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An Optimized and Trained Model of Cooperative Sensing for Cognitive Radio Networks

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Abstract*: Sensing based spectrum allocation is one of the solutions to bridge the gap between spectrum scarcity and underutilization of allocated spectrum. In this context, cognitive radio technology has become the prominent solution for future wireless communication problems. To accurately detect the spectrum availability, CRN uses cooperative spectrum sensing where N number of selected nodes will be involved in making a decision on spectrum occupation. Various sensing parameters such as sensing duration (τ), decision threshold (λ), number of nodes (N) and decision rule (K) have huge impact on the performance of cooperative spectrum sensing. In addition, there are constraints on energy consumption and protection of licensed user's needs to be considered. Our work focuses on optimization of sensing parameters to maximize the throughput of the cognitive radio network maintaining the energy efficiency and protecting the licensed users from the interference caused by the secondary users. The proposed work uses convex optimization to optimize sensing duration and two-dimensional search algorithm to find the values N and K. Further optimization is done by comparing local decision with cooperative decision.

Keywords*: Cognitive radio, Fusion rule, Cooperative sensing, Detection accuracy, Misdetection, False alarm.

I. INTRODUCTION

In recent years, the emerging trends in wireless devices and services has resulted in increased spectrum scarcity. On the other hand, Federal communication committee (FCC) has stated on underutilization of allotted spectrum in various bands. This has inspired the vision towards the effective utilization and reuse of spectrum bands. . Cognitive radio (CR) technology enables the transmission of unlicensed secondary users in licensed spectrum bands, while preventing incumbent transmission from harmful interference. Cognitive radio enabled communication is a promising technology towards effective spectrum utilization for future wireless communication networks.

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Currently dynamic spectrum access (DSA) is supported by many international standards [1] like 802.11, 802.22 and 802.15 etc, so by sharing the underutilized licensed bands for secondary communication, spectrum demands can be easily met. Maintaining the interference imposed on incumbent users below certain threshold and addressing coexistence issues are major challenges in dynamic spectrum access.

There are variety of sensing algorithms [2] available to detect the spectrum white space such as energy detection, feature based detection, matched filter detection etc.

Matched filter detection is quick and accurate but requires prior information/knowledge about the primary user (PU) signal which is not possible to get in practical scenarios. Feature based technique is simple and accurate method, but it requires more time to detect the cyclo-stationary feature of the signal. Energy detection (ED) is the most preferred spectrum sensing technique because of its simplicity and it doesn't require any information about PU signal in prior.

Several studies have shown that single node spectrum sensing is not accurate enough to sustain the sharing of licensed channel by the secondary user. Thus, to increase the reliability of the spectrum sensing, cooperative based spectrum sensing is employed in cognitive radio networks. Cooperative based spectrum sensing not only improves the detection accuracy, also provides a centralized management system for spectrum sensing, monitoring and allocation which will enable the coexistence of multiple secondary networks without any interference.

Multiple studies have been carried on the optimization of local spectrum sensing parameters (τ, λ). In [3]-[5], authors have worked on the optimization of sensing duration (τ) considering throughput maximization as a primary factor. In another work [6], objective of optimization is to maximize the probability of detection under the limitations of given false alarm rate. The main practical problem with the existing works is that, they all have assumed noise distribution as white Gaussian noise with mean zero but not included any corrective measures to regulate the parameters according to the practical scenarios. Proposed work is emphasized on the optimization of τ towards the throughput maximization subjected to the constraint on detection accuracy and further optimization of τ and λ is done by comparing local decision with global decisions during training period.

Pertaining to cooperative decision making, many researchers [7]-[10] have proposed and implemented different kinds of fusion rules considering the parameters such as communication overhead, processing time, complexity and detection accuracy. The author in [11] jointly optimized the sensing time (τ) and number of nodes required (N) with the objective of throughput maximization but shown any insight into the effect of fusion rule on these parameters.

The optimization of number of nodes (N) is done in [12] for the given τ by assuming same values of P_d and P_f for all participating nodes. Technical details on the selection of nodes among the available nodes are not presented in the literatures. [13], [14] have worked on reducing the number of required nodes and finding the optimal value of K but not shown the details on selection of nodes among the available nodes. In our proposed method, firstly censoring of nodes is done according to their correctness metric and then determined the optimal values of (N, K) keeping all necessary constraints in mind.

The organization of the rest of the paper is as follows: Section I shows the system model for cooperative sensing configuration where all the necessary parameters are defined. Section II is on optimization of local spectrum sensing parameters -decision threshold (λ) and sensing duration (τ). Section III provides the joint optimization of N and K values of the cooperative decision making. We have presented the simulation results of section II and section III in section IV. Conclusions and remarks on the numerical results is described in section V.

II. COOPERATIVE SENSING SYSTEM MODEL

Throughput of the cognitive radio network depends on various sensing parameters mainly sensing duration, detection threshold, number of nodes involved and the decision rule of cooperative system. Cooperative spectrum sensing involves four discrete phases [15]: Local spectrum sensing, local decision reporting, Decision fusion and Global decision broadcasting.

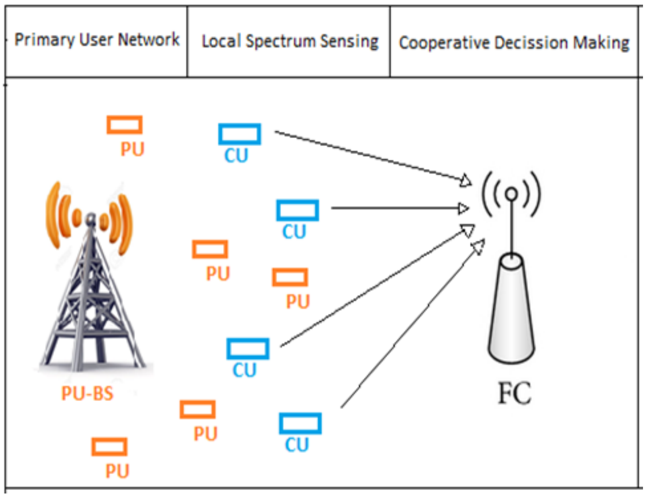

Fig.1. Cooperative spectrum sensing model

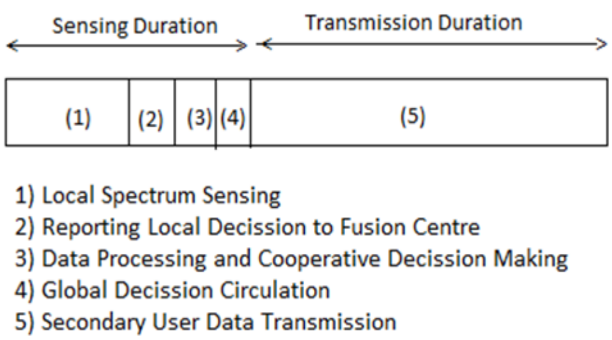

Fig.2.Representation of sensing and transmission period

A. Local node spectrum sensing:

There are different sensing algorithms available to detect the spectrum status such as energy detection, feature based detection, matched filter detection etc. Energy detection is the most preferred technique in single node sensing due to its reliability and low complexity [16]. To make a local decision each cognitive radio user is employed with energy detector which compares the accumulated energy of the received samples with the predefined/dynamic threshold in deciding the presence of primary user signal. Spectrum sensing decision can be modelled as binary hypothesis (1) problem.

$$D(x) = \begin{cases} H_0 & r(x) = n(x) \\ H_1 & r(x) = s(x) + n(x) \end{cases} \tag{1}$$

Hypothesis H_0 indicates the absence of primary user where received signal is only noise n(x) and hypothesis H_1 indicates the occurrence of primary user where received signal is combination of primary signal (s(x)) and noise (n(x)). Here in single node sensing, parameters need to be considered are detection threshold (λ), sensing duration (τ), observed number of samples (M) and received energy (E). Quality of sensing is represented by probability of detection (P_d), probability of misdetection (P_{md}) and probability of false alarm (P_f).

B. Local decision reporting:

Each secondary user identifies the status of PU by energy detection and reports their local decision to fusion center (a centralized system for spectrum management) in their own timeslot via dedicated channel. There are two ways of reporting [17] hard decision reporting and soft decision reporting. Hard decision is very simple and concise way of reporting, sends only the binary information 1 or 0 to indicate the presence or absence of the PU signal. In contrast, soft decision is very precise but not concise, sends additional useful information along with the PU status. To avoid the burden of extra communication overhead caused by the additional information, we use hard decision reporting in our proposed work. In addition to this, number of nodes participated in the cooperative decision making has direct effect on detection accuracy and energy efficiency of the system. Thus, we are addressing the optimization of number of cooperative nodes needed to accurately detect the PU activity under the constraint of energy efficiency.

C. Decision fusion:

Fusion center must collect the local decision from the N selected nodes and make the final decision by adopting an effective fusion rule. Selection of fusion rule depends on the required detection accuracy and network topology. There are few widely used cooperative decision rules [7]-[10] the OR rule, the AND rule, the K out of N rule and machine learning approaches. OR is 1 out of N rule, AND is N out of N rule and K out of N is the flexible rule where K value can be varied as per the requirements. The overall detection probability and throughput of the system depends on the choice of K value.

Thus, in our proposed work we optimize the value of K to maximize the throughput subjected to the constraint on detection accuracy (P_d). The global detection probability (2) and false alarm probability (3) for K out of N rule are expressed as:

$$Q_d = \sum_{i=K}^{N} \binom{N}{i} P_d(\tau,\lambda)^i (1 - P_d(\tau,\lambda))^{N-i} \quad (2)$$

$$Q_f = \sum_{i=K}^{N} \binom{N}{i} P_f(\tau,\lambda)^i (1 - P_f(\tau,\lambda))^{N-i} \quad (3)$$

Where P_d is the probability of detection and P_f is the probability of false alarm of i^{th} node.

D. Global decision broadcasting:

Last step in the cooperative spectrum sensing is the distribution of global decision to all secondary users. This can be done by either broadcasting or by sending through cluster-heads depending on the topology. In our proposed work, we use this global information as a feedback for further optimization of local sensing parameters.

III. LOCAL SENSING OPTIMIZATION

This section of the paper emphasizes on the optimization of sensing duration τ and the corresponding threshold value λ for single node sensing. In the proposed work, we have used energy detection method for local spectrum sensing. In single node energy detection method, the accumulated energy (4) of the M observed samples is computed using the following formula:

$$E = \sum_{i=1}^{M} y(i)^2 \quad (4)$$

Then E is compared with the threshold λ to make local decision:

$$D = \begin{cases} E \geq \lambda & H_0 \\ E \leq \lambda & H_1 \end{cases} \quad (5)$$

The expressions for local probability of detection and false alarm are given by:

$$P_d = Q\left(\frac{\lambda - M({\sigma_w}^2 + {\sigma_x}^2)}{\sqrt{(2M({\sigma_w}^2+{\sigma_x}^2)})}\right) \quad (6)$$

$$P_f = Q\left(\frac{\lambda - M\,{\sigma_w}^2}{\sqrt{(2M\,{\sigma_w}^4)}}\right) \quad (7)$$

The (6) and (7) are represented in terms of SNR γ, sensing time τ, and sampling frequency f_s as equations shown below:

$$P_d = Q\left(\left(\frac{\lambda_i}{{\sigma_x}^2} - \gamma_i - 1\right)\sqrt{\frac{\tau\, f_s}{2\,\gamma_i + 1}}\right) \quad (8)$$

$$P_f = Q\left(\left(\frac{\lambda_i}{{\sigma_x}^2} - 1\right)\sqrt{\tau\, f_s}\right) \quad (9)$$

$$SNR\ \ \lambda_i = \frac{{h_i}^2 {\sigma_x}^2}{{\sigma_w}^2} \quad (10)$$

Where Q(.) is Gaussian distribution function with zero mean and standard deviations σ_u and σ_w for signal and noise respectively.

A. Detection threshold:

In this section, we have discussed threshold optimization problem. Threshold value depends on number of samples observed during sensing interval τ. If f_s is the sampling frequency, then $M=f_s\tau$. Larger sensing duration requires higher threshold value, but what should be the exact threshold value for the given sensing duration? That depends on targeted detection accuracy. For the given sensing duration, increase in detection threshold decreases the probability of detection. However, decrease in detection threshold increases the false alarm rate. So, threshold value should be optimized to satisfy these two conditions $P_d > \overline{P_d}$ and $P_f < \overline{P_f}$.

The performance of the energy detection also depends on noise uncertainty of the channel. If noise energy is too high or the threshold value is too lower than the required value, then the detection error increases. Thus, detection threshold should be set to minimize the detection error as low as possible. Therefor the objective of threshold optimization is to reduce both probability of misdetection and probability of false alarm.

The problem can be described as:

$$\lambda = \arg\max(P_d) \quad \text{st}\ \ P_f < \overline{P_f} \quad (11)$$

OR

$$\lambda = \arg\min\,(P_e) \quad (12)$$

The expression for probability of error P_e is given by

$$P_{ei} = P(H_0)P_{fi} + P(H_1)P_{mi} \quad (13)$$

The solution to the above closed form expression is: [18]

$$\lambda_i = \frac{{\sigma_w}^2}{2} + {\sigma_w}^2\sqrt{\left(\frac{1}{4} + \frac{\gamma_i}{2} + \frac{4\gamma_i + 2}{M\gamma_i}\ln\left(\eta\sqrt{(2\gamma_i + 1)}\right)\right)} \quad (14)$$

Where $\eta = P(H_0)/P(H_1)$

B. Noise effect on sensing threshold:

The threshold value calculated from the expression (14) can be used as initial threshold value to start with but can't be used as final optimized value because P_d and P_f are calculated by approximated Gaussian distribution values. Some of the researchers have proposed SNR based threshold optimization to deal with noise effects. Since P_d and P_f are calculated as a function of noise variance, we have proposed a training-based model where we compare local decision with global decision for certain number of iterations Based on this comparative feedback, threshold value is further optimized to meet the requirements. Iterations are repeated for different scenarios until we achieve the targeted detection probability and false alarm probability (given in algorithm1).

C. Sensing duration optimization:

In this section, we have presented a method to find the optimal value of sensing time τ, by considering total frame duration as T sec and transmission duration as T_r. Throughput of the system can be calculated by the expression (16).

To maximize throughput R, what should be the apt value for τ? Quality of signal estimation directly depends upon the number of samples taken to measure energy or pattern of a signal which actually depends upon the sensing duration. Longer sensing duration yields in accurate spectrum detection but reduces the transmission phase. The increase in sensing duration also produces negative impact on energy efficiency.

On the other hand, shorter the sensing duration, lesser the probability of detection or may increase the burden of retransmission due to miss detection. To calculate the sensing duration/observation period [12], it is necessary to consider parameters such as spectrum efficiency, energy efficiency and expected probability of detection. τ should be such that error probability $P_e < \overline{P_e}$ and maximize the throughput. Thus, we define the problem as follows: Optimization of sensing duration to maximize the throughput R subjected to the condition of expected minimum probability of detection.

$$\begin{aligned} &\tau = \arg\max(R) \\ &st\ \ P_d > \overline{P_d}\ \ \&\ \ P_f < \overline{P_f} \end{aligned} \tag{15}$$

Here R is the unimodal function of τ for the given values of other parameters.

$$R = \left(\frac{T - \tau - NT_r}{T}\right)(1 - Q_f)C_0 P(H_0) \tag{16}$$

We can't find a single expression for τ since it is in non-closed form, but it can be solved by using exhaustive search algorithms. In our work we use convex optimization search algorithm to solve the above defined problem (15).

Algorithm1: Optimization of Sensing during based on the comparative feedback.

Input: T-frame duration, P_d, P_f, P_e, γ.

Initialization: P_d =0.9 (P_{md}=0.1), P_d=0.1, P_e =0.1

1. Find the optimal value of τ using convex optimization.
2. Calculate the corresponding value of threshold for τ.
3. Repeat
   - For the duration τ, compare the measured energy E with threshold and make the local decision.
   - Compare local decision with the received global decision to calculate P_x, P_y and P_z.
   - If local decision and global decisions are same, then add 1 to variable X.
   - eslif, local decision is H_1 and global decision is H_0, then add 1 to variable Y.
   - eslif local decision is H_0 and global decision is H_1, then add 1 to variable z.

   Repeat this for N iteration.
4. Normalize X, Y and Z values to calculate P_x, P_y and P_z respectively.
5. Further optimization of τ and λ is as follows:
   - if ($P_y > P_f$ and $P_z < P_{md}$)
     then increase the threshold value by $\delta\lambda$
   - elseif ($P_z > P_{md}$ and $P_y < P_f$)
     then decrease the threshold value by $\delta\lambda$
   - elseif ($P_y > P_f$ and $P_z > P_{md}$)
     then increases the τ by $\delta\tau$
   - else
     continue with existing (τ, λ) and goto end
6. Repeat step (3) to (5) until $P_y < P_f$ and $P_x < P_{md}$ ($P_e < \overline{P_e}$)

IV. COOPERATIVE SENSING OPTIMIZATION

The main goal of cooperative method is not to relay on decision of one node, instead decision is taken based on the collective opinion of the cooperative nodes.

A. Number of cooperative nodes:

Number of nodes involved in the cooperative decision making has direct effect on detection accuracy and energy efficiency of the system [15]. Thus, we are addressing the optimization of number of cooperative nodes needed to accurately detect the PU activity under the constraint of energy efficiency. From the eqn (16), we can also see that there is a little impact of N on R. However, the value of N has more impact on global detection probability and communication overhead. Thus, the goal is to find the smallest value of N which maximizes the throughput R subjected to the constraint of minimum global probability of detection. The problem can be expressed as:

$$\begin{aligned} &N = \arg\max(R) \\ &st\ \ Q_d > \overline{Q_d}\ \ \&\ \ Q_f < \overline{Q_f} \end{aligned} \tag{17}$$

Overall error probability Q_e is a function of Q_d and Q_f, thus eqn (16) can also be written as

$$\begin{aligned} &N = \arg\max(R) \\ &st\ \ Q_e < \overline{Q_e} \end{aligned} \tag{18}$$

The Values of Q_d and Q_f are calculated using the expressions (2) and (3), but we require P_d and P_f values of all participating nodes. In most of the works [12], P_d and P_f values are assumed to be constant, but they are dependent on network conditions of the node. Considering this problem, first we have performed organization of nodes according to their correctness metric before calculating the optimal values of N.

B. Censoring of nodes [19]**:**

The behavior of a radio environment is always unique, and it can't be calculated or predicted exactly without interacting with it.

Thus, to fix the values of N and K, it is necessary to train the model involving all possible nodes from different geo-locations under different network conditions. We assume that there are N_T secondary nodes, out of which N nodes need to be selected for cooperative spectrum sensing and decision making. To select N nodes from available N_T nodes, following steps are proposed.

1. In test mode, all possible secondary nodes from different geographical locations are involved in cooperative decision making.
2. Data is gathered for say I number of iterations under different network conditions.

3. Based on the test data, correctness metric is calculated for all nodes.
4. Nodes are arranged in descending order according to their correctness metric.
5. Using this huge test data, optimized values for N and k are calculated using two-dimensional search algorithm.
6. After finding the N value, first N nodes from the list are selected as agents for sharing their local decision.

C. Correctness metric:

This metric represents the quality of local decision made by the individual nodes. The simple way of calculating correctness metric is by comparing local decision with the global decision. If local decision is matching with global decision for i^{th} iteration, and then the corresponding node's correctness metric is incremented, otherwise probabilities P_{yi}, P_{zi} are calculated (as given in algorithm1). This comparison is repeated for I iteration. Since the single node decision depends on channel condition, noise uncertainty and SNR etc, correctness metric indirectly represents all the above network parameters.

D. Decision rule K out of N:

What should be the optimal K value? It can be decided by considering the factors affected by the value of K. If we increase K value, it tends towards the AND rule, which will show more spectrum opportunities with less probability of detection. If we decrease K value, it tends towards OR rule, which will reduce the spectrum opportunities but increases the detection accuracy.

The global detection accuracy and throughput of the system is finally decided by the K out of N rule [14]. Fusion rule which we adopt also has effect on the selection of nodes. Since we are using K out of N fusion rule in our proposed work, it is necessary to jointly optimize N and K values to achieve the given objectives.

$$(N, K) = \arg\max(R) \qquad \text{st } Q_d > \overline{Q_d} \;\; \& \;\; Q_f < \overline{Q_f} \tag{19}$$

We used exhaustive search algorithm to solve the objective function (19).

Algorithm 2: Fusion rule optimization- To find the values of N and K and select N nodes from N_T.

Input: P_{d1}, P_{d2}, P_{d3}----P_{d3}, N_T, T, τ, Q_d, Q_f.
Initialization: N_T=15, N=1, I=10
//Training Phase
1. Use Majority fusion rule during training phase
2. Calculate the correctness metric for all N_T nodes.
- Compare the Global decision with the received local decision of node i
- if the decisions are same, increment the correctness metric by 1
- else calculate the P_{yi}, P_{zi} probabilities as shown in algorithm 1
- Repeat this for all nodes for I number of iterations

3. Arrange the nodes in descending order according to their correctness metric.
//finding optimal values of N, K
4. for N $\leftarrow$1 to N_T do
  for K $\leftarrow$ 1 to N do
    calculate R, Q_d, Q_f and Q_e for every (N, K) using equations (16), (2), (3), and (13)
  end
5. Choose the minimum value of N and corresponding K that satisfy the condition shown in (19)

6. Select the first N nodes from the list of N_T.

V. SIMULATION RESULTS

In this section, we present some of the numerical results to verify the performance of our proposed algorithm in comparison to the standard methods (OR and AND fusion rule). Simulations are carried out to find the optimal values of τ (corresponding λ), number of nodes N and decision threshold K to maximize the throughput under the condition of P_d and P_f. Simulation scenario for our proposed algorithm has been formulated to meet all the necessary requirements of IEEE 802.22 WRAN standard [1], [20] and also assumed that secondary network has no prior information about PU activities. We have set N_T=15, frame duration T=20ms, I=10 and sampling frequency 6MHz. The minimum targeted probability of detection is 0.9, maximum allowable false rate is 0.1. These simulations are performed when the SNR of the received signal at the secondary nodes vary from -20dB to 0dB.

A. Sensing duration:

Fig (3) shows that required sensing duration increases as the noise uncertainty increases. We have used convex optimization to find the optimal τ which maximizes R subjected to the conditions of P_d and P_f. It can be observed that, our proposed method gives the similar results as compared to the conventional methods; however proposed algorithm1 for further optimization based on the comparison of local and global decision brings the best results in practice. To check the correctness of the algorithm 1, we have presented following test cases:

Case1: Assumed SNR= -10dB, τ=1.5ms, iterated 10 times and upon comparing local decision with the actual value, we got an accuracy of 80% and 2 false alarm. Then applying our proposed algorithm by setting δλ=0.1λ, got approximately around 90% detection accuracy and 1 false alarm.

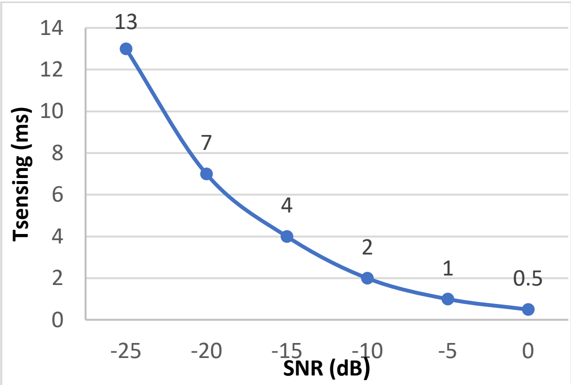

Fig.3. Plot of sensing time for different SNR

Case 2: Assumed SNR= -10dB, τ= 1.5ms, iterated 10 times and upon comparing local decision with the actual value, we got an accuracy of 70% and 3 misdetection. Then applying our proposed algorithm by setting δλ=0.1λ, got approximately around 80% detection accuracy and 2 misdetections. Case1 and case 2 results show that keeping τ constant and just adjusting λ, we can improve the detection accuracy.

Case 3: Assumed SNR= -15dB, τ=2ms, iterated 15 times and upon comparing local decision with the actual value, we got an accuracy of 78%, 2 misdetection and 2 false alarm. Then applying our proposed algorithm by setting δτ =0.1τ, got approximately around 86% detection accuracy, 1 misdetection and 1 false alarm.

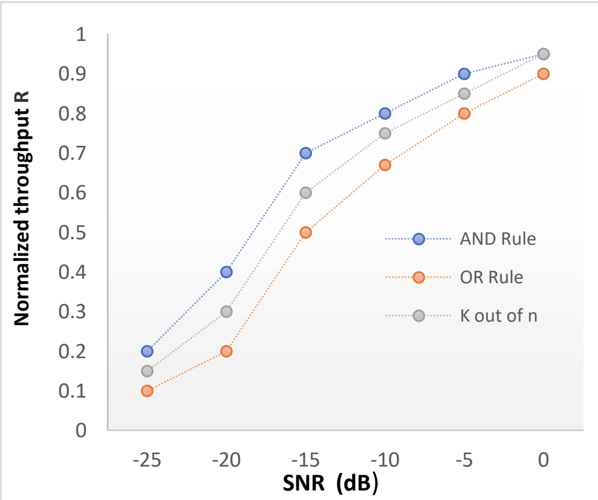

Fig.4. Plot of Throughput for different SNR's

According to Fig (4), AND fusion rule outperforms the proposed K out of N in terms of throughput. However, the number of cooperative nodes required to meet the desired probability of detection is more in case of AND fusion rule.

B. Finding N and K values:

Fig (5) shows the optimal number of nodes required for cooperative decision making to improve the detection accuracy not creating further communication overhead. As shown in algorithm 2, first we organized the nodes by calculating their correctness metric for 10 iterations and then performed two-dimensional exhaustive search to find the values of N and K. Despite calculating the value of N, we have also censored N nodes from the set of N_T. These N nodes are used as agents for cooperative spectrum sensing.

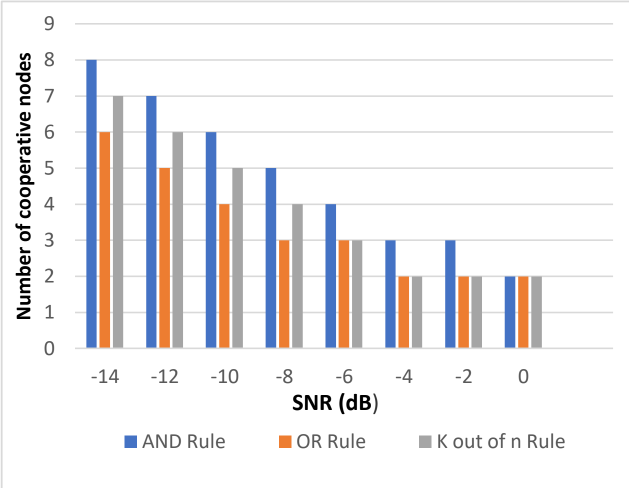

Fig.5. Plot of required N for different SNR values

Fig (6) shows the plot of global probability Qe function of two variables (N, K). The following conclusions can be drawn from the above plots: The performance of K out of N rule lies between OR and AND rule in terms of R, Q_d, and Q_f. However, to maximize the throughput under the constraint of primary user protection, proposed model of K out of N makes the best fusion rule.

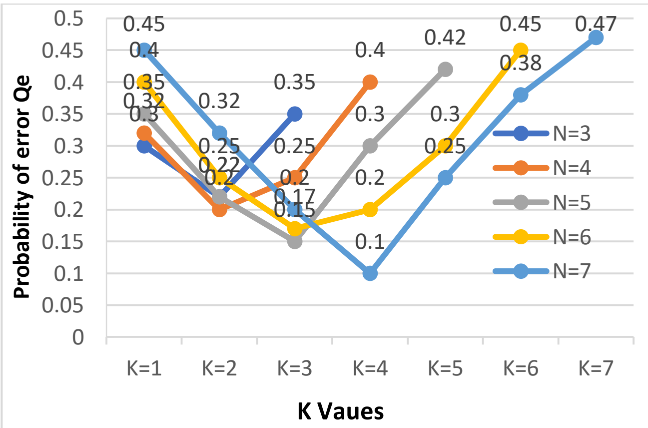

Fig.6. Plot of Global Probability of error versus K values

Most of the existing algorithms have jointly optimized the parameters of local and global decision making. Since we have separated the optimization of local sensing and cooperative decision making, it is also possible to have different sensing durations for different nodes.

VI. CONCLUSION

Cooperative sensing is a reliable method of identifying the spectrum whitespaces with additional communication overhead. In this paper, the throughput maximization problem in cognitive radio network is examined by optimizing the parameters of local sensing and cooperative decision making.

The objective function is solved in two levels: optimization of local sensing parameters (τ, λ) and joint optimization of fusion rule parameters (N, K).

The synchronization between these two levels is brought by comparing local decisions and global decision. The task of reducing the number of nodes and censoring of nodes are also incorporated in the proposed work. Simulation results exhibits the effectiveness of our proposed research work. The further optimization of fusion rule parameters can be done by considering achieved spectrum efficiency and number of retransmissions occurred during the given interval.

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