# Optimization of Secondary User Capacity in Dual Threshold Scheme in Cognitive Radio Using Evolutionary Algorithm

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**Abstract- In cognitive radio network, through efficient spectrum utilization the secondary user (SU) capacity maximization is an important work, here we optimize the secondary user capacity through threshold in the dual threshold scheme of cooperative spectrum sensing by taking the primary user( PU ) on priority as well as SU on priority in AWGN and Rician channel with the evolutionary optimization technique GAPSO.**

**Keywords – Cognitive radio; Normalize capacity; threshold; Probability of detection; optimization**

## I. Introduction

Spectrum being a natural resource and not abundant, we necessitate to efficiently use to prevent underutilization and wastage of valuable frequency resources **[1]**. In cognitive radio network PUs are the licensed user and any SU are allowed to use the unutilized spectrum without any interferences to the existing PUs [2]-[3]. Energy detection scheme of spectrum detection is a widely used method and optimal selection of the threshold is an important function of the CR. The threshold needs to change adaptively with the environment to ensure the PUs protection and at the same time need to look at the maximum capacity achievement for the SU [4]. Here we consider the censor based co-operative CR network where *bi-threshold* scheme is applied and the estimated energy test statistic fall within the range will be send to the *decision centre* [5]-[7]. We proposed an optimizer in place of that decision centre to get the optimal value of the threshold. The detection performance and the computational complexity should be considered at the same time to ensure the sensing quality and the CR throughput. As the minimum computational complexity raise the throughput of CR. The cooperative SUs whose energy statistics fall into the optimal censoring interval, send the information to the optimizer to get the optimal threshold level with the help of an efficient optimization technique. Particle swarm optimization (PSO) [8] is a population-based intelligent algorithm, and it has been widely employed to solve various kinds of numerical and combinational optimization problems because of its simplicity, fast convergence, and high performance. The speed up of convergence rate with least computation cost are two major advantage of PSO and GAPSO is the result of hybridizing genetic algorithm GA with PSO, for example hybrid particle swarm optimizer with mutation (HPSOM) [9] form by integrating the mutation process often used in GA [10,11] into PSO and by varying the mutating space along the search, This process allows the search to escape from local optima and search in different zones of the search space. As a result, this algorithm has the automatic balance property between global and local searching abilities to guarantee better convergence. Simulations show that the proposed hybrid algorithms possess better ability to find the global optimum than that of the standard PSO algorithm.

## II. Proposed Algorithm

### *A. Threshold Formulation–*

The essence of spectrum sensing problem in CR is to decide between the following binary hypotheses:

$H_0$: PU signal is absent
$H_1$: PU signal is present

The central unit manages the CR network and all cooperative SUs. Assuming that each cooperative SU performs local spectrum sensing independently. Firstly, we consider the ith cooperative SU in the following. The local spectrum sensing problem is to decide between the binary hypotheses:

$$H_0: \; r_i(t) = n_i(t)$$

$$H_1: \; r_i(t) = h_i s(t) + n_i(t)$$

where $r_i(t)$ is the received signal of the $i^{th}$ SU, s(t) is the PU signal to be detected, ,$n_i(t)$ is the additive noise to PU signal, and $h_i$ is the channel gain of the sensing channel between the PU and the $i^{th}$ SU. $H_0$ is a null hypothesis, which states that there is no PU signal in a certain spectrum band. On the other hand, H1 is an alternative hypothesis, which indicates that the channel is occupied.
Energy based spectrum sensing using bi-threshold energy detection, Optimum value of the threshold selection is done from the two lower and upper bound value of threshold, the proposed system where the optimized value of threshold is consider is shown in fig. 1.

Energy detection is an optimal detector in random Gaussian noise channel [15]. The ith SU perform energy detection by measuring the energy of the received signal $r_i(t)$ in a fixed bandwidth over certain observation time. So the test statistic of energy detection for the $i^{th}$ SU can be obtained by the likelihood ratio as

$$T_i = \frac{1}{N} \sum_{t=0}^{N-1} r_i^{\,2}(t)$$

where N is greater than or equal to double of the time bandwidth product.

In energy detection, decision $H_1$ will be made by the ith SU if its statistic exceeds the threshold $\lambda$. Otherwise, decision H0 will be considered to be true by the ith SU as shown in the fiure 2. Conventional censoring cooperative spectrum sensing method, whose model is illustrated in Figure 2(b),where two thresholds $\lambda_1$ and $\lambda_2$ are introduced to measure the reliability of the statistic made by the ith SU.

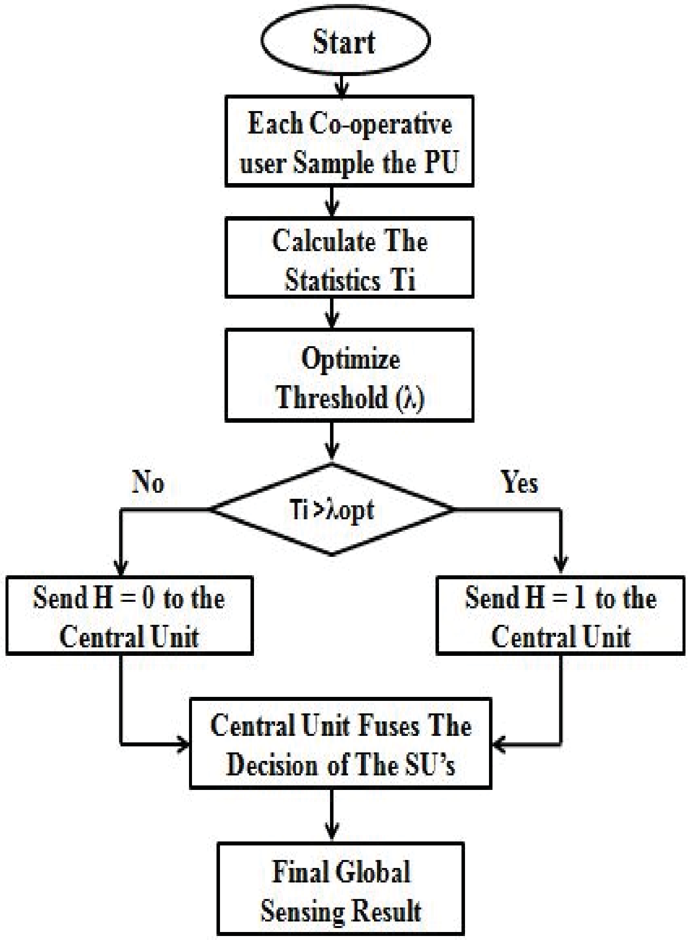


Figure 1. Flowchart of the proposed censoring cooperative spectrum sensing scheme

The channel is considered to be occupied if energy of the the $i^{th}$ SU is greater than or equal to $\lambda_2$ and vacant if the energy is less than$\lambda 1$. When $\lambda_1 < T_i < \lambda_2$, statistic of the $i^{th}$ SU is considered to be unreliable and the ith SU will send nothing [3] or send local energy values in hard combination [4] to the central unit in conventional censoring cooperative spectrum sensing scheme.

The decision statistic T in this case will have a non-central $\chi^2$ distribution with 2u degrees of freedom, we can describe the decision statistic as

$$T \sim \begin{cases} {\chi_{2u}}^2, & H_0 \\ {\chi_{2u}}^2(2\gamma), & H_1 \end{cases} \tag{1}$$

The probability density function (PDF) of T can then be written as

$$f_Y(y)=\begin{cases}\dfrac{1}{2^u\Gamma(u)}y^{u-1}e^{-\frac{y}{2}}, & H_0\\ \dfrac{1}{2}\left(\dfrac{y}{2\gamma}\right)^{\frac{u-1}{2}}e^{-\frac{2\gamma+y}{2}}I_{u-1}\left(\sqrt{2\gamma y}\right), & H_1\end{cases} \tag{2}$$

Where Γ(.)is the gamma function and $I_v(.)$ is the $v^{th}$-order modified Bessel function of the first kind.

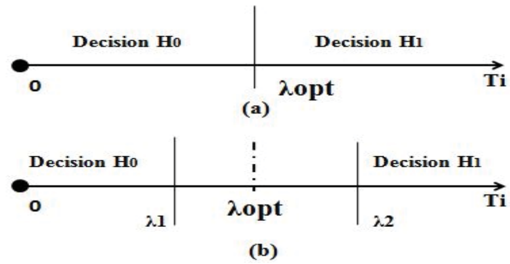


Figure. 2 (a): Conventional detection method with one threshold for the $i^{th}$ SU.
2(b): Censor based detection method with two thresholds for the $i^{th}$ SU

Here in our proposed theme we consider the total gap between λ1 and λ2 as a percentage wise increasing from left to right as shown

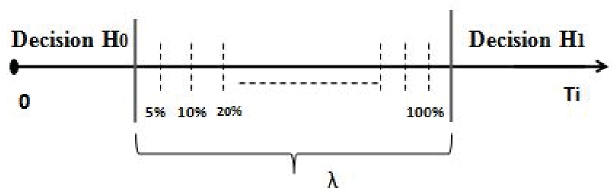


Figure 3**:** Bi-threshold detection scheme with decision zone grading on percentage.

Then we show the probability of detection and capacity change with every small percentage change in threshold on that test statistic period of spectrum sensing. Here in our analysis we consider two channel fading conditions ; AWGN and Rician channel. In Section III we show the formulation of Pd and Pf. Section IV shows the proposed optimization formulation, followed by Section V where results and discussions are included. Section VI concludes the work and cite future scope of work.

## III. AVERAGE DETECTION PROBABILITY OVER FADING CHANNELS WITH NO DIVERSITY

Detection and false alarm probability can be written for the AWGN and Rician channel as [16]

*AWGN channel:*

The probability of detection and false alarm can generally be computed by

$$P_d = P_r(Y > \lambda|\mathrm{H}_1) \tag{3}$$

$$P_f = P_r(Y > \lambda|\mathrm{H}_0) \tag{4}$$

Where λ is the decision threshold and Y is the decision statistics.

Using equation (2) to evaluate (4) yields

$$P_f = \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma(u)} \tag{5}$$

And probability of detection can be written as

$$P_{dawgn} = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) \tag{6}$$

$P_f$ will remain the same under any fading channel Since $P_f$ is considered for the case of no signal transmission and as such is independent of SNR.

*Rician Channel*

If the signal strength follows a Rician distribution [16]

$$\overline{P}_{dRic|u=1} = Q\left(\sqrt{\frac{2\lambda\overline{\gamma}}{K+1+\overline{\gamma}}}, \sqrt{\frac{\lambda(K+1)}{K+1+\overline{\gamma}}}\right) \tag{7}$$

## IV. OPTIMIZATION PROBLEM FORMULATION

To maintain both the proposed cooperative spectrum sensing scheme and the conventional cooperative spectrum sensing method, which all the cooperative SUs use the energy detection only have the same false alarm rate, the following formula should be satisfied:

$$P(T_i \geq \lambda_2 | H_0) + P(T_i \geq \lambda_{opt}, \lambda_1 \leq T_i < \lambda_2 | H_0) = P(T_i \geq \lambda | H_0) \tag{8}$$

Each cooperative SUi,(i=1,2,⋯,K) calculates its test statistic Ti and compares with the two thresholdsλ1 andλ2. The ith SU sends H=0 for $0 \leq T_i < \lambda_1$ and H=1 for $T_i \geq \lambda_2$ to central unit where H is the decision. Optimized threshold based energy detection will be employed where $\lambda_1 \leq T_i < \lambda_2$ and the ith SU will send H=1when $T_i \geq \lambda_{opt}$ and H=0 when $T_i < \lambda_{opt}$ to central unit.

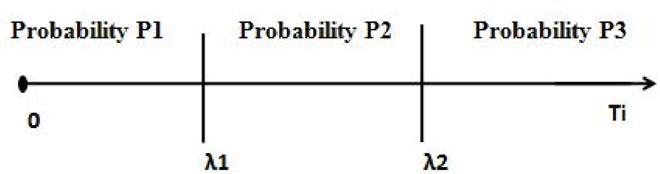


Figure 4: Bi-threshold detection scheme grading on corresponding probability

Where, $P_1 = P(\mathrm{T}_i < \lambda_1 | H_1)$, $P_2 = P(\lambda_1 \leq T_i < \lambda_2 | H_1)$ and $P_3 = P(\mathrm{T}_i \geq \lambda_2 | H_1)$ clearly $P(\mathrm{T}_i \geq \lambda_2 | \mathrm{T}_i < \lambda_1, H_1) = 0$ and $P(\mathrm{T}_i \geq \lambda_2 | T_i \geq \lambda_2, H_1) = 1$.Therefore, the detection probability Pd can be simplified as

$$P_d = P(T_i \geq \lambda_{opt} | \lambda_1 \leq T_i < \lambda_2, H_1).P_2 + P_3 \tag{10}$$

The probability of detection with threshold λ1 is

$$P_1 = P(\mathrm{T}_i < \lambda_1 | H_1) = 1 - Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda_1}\right) \tag{11}$$

The probability of detection with threshold λ2 is

$$P_3 = P(\lambda_1 \le T_i < \lambda_2 | H_1) = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda_2}\right) \tag{12}$$

And from above two p2 can be written as

$$P_2 = 1 - P_1 - P_3 \tag{13}$$

So the probability of detection for AWGN and Rician can be computed from (11),(12), and (13)

Here we consider the two operation mode of cognitive radio network first one is a) where the PUs are give more attention or priority and second one is where the SUs are given more priority than PU.

So the capacity formulation for primary user on priority (PUOP) and secondary user on priority (SUOP) is as follows

$P_f$ for PUOP in OR fusion can be derived as

$$P_f = 1 - \prod_{i=1}^{N} (1 - Q(Q^{-1}\left\{(1 - \left(1 - \bar{P}_d\right)^{1/N}\right\}\left(1 + SNR_{P,i}\right) + SNR_{P,i}\sqrt{k/2}) \tag{14}$$

$P_f$ for PUOP in AND fusion can be derived as

$$P_f = \prod_{i=1}^{N} Q(Q^{-1}\left(\left(\bar{P}_d\right)^{1/N}\right)\left(1 + SNR_{P,i}\right) + SNR_{P,i}\sqrt{k/2}) \tag{15}$$

And for SUOP in OR fusion scheme probability of detection(Pd) can be written as

$$P_D = 1 - \prod_{i=1}^{N} 1 - Q\left(\frac{(Q^{-1}\left(1 - \bar{P}_f\right)^{1/N} - \sqrt{\frac{K}{2}}SNR_{p,i}}{1 - SNR_{P,i}}\right) \tag{16}$$

And for SUOP in AND fusion scheme Pd can be written as

$$P_d = \prod_{i=1}^{N} 1 - Q\left(\frac{(Q^{-1}\left(\bar{P}_f\right)^{1/N} - \sqrt{\frac{K}{2}}SNR_{p,i}}{1 + SNR_{P,i}}\right) \tag{17}$$

where, K is the product of sensing time times the sampling frequency,

In WRAN system, each frame consists of one sensing slot (ts) Plus one data transmission slot ($T_f$- $t_s$), where Tf is the total frame duration. Indeed, short sensing slots should be always targeted as it results in longer data transmission slot and therefore, higher throughput capacity

After computing the Pd and Pf accordingly for both the channel the maximum normalize capacity can be computed as

$$MaxC = \left(1 - \frac{t_s}{T_f}\right)\left((1 - P_f)(P_1 + P_2) \quad + (1 - P_d)P_3\right) \tag{18}$$

s.t.. $0 \le \lambda_1 \le 3$ and $7 \le \lambda_1 \;\; \lambda_2 \le 10$

## V. RESULTS AND OBSERVATION:

Here firstly we optimize the parameter for AWGN channel, the optimum Pd and capacity corresponding to every small percentage change in threshold is shown in the table below

Table I: Optimized result for Probability of detection and maximum SUs capacity corresponding to threshold value.

| | PUOP | | SUOP | |
|---|---|---|---|---|
| Threshold | Pd | Capacity | Pd | Capacity |
| 5% | .93 | .74 | .89 | .78 |
| 10% | .92 | .756 | .86 | .79 |
| 20% | .91 | .767 | .83 | .808 |
| 30% | .888 | .778 | .8 | .82 |
| 40% | .86 | .785 | .78 | .83 |
| 50% | .845 | .798 | .76 | .857 |
| 60% | .82 | .812 | .74 | .88 |
| 70% | .78 | .821 | .72 | .902 |
| 80% | .769 | .832 | .70 | .912 |
| 90% | .74 | .837 | .68 | .919 |
| 100% | .72 | .84 | .65 | .923 |

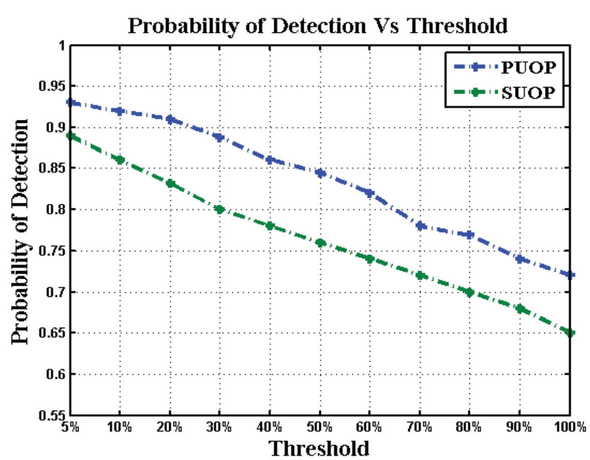


Figure 4: Optimal Probability of detection versus Threshold position for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

As shown in the diagram above the probability of detection(Pd) is more in the lower region of decision zone and Pd is more for PUOP as compare to SUOP as the detection of PU is more in PUOP and give high priority to them. Normalize Capacity versus Threshold for AWGN channel

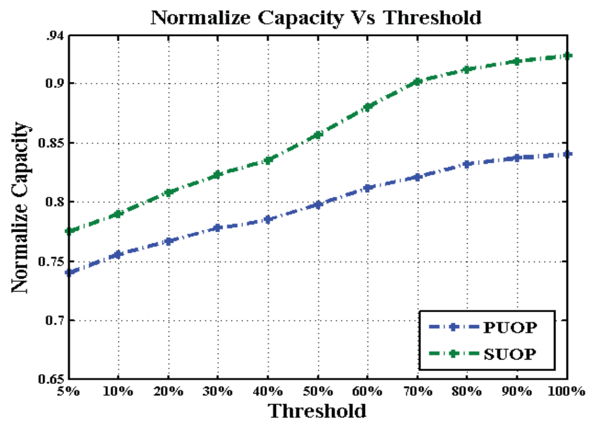


Figure 5: Optimal Normalize Capacity versus Threshold position for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

The Normalize capacity is more case of SUOP as the SU give more priority than PU and its gradually increasing towards the higher region of decision zone.

The Pd versus normalize capacity plot for AWGN channel

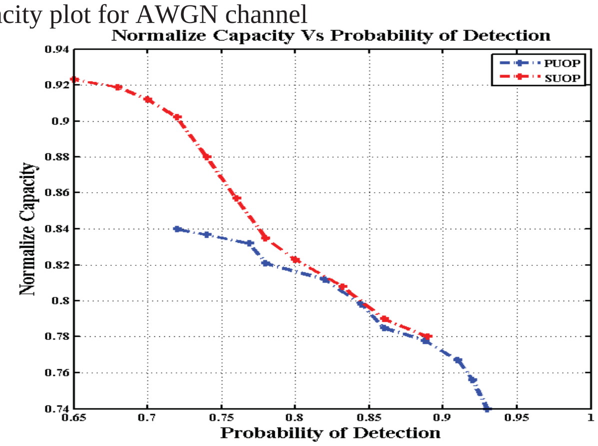


Figure 6: Optimal Normalize Capacity versus Probability of detection for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

Figure above shows that the capacity of SU is highest in SUOP when the Pd is .68 and lowest when Pd is .89 and in case of PUOP the capacity of SU is highest in SUOP when the Pd is .74 and lowest when Pd is .93

Secondly we optimize the parameter for Rician channel, the optimum Pd and capacity corresponding to every small percentage change in threshold is shown in the table below.

TABLE II: Optimized result for Probability of detection and maximum SUs capacity corresponding to threshold value.

| | PUOP | | SUOP | |
|---|---|---|---|---|
| **Threshold** | **Pd** | **Capacity** | **Pd** | **Capacity** |
| **5%** | **.89** | **.77** | **.81** | **.81** |
| **10%** | **.87** | **.778** | **.78** | **.829** |
| **20%** | **.83** | **.789** | **.765** | **.837** |
| **30%** | **.805** | **.795** | **.75** | **.85** |
| **40%** | **.78** | **.8** | **.73** | **.86** |
| **50%** | **.77** | **.804** | **.71** | **.88** |
| **60%** | **.74** | **.812** | **.67** | **.901** |
| **70%** | **.72** | **.823** | **.65** | **.912** |
| **80%** | **.7** | **.831** | **.64** | **.923** |
| **90%** | **.68** | **.842** | **.61** | **.932** |
| **100%** | **.66** | **.85** | **.58** | **.945** |

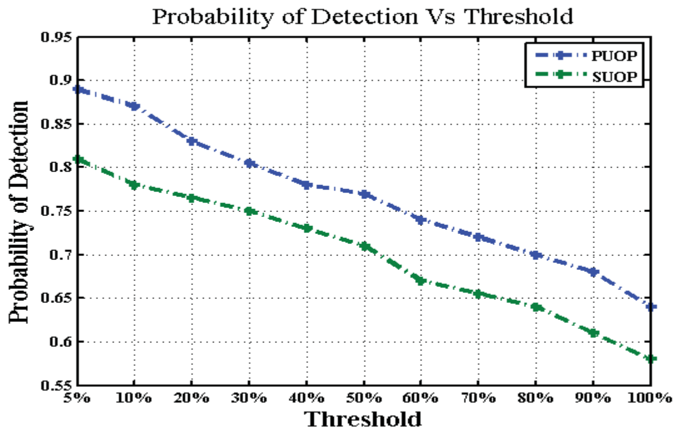


Figure 7: Optimal Probability of detection versus Threshold position for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

Here also as like AWGN channel the Pd is more in PUOP as compare to SUOP. Pd for PUOP is highest at 5% of threshold of the decision region and is of .89 and lowest at the highest position of threshold. Same as in SUOP scenario Pd is high of .81 at 5% and low at 100% is of .58.

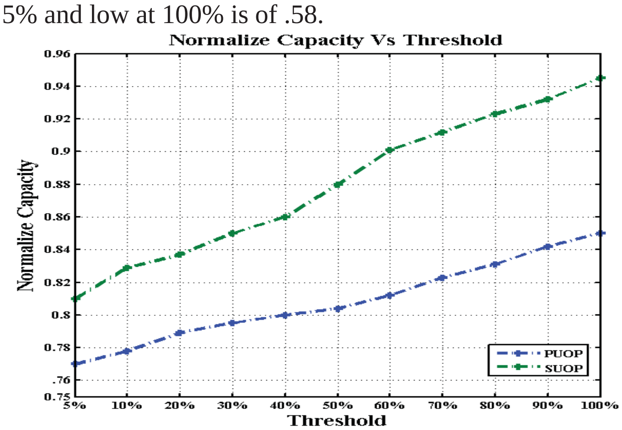


Figure 8: Optimal Normalize Capacity versus Threshold position for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

As like AWGN the capacity is more in case of SUOP and is of .945 at 100% of the decision region and very low in case of PUOP of .77 at 5% of the decision region.

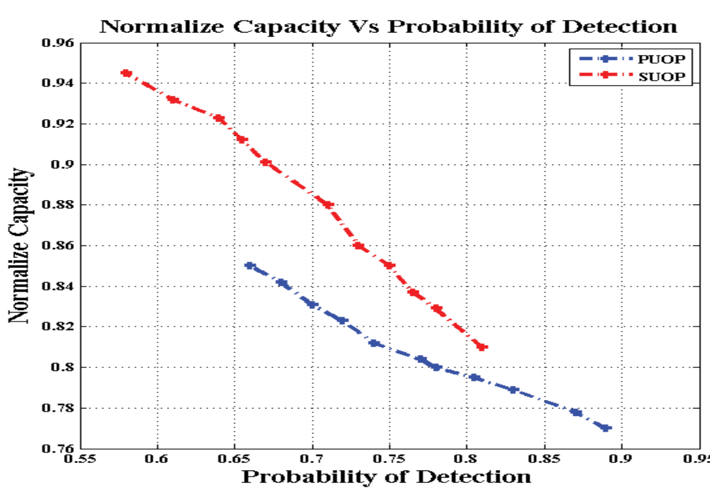

Figure 9: Optimal Normalize Capacity versus Probability of detection for AWGN channel in PUOP and SUOP operation mode using AND fusion scheme.

Here also capacity is gradually decreases with the increase of Pd in both SUOP and PUOP and the figure shows that the normalize capacity is decreases with the increase of Pd and highest of .94 is achieve at 100% of the decision zone in case of SUOP and lowest of .77 is achieved at 5% of the decision zone in case of PUOP.

## VI. CONCLUSION

In our paper we analyzed the capacity of SU and probability of detection(Pd) of PU with the threshold position as parameter under AWGN and Rician fading channels. The simulated result shows that the pd is more in the lower region of the decision zone compare to the higher region and the capacity is maximum in the higher region as the detection of PU is less so the capacity of SU is more which justify the result. And Implementation of adaptive threshold method under the presented scenario is also considered in our future research.

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