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OPTIMIZATION OF MAJORITY-LOGIC FUSION IN COGNITIVE RADIO NETWORK USING PARTICLE SWARM OPTIMIZATION

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Abstract: This Cognitive radio network is an emergent technology that opportunistically uses white holes in the RF spectrum. Sensing the spectrum is foremost principle of cognitive radio. In this paper the authors propose a novel method to optimize the total performance of cooperative sensing. The optimization starts by optimizing the sensing with energy detection to cooperative spectrum sensing using ML rule. The optimization is done in order to maximize the probability of detection and minimize the total error rate. The optimal number of cognitive radios is worked upon. The energy detection non-cooperative sensing technique is used at each local cognitive radio. The work focus on finding the optimal value of probability of detection and total error rate in case of Majority-Logic cooperative spectrum sensing. Results show that CR = 5 is the optimal choice to minimize the total error probability.

***Index Terms* - PSO, Energy Detection, Cooperative Sensing, Optimum number of CR, Majority-Logic (ML) rule, Probability of detection, Probability of Missed detection, Total Error Rate**

I. INTRODUCTION

Particle swarm optimization is a computer method used to optimize a problem through iterations to improve a candidate solution with regard to a given quality of measure [wikipedia]. PSO was proposed by Eberhart and Kennedy in 1995 dedicated for simulating social behaviour of animals. Particle swarm optimization algorithm is an optimization algorithm based on the moment and intelligence of swarms [1]. PSO techniques simulates animal's social behaviour including insects, herds, birds and fishes. Solution to a problem can be obtained by learning the concept of social interaction of animals.

In cognitive radio network a SU can access spectrum allotted to a primary user if he is not using it. But the SU needs to leave that frequency band as soon as the PU starts his transmission thereby creating negligible interference for the PU. This deployment of the primary user's resources by the secondary user is known as Dynamic Spectrum Access. In DSA the SU fulfils its bandwidth requirement without interfering the PU's transmission [2]. Spectrum sensing can be carried out either by an individual SU or simultaneously by multiple SUs. However multipath fading, shadowing and other environmental effects make it difficult for a SU to detect the PU properly. The SU cannot distinguish between a white space and a deep fade. Cooperative sensing in which multiple SUs collaborate to detect the presence of a PU can be used to attain diversity gain to combat the detrimental effects of fading. It in fact increases the SNR gain and the network coverage. Novel models that model the cooperation between CR users and PUs and for cooperative communications and cooperative sensing such as the one in [3] are preferred. In addition, the recognition of small-scale mobile PUs such as radio wireless microphones is a recognized open challenging research difficulty, which will need a novel model for cooperative sensing. The PSO presents a compromise between the complexity and the reliability of the obtained solution

The cognitive radio works in two network modes - individual spectrum sensing and cooperative Spectrum Sensing with an additional fusion center. In the case of individual each SU individually senses the spectrum and decides on the presence of Primary User (PU). The sensing degrades due to fading, shadowing and hidden node problem [4]. The CSS is introduced to improve the performance of SUs. In the case of CSS with a FC each SU will sense PU signal and send it to Base Station (BS), final decision is taken by BS and accordingly spectrum allocation is done to SU. The BS keeps control on PU and SU in the network. Energy Detection is the simplest and inexpensive technique and it does not need a prior knowledge of the transmitted

PU signal, hence in this paper ED technique is sued for spectrum sensing under consideration of CSS. In this work the channel is individually detected and total information is sent to the BS. The BS takes the final decision on existence of PU [5]. The work aims to optimize the spectrum sensing. Various types of sensing optimization are considered by researchers. Parameters affecting on spectrum sensing and signalling quality are sensing time, energy consumption and throughput of a system [6]. This work is focused on detection optimization. In the next section the techniques used for detection optimization are reviewed.

II. SYSTEM MODEL

A number of energy detectors individually senses the channel of interest and send their 1-bit decision to the fusion center where the results are merged using Majority-Logic. The consolidated result is optimized to find the best value for probability of detection and total error rate. The work flow is shown in figure 1.

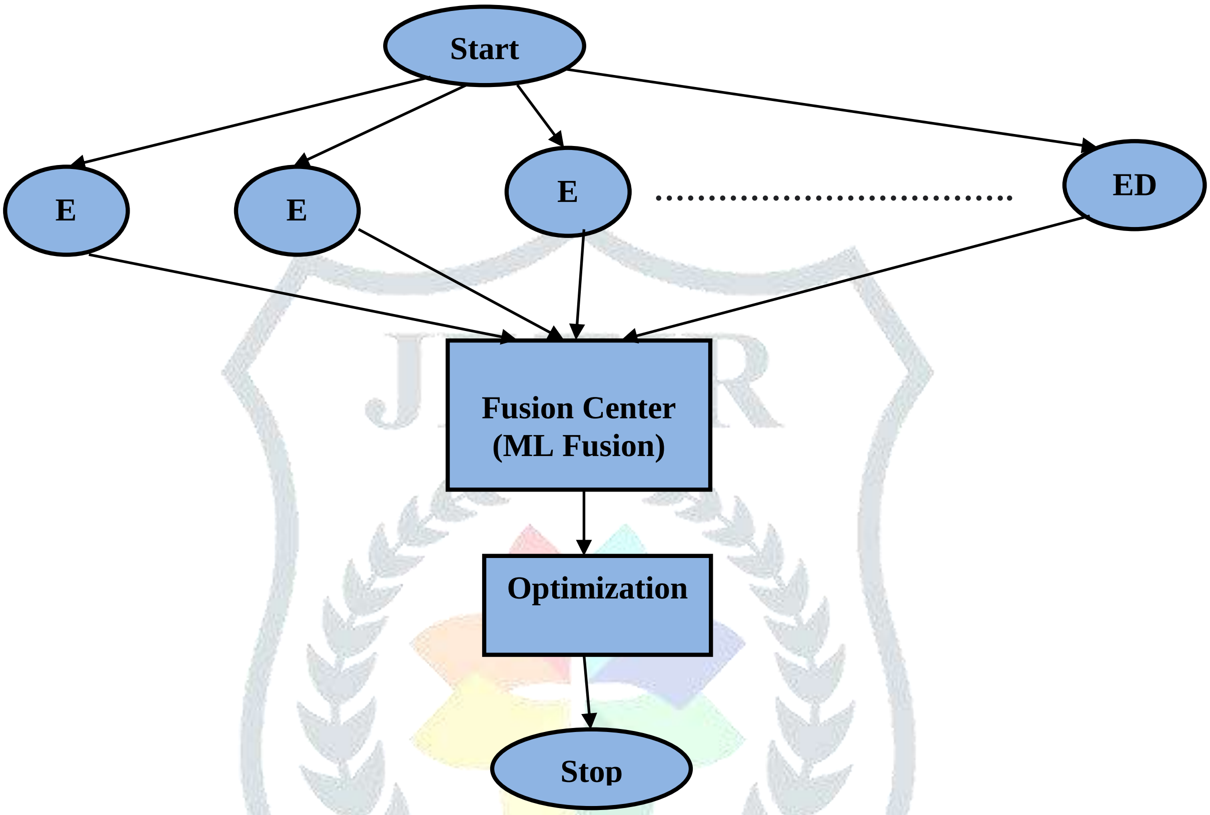

Figure 1: Flowchart of the work

III. ANALYTICAL DESIGN OF THE SYSTEM

3.1 Mathematical Design for Energy Detection

When the sensor has no prior knowledge of the transmitted waveform characteristics of the PU, it measures the energy of the PU signal present in that channel. Estimation of the single energy along with noise energy when PU signal is present and estimation of the noise energy alone when PU signal is not present is done by the sensing node. The existence or non-existence of the PU can be examined with the help of a hypothesis testing problem as defined below.

H_0 True: $y(t) = n(t)$: only noise received (1)

H_1 True: $y(t) = h.\, s(t) + n(t)$: both noise and signal received (2)

Where y(t), s(t) and n(t) are the received, transmitted and noise signals respectively. h is the channel gain. H_0 and H_1 are the hypothesis among which only one can be true.

The expected value and variance of the transmitted signal is normalized to unity.

$$E[|s|^2] = 1$$

$$\sigma^2[s] = 1$$

Energy of the signal y(t) can be computed by the average of the received signal samples over a time duration T can be used as the test statistic for the decision making as

$$y = \sum_{n-1}^{N_s} [|y(t)|^2] \tag{3}$$

when N_s is the number of samples is large, y tends to Gaussian random variables exhibiting expected value and variance as

$$E[y] = \begin{cases} N_s\,\sigma_n^2 & H_0 \\ N_s\,[|h|^2 + \sigma_n^2] & H_1 \end{cases} \tag{4}$$

$$\sigma_y^2 = \begin{cases} 2N_s\,\sigma_n^4 & H_0 \\ 2N_s\,\sigma_n^4[2|h|^2 + \sigma_n^2] & H_1 \end{cases} \tag{5}$$

The decision about the existence of the signal can be taken as

$$\begin{cases} y > \lambda, & H_1 \text{ is true} \\ y < \lambda, & H_0 \text{ is true} \end{cases} \tag{6}$$

where λ is the threshold.

There can be untrue alarms i.e. the decision variable exceeds the threshold even when only noise is present and as a consequence the sensor gets an indication of that the signal is present. The probability for these false alarms is

$$P_F(\lambda) = \Pr(y > \lambda|H_0) = Q\left[\frac{(\lambda - N_s\,\sigma_n^2)}{(\sigma_n^2\sqrt{2N_s})}\right] \tag{7}$$

Where Q(x) is the well-known Q-function.
Similarly true detections can be missed when the decision variable remains below the threshold even when the signal is present. The probability for the miss detection is

$$P_{MD}(\lambda) = \Pr(y < \lambda|H_1) = 1 - Q\left[\frac{(\lambda - N_s\,[|\,h|^2 + \sigma_n^2])}{(\sigma_n\sqrt{2N_s}\,[2|h|^2 + \sigma_n^2])}\right] \tag{8}$$

The probability of detection is given by the relation

$$P_D(\lambda) = 1 - P_{MD}(\lambda) \tag{9}$$

3.2 Mathematical Design for Majority-Logic fusion

The performance of Energy detection is enhanced by using cooperative spectrum sensing by using Majority-Logic (ML) fusion. This fusion technique combines the results of majority of the similar 1-bit individual results from the energy detectors to form a fusion result. The various probabilities for the fusion technique are as follows:

$$P_{D\,ML} = \sum_{j=k}^{K} (P_{Dj})^j\ (1 - P_{Dj})^{M-j} \tag{10}$$

$$P_{F\,ML} = \sum_{j=k}^{K} (P_{Fj})^j\ (1 - P_{Fj})^{M-j} \tag{11}$$

$$P_{MD\,ML} = 1 - P_{D\,ML} \tag{12}$$

3.3 Particle Swarm Optimization

A basic variant of the PSO algorithm works by having a population called a swarm of candidate solutions called particles. The movements of the particles are guided by their own best-known position in the search-space as well as the entire swarm's best-known position.

It uses a number of particles agents that constitute a swarm moving around in the search space looking for the best solution. Each particle in the swarm looks for its positional coordinates in the solution space which are associated with the best solution that has been achieved so far by that particle. It is known as p_{best} or personal best. Another best value known as g_{best} or global best is tracked by the PSO. This is the best possible value obtained so far by any particle in the neighborhood of that particle. It is insensitive to scaling of design variables. PSO can be easily parallelized for concurrent processing as it uses very few algorithm parameters. In some conditions PSO's optimum local search ability is weak The most exciting part of PSO is there is a stable topology where particles are able to communicate with each other and increase the learning rate to achieve global optimum. The metaheuristic nature of this optimization algorithm gives a lot of opportunities to improve a candidate solution.

Particle swarm optimization is a population based random search algorithm based on swarm behavior of bird flocking and fish schooling. In PSO, a population, also known as swarm, is initially created based on the search space of a given optimization problem. Each member in the swarm, also referred to as particle, is distributed randomly within the predefined search space. This population will randomly 'fly' through the search space to look for the global optimum. The trajectory of each particle is influenced by the best position personally found so far, which is p_{best} and the best position found by the entire swarm g_{best}.

$$v_{ij}(t + 1) = v_{ij}(t) + c_1 r_1 (y_{ij}(t) - x_{ij}(t)) + c_2 r_2 (\bar{y}_j(t) - x_{ij}(t)) \tag{13}$$

$$x_{ij}(t + 1) = x_{ij} + v_{ij}(t + 1) \tag{14}$$

Where $v_{ij}(t)$ denotes the velocity of i^{th} particle in j^{th} dimension at t^{th} iteration, c_1 and c_2 are referred as acceleration constants, r_1 and r_2 are uniformly distributed random values ranging in [0,1]. $y_{ij}(t)$ is referred as p_{best}, which is the best position found by the i^{th} particle in j^{th} dimension so far by the t^{th} iteration whereas $\bar{y}_j(t)$ is referred as g_{best}, which is the best position found by the entire swarm in j^{th} dimension so far at the t^{th} iteration. $x_{ij}(t)$ denotes the position of i^{th} particle in j^{th} dimension at t^{th} iteration. Another parameter maximum velocity v_{max} is imposed to limit the velocity of each particle to ensure exploration within the search space.

3.4 Total Error Rate

The total error probability of sensing is calculated as

$$P_E = P_M + P_F \tag{15}$$

IV. SIMULATION DETAILS AND RESULT ANALYSIS

Simulation Setup is created in order to simulate the above model for optimizing the performance of energy detection at each CR. The performance is measured in terms of different probabilities. The setup includes a single PU, 10 SUs and a FC. Each SU tests 1000 samples for sensing the PU signal. The targeted SNR for the simulation purpose is -20 dB to 20 dB as each CR may sense the channel at a different value of SNR. Computer simulations are run for 1000 iterations to obtain the best values of P_D (Probability of Detection) and T_E (Total Error Rate). Simulation Setup is created in order to simulate the values of P_f even at low SNRs also.

Figure 2 shows the variation of P_D with P_F. It shows that as detection capability increases at the expense of false alarms. These values are calculated at SNR = -10 dB. It is clear that the performance of ML is better than non-cooperative energy detection. Also optimization is done to obtain a maximum value of P_D. The different values are plotted in table 1 below.

Table 1: P_D for different schemes

Scheme	ED	ML	PSO
P_D	0.3	0.5	0.56

The variation of P_D with SNR is shown in figure 2. It is obvious that all the schemes work well even at small SNRs but they show excellent performance at positive SNRs. It is noteworthy that ML outperforms ED as SNR increases. The detection performance of ED is 100% at 0 dB in contrast to ML at -10 dB only. Optimized values are far better than ED. Both the figure shows major improvement in detection capability of optimized ML as compared to single energy detection case.

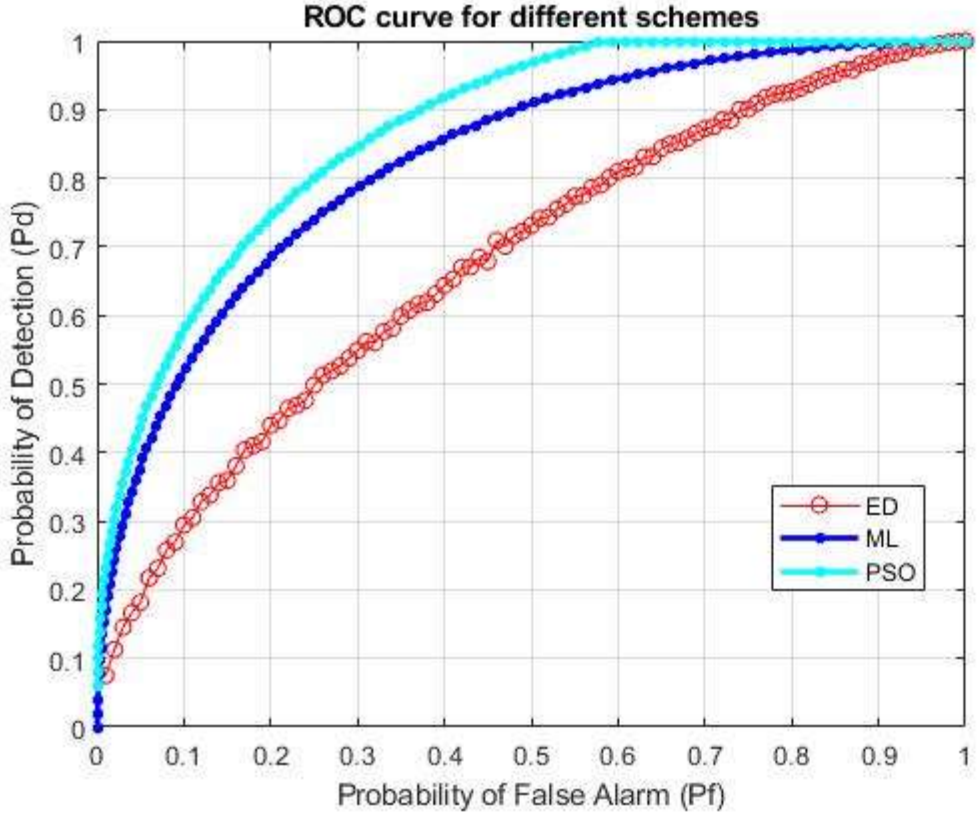

Figure 2: PD vs PF at SNR = -10dB for different schemes

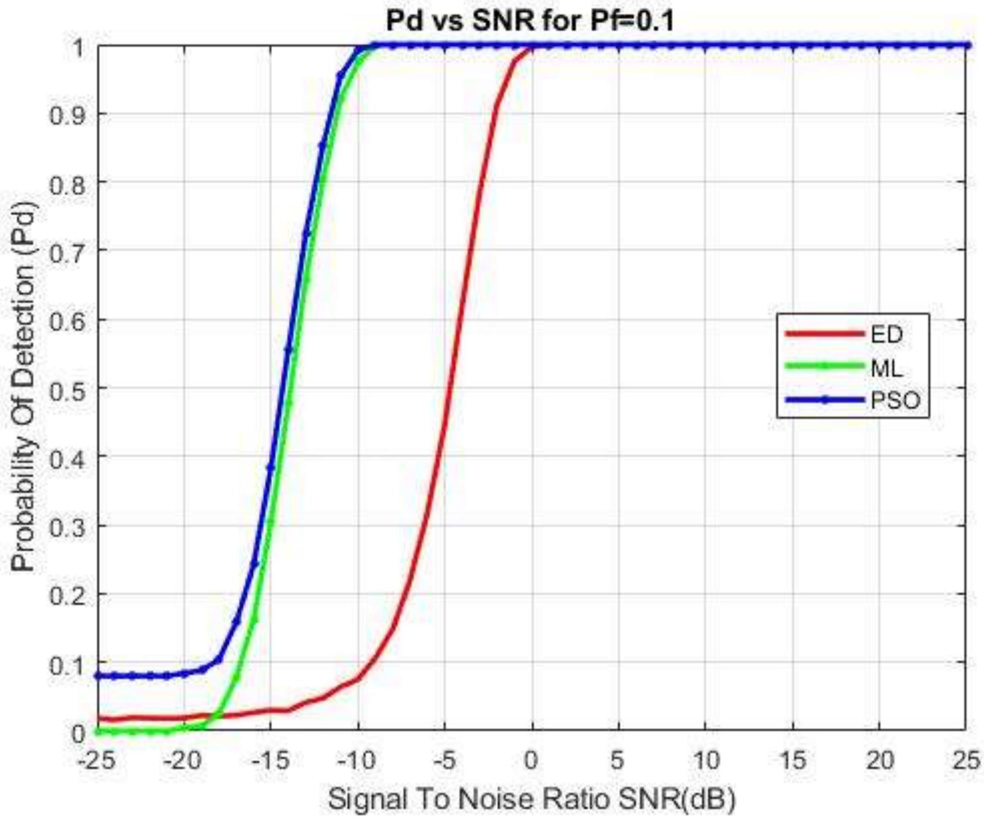

Figure 3: PD vs SNR at PF = 0.1 for different schemes

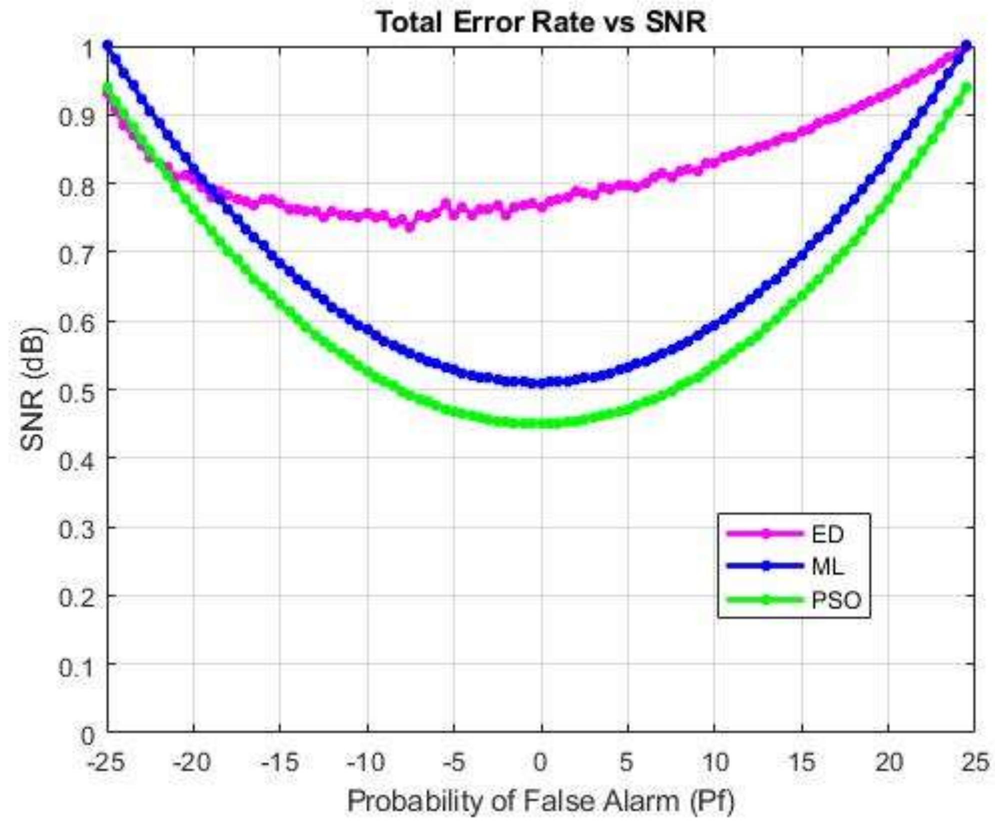

Figure 4: Total Error Rate vs SNR

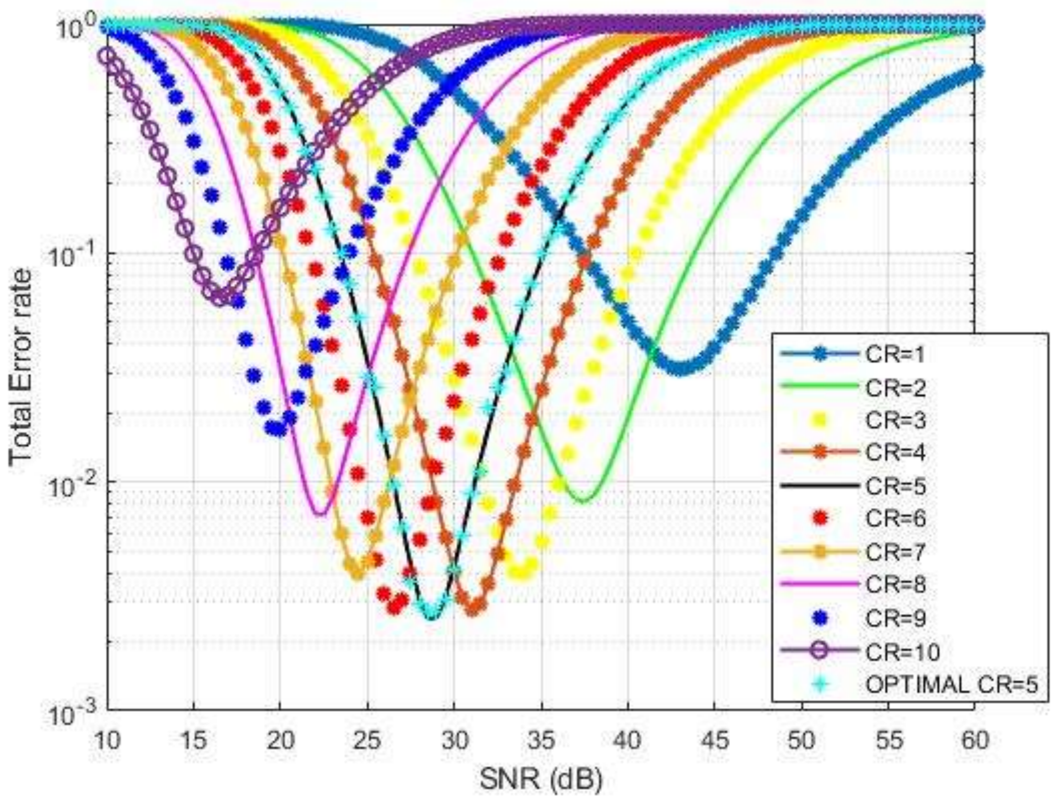

Figure 5: Optimal Number of CRs based on Total Error Rate

The other parameter in examining the performance of spectrum sensing is the total error rate as shown in figure 4. It is observed that ED shows the maximum value of T_E as compared to ML and PSO. The majority logic shows a lower value of error probability followed by PSO showing minimum total error. The values are tabulated below.

Table 2: T_E for different schemes

Scheme	P_D
ED	0.7471
ML	0.5101
ML with PSO	0.4501

Finally the optimal number of CRs that should be used for CSS is worked upon and turned out the 5. From figure 5 it is clear that the total error rate is minimum for 5 CRs. These error rates are calculated using PSO.

V. CONCLUSION

Results reveal that cooperative spectrum sensing performs much better than non-cooperative sensing. Energy detection shows fair detection probability, however fusion enhances its performance to a major extent. Majority logic fusion shows major improvement in terms of probability of detection and total error rate. Further the optimization of majority-logic is done to find the best possible value for P_D and T_E. The graphs plotted demonstrate the different values of P_D and T_E for different cases. PSO gives the optimum values of P_D = 0.56 and T_E = 0.4501. Finally optimal number of CRs that should participate in cooperative sensing turns out to be CR = 5.

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