Optimization of secondary user capacity in a centralized cooperative cognitive radio network with primary user under priority

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Abstract
The primary objective of cognitive radio is to maximize the spectrum utilization and the capacity of secondary users under standard parametric constraints. The radiometer, or energy detection, is one of the convenient methods of spectrum sensing under a cooperative communication framework. However, the selection of a suitable threshold is a major issue in order to optimize the secondary user capacity considering primary user on priority. In this article, we investigate a double threshold energy detection scheme and obtain an analytical model for optimum thresholding in diverse fading conditions under the constraint of the probability of detection. We use a meta-heuristic optimization algorithm, namely, the particle swarm optimization with an aging leader and challengers, to observe the effect of varying threshold levels in fusion region, signal to noise ratio (SNR) levels of primary user, and calculate the normalized achievable capacity of secondary user for various fading channels. The results show that, with increasing value of threshold within the decision region, the probability of detection decreases while the normalized secondary user capacity is enhanced. Conversely, the probability of detection increases and the normalized secondary user capacity decreases with increasing values of the SNR level. We also observe the effect of receiver diversity with maximal ratio combining for Nakagami-m fading channel coefficients. The result shows that the probability of detection and normalized capacity decrease with an increase of the number of receiver branches.

KEYWORDS
ALC-PSO, cognitive radio network, optimization, PUOP, SU’s capacity maximization

1 | INTRODUCTION

To alleviate spectrum scarcity due to static allocation policy in existing sub 6 GHz communication, cognitive radio reconnoiter dynamic spectrum allocation in order to utilize the unused licensed spectrum by allowing them to be used by...
secondary users, without causing any harmful interferences to either of the network. The most significant feature of such a scenario is to sense the available spectrum with high accuracy and allocate to unlicensed secondary users.

Ghasemi et al. has given a detailed comparison about different methods for identifying white spaces. Energy detection (ED) is considered to be the simplest and most convenient method in the literature. Sun et al. introduced double threshold energy detection (DTED) technique and showed that the method offered better results under limited bandwidth constraint in comparison to the single threshold method. Zhu further modified the DTED system and proved better performance metrics in the case of additive white Gaussian noise (AWGN) channel. Vien et al has proposed a new hybrid DTED for cooperative spectrum sensing in which they have taken local as well as global decision in account for saving energy and the bandwidth. Number of required CR users and sensing bits are optimized for the DTED by Bhowmick et al. An optimal sensor selection algorithm and ED threshold is developed by Ebrahimzadeh et al. Whereas an optimal fusion rule for cooperative spectrum sensing is given Reference 9 under Rayleigh fading environment and number of optimum users required for decision making at fusion center (FC) is derived for a given error bound. Improved energy detector under Gaussian noise is devised by Chen in which other than squaring operation arbitrary positive power operation is considered for energy calculation. Authors in Reference 11 derived local as well as global optimum thresholds and shown that the decision is carried by weighted fusion based on likelihood ratio test. A hybrid two level threshold detection technique is suggested by authors in Reference 12 where ED is performed in two sequential levels.

Proper trade-off between harvested energy and packet transmission with optimal transmission time allocation for PUs and SUs are key strategy to maximize the total throughput of cooperative cognitive radio network (CRN). To maximize the expected achievable sum throughput of cooperative CRN, in Reference 14 authors addressed throughput maximization problem under the constraint of average tolerable interference to the PU and energy causality at the SU. Similarly, the sum throughput maximization problem in CR assisted device to device network scenario is presented in Reference 15, where authors discussed on the throughput maximization of cellular and D2D users while taking power allocation, channel assignment, user pairing, and transmission time ratio allocation into consideration. Whereas under the constraint of data rate of PU, outage of SU, and reliability of sensing, maximization of sum throughput of cooperative CRN is presented in Reference 16, and the presented model ensured the outperform gain of 25.43% on the sum throughput over the base models. On maximization of throughput of CRN considering energy as the key constraint, in Reference 17 author presents an analytical approach considering SU equipped with full duplex multiple antenna. The results guaranteed that significant improvement in throughput can be achieved even in presence of self-interference. The analysis of throughput in multiuser multiple input and multiple output-based CRN with the usages of weighted eigenvalue-based detection, results depicts the effectiveness of the scheme in enhancement of system throughput with the saving of energy in the CR nodes. In throughput analysis of IEEE 802.11 distributed coordination function with CR network, it could also be observe that when the SU nodes are active, the throughput of SU decreases with the increasing arrival rate of the PU.

In Reference 20, authors present an analytical model to estimate the performance of SUs in heterogeneous spectrum environment of license bands, they analyzed the throughput performance of SU while considering interpool as well as intrapool spectrum handoff in CRN.

The performance of various powerful spectrum sensing techniques are discussed in Reference 21, where author mostly discuss on the challenging aspects of cooperative spectrum sensing to utilize the network resources efficiently. Spectrum sensing is the most important component for setup efficient communication in CRN. The ED scheme of spectrum sensing is mainly considered when no prior knowledge about the PU signals is available. The analysis of cooperative spectrum sensing using “k-out of-n” decision fusion rule for both multipath fading and shadowing is discussed in Reference 23. Where author also discussed on the data fusion scheme of the cooperative spectrum sensing to achieve a comprehensive comparative results. Considering Nakagami-m fading channel, ED scheme of spectrum sensing for multiple PU scenario is investigated in Reference 24, also a close form expression for false alarm and detection probability of PU is deliberated. ED using Bartlett’s estimation is presented in Reference 22, where author derived a cumulative distribution function for both the Rayleigh and Rician fading channels to perform the analysis of unknown signals with complex envelopes. It is observed that Bartlett’s estimation with additional degrees of freedom permit excellence in the performance. In Reference 25, author proposed three generalize detection framework based on the eigenvalue, namely, eigenvalue ratio detector, geometric mean detector (GEMD), and arithmetic mean detector (ARMD) to analysis the spectrum sensing performance. Results show that the performance of the GEMD and ARMD is considerably better in comparison to the traditional ED but lacks in the complexity.

In Reference 26, energy efficient ergodic capacity, outage capacity, and minimum rate capacity is analyzed under the constraint of average and peak transmit power. Here, the authors have discussed about the energy efficiency maximization of SU in delay sensitive and delay in-sensitive CR network with the paradigm of spectrum sharing. The optimization
of SU’s capacity for optimal threshold in double thresholding ED spectrum sensing is not considered by the author in Reference 26. In case when spectrum sensing and channel state information is imperfect, concurrent wireless information and power transfer for resource allocation in CR is considered to be a promising solution. A robust max-min fairness resource allocation problem with infinite inequality constraints is discussed in Reference 27, where authors have analyzed the throughput maximization under the defined power constraint and shows that spectrum sharing based on sensing in wideband CR is comparatively better than traditional spectrum access scheme at the cost of additional complexity. The article did not discuss about optimal secondary user capacity in primary user on priority (PUOP) scenario of a centralized cooperative CRN using ED spectrum sensing scheme. In Reference 28, authors proposed an improved version of the ED scheme to overcome the demerits of traditional ED scheme. Instead of considering only the received signal power for detection an additional optimal exponent varying in [0, 2] is used for observing the detection and false alarm probability and the result showed that the proposed i-ED outperformed ED. The analysis of miss-detection and false alarm probability based on user characteristics in dynamic double threshold energy detection (DDTED) scheme of CRN are presented in Reference 29. The analysis of user characteristics on the performance of cooperative spectrum sensing depicts that the performance of the cooperative CRN is highly influenced by the user characteristics variation. Moreover, the results confirm that the performance of the DDTED is superior to the existing model.

In the present scenario the system model comprises of double threshold detection scheme and uses ED as spectrum sensing technique. We consider a PUOP model to formulate the problem statement. The objective of finding out the optimal secondary user capacity considering SNR and threshold as controlling parameters under the constraint of high probability of detection in a cooperative centralized CRN is not discussed in the literature.

To solve the problem of secondary user capacity maximization under high probability of detection, selection of efficient meta-heuristic optimization technique is an important task. With fast convergence rate, simple algorithm structure, and less parameter to tune, particle swarm optimization (PSO)\textsuperscript{30} could be a choice but has the issue of getting confined at local optima. Thus to avoid this situation, hybrid meta-heuristic optimization techniques are the efficient approach for solving such problems of CR.\textsuperscript{31} Here a variant of PSO, namely, ALC-PSO developed by Chen et al.\textsuperscript{32} is used for the proposed maximization problem. In ALC-PSO a leader is assigned an age or lifespan and the age of leader is controlled by lifespan controller according to the leading capability of the leader. Once the age of the leader is exhausted, new challenger emerges as leader of the swarm if outperforming the existing leader. Hence, the swarm is not confined to a local region as the new challengers are appraising the fitness from the same search space and comparing with existing best which leads the swarm toward global solution. The velocity $v_i$ and position $X_i$ update equation is as below:\textsuperscript{32}:

$$v_i^{t+1} \leftarrow w \cdot v_i^t + c_1 \cdot r_1^t (p_{Best}^t - x_i^t) + c_2 \cdot r_2^t (Challenger^t - x_i^t),$$

$$X_{i+1} = X_i + v_i^{t+1},$$

(1)

where $w$ is the inertia weight, $c_1$ is acceleration parameter for local search, $c_2$ is acceleration parameter for global search, $i$ and $j$ are particle and dimension of set of variable, respectively.

The proposed model is having double thresholds and one soft decision boundary. The proposed model intend to reduce the soft decision overhead of the network by disallowing insignificant test statistics to merge to central FC. Therefore, finding the optimal threshold is an important aspect in regards of minimizing the network overhead and maximizing the SU’s capacity. In this work, our main objective is to maximize secondary user capacity considering optimal threshold and signal to noise ratio (SNR) under the constraint of high probability of detection in a cooperative centralized cognitive radio with ED spectrum sensing technique. Here, we consider PUOP model ($P_d$ is kept high >0.9)). The system model consists of double threshold for hard decision transmission and soft decision boundary to lessen the number of soft decision SU nodes.

The following are the key contribution of this work

1. We formulate secondary user capacity maximization problem under the constraint of threshold and SNR with AND and OR fusion schemes in a cognitive radio.
2. We evaluate the optimal threshold level within the decision region and required SNR level of primary user signal under the constraint of $P_d \geq 0.9$ for primary users under various fading channels.
3. The performance of the model is analyzed under diverse nonfading and fading channels such as AWGN, Rayleigh, Rician, and Nakagami in terms of parameters such as probability of false alarm, probability of detection.
4. We also observe the effect of diversity reception using maximal ratio combining (MRC) technique under Nakagami fading channel and optimize the results for secondary user capacity maximization.

The rest of the article is organized as follows. In Section 2, the system model and algorithm for channel sensing is presented. In Section 3, the standard formulae of optimum threshold and SNR is established. The Numerical results and observations are presented in Section 4. Finally conclusions are drawn and stated in Section 5.

2 | SYSTEM MODEL

2.1 | Formation of region

All in spectrum sensing for cognitive radio we have to decide between two hypotheses $H_0$ and $H_1$ below.

$H_0$: There is no PU.
$H_1$: There is PU

\[ H_0 : r_i(t) = n_i(t), \]
\[ H_1 : r_i(t) = h_i s(t) + n_i(t), \]

where $r_i(t)$ is received statistics of the $i$th secondary user, $n_i(t)$ is noise in the channel, $s(t)$ is signal from PU, and $h_i$ is channel fading coefficient. We let the noise to be Gaussian distributed with zero mean and $\sigma_n^2$ variance. We assume noise to be uncorrelated with signal $s(t)$. Here channel gain $h_i$ can be modeled as different distribution functions. For our analysis we would take

1. No fading—AWGN channel
2. Rician fading channel
3. Nakagami fading channel

2.1.1 | Energy detection

We undergo ED technique for the spectrum sensing in this work as it is considered to be the simplest and most convenient method. To overcome the limitation in the typical simplification considering improper assumption, an accurate and improved version of the probability density function is derived in Eigenvalue-based cooperative spectrum sensing. Based on finite random matrix, Zhou et al proposed an efficient spectrum sensing algorithm for CRN and observed an improved results from the previous eigenvalue-based algorithm. Where Cholesky decomposition is performed over the covariance matrix to acquire the spectrum sensing.

Though both the techniques presented in References 36, 37 offer better results as compared with the conventional ED, the main reason behind the selection of ED technique are summarized below.

1. ED does not require a priori knowledge about the primary user transmission and it detects spectrum holes based on the sensed energy at the receiver. To perform ED, a CR needs to estimate the energy level in a spectrum band (or channel) for a certain time duration $T_s$ (sensing time).
2. ED is the most popular signal detection method due to its simplicity and ease of circuit implementation. The principle of energy detector is finding the energy of the received signal and compares that with the threshold.
3. ED is not optimal but simple to implement, so it is widely adopted. The signal is detected by comparing the output of energy detector with threshold which depends on the noise floor. To adjust the threshold of detection, energy detector requires knowledge of the power of noise in the band to be sensed.

Conventional ED is shown in the Figure 1 below:

A bithreshold ED scheme is proposed by Sun et al where the authors have developed a cooperative spectrum sensing algorithm which is efficient in the limited bandwidth case for control channel. The proposed method was used to reduce the network overhead originated due to soft decisions transmitted to FC.
We form a soft decision region from $\lambda_1$ to $\lambda_2$ as shown in Figure 2 with putting PU on priority that by right should not be affected by SU. This is done by keeping $P_d$ as high as possible (let 90%). Then we observe the effect of varying the threshold from $\lambda_1$ to $\lambda_2$ on both $P_d$ of PU and capacity of SU.

In double threshold ED, hard decision is performed based value of test statistic $T_i$. If test statistic $T_i$ falls in region-0 ($T_i < \lambda_1$): decide locally by hard decision that there is no PU present. Similarly, if $T_i$ falls in region-2 ($T_i > \lambda_2$): decide by hard decision that there is PU present in the sensed channel. And if $T_i$ falls in region-1 then perform soft decision according to $\lambda_{opt}$ while sending the sensed data to the FC with optimal fusion rule.\(^{38}\)

We calculate test statistics as:

$$T_i = \frac{1}{M} \sum_{t=0}^{M-1} r_i^2(t),$$  \hspace{1cm} (4)

where $M$ equals two times the time-bandwidth product.

As $T_i$ is a summation of $M$ i.i.d. random variables, it will have chi-square distribution. Under $H_0$, $r_i(t)$, as there is noise only (no signal) with zero mean, is centrally distributed chi-square distribution with $M$ degrees of freedom. Under $H_1$, $r_i(t)$ will be noncentrally distributed chi-square distribution with $M$ degrees of freedom and $2\gamma$ as noncentrality parameter from Reference 39.

$$f_{(T_i)}(t) = \begin{cases} \frac{1}{2} \left( \frac{t}{2} \right)^{\frac{M-1}{2}} e^{-\frac{t}{2}} I_{\frac{M-1}{2}}(\sqrt{2\gamma}t) & \text{H}_1 \\ \frac{1}{2^{\frac{M}{4}+1/2}} I_{\frac{M}{2}}(\frac{\gamma}{2}t^2) e^{-t/2} & \text{H}_0 \end{cases}. \hspace{1cm} (5)$$

The algorithm presented in Figure 3 is described in eight steps. In step-1, collection of sampling signal of SU to sense the presence of PU. Evaluation of test statistics is performed in step-2 through received signals from each SU. The formation of decision region (Region-1) is performed in step-3; in region-1 the optimal selection of threshold ($\lambda$) is done on the basis of cooperative decision and through maximizing the capacity of the SU. The hard decision is taken place in regards for PUs presence and absence in step-4. Step-5 is considered as the key step in deciding the optimal location of the threshold, in decision region (Region-2) through application of meta-heuristic optimization algorithm (ALC-PSO). We evaluate the optimal location of threshold in the 30% to 70% range of test statistics within Region-2.

In step-5, initialization of optimization parameter is done in step-5.1. Initialization of position and velocity is evaluated in step-5.3 to step-5.7. The fitness value of the objective function for each particle is evaluated in step-5.10 followed by evaluation of $pBest$ and $gBest$ in step-5.12 and step-5.13, respectively. Update of velocity and current position of each particle is performed in step-5.19 and step-5.20. On checking and evaluation of the guidance power of the leader particle,
Algorithm

Step 1: Every SU take samples to sense PU Signal.

Step 2: Calculate Test Statistics ($T_i$).

Step 3: Formation of decision region by calculating $\lambda_{opt}$ such that $0.3 T_i \leq \lambda_{opt} \leq 0.7 T_i$. That is the decision region is formed in between $(\lambda_1 - \lambda_2)$. Where $\lambda_1 = \lambda_{opt} - 5$ and $\lambda_2 = \lambda_{opt} + 5$.

Step 4: Taking hard decision

- if $T_i \leq \lambda_1$: Detect $H_0$ locally for PU absent.
- if $T_i \geq \lambda_2$: Detect $H_1$ locally for PU present.

Step 5: Finding optimum point of threshold ($\lambda_{opt}$) and optimum value of SINR ($SINR_{opt}$) in the decision region for $0.3 T_i \leq \lambda_{opt} \leq 0.7 T_i$ and $3 \text{dB} \leq SINR_{opt} \leq 18 \text{dB}$.

5.1 Initialize swarm of 500 particle, iteration = 500, Life Span (LS) = 50

5.2 for each particle $i$

5.3 for each dimension $d$

5.4 Initialize position $x_{i,d}$ randomly within the permissible range of $\lambda$ and $SINR$.

5.5 Initialize velocity $v_{i,d}$ randomly

5.6 end for

5.7 end for

5.8 while maximum iteration not reach (start of iteration ‘$k$’) 

5.9 for each particle $i$

5.10 Calculate fitness value of objective function for all particle

5.11 if fitness value $\geq pBest_{i,d}$ in histry

5.12 Set current fitness as $pBest_{i,d}$

5.13 Set best among $pBest_{i,d}$ as $gBest_d$

5.14 end if

5.15 end for

5.16 for each particle $i$

5.17 for each dimension $d$

5.18 Calculate velocity according to equation (1)

5.19 Update position according to equation (1.1)

5.20 end for

5.21 end for

5.22 $k = k+1$

5.23 if $k \geq \text{LS}$

5.24 Generate Challenger by repeat Step 2 to 14.

5.25 Compare challenger with the earlier $gBest_d$ for finding the Global Solution

5.26 end if

5.27 Check for the maximum iteration criteria ($k = \text{maximum iteration}$)

5.28 Report the best solution for threshold ($\lambda_{opt}$) and SINR ($SINR_{opt}$) find by the algorithm.

Step 6: if $T_i \leq \lambda_{opt}$; Send $H_0$ to the fusion center (FC).

- if $T_i \geq \lambda_{opt}$; Send $H_1$ to the fusion center (FC).

Step 7: Fusion Center fuses the result.

Step 8: Obtain global result of sensing.

**FIGURE 3** Algorithm of proposed cooperative spectrum sensing
the algorithm performs step-5.24 to step-5.27 to generate new challenger and updates the gBest solution. Mitigation of the stopping criteria is checked in step-5.28 followed by reporting the optimal threshold and SNR value as a global optimal solution in step-5.29.

After evaluation of optimal threshold value ($\lambda_{opt}$), in step-6 sensing decision is sent to the FC via binary hypothesis testing. In step-7, FCs applied fusion schemes (AND/OR) and final global sensing result is achieved at step-8.

2.2 Average probability of detection over various fading channels

Probability of false alarm and probability of detection are two significant parameters for performance analysis of any CRN, and for binary hypothesis scenario it can be modeled as:

$$P_f = P_r(T_i > \lambda|H_0)$$ \hspace{1cm} (6)

$$P_d = P_r(T_i > \lambda|H_1)$$ \hspace{1cm} (7)

2.2.1 Probability of false alarm

Since for every fading channel, $r_i(t)$ will be same due to absence of PU signal probability of false alarm $P_{fal}$ will be same for all cases. From Equations (5) and (6) we may obtain $P_{fal}$ as Reference 35.

$$P_{fal} = \frac{\Gamma\left(M, \frac{\lambda^2}{2}\right)}{\Gamma(M)}.$$ \hspace{1cm} (8)

2.2.2 Probability of detection

Probability of detection fundamentally depends on channel conditions and threshold. A standard form of $P_{dx}$ various fading conditions are obtained as follows:

**AWGN channel**

For an AWGN channel, $P_{det}$ can be calculated as Reference 35.

$$P_{dAWGN} = Q_M(\sqrt{2\varphi}, \sqrt{\lambda})$$ \hspace{1cm} (9)

where $Q_M(.)$ is generalized Marcum Q function and $\varphi$ is the SNR.

**Rician channel**

For Rician distributed fading environment, $P_{dx}$ can be calculated as Reference 35,

$$P_{dRic} = Q\left(\sqrt{\frac{2\varphi}{K + 1 + \bar{\gamma}}} \cdot \sqrt{\frac{\lambda(K + 1)}{K + 1 + \bar{\gamma}}}, \frac{\lambda(K + 1)}{K + 1 + \bar{\gamma}}\right).$$ \hspace{1cm} (10)

where $K$ is Rician factor or LoS component and $\bar{\gamma}$ is average SNR.

**Nakagami channel**

In case of Nakagami-m distributed channel model $P_{dx}$ can be obtained for two different cases:
1. Without diversity:

In no diversity condition $P_d$ can be calculated as Reference 35.

$$P_{d\text{Nak}} = \alpha \left[ G_1 + \beta \sum_{n=1}^{M-1} \frac{(\lambda/2)^n}{2(n!)} \frac{1}{\Gamma(m+\frac{\lambda}{2m+\frac{\lambda}{2}})} \right],$$  \hspace{1cm} (11)

where

$$\alpha = \frac{1}{\Gamma m \times 2^{m-1}} \left( \frac{m}{\frac{\lambda}{2}} \right)^m,$$  \hspace{1cm} (12)

$$\beta = \Gamma(m) \left( \frac{2\frac{\lambda}{2}}{m+\frac{\lambda}{2}} \right)^m e^{-\frac{\lambda}{2}}.$$

(13)

$$_1F_1(a; b; c)$$ is confluent hyper geometric function and $G_1$ can be calculated for integer $m$ as follows

$$G_1 = \frac{2^{m-1}(m-1)!}{(\frac{m}{\frac{\lambda}{2}})^m} \frac{\frac{\lambda}{2}}{m+\frac{\lambda}{2}} e^{\frac{\lambda}{2}}$$

$$\left[ \left( 1 + \frac{m}{\frac{\lambda}{2}} \right) \left( \frac{m}{m+\frac{\lambda}{2}} \right)^m \sum_{n=0}^{m-2} \frac{1}{n!} \left( \frac{\lambda}{2m+\frac{\lambda}{2}} \right)^{n} L_n \left( -\frac{\lambda}{2m+\frac{\lambda}{2}} \right) \right],$$  \hspace{1cm} (14)

where $L_n(x)$ is the Laguerre polynomial of degree $n$.

2. With diversity:

MRC diversity scheme is considered due to its superiority over other diversity techniques in terms of efficiency and complexity. The signal received after $L$ number of diversity branch combining can be written as Reference 35:

$$y_{MRC}(t) = \sum_{l=1}^{L} h_l^* y_l(t).$$  \hspace{1cm} (15)

The probability of detection for $L$ number of diversity branches is given by Reference 40:

$$P_{d,\text{NAK, MRC}} = 1 - e^{-\frac{\lambda}{2}} \left( \frac{m}{\frac{\lambda}{2} + m} \right)^L \sum_{n=0}^{\infty} \frac{1}{n!} \left( \frac{\lambda}{2} \right)^n \frac{1}{\Gamma(M)} \frac{1}{\Gamma(m+\frac{\lambda}{2})}.$$  \hspace{1cm} (16)

3 \hspace{1cm} FORMATION OF PROBLEM

The main objective of a CR network is to maximize the sum capacity of SU without causing harmful interferences to the PU and hampering quality of service parameters.

For the presented scenario the probability of false alarm in Region-0 with threshold $\lambda_1$ is derived as:

$$P_{fal-0} = p_r(T_i < \lambda_1|H_0) = 1 - \frac{\Gamma(M, \frac{\lambda}{2})}{\Gamma(M)}.$$  \hspace{1cm} (17)

The probability of false alarm in Region-2 with threshold $\lambda_2$ is obtained as:

$$P_{fal-2} = p_r(T_i > \lambda_2|H_0) = \frac{\Gamma(M, \frac{\lambda}{2})}{\Gamma(M)}.$$  \hspace{1cm} (18)

The probability of false alarm within Region-1 (decision zone) is expressed as:

$$P_{fal-1} = p_r(\lambda_1 \leq T_i < \lambda_2|H_0) = \frac{\Gamma(M, \frac{\lambda}{2})}{\Gamma(M)}.$$  \hspace{1cm} (19)
Under AWGN Channel the probability of detection for three sectored regions may be obtained as:

a) For Region-0 with threshold $\lambda_1$ is obtained as:

$$P_{\text{det} - 0} = p_r(T_i < \lambda_1 | H_1) = 1 - Q_M(\sqrt{2\gamma}, \sqrt{\lambda_1}).$$

(20)

b) For Region-2 with threshold $\lambda_2$ is obtained as

$$P_{\text{det} - 2} = p_r(T_i > \lambda_2 | H_1) = Q_M(\sqrt{2\gamma}, \sqrt{\lambda_2}).$$

(21)

c) For Decision zone

$$P_{\text{det} - 1} = p_r(\lambda_1 \leq T_i < \lambda_2 | H_1) = Q_M(\sqrt{2\gamma}, \sqrt{\lambda_{\text{opt}}}).$$

(22)

Quantized values of samples fall into decision zone is sent to FC for combining and fuse to a centralized decision. There are two prominent fusion rules which are widely used:

1. AND fusion: In Bayesian detection if a priori probability of $H_0$ is typically between 0.5 and 0.98 then AND rule is used as optimal fusion and for independent observations with identical thresholds the probability of detection is given as

$$P_{\text{det} - \text{fusion}} = \prod_{i=1}^{N} P_{\text{det} - 1}^i$$

(23)

and probability of false alarm is obtained as:

$$P_{\text{fal} - \text{fusion}} = \prod_{i=1}^{N} P_{\text{fal} - 1}^i.$$ 

(24)

In AND fusion scheme, let $D_i$ be local decisions then, if $\Lambda(FC) = 1$ FC decides the presence of PU else absent, where $\Lambda(FC) = \prod_{i=1}^{N} D_i$.

2. OR Fusion: In Bayesian detection framework if a priori probability of $H_0$ is in between 0.012 and 0.5 then OR fusion rule is specified to be optimum. The performance measuring parameters under such fusion scheme are given by

$$P_{\text{det} - \text{fusion}} = 1 - \prod_{i=1}^{N} (1 - P_{\text{det} - 1}^i),$$

(25)

$$P_{\text{fal} - \text{fusion}} = 1 - \prod_{i=1}^{N} (1 - P_{\text{fal} - 1}^i).$$

(26)

In OR fusion rule if $\Lambda(FC) \geq 1$ FC decides PU is present else absent where $\Lambda(FC) = \sum_{i=1}^{N} D_i$.

According to Chair-Varshney fusion rule appearance of a primary user can be find out from the threshold test given:

$$\Lambda_0 = \sum_{i=1}^{N} \left[ D_i \log \left( \frac{P_{\text{det} - 1}^i}{P_{\text{fal} - 1}^i} \right) + (1 - D_i) \log \left( \frac{1 - P_{\text{det} - 1}^i}{1 - P_{\text{fal} - 1}^i} \right) \right] + \log \left( \frac{P(H_1)}{P(H_0)} \right).$$

(27)

If the $\Lambda_0 \geq 0$ then FC decides for $H_1$ or else $H_0$.

The SU can send data in two cases:

Case1: There is no PU and SU detects it correctly.

Case2: There is PU but SU miss the detection.

Let $P_{\text{present}}$ denotes the a priori probability of $H_1$, that is, PU being present in a channel and $P_{\text{absent}}$ denotes the probability of $H_0$, that is, PU being absent in a channel. It is observed form the statistical data that $P_{\text{present}}$ is generally very less.
\[ P_{\text{present}} + P_{\text{absent}} = 1. \] \hspace{1cm} (28)

In WRAN system, where frame of total time duration \( T_{\text{frame}} \) consists of sensing slot \( (T_{\text{sense}}) \) and data transmission slot \( (T_{\text{frame}} - T_{\text{sense}}) \) can be used to calculate the secondary user capacity from the above formulated parameter as:

\[
C_{\text{norm}} = \left( 1 - \frac{T_{\text{sense}}}{T_{\text{frame}}} \right) \left( (1 - P_{\text{fal}}) P_{\text{absent}} + (1 - P_{\text{det}}) P_{\text{present}} \right). \hspace{1cm} (29)
\]

As the secondary user capacity maximization is a prior task to solve by the CR. Therefore, here we formulate the objective of the problem for maximization of normalized SU capacity as:

\[
\text{Maximize} \{ C_{\text{norm}} \} \hspace{1cm} (30)
\]

Subject to: \( 0.3 T_i \leq \lambda_{\text{opt}} \leq 0.7 T_i \) and \( 0 \text{dB} \leq \text{SNR} \leq 20 \text{dB} \)
Under the constraint of \( P_d \geq 0.90 \).

4 | RESULTS AND DISCUSSION

For diverse fading conditions we examine the optimum threshold level and SNR values satisfying \( P_d \geq 0.9 \) and maximum normalized capacity of SUs. In first case, the analysis of probability of detection for various threshold values between \( \lambda_1 \) and \( \lambda_2 \) (percentage wise) keeping SNR constant is performed. Similarly, to observe the effect of SNR on \( P_d \) and \( C_{\text{norm}} \), the average SNR level is vary from 0 to 20 dB keeping threshold at a constant value. Table 1 shows the different threshold and SNR levels for different fading channel.

4.1 | AWGN channel

In case of AWGN channel, the optimum value of threshold and SNR for which \( P_d = 0.90 \) are found to be \( \lambda_{\text{opt}} = 9.5 \) and \( \text{SNR}_{\text{opt}} = 9 \text{ dB} \), respectively.

4.1.1 | Effect on probability of detection

Figure 4A shows the characteristics of \( P_d \) vs threshold level in Region-1. Observe that with the increase of threshold from 0% to 100%, the probability of detection is decreases from 0.98 to 0.71. Whereas with increase in SNR the probability of detection increases from 0.32 to 0.99 as shown in Figure 4B. Which depicts that there is a well trade-off exist between threshold level and SNR. Thus proper balancing between these two is necessary to achieve high probability of detection.

4.1.2 | Effect on normalized capacity

With increasing SNR the normalized capacity of SU decreases from 0.845 to 0.78 as shown in Figure 5B due to unavailability of resources which is instinctively justify. On the other hand, with increasing threshold from 0% to 100%, the

| Channel                        | Parameter value | \( \lambda_{\text{opt}} \) | \( \text{SNR}_{\text{opt}} \) |
|-------------------------------|-----------------|---------------------------|-----------------------------|
| AWGN                          | NA              | 9.5                       | 9                           |
| Rician                        | \( K = 4 \)     | 8                         | 15                          |
| Nakagami (without diversity)  | \( M = 4 \)     | 10                        | 14                          |
| Nakagami (with MRC diversity) | \( M = 4 \)     | 9                         | 5                           |

TABLE 1 Different threshold and SNR levels for different fading channel

Abbreviations: AWGN, additive white Gaussian noise; SNR, signal to noise ratio.
Normalized capacity increases from 0.782 to 0.836 as shown in Figure 5A. As $P_d$ decreases with increase of threshold level, the normalize capacity of SU increases and the opposite happens in case of SNR increment. Thus in order to achieve high capacity of secondary user the optimal location of threshold level and SNR are at 9.5 and 9 dB, respectively.

### 4.2 Rician channel

In case of Rician fading channel for having $P_d = 0.90$ and at $k = 4$ we found that the value of $\lambda_{opt} = 8$ and $\text{SNR}_{opt} = 15$ dB. We observe the effect in both cases as previously.

#### 4.2.1 Effect on probability of detection

Here the same analysis is perform as of AWGN. Figure 6 realize that as LoS component is decreased from $k = 4$ to $k = 0$, the maximum probability of detection decreases from 0.97 to 0.91 for varying threshold and 0.92 to 0.81 for varying SNR. Figure 6 depicts the relevant effect of LoS component, threshold level, and SNR parameter on the probability of detection. Observed that at $k = 4$, Probability of detection is maximum.

#### 4.2.2 Effect on normalized capacity

The effect of varying threshold level and SNR on SU’s capacity is observed for different LoS component. As we keep increasing LoS component from 0 to 4 SU has lesser chances to transmit and the capacity decreases from minimum of 0.95 to 0.88 for varying SNR and 0.89 to 0.82 for varying thresholds. It is observed that at $k = 0$, the achieved capacity of SU is maximum.
As shown in Figure 7, with the increment of threshold level and decrement of SNR value the normalize capacity of the secondary user increases. Thus optimal selection of $\lambda_{\text{opt}}$ at 8 and $\text{SNR}_{\text{opt}}$ at 15 dB provides the maximum balancing between the threshold level and SNR in order to achieve high capacity of SU.

### 4.2.3 Probability of detection vs capacity

From the above analysis it can be observed that either probability of detection or SU capacity only can be maximize at a particular time. At the starting edge of region-1 probability of detection is maximum whereas at the end of region-1 capacity of SU is maximum. At a fixed SNR of PU, for different $k$ factors the optimal threshold level selected for required probability of detection and normalized capacity is shown in Figure 8A.

In Figure 8B, we analyse the effect of different SNR levels of PU on different combinations of probability of detection and normalized capacity. From Figure 8A, it can be observe that with the increase of threshold from 0 to 100% of the decision region and probability of detection of PU from 1 to 0.6, normalize capacity of SU increases from 0.82 to 0.98. From Figure 8B given above it is clear that normalize capacity of SU decreases from 0.97 to 0.88 with the increase of SNR from 3 to 18 dB and $P_d$ from 1 to 0.

### 4.3 Nakagami channel

In case of Nakagami fading channel without diversity case, the optimal value of threshold ($\lambda_{\text{opt}}$) and SNR (SNR$_{\text{opt}}$) for having $P_d = 0.90$ at $m = 4$ are of 10 and 14 dB, respectively. Here, we analyse the effect of varying threshold and SNR as previously. Furthermore, we have analyse the results for MRC diversity reception case and found that for having $P_d = 0.90$ with $L = 2$ and $m = 4$ the optimum level of threshold $\lambda_{\text{opt}} = 9$, and required SNR level of PU signal SNR$_{\text{opt}} = 5$ dB.
**Figure 8** Probability of detection and normalized capacity with (A) threshold level in % and (B) different SNR levels for different Rician factor values. SNR, signal to noise ratio.

**Table 2** Percentage change in average probability of detection with different parameter variations

| Kept constant | Changing parameter | Avg. prob. of detection | % Change |
|---------------|--------------------|-------------------------|----------|
| Varying threshold | $L = 2$ | $m = 4$ | 0.884 | 4.30↑ |
| | $m = 2$ | 0.841 | | |
| | $m = 4$ | $L = 2$ | 0.884 | 33.00↑ |
| | | $L = 1$ | 0.554 | |
| Varying SNR | $L = 2$ | $m = 4$ | 0.8588 | 3.78↑ |
| | $m = 2$ | 0.8210 | | |
| | $m = 4$ | $L = 2$ | 0.8588 | 30.24↑ |
| | | $L = 1$ | 0.5564 | |

Abbreviation: SNR, signal to noise ratio.

### 4.3.1 Effect on probability of detection

Observed that with the increasing SNR the probability of detection keep increasing and with the increase of threshold from 0% to 100% in the decision zone, the probability of detection keeps decreasing.

Furthermore, we observe that for decreasing the Nakagami parameter from $m = 4$ to $m = 1$ the probability of detection decreases from a maximum of 0.97 to 0.84 for varying threshold and from 0.99 to 0.87 for varying SNR. It is noticed that at $m = 4$, the probability of detection is maximum. Table 2 shows the percentage change in average probability of detection with different parameter variations.

From Figure 9A it can be observe that for different value of $m$ probability of detection of PU decreases with the increase of threshold level. The variation of $P_d$ of PU with SNR value corresponds to different value of $m$ is shown in Figure 9B.

From the numerical values plotted in Figure 10 it can be observe that with the increase in number of receive branches from 1 to 3 there is a significant increment in the required SNR level of the PU signal. The probability of detection increases from a maximum of 0.5410 to 0.9788 at SNR = 5 dB and threshold = 9 as we increase number of receive branches from $L = 1$ to $L = 3$ for $m = 4$.

With the implementation of MRC diversity the observed optimum value of $P_d$ with respect to threshold level increases up to 6% (as if consider $m = 2$ and $L = 3$) as compare to without diversity case, as shown in Figure 10A. Figure 10B depicts that the $P_d$ increases with SNR, it is also observed that at SNR =3, the value of $P_{det} = 0.88$ with diversity ($m = 1$, $L = 3$) and where $P_d = 0.1$ in without diversity case for $m = 1$. 
### Table 3
Percentage change in average normalized capacity with different parameter variations

| Kept constant | Changing parameter | Avg. normalized capacity | % Change |
|---------------|--------------------|--------------------------|----------|
| Varying threshold | $L = 2$ | $m = 4$ | 0.8664 | 2.91$^{\text{ii}}$ |
| | $m = 2$ | 0.8955 | | |
| | $m = 4$ | $L = 2$ | 0.8664 | 8.45$^{\text{ii}}$ |
| | | $L = 1$ | 0.9509 | | |
| Varying SNR | $L = 2$ | $m = 4$ | 0.8764 | 2.12$^{\text{ii}}$ |
| | $m = 2$ | 0.8976 | | |
| | $m = 4$ | $L = 2$ | 0.8764 | 8.60$^{\text{ii}}$ |
| | | $L = 1$ | 0.9624 | | |

Abbreviation: SNR, signal to noise ratio.

#### 4.3.2 Effect on normalized capacity

Here, we analyse the effect of varying operator on the normalize capacity of SU, first consider the case of without diversity reception in Nakagami fading channel. Table 3 shows the percentage change in average normalized capacity with different parameter variations.

Normalize capacity of SU increases with increasing value of threshold. Where at $m = 1$, the normalized capacity of SU is maximum. As we keep increasing the value of the Nakagami parameter from $m = 1$ to $m = 4$ the normalized SU
FIGURE 11  Normalized capacity for different (A) threshold level in % and (B) SNR level with AND fusion for different Nakagami factor values without diversity. SNR, signal to noise ratio.

FIGURE 12  Normalized capacity for different (A) threshold level in % and (B) SNR level with AND fusion for different Nakagami factor values with MRC diversity. MRC, maximal ratio combining; SNR, signal to noise ratio.

capacity decreases as shown in Figure 11A. On the other hand normalize capacity of SU decreases from 0.975 to 0.862 with the increasing value of SNR from 3 to 18 dB. Though it can be seen that the minimum value of capacity degradation from 0.96 for $m = 1$ to 0.862 for $m = 4$ at SNR = 18 dB as shown in Figure 11B.

In reception with MRC diversity, the variation of normalize capacity with threshold level and SNR is analyzed. From Figure 12A it is observed that the optimum value of normalize capacity decreases with the increment in diversity reception branches that is quite obvious as because with diversity reception $P_d$ of PU increases which has direct impact on the SU capacity. From the simulation results of Figure 12B it can be observed that with increase of number of branches from $L = 1$ to $L = 3$, the $P_d$ increases thus the normalized capacity of a SU falls from a maximum of 0.9632 to 0.7998 at SNR = 5 dB as shown in the Figure 12B above.

4.3.3  Probability of detection vs capacity

The variation of SU’s normalize capacity with SNR and $P_d$ in both diversity and without diversity reception under Nakagami fading channel is analyzed in this section.

First analyzed the case of without diversity reception, and observe how optimal threshold can be chosen for different combinations of probability of detection and normalized capacity at a fixed optimum SNR level of PU as shown in Figure 13A. In Figure 13B the effect of different SNR levels of PU on both probability of detection and normalized capacity of SU for a fixed optimum threshold level is shown.

Form Figure 13A, it can be observe that the optimum value of normalize capacity achieve was 0.98 for $P_d$ of 0.6 and threshold level of 100%. Whereas normalize capacity is high at SNR value of 5 and $P_d$ of 0.6 as shown in Figure 13B. Which justify the result as because the SU capacity seems to be high if the presence of PU is low and observe that with the increase of threshold level a significant reduction in the detection of PU is occur.
FIGURE 13 Probability of detection and normalized capacity with (A) threshold grading in % and (B) different SNR levels for different Nakagami parameter values without diversity. SNR, signal to noise ratio

FIGURE 14 Probability of detection and normalized capacity with (A) threshold grading in % and (B) different SNR levels for different Nakagami parameter values with MRC diversity. MRC, maximal ratio combining; SNR, signal to noise ratio

Next analyse the same for the case of MRC receiver diversity as shown in Figure 14, first the analysis of probability of detection of PU against the normalized capacity of SU with respect to different threshold levels for fixed value of SNR is performed. From Figure 14A, it is observed that the maximum value of achieved optimal normalize capacity value was 0.93 which is less as compare to without diversity case by 0.05 as because with receiver diversity $P_d$ increase by 6%. Further from the Figure 14A, we can perceive the optimal operation threshold parameter at the desired levels of the probability of detection and normalized capacity of secondary user at different severity levels of fading.

From Figure 14B, the effect of receiver diversity branch “$L$” and Nakagami parameter “$m$” to normalize capacity with $P_d$ and SNR can be visualize. Here it is observed that maximum achieved normalize capacity is 0.98 for $L = 1$ and $m = 2$ which was 0.96 for $m = 2$ in without diversity case.

5 | CONCLUSION

In this article, we have analyzed the maximum attainable capacity of secondary user and calculate the value of optimum threshold and SNR under the constraint of probability of detection of PU. Considering the PUOP scheme, analysis the effect of different threshold under diverse fading condition in cooperative spectrum sensing are presented. It is observed that the probability of detection falls with increase in threshold in Region-1 which is intuitively justified as it ensures less number of test statistics within the region. On the other hand the normalize capacity of SUs increased in AWGN, Rician, and Nakagami fading environment. In the analysis of SUs capacity under MRC receiver diversity, it is observed that the increase in receiver diversity causes significant improvement in the probability of detection which results fall in
the normalize capacity of SU. With different diversity schemes, the effect of optimum threshold level in detection of PU, depicts the requirements for achieving maximum normalized capacity of SU.

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CONFLICT OF INTEREST
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