probability of detection ($P_d$) vs. probability of false alarm ($P_f$) for the proposed reporting system using SNR = 10 dB.](image)

**Fig. 14** Probability of detection $P_d$ vs. probability of false alarm $P_f$ for the proposed reporting system using $SNR = 10$ dB
the system performance is, i.e., high probability of detection and low probability of a false match. For instance, if $K = 64$ with our DCS-based fusion node approaches, the optimal ROC values for $P_f$ and $P_d$ are 0.04 and 0.8, respectively.

Benchmarking is conducted by using a similar number of users $K$ and channel with Rayleigh fading characteristics for the previous related scheme proposed in [13]. The optimal ROC values for $P_f$ and $P_d$ are 0.07 and 0.4, respectively. Figure 14 illustrates that normalization of the mean reported bits is dramatically improved when benchmarked with related works in [9], where the two threshold levels schemes show their effectiveness. The censoring phase results in the deterioration of false alarm probability. This is due to the increases in the ‘No decision’ section. Figure 15 shows the benchmarking for autocorrecting selection method vs. two threshold and conventional methods in terms of BER. The evaluation indicates that auto-correction has less BER and better performance (Fig. 16).

5.3 Received Power Sensitivity

The receiver sensitivity level tells us the weakest signal that a receiver will identify and process. It can be improved by reducing the noise level and bandwidth of the receiver. The threshold should be set to three standard deviations away from the mean to have a net probability of false alarm $P_f$ around 0.1.

This places the threshold at: $\alpha_{max}^{1}$ where $\lambda_1 = 2^2 \left( 1 + \sqrt{2(9 + \ln(G_j)/N)} \right)$. The factor $\alpha_{max}^{2}$ is the worst-case noise variance power. If we bound system performance by assuming that all provided samples to Cognitive radio (CR) using the best SNR channel. In that case, the false alarm probability threshold can be set at: $\alpha_{max}^{2}$ where $\lambda_2 = 2^2 \left( 1 + 3 \sqrt{2/G_jN} \right)$ and $G_j$ is the CR nodes number in the group [63].

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![Fig. 15](image-url) The comparison of auto-correction (single threshold) and bi-threshold, the normalized average number of sensing bits $\bar{K}$ vs. $P_f$, $N = 10$, and SNR = 10 dB
To perceive the sensitivity variation, we simulated two sensing groups with the same reporting channel with SNR, $\gamma = 10$ dB. The number of users in all groups was varied, and the effect of 90% and 95% radiosensitivity in a detection probability was examined. The effect of the cooperation process on the sensitivity threshold ($m$) of single radio can be shown in Fig. 17 illustrates the un-bounded enhancement of the

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**Fig. 16** Benchmarking for of autocorrection (single threshold) method vs. two thresholds (a.k.a. two levels quantization) and conventional methods in terms of BER

**Fig. 17** Un-bounded enhancement of sensitivity threshold in m watt with various users and two different detection probabilities ($P_f = 0.1$)
sensitivity threshold in $m$ watt with the various number of users. Sensitivity variation with many users and two different detection probabilities ($P_f = 0.1$). Unbounded means it appears to have no limits, wherein the Figure when we increase the number of users the sensitivity enhancements increased accordingly. If it bounded at specific points, it saturated for a certain constant point or appeared to have a maximum point and returned.

Our ultimate aim is sensing time minimization in a cooperative environment. The average power for the primary channel has to be inspected to calculate the detection probability. In addition to that, energy detection (ED) in the channel, which is the vital coefficient for detection performance. Hereafter it minimizes the sensing phase duration for efficient utilizes of radio resources.

In addition, threshold value and SNR (signal-to-noise ratio) have to be determined to identify the probability of detection in a renewal process [64]. Hence the probability of detection would be efficient based on two major factors with less interference and primary channel transition state. These are two main factors for efficient probability of detection in vehicular networks. In addition to that, the fake SU issue is also a significant concern. However, in cooperative spectrum sensing involvement, a fake user in graduation decreases due to a centralized approach.

6 Proposed Scheme Advantages and Disadvantages

1. The paper proposed a single threshold i.e., adapted threshold based on controlled false alarm probability not only the number of reporting bits but also improve sensing reliability and efficiency. The detection threshold is calculated adaptively using the Link Quality Indicator (LQI) of the sensing highly Rayleigh faded channel environment. The adaptability of the threshold combats the misdetection of data samples near the boundary region.
2. The ED method is a basic sensing technique that does not need any prior knowledge about the PU signal. This method has been considered as the most straightforward method among the other detection methods here. In this work, we use it as our focus in the cooperative fusion architecture-based distributed spectrum sensing. However, if a more sophisticated detection method is used, we can get better performance; however, the cost and complexity of sensing nodes will be increased.
3. Due to the adaptability of the single threshold, it is required to estimate the noise frequently.
4. In a bi-threshold scheme, only OR-rule can be implemented for fusion. Fusion decision is the joining of CR sensing data or data processed from different CR nodes, where data usually have lower uncertainty when using individual nodes. The term uncertainty enhancement means exhaustive, dependable, or accurate. Figure 18 illustrates the analysis and comparison between OR-rule (one-out-of-N) and AND-rule for a different number of candidate node perfusion decision groups. OR-rule is the result of emerging all mutually exclusive sensing reports in a group of cooperative distributed spectrum detection processes compared to AND-rule. The results show that when the false alarm probability is less than 0.04, AND-rule decision based is out-perform OR-rule based decision.
7 Conclusions

The cooperative spectrum sensing and reporting performance in cognitive radio networks can overcome fading impact using a distributed group sensing approach. This is by exploiting the reporting channel selection diversity to enhance reporting stage. The proposed cooperative scheme would have shortened the protocol messages overhead as far as the CR network nodes grow. The paper also proposed an auto-correction scheme for reported bits error. The normalized average number of reported bits is also significantly reduced and enhanced efficiency. The simulation results examined and analyzed the proposed algorithm performance in cooperative spectrum sensing with distributed fusion selection. The numerical simulation and analytical derivation recommend that the algorithm significantly enhance the detection probability, and the number of nodes that cooperate in fusion decision is also reduced. The distributed fusion scheme combined with the conventional ED (energy detection) was modeled to accomplish the best reporting and sensing probabilities. The network throughput is optimized using the receiver operating characteristic curve through the simulation model by varying the sensing time in nodes with a hierarchical multilevel reporting procedure. Other parameters such as clustering and grouping procedures, users per group optimization, space diversity, and coverage area can be considered for further research works.

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**Code availability** The code generated during the current study is available from the corresponding author on reasonable request.

**Declarations**

**Conflicts of interest** All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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