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Cooperative Spectrum Sensing in Cognitive Radios with Improved Energy Efficiency and Throughput

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Abstract: *In cognitive radio network, improvement in the spectrum efficiency is achieved by employing the cognitive radios that act as secondary users to opportunistically access the under-utilized frequency bands. Spectrum sensing, as a key technology in cognitive radio networks is used to detect the signals from licensed primary radios to avoid harmful interference. However, due to fading, individual cognitive radios may not be able to reliably detect the existence of a primary radio. To mitigate such effects, cooperative sensing is proposed while satisfying a constraint on the detection performance. This paper presents the mathematical derivation for the optimal number of cooperating cognitive radios under two scenarios: energy efficient and a throughput optimization setup. In the energy efficient setup, the number of cognitive radios is minimized for a k-out-of-N fusion rule with a constraint on the probability of detection and false alarm. Hard fusion scheme k-out-of-N is considered due to its improved energy and bandwidth efficiency. In the throughput optimization setup, the throughput of the network is maximized by deriving the optimal reporting time in a sensing time frame subject to a constraint on the probability of detection. Computer simulations show that OR rule outperforms the AND rule both in terms of energy efficiency and throughput optimization with a smaller number of users.*

Keywords: *Cognitive radios, Cooperative Spectrum Sensing, Energy Efficiency, Hard Decision Fusion, Throughput Optimization****.***

I. Introduction

One of the most prominent features of cognitive radio networks is the ability to switch between radio access technologies, transmitting in different portions of the radio spectrum as unused frequency band slots arise [1]. This dynamic spectrum access is one of the fundamental requirements for transmitters to adapt to varying channel quality, network congestion, interference, and service requirements. Cognitive radio networks also called as secondary networks will also need to coexist with legacy ones also called as primary networks, which have the right to their spectrum slice and thus cannot accept interference. Based on these facts, under-utilization of the current spectrum and the need to increase the network capacity is pushing research towards new means of exploiting the wireless medium.

Primary User (PU): A user w o has higher priority or legacy rights on the usage of a specific part of the spectrum.

Secondary User (SU): A user who has a lower priority and therefore exploits the spectrum in such a way that it does not cause interference to primary users.

In this paper we consider a cognitive radio network where each cognitive user makes a local decision about the presence or absence of a primary user. The result is sent to a fusion center (FC) using different time slots for each cognitive user in a time division multiple access (TDMA) approach. The final decision is then made at the FC. Several fusion strategies have been proposed in the literature [3], [4]. We consider a hard decision fusion scheme due to its improved energy and bandwidth efficiency. We employ a k-out-of-N rule with k = 1 (OR) and k = N (AND). In a k-out-of-N rule, the FC decides the target presence, if at least k-out-of-N sensors report to the FC that the target is present [3].

The authors have developed an optimal linear framework for cooperative spectrum sensing in cognitive radio networks [7]. In [10], the cognitive radio network throughput is optimized subject to a detection rate constraint in order to find different system parameters including the detection threshold, sensing time and optimal k for a fixed number of users. However, the effect of the reporting time corresponding to the number of cognitive radios on reducing the throughput of the cognitive radio network has not extensively been studied.

The remainder of the paper is organized as follows. In Section II, we present the key terms used in cognitive radio technology and an illustration for centralized cooperative spectrum sensing process. In Section III, we present the cognitive radio frame structure along with the cooperative sensing system model and provide analytical expressions for the local and global probabilities of false alarm and detection. Simulation results are discussed in Section IV and finally we draw our conclusions in Section V.

II. Spectrum sensing

Spectrum sensing is one of the key enabling functions in CR networks that are used to explore vacant spectrum opportunities and to avoid interference with the PUs. The two main approaches for spectrum sensing techniques for CR networks are primary transmitter detection and primary receiver detection. The primary transmitter detection is based on the detection of the weak signal from a primary transmitter through the local observations of CR users. The primary receiver detection aims at finding the PUs that are receiving data within the communication range of a CR user. In this approach, the main objective is to find the sensing that minimizes the missed detection probability, i.e. determining the spectrum to be unoccupied when there is an active PU, and conversely, the false alarm probability, i.e. incorrectly inferring the presence of a PU in a vacant spectrum band. Several spectrum sensing methods have been proposed which require some knowledge of the potential interferer, including matched filter detection for specific systems and cyclostationary detectors for known modulations based on spectral correlation theory. These methods will be helpful for detecting known primary systems.

Probability of Detection (P_d)

The probability of detection is the time during which the PU (licensed) is detected. The throughput of system depends upon P_d. If the sensing time is increased then PU can make better use of its spectrum and the limit is decided that SU can't interfere during that much of time. More the spectrum sensing more Pus will be detected and lesser will be the interference because PU can make best use of their priority right. Secondary users might experience losses due to multipath fading, shadowing, and building penetration which can result in an incorrect judgment of the wireless environment, which can in turn cause interference at the licensed primary user by the secondary transmission. This raises the necessity for the cognitive radio to be highly robust to channel impairments and also to be able to detect extremely low power signals. These stringent requirements pose a lot of challenges for the deployment of CR networks.

Probability of False Alarm (P_f)

Probability of False Alarm refers to the probability of the sensing algorithm mistakenly detecting the presence of PUs while they are inactive. Low probability of false alarm should be targeted to offer more chances for SUs to use the sensed spectrum. The lower the probability of false alarm, the more chances the channel can be reused when it is available, thus the higher the achievable throughput for the secondary network. From the secondary user's perspective, however, the lower the probability of false alarm, there are more chances for which the secondary users can use the frequency bands when they are available. Obviously, for a good detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible.

Cooperative Spectrum Sensing

The spectrum-sensing capability is critical to enable CR features and enhance spectrum utilization. Local spectrum-sensing techniques do not always guarantee a satisfactory performance due to noise uncertainty and channel fading. For example, a CR user cannot detect the signal from a primary T_x behind a high building, and it may access the licensed channel and interfere with the primary R_x's. Through the collaboration of multiple users in spectrum sensing, the detection error possibility will be reduced by the introduced spatial diversity, and the required detection time at each individual CR user may also decrease. In cooperative spectrum sensing, CR users first send the raw data that they collect to a combining user or fusion center. Alternatively, each user may independently perform local spectrum sensing and then report either a binary decision or test statistics to a combining user. Finally, the combining user makes a decision on the presence or absence of the licensed signal based on its received information.

High sensitivity requirements on the cognitive user can be alleviated if multiple CR users cooperate in sensing the channel. Various topologies are currently used and are broadly classifiable into three regimes according to their level of cooperation.

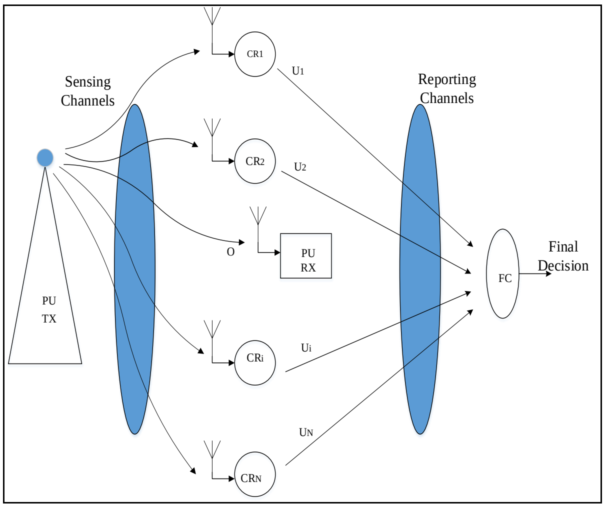

Fig.2: Centralized cooperative spectrum sensing process

III. System model

A network with N identical cognitive radios has been considered under a cooperative spectrum sensing scheme. Each cognitive radio senses the spectrum periodically and makes a local decision about the presence of the primary user based on its observation. The local decisions are to be sent to the fusion center (FC) in different time slots based on a TDMA scheme. The FC employs a hard decision fusion scheme due to its higher energy and bandwidth efficiency over a soft fusion scheme along with a reliable detection performance that is asymptotically similar to that of a soft fusion scheme. To make local decisions about the presence or absence of the primary user, each cognitive radio solves a binary hypothesis testing problem, by choosing H_1 in case the primary user is present and H_0 when the primary user is absent. Denoting y[n] as the n^{th}sample received by the cognitive radio, w[n] as the noise and x[n] as the primary user signal, the hypothesis testing problem can be represented by the following model,

H_0 : y[n] = w[n], n = 1,...,M
H_1:y[n]=x[n]+w[n],n=1,...,M (1)

Where the noise and the signal are assumed to be i.i.d Gaussian random processes with zero mean and variance σ_ω^2 and σ_x^2 respectively, and the received signal-to-noise-ratio (SNR) is denoted by $\gamma = \frac{\sigma_x^2}{\sigma_\omega^2}$.
Each cognitive radio employs an energy detector in which the accumulated energy of M observation samples is to be compared with a predetermined threshold denoted by λas follows:

$$E=u_i = \sum_{n=1}^{M} y^2[n] \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \quad (2)$$

For a large number of samples we can employ the central limit theorem, and the decision statistic is distributed as:

H_0: E~ N (Mσ_w^2,$2M\sigma_w^2$)
H_1:E~N(M$(\sigma_w^2 + \sigma_x^2)$,$2M((\sigma_w^2 + \sigma_x^2)^2$ (3)

Denoting Pf and Pd as the respective local probabilities of false alarm and detection P_f= P_r(E≥λ|H0) and P_d= P_r(E≥λ|H1) are given by:

$$P_f=Q(\frac{\lambda - M\sigma_W^2}{\sqrt{(2M\sigma_W^4)}}) \text{and } P_d=Q(\frac{\lambda-(M(\sigma_W^2+\sigma_x^2)}{\sqrt{2M((\sigma_W^2+\sigma_x^2)^2)}} \quad (4)$$

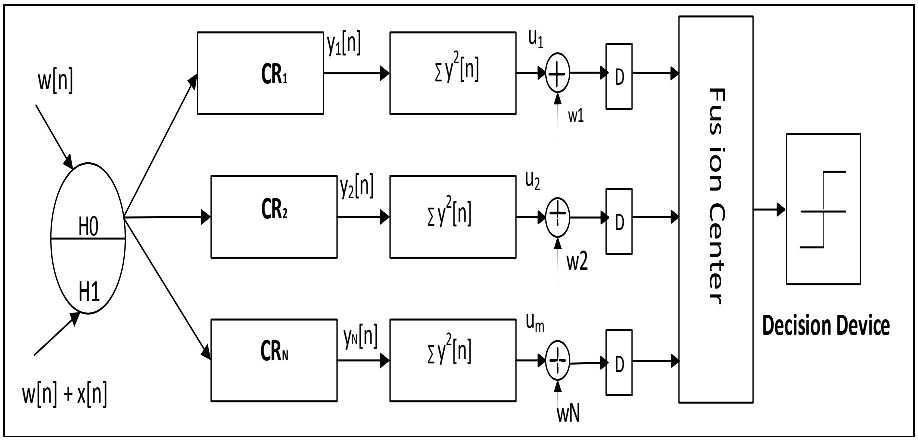

Fig.2: Schematic representation of weighting cooperation for spectrum.

The reported local decisions are combined at the FC and the final decision regarding the presence or absence of the primary user is made according to a certain fusion rule. Due to its simplicity in implementation, lower overhead and energy consumption, we employ a k-out-of-N rule to combine the local binary decisions sent to the FC. Thus, the resulting binary hypothesis testing problem at the FC is given by, $I = \sum_{i=1}^{N} D_i <$ k for H_0 and $I = \sum_{i=1}^{N} D_i \geq$ k for H_1 where Di is the binary local decision of the i^{th} cognitive radio which takes a binary value 0 if the local decision supports the absence of the primary user and 1 for the presence of the primary user. Each cognitive radio employs an identical threshold λ to make the decision. Hence, the global probability of false alarm (Q_f) and detection (Q_d) at the FC is given by,

$$Q_d = \sum_{i=k}^{N} (\binom{N}{i} P_d^i (1 - P_d)^{(N-i)},$$
$$Q_f = \sum_{i=k}^{N} (\binom{N}{i} P_f^i (1 - P_f)^{(N-i)} \quad (5)$$

Each cognitive radio employs periodic time frames of length T for sensing and transmission. The time frame for each cognitive radio is shown in fig.3. Each frame comprises two parts namely a sensing time required for observation and decision making and a transmission time denoted by T_x for transmission in case the primary user is absent. The sensing time can be further divided into a time required for energy accumulation and local decision making denoted by T_s and a reporting time where cognitive radios send their local decisions to the FC. Here, we employ a TDMA based approach for reporting the local decision to the FC. Hence, denoting T_r as the required time for each cognitive radio to report its result, the total reporting time for a network with N cognitive radios is NT_r. Considering the cognitive radio time frame, the normalized effective throughput, R, of the cognitive radio network is given by,

$$R = (\frac{T - T_s - NT_r}{T}) (1 - Q_f) \quad (6)$$

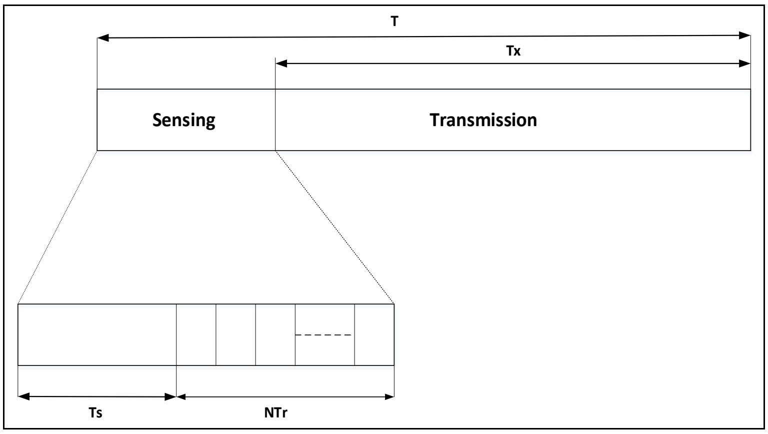

Fig.3: Cognitive Radio Time Frame

A. Energy efficient setup

The detection performance of a cognitive radio network is closely related to the number of cooperating cognitive radios. The larger the number of cognitive radios, the higher the detection performance, which in turn increases the network energy consumption. The current standards impose a lower bound on the probability of detection and an upper bound on the probability of false alarm. Therefore, as soon as these constraints are satisfied, increasing the number of cognitive users is a waste of energy which is very critical for cognitive sensor networks. Hence, it is necessary to design an efficient mechanism to reduce the network energy consumption while still maintaining the standard requirements on the interference and false alarm. Energy efficient optimization problem has been defined here so as to minimize the total number of cooperating cognitive users to attain the required probability of false alarm and probability of detection for a fixed k as follows,

$$\min_N N \text{ Subject to } Q_d \geq \alpha \text{ and } Q_f \leq \beta \tag{7}$$

The optimal value of N is attained for a minimum value of N in the feasible set of (7). We can rewrite (5) using the binomial theorem as follows,

$$\begin{aligned} Q_f &= 1 - \psi(k-1, P_f, N), \\ Q_d &= 1 - \psi(k-1, P_d, N) \end{aligned} \tag{8}$$

Where, ψ is the regularized incomplete beta function as follows,

$$\begin{aligned} \psi(k,p,n) &= I_{1-p}(n-k, k+1) \\ &= (n-k)\binom{n}{k}\int_0^{1-p} t^{n-k-1}(1-t)^k dt \end{aligned}$$

Denoting P_x as the local probability of detection or false alarm and $Q_x$as the global probability of detection or false alarm, we can define $P_x = \psi^{-1}(k, 1-Q_x, N)$ as the inverse function ψ in the second variable. For a given k and N, since ψ and ψ^{-1} are monotonic increasing functions in P_x and Q_x, respectively, the constraints in (7) become:

$$P_f = \psi^{-1}(k-1, 1-Q_f, N) \leq \psi^{-1}(k-1, 1-\beta, \mathrm{N}) \tag{9}$$

$$P_d = \psi^{-1}(k-1, 1-Q_d, N) \geq \psi^{-1}(k-1, 1-\alpha, \mathrm{N}) \tag{10}$$

From the P_d expression in (4) we obtain; $\lambda = \sqrt{2M(\sigma_w^2+\sigma_x^2)^2}Q^{-1}(P_d) + M(\sigma_w^2+\sigma_x^2)$. Inserting λin P_f, we obtain:

$$P_f = Q\left(\frac{M\sigma_x^2 + Q^{-1}(P_d)\sqrt{2M(\sigma_w^2+\sigma_x^2)^2}}{\sqrt{2M\sigma_w^4}}\right).$$

Applying this to (10) and performing some simplifications we obtain;

$$P_f \geq Q\left(\frac{M\sigma_x^2 + Q^{-1}(\zeta_\alpha)\sqrt{2M(\sigma_w^2+\sigma_x^2)^2}}{\sqrt{2M\sigma_w^4}}\right) \tag{11}$$

Where $\zeta_\alpha = \psi^{-1}(k-1, 1-\alpha, N)$.

Therefore for any k, based on (9) and (11), the optimal N will be the minimal solution of the following inequality.

$$Q\left(\frac{M\sigma_x^2 + Q^{-1}(\zeta_\alpha)\sqrt{2M(\sigma_w^2+\sigma_x^2)^2}}{\sqrt{2M\sigma_w^4}}\right) \leq \zeta_\beta, \tag{12}$$

Where $\zeta_\beta = \psi^{-1}(k-1,1-\beta,N)$and $Q^{-1}(x)$ is the inverse Q function. Therefore, the optimal value of N has been found by an exhaustive search over N from 1 to the first value that satisfies (12).

Based on (12), the optimal N for the AND rule is the minimum solution of the following inequality problem,

$$Q\left(A + BQ^{-1}\left(\alpha^{\frac{1}{N}}\right)\right) \leq \beta^{\frac{1}{N}} \tag{13}$$

and for the OR rule, the optimal N is the minimum solution of the following inequality,

$$Q\left(A + BQ^{-1}(\alpha^{\iota})\right) \leq \beta^{\iota}, \tag{14}$$

Where $\alpha^{\iota} = 1-(1-\alpha)^{\frac{1}{N}}$, $\beta^{\iota} = 1-(1-\beta)^{\frac{1}{N}}$, $A = \gamma\sqrt{\frac{M}{2}}$ and $B = 1+\gamma$.

B. Throughput optimization setup

Optimization of the reporting time has received less attention in the literature, although it is a necessary redundancy in the system. Reducing it leads to an increase in the throughput of the cognitive radio network. Here, we fix the sensing time,T_s, and focus on optimizing the reporting time $NT_r$where $T_r = \frac{1}{R_b}$, with R_b the cognitive radio transmission bit rate. The energy efficient setup also increases the throughput by reducing the reporting time for a bounded probability of false alarm. Here, that feature has been exploited in more detail and the problem has been defined as to maximize the throughput of the cognitive radio network, while maintaining the required probability of detection specified by the standard. The solution for the optimization problem determines the optimal N that maximizes the throughput yet meeting the specified constraints. First, the optimization problem has been presented for an arbitrary k and then the focus has been made on the optimization problem for two special cases: the OR and AND rule. The optimization problem is given by,

$$\max_{N, P_f} \left(\frac{T - T_s - NT_r}{T}\right)(1-Q_f)$$

$$\text{Subject to } Q_d \geq \alpha \text{ and } 1 \leq N \leq \left[\frac{T-T_s}{T_r}\right] \tag{15}$$

For a given N the optimization problem reduces to,

$$\max_{P_f} (1-Q_f)$$

$$\text{Subject to } Q_d \geq \alpha \tag{16}$$

This can be further simplified to

$$\min_{P_f} Q_f$$

$$\text{Subject to } P_d \geq \psi^{-1}(k-1,1-\alpha,N) \tag{17}$$

Since the probability of false alarm grows with the probability of detection, the solution of (17) is the P_f that satisfies $P_d = \zeta_\alpha = \psi^{-1}(k-1,1-\alpha,N)$. Hence, the optimal P_f is given by,

$$\widetilde{P_f} = Q\left(\frac{M\sigma_x^2 + Q^{-1}(\zeta_\alpha)\sqrt{2M\left(\sigma_W^2+\sigma_x^2\right)^2}}{\sqrt{2M\sigma_W^4}}\right) \tag{18}$$

Inserting $\widetilde{P_f}$ in (15), we obtain a line search optimization problem as follows

$$\max_{N} \left(\frac{T - T_s - NT_r}{T}\right)(1-\widetilde{Q_f})$$

Subject to $1 \leq N \leq \left[\frac{T-T_s}{T_r}\right]$ (19)

Where $\widetilde{Q_f} = 1 - \psi(k-1, \widetilde{P_f}, N)$,

Based on what we have shown for a general k, denoting $\widetilde{P_f}$, AND as the P_f evaluated at $P_d = \alpha^{1/N}$ for the AND rule, the optimal global probability of false alarm for a given N is $\widetilde{Q_f} = \widetilde{P^N_{f,AND}}$ and thus the optimization problem can be rewritten as follows:

$$\max_{n} \left(\frac{T-T_s-NT_r}{T}\right)\left(1-\widetilde{P^N_{f,AND}}\right) \tag{20}$$

Subject to $1 \leq N \leq \left[\frac{T-T_s}{T_r}\right]$,

Where $\widetilde{P_f}$,AND $= Q\left(\frac{M\sigma_x^2 + Q^{-1}(\alpha^{1/N})\sqrt{2M(\sigma_W^2+\sigma_x^2)^2}}{\sqrt{2M\sigma_W^4}}\right)$

$$= Q\left(A + BQ^{-1}\left(\alpha^{\frac{1}{N}}\right)\right) \tag{21}$$

With A and B as in (13) and (14).

As for the AND rule, the optimization problem for the OR rule can be simplified to a line search optimization problem as follows:

$$\max_{N, P_f} \left(\frac{T-T_s-NT_r}{T}\right)\left(1-\widetilde{P^N_{f,OR}}\right)$$

Subject to $1 \leq N \leq \left[\frac{T-T_s}{T_r}\right]$ (22)

Where,

$\widetilde{P_f}$,OR $= Q\left(\frac{M\sigma_x^2 + Q^{-1}(\alpha^{\iota})\sqrt{2M(\sigma_W^2+\sigma_x^2)^2}}{\sqrt{2M\sigma_W^4}}\right)$

$$= Q\left(A + BQ^{-1}(\alpha^{\iota})\right) \tag{23}$$

With $\alpha^{\iota} = 1 - (1-\alpha)^{1/N}$, and A and B as in (13) and (14).

The optimal value of N for both (20) and (22) can be found by a line search over N from 1 to $\left[\frac{T-T_s}{T_r}\right]$.

IV. Simulation results and analysis

A cognitive radio network with varying numbers of secondary users has been considered for simulation. To make the local decision each cognitive radio employs $M = 275$ observation samples in the energy detector. The received SNR at each Cognitive Radio is assumed as $-7dB$. Simulations has been performed for different Cognitive Radio transmission bit rates R_b= 50 Kbps, 75 Kbps and 100 Kbps. The sampling frequency is assumed to be 6 MHz.

Fig.4 shows the response of optimal N versus the probability of false alarm constraint β for the energy efficient setup. Simulation has been performed for both the OR and AND rules. The probability of detection constraint has been fixed for two values $\alpha = \{0.9, 0.95\}$. Moreover, it is shown that the AND rule is the worst choice for the energy efficient setup. For the value of β ranging from 0.01 to 0.02, the slope of the response is much significant.

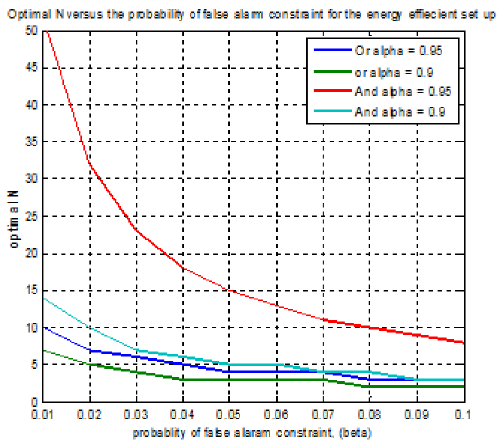

Fig.4: Optimal N versus the probability of false alarm detection constraint for the energy efficient setup.

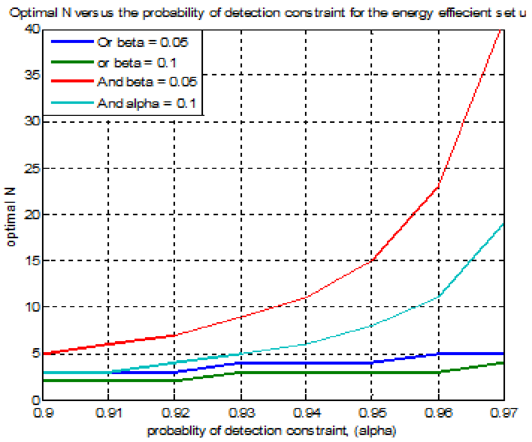

Fig.5: Optimal N versus the probability of constraint for the energy efficient setup.

Beyond that range it decreases with lesser gradients. However, it can be deduced that even in the case of AND rule the performance is better with lesser value of probability of detection constraint α.

Suppose if the probability of false alarm constraint β of the network employing the AND rule is 0.09 and we need to reduce it to 0.02 for betterment, we have the option to increase the number of cognitive radios. But from the above figure it is observed that we need to increase the number of radios substantially. The goal might not be achieved by simply increasing the number of cognitive radios by just five or ten. However, in case of OR rule the goal can be achieved simply by reducing the number of radios slightly.

In Fig.5 we again considered the energy efficient setup performance when the probability of detection constraint, α, changes from 0.9 to 0.97 for two fixed values of probability of false alarm constraint, $\beta = \{0.05, 0.1\}$. It has been seen that similar to the previous scenario, the OR rule performs better than the AND rule over the whole α range. The least number of optimal N has been obtained in the case of β valued 0.1.The purpose of any cognitive radio network is to increase the probability of detection and decrease the probability of false alarm. Therefore, similar to the case of Fig.4, if we need to increase the value of probability of detection constraint α then we have to increase the number of cognitive radios but not necessarily by the value as large as in case of Fig. 4.

In Fig.6, the optimal number of cognitive users N that maximizes the throughput has been considered for a probability of detection constraint $0.9 \leq \alpha \leq 0.97$. We can see that for different bit rates R_b= {50 Kbps, 75 Kbs, 100 Kbps}, the OR rule performs better than the AND rule by achieving the same detection reliability with less cognitive radios. It has been seen that for the alpha values of 0.9, 0.91and 0.92 the value of optimal N for different bit rates coincide.

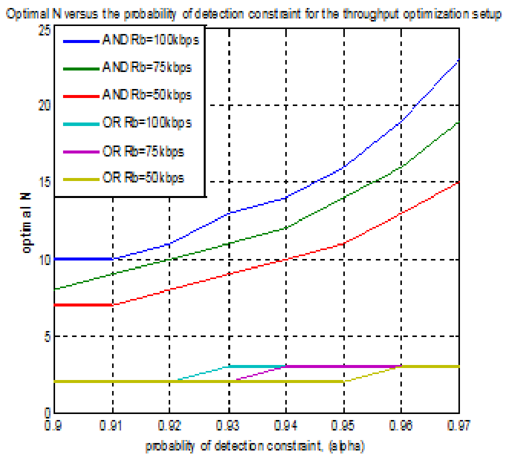

Fig.6: Optimal N versus the probability of detection of detection constraint for the throughput optimization setup

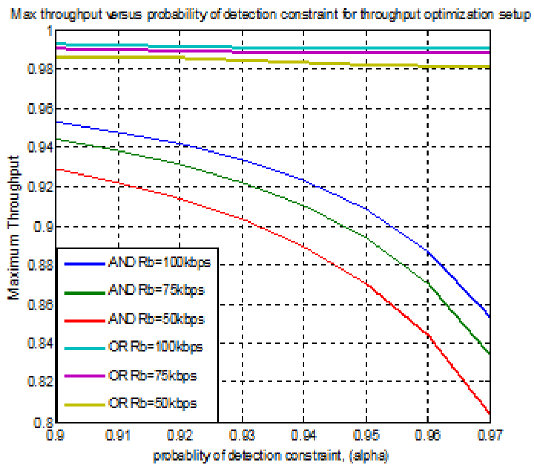

Fig.7: Maximum throughput versus the probability constraint for the throughput optimization setup

The corresponding throughput for the probability of detection constraint $0.9 \leq \alpha \leq 0.97$ is shown in the Fig.7. The results show that OR rule is better over AND rule thereby giving a higher throughput for the same probability of detection constraint with less users. The effect of cognitive radio transmission bit rate R_b on the maximum throughput can be studied from Fig.7.It has been seen that the throughput with bit rate 100 Kbps is higher than that of 75 Kbps and 50 Kbps. Higher the bit rate, better is the throughput. With the increment in the probability of detection constraint, α, throughput has been decreased. The slope of decrement in the throughput is significant when the value of α changes from 0.96 to 0.97.However, in case of OR logic the effect of bit rate on the throughput is pronounced less. In this case, throughput values for different bit rates are comparable to each other.

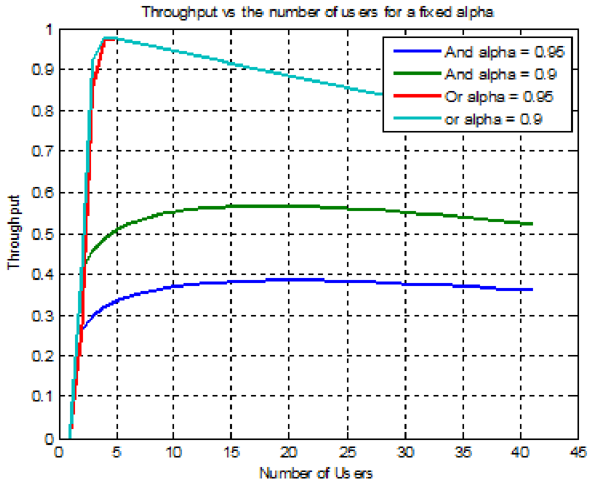

Fig.8: Throughput versus the number of users

Fig.8, shows the throughput versus the number of cognitive users for two fixed values of the probability of detection constraint, α= {0.9, 0.95}, for the AND and OR rule. It has been shown that there is an optimal N that maximizes the network throughput. Further, we can see that for the whole N range, the OR rule gives a better performance than the AND rule for a fixed α. The value of optimal N yielding the maximum throughput in case of AND and OR logic differs significantly. The optimal N for the AND logic with $\alpha = 0.95$ and 0.9 is 20. The optimal N for the OR logic with 0.95 and 0.9 is 5. The corresponding throughput values differ for the different α values. It is around 0.38 for $\alpha = 0.95$ and 0.56 for $\alpha = 0.9$ in case of AND rule. In case of OR rule it is almost around 0.98 for both the values of $\alpha = 0.95$ and 0.9.As the number of users increases congestion in the network also increases which results in the decrement of throughput.

V. Conclusion

The issue of cognitive radio network optimization both in energy efficiency and throughput has been dealt with in case of cooperative spectrum sensing scenario. The optimal number of cognitive users satisfying the defined constraints of probability of false alarm and probability of detection has been derived. It includes the two different setups, energy efficient setup and the throughput optimization setup. In case of energy efficient setup the network energy consumption has been reduced by minimizing the number of cognitive users subject to both of the constraints. In case of throughput optimization setup, the network throughput is maximized subject to a detection rate constraint since throughput of the system depends significantly upon the probability of detection. The OR and AND rules are special cases of more general k-out-of-N rule with k = 1 for OR and k = N for AND rules. It is shown from the simulation results that OR rule is more energy efficient than AND rule. This case also holds true for the throughput achieved by the network. For both types of setup, OR rule outperforms AND rule by exploiting less number of cognitive radios.

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