Cooperative Sensing Framework Using IEEE 802.22-Standard

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Abstract— **Cognitive Radio Network (CRN) introduces a new direction in today's wireless technology, providing an efficient mechanism of spectrum utilization by exploiting the unused spectrum without creating interference to the licensed users, namely primary users (PUs). In order to efficiently facilitate dynamic spectrum access (DSA) to the unlicensed users, namely secondary users (SUs), sensing the spectrum (not only unused but whole spectrum) is a necessary mechanism. In this paper, we propose a co-operative sensing framework, in conformation to the regulations stipulated by IEEE 802.22 WRAN standard. The objective of our work is to provide an efficient, yet, easily implementable spectrum discovery scheme following 802.22 standard. Through our work, we have shown that our proposed sensing framework achieves a lower probability of false detection and shows that the sensing procedure can be carried through less expensive receivers with lower sensitivity than those used in other traditional centralized sensing frameworks.**

Keywords—spectrum; dynamic spectrum access; IEEE 802.22 standard; co-operative sensing; user selection; spectrum allocation

I. INTRODUCTION

The unhindered growth of wireless networks, over the past few decades, has contributed to a huge spectrum demand, which in turn, has led to the demand of new wireless communication technologies. The development of wireless technology calls for efficient spectrum utilization, and hence the transition from fixed spectrum allocation to dynamic spectrum allocation becomes necessary. Cognitive radio (CR) technology enables the access to irregular periods of unoccupied spectrum, known as *spectrum holes* or more generally *white spaces*, in order to improve the spectrum usage. The concept of CR evolved from the research in the field of software-defined radio (SDR), but since then, it has its own field of research. The SDR can observe its environment and modify its transmission characteristics accordingly, as required. The spectrum consists of distinct frequency bands, which are licensed to PUs. The basic task of CR technology lies in sensing and identifying the *white spaces*, and providing access to the secondary users, which are the unlicensed users. The process of sensing, is more generally, termed as *spectrum sensing*. In this paper we formulate a co-operative spectrum sensing technique to detect the idle PUs so that the *spectrum manager* (SM) in the Base Station (BS) can perform *spectrum allocation scheme,* hence enabling the SUs to operate in the best available channel. After allocation of channel to the unlicensed users called *secondary users* (SUs), there should be a provision of evacuation of channel, if the PU is detected again. This task is done by SUs along with the BS, in order to ensure that the transmission that the SU or more commonly known as customer premises equipment (CPE) was involved in, is seamless, that is, the SU needs to perform *spectrum handover* function. The main objective behind the CR technology is co-existence of SUs and PUs, i.e., the efficient utilization of the spectrum by SU, while the PU is idle, with the interference level as low as possible.

A. Spectrum sensing standard in 802.22

We will consider spectrum sensing standard given in IEEE 802.22 in this work. According to this standard, a SU is restricted from sensing multiple channels simultaneously and they can only be allocated channels only when the PUs have completely ceased transmission. In [4], Carl Svenson et al, delineates different standardized parameters, such as range of transmission, EIRP (Equivalent Isotropically Radiated Power), probability of false detection, probability of miss detection, threshold sensitivity levels etc. In the earlier works, centralized sensing was mainly used in CRN or sometimes cooperative sensing was also deployed [1],[11]. There was no works seen on the complete model of sensing along with allocation. In [1],[11], authors discussed the different sensing techniques, while in [12] authors discussed the allocations of the channels. The paper is organized as follows: section II describes the basic idea of spectrum sensing, section III describes how we build our framework of co-operative sensing. Finally, section IV shows the simulation results of our work.

II. SPECTRUM SENSING

A. The basic idea of spectrum sensing

Spectrum sensing refers to a procedure of observing the frequency bands for the efficient identification of the white spaces in the frequency spectrum. The objective of spectrum sensing involves i) the SUs performing sensing without causing any interference to the PUs and ii) SUs efficiently identifying the white spaces so that they can use them.

The performance of sensing: The performance of sensing depends on three parameters which are mainly,

i) The probability of false alarm (P_{fa}), i.e., the probability that the SU detects a signal, in the event of a PU not transmitting in that channel.

ii) The probability of miss detection (P_m), i.e., the probability that a SU fails to detect the presence of signal, in the event of a PU transmitting in the channel.

iii) Probability of detection (P_d), i.e., the probability that an SU correctly determines the presence or absence of both idle and active PU.

The first two parameters are basically the probability of false detection and the third one is the probability of correct detection. These two are interrelated, i.e., the sum of the false detection and correct detection is equal to 1. Efficiency of CR system can be improved by minimizing the probability of false alarm and probability of miss detection and thereby maximizing the probability of detection. The main external factors that lead to the occurrences of misses or false alarms are shadowing, multipath fading, and noise in the communication channel and receiver uncertainty [6], which significantly affect the sensing performance. In order to mitigate the problem of non-uniform fading, co-operative sensing is performed, where the SUs, who are spatially, in a more favorable position to detect the presence or absence of an active PU. The SUs are then deployed for sensing and the sensing results are shared with the SM in the BS for the next stage i.e. spectrum allocation.

B. Types of Sensing:

Spectrum sensing can be broadly classified in the following three ways:

i) Centralized sensing: In this type of sensing, the SM performs the entire sensing procedure by itself without the co-operation of the SUs. The advantage of this type of sensing procedure is that no SUs have any participation in the entire sensing procedure, but the disadvantage is that there remains a high chance of missing probability, as the SM fails to detect PUs remotely placed due to shadowing and multipath fading.

ii) Distributed sensing: In this type of sensing, there is no notion of SM. Instead, the SUs co-operate with each other in finding white spaces and use the unused spectrum. Though this type of sensing is highly efficient in identifying white spaces with low missing probability, it involves a considerable amount of overhead.

iii) Co-operative sensing: Combining the above-mentioned sensing procedures, the idea of co-operative sensing evolves. In this sensing procedure, the SUs co-operate with the SM in performing sensing. This, generally, provides a high efficiency, as it nullifies the hindrances that the SM faces, in terms of shadowing and multipath fading to some extent.

C. *Co-operative Spectrum Sensing:*

The main idea of co-operative sensing emanates from the need to counter the problems faced in PU detection. The factors like multipath fading and shadowing affects the signal to noise ratio (SNR) of the PUs which make the detection task difficult. Higher receiver sensitivity would be required to detect low SNR values, which in turn, would increase cost and complexity. Co-operative sensing provides the opportunity of efficient detection performance at feasible receiver sensitivity with help of sharing of the sensing load between spectrum manager and SUs. By co-operation, SUs can share their sensing information for making a combined decision more accurate than the individual decisions [10]. Co-operative sensing does face some challenges in terms of overheads like sensing delay or spatially correlated sensing results. More spatially correlated SU's participating in cooperation can be detrimental to the detection performance [9], [13].

It may be broadly classified into three broad categories

i) Centralized – The fusion centre (FC) deploys the SUs to sense the availability of PU in a given channel and the SU reports the sensing data to the FC, through a control channel. In centralized sensing all the SUs sense the channel independently and sends the information to the spectrum manager.

ii) Distributed – The concept of FC ceases in this case, as the SU co-operates with each other and converge to a unified decision on the presence or absence of PUs by sending their local sensing results to other users. So here the whole sensing procedure and decision making is carried out by the SUs.

iii) Relay-assisted – In addition to centralized and distributed co-operation, the relay-assisted co-operation exists, which is based on the sharing information regarding sensing and reporting channels between different users, and to forward the results to each other through multiple hops.

As we are concerned with the specifications, stipulated by the IEEE 802.22 standard, we would discuss our work on the platform of centralized co-operative sensing.

D. Related works

To meet the demand of spectrum, we need to use the unused or underutilized spectrums more efficiently, which are called white spaces in literature [7]. In the earlier works, centralized sensing was mainly used in CRN or sometimes cooperative sensing is also deployed like discussed in [1], [11]. Besides, the simulation models, that were generally tested, were not tested with IEEE 802.22 standard protocol. In [8], it is highlighted that "Interestingly among all presented demonstrations, not a single one implemented the IEEE 802.22 protocol stack". There were no works seen on the complete model of sensing along with allocation like we found in [1] and [11] the, different sensing techniques were discussed whereas in [12] allocations of the channels were discussed. We noticed none of the previous works were dealing with the complete sensing environment and also allocating the channels. The novelty of our approach is that we use this cooperative method of sensing in an effective way using user selection technique to sense the spectrum along with the efficient model for allocating the available channels to the proper secondary users and our work is totally based on the IEEE 802.22 standard protocol.

III. PROPOSED WORK

A. Co-operative sensing framework

In our work, we propose a co-operative sensing framework following the IEEE 802.22 standard.

We will build the co-operative sensing framework using four important building blocks, which are shown in Figure 1, as follows:

i) user selection,
ii) sensing techniques,
iii) standardized reporting, and
iv) data fusion.

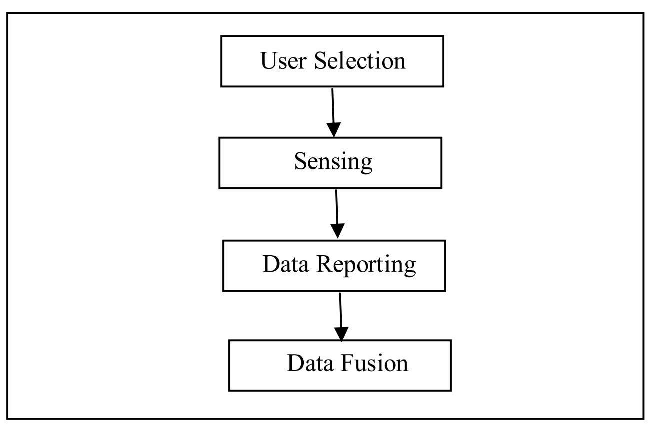


Fig 1. Basic pillars of co-operative sensing framework

Figure 1 shows the basic pillars of sensing framework and also the flow of operations from user selection to data fusion.

User selection in co-operative sensing plays an important role, as it minimizes the co-operative overhead and improves the co-operative gain. Selecting independently correlated users (SUs) improves the detection probability. After the user selection we proceed to the different sensing mechanisms used by the SUs. There are three basic types of sensing techniques which can be used for detecting if the PU is transmitting a signal or not. Each of these sensing techniques has its own merits and demerits. We use energy based sensing as our sensing mechanism because it is both efficient and also easy to implement. After completion of sensing, the next step is to *report the sensing data* to the BS. The next pillar of this framework is the *data fusion* which is performed by the SM section of the BS.

B. Building the co-operative sensing framework

Before we begin with the sensing framework, we define our work on one single, dedicated BS. The different steps in the sensing process are:

i) User selection

The sensing framework commences with the user selection procedure, shown in Fig. 2, where the SM will select the necessary SUs, to be deployed for the sensing.

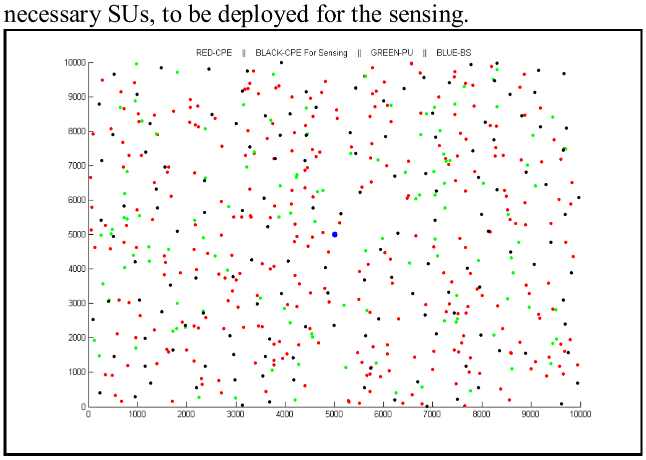


Fig. 2: User selection among the SUs

The need for this selection arises from the fact that the SUs who undergo correlated fading or shadowing characteristics, will report correlated data to BS, contributing to additional co-operative overhead. We begin with the correlation characteristics of channels. We assume a widely accepted model for the autocorrelation function [1],

$$\ln\left(\phi(\Delta x)\right) = -\Delta x / l \qquad (1)$$

Here, l is the environment parameter and is called the de-correlation distance. It is the shortest distance between any two points, required for the shadowing correlation to fall below a determined threshold. For shadowing correlation below the threshold, we will use the term *uncorrelated shadowing*. We define the threshold of shadowing to be e^{-1}. So, putting $\Delta x = l$ in (1), and equating with, $\phi(\Delta x) = e^{-1}$, we get the value of l as, where $l \approx 8.3056$ m in non-line of sight (NLOS) environment and $l \approx 500$m in suburban environments.

We employ a general user selection algorithm [5] in our co-operative sensing framework. The term “users”, used in the algorithm refer to SUs. We use the de-correlation distance as determined in the user selection algorithm with the concept that two users *i* and *j,* whose distance of separation $r_{ij} \geq l$, are said to experience uncorrelated shadowing. Now, let us define a correlation measure $c_{ij} = f(l)$, such that, if $r_{ij} \geq l$, then $c_{ij} = 0$, else $c_{ij} = 1$. The symmetric condition in case of the correlation measure holds, such that, $c_{ij} = c_{ji}$. Here, $r_{ij} = \left\| \vec{r}_i - \vec{r}_j \right\|$. We proceed to our algorithm, whose steps are given below:

1) Construct a matrix with the elements c_{ij}, where the index i indicates the row and the index j indicates the column. If N = total number of users, then the dimension of the matrix will be $N \times N$

2) Add BS to the active set A

3) Arrange the users, not allocated to the active or passive set, into the candidate set

4) If $\left\| \vec{r}_i - \vec{r}_{BS} \right\| \geq l$ and $c_{ij} = 1\ \forall j \in A$, then add user i to the active set, else add user i to the passive set. If there are no users in the active set, then the first condition is sufficient

5) Repeat steps 3 for all i, until the target number of users to be selected, is reached or the candidate set is empty.

The basic idea behind this algorithm is to deploy the users who experience uncorrelated shadowing that we have defined earlier. We compare the distance between the users, with the de-correlation distance and define a correlation measure, which essentially indicates the presence or absence of correlated shadowing with respect to each other, by the value 1 or 0, respectively. In the algorithm, we maintain three sets, the *candidate set*, which keeps account of all users, who have not yet been allocated a set, the *active set*, which keeps account of the users selected for sensing, and the *passive set,* which keeps account of the users who are not selected for sensing. The active set starts with the FC. If the condition of the de-correlation distance is satisfied with respect to the FC, along with other users in the active set, the user, in concern, is added to the active set else it is added to the passive set. This process is continued until the target number of users is achieved (refer to Section IV for simulation results) or the candidate set is exhausted (refer to Section IV). This algorithm on user selection will provide us with say M users, who will deploy for sensing, using different sensing techniques, which we will discuss in the next section.

ii) Sensing techniques:

The most important aspect of Cognitive Radio is that the SUs need to detect the presence of active PUs in the licensed spectrum so that the SUs can use the white space for data communication. For this different sensing techniques are employed. *Sensing techniques* involve the three basic types of sensing [13], i.e.,

I. energy based sensing,
II. cyclostationary feature detection and
III. matched-filter based sensing

Matched-filter based sensing: This type of sensing technique uses a linear filter to maximize the output SNR for a given input signal. If the secondary user has priori information regarding the PU signals then this type of sensing technique can be applied. In the Matched Filter, we basically perform the correlation of the unknown signal with the impulse response of the filter i.e., we perform the convolution of the received unknown signal with the mirrored and time-shifted version of the reference signal. The impulse response of the matched filter, 'h', is matched with that of the unknown signal to make the output SNR maximum.

Cyclostationary feature detection: This technique exploits the periodicity in the received primary signal to detect the presence of PU. In this type of sensing technique Fast Fourier Transform (FFT) based sensing is used. In this type of sensing technique the signal received from the PU (x(t)) is first sampled to get the discrete version of the analog signal (x(n)). Then the FFT of x(n) is taken to get the frequency domain representation(X(k)) of the given signal. The average power of the signal can be now computed form the Power Spectral Density (PSD) of this sampled frequency domain signal. The average power can now be compared with the threshold value of detected signal to determine if the PU is idle or active.

Energy Based Sensing: In our work, we will use energy based sensing technique [9], [13] to detect the presence of PU in its channel, by comparing the SNR value of that signal with a given threshold value. Due to its simplicity and no requirement of apriori knowledge of the signal, transmitted by the PU, this technique is most popular in *co-operative sensing*.

Regardless of the co-operation models, the process of co-operative sensing starts with local spectrum sensing at each co-operating SU. We consider energy based sensing technique in our work. Assume the hypothesis model of the received signal:

$$\mathcal{H}_0: y(t) = n(t)$$

$$\mathcal{H}_1: \; y(t) = h(t) * x(t) + n(t) \qquad (2)$$

Here we have, *x(t)* as the PU's signal which is sensed at the receiver end of the CPE, *n(t)* is the environmental noise, here we use AWGN or additive white Gaussian noise as the noise parameter, and *h* is the channel transfer function from the PU's transmitter to the CPE's receiver. In case of no transmission we have the null hypothesis or $\mathcal{H}_0$, which defines the absence of the signal x(t), transmitted by PU in the channel. But if the PU sends a signal x(t) we have the finite hypothesis as $\mathcal{H}_1$ given in equation (2), indicating the presence of PU transmission. So for 2nd hypothesis, we het y(t) is the convolution of x(t) and y(t), and the AWGN noise n(t) is added to that.

Let P_0 be the average power of N observed samples

$$P_0 = \frac{1}{N} \sum_{t=1}^{N} | y(t) |^2 \qquad (3)$$

The decision whether the spectrum is being occupied, is made by comparing P_0 with a threshold SNR level λ, such that hypothesis $\mathcal{H}_0$ is satisfied for $P_0 < \lambda$ and $\mathcal{H}_1$ is satisfied for $T \geq \lambda$. The performance of the detector is indicated by two probabilities, the probability of false alarm P_{fa}, and the probability of detection P_d, where

$$P_{fa} = \Pr(P_0 > \lambda \mid \mathcal{H}_0)$$

$$P_d = \Pr(P_0 > \lambda \mid \mathcal{H}_1) \qquad (4)$$

The selected SUs, after the user selection procedure, are required to perform energy detection along with the BS to detect the channels currently unused. Each SU performs the sensing procedure independently, and hence the sensing results are independent. The sensing mechanism is described in Fig. 3, where it shows that the selected SUs (marked with green squares) sense the channels through energy based sensing. The signal of PUs that are remotely located with respect to the BS, fail to reach the BS. The SUs near those PUs help in reporting the availability of channels of remotely located PUs to the BS.

Comparing the three types of sensing techniques, it can be concluded that matched filter based detection is complex to implement in CRs, but it has the highest accuracy. Also it can be said that the energy based detection is the least complex to implement in CR systems but its accuracy is lesser than that compared to other approaches. And the cyclostationary feature detection is in the middle of these two.

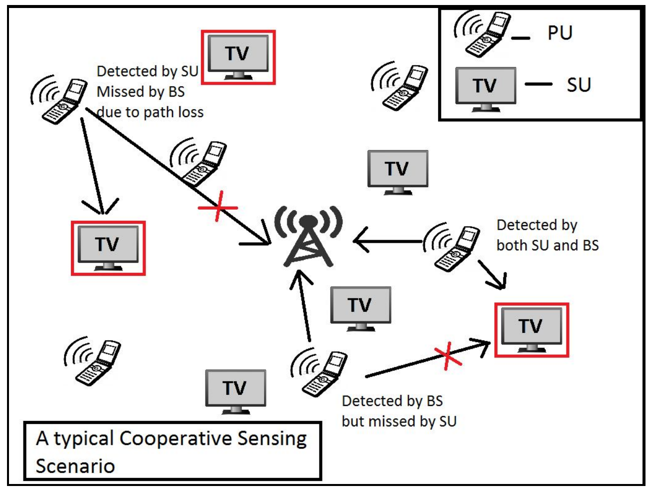


Fig. 3: Cooperative sensing-an illustration

iii) Standardized reporting

For co-operative sensing technique we use a common control channel to report the local sensing data. These sensing data are the free channels, number of free PUs or SU demanding the availability of a channel or the threshold level in a channel or any other parameters related to sensing in a channel. All these parameters are now reported to the BS via the control channel. This control channel is a dedicated channel which is implemented in both licensed and unlicensed band. But if there is a constraint in bandwidth then there might be a restriction to the amount of data sent to the BS. This standardized reporting is important because all the decisions of taken during channel allocation which follows the sensing is taken by the BS. The results of the sensing are now passed onto the Fusion Centre or FC which will decide if the channel is at all allocable or not.

iv) Data fusion

Different sensing results obtained from the SUs and the sensing results at the BS are then fused or mixed or compared logically at the FC i.e., the BS. Consider a channel C_j, the decision of i^{th} SU is d_{ij} (1= PU is present, 0= PU is absent) then the FC may take the decision by unanimous voting (all CPEs) agree on the specific channel) or simple majority (predicted by at least one more than half the number of classifiers). In this paper we have used this data fusion scheme using the method of weighted majority voting. Consider, the weight for each of the K users/ BS which senses a particular channel C_j is b_i, then the FC will decide there is a PU in that channel if

$$\sum_{i=1}^{K} d_i \geq K/2 \tag{4}$$

The FC makes a correct decision if (K/2)+1 number of sensing result is correct. If for each user the probability of sensing the channel correctly is p then the probability of the success of FC is

$$P = \sum_{m=(K/2)+1}^{K} \left(C_m^K\right) p^m (1-p)^{1-p} \tag{5}$$

Assuming b_j =1 for all j. To maximize the success rate, we have to choose

$$e^{b_i} \propto (p_i/1-p_i) \tag{6}$$

As the sensing ability of BS is higher than any -SU, in this paper we have given a higher priority to BS.

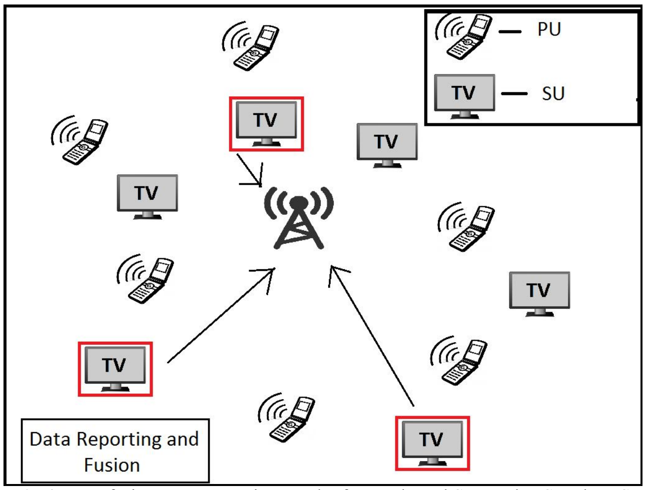


Fig 4. Data fusion among sensing results from selected SUs and BS at the BS

Figure 4 describes the data reporting and fusion procedure. The selected SUs report their sensed data to BS where their fusion is done.

IV. SIMULATIONS

All simulation results provided are obtained by simulation done by MATLAB version 2011a. The experimental parameters used in a typical setup used for the simulation of the proposed algorithm is listed in TABLE I. All data provided are average over 20 runs.

TABLE I. SET-UP USED IN SIMULATION

Experimental Parameters	**Values**
No. of PU	80, 120
No. of SUs	200
Area under one Base Station	10km x 10km
Sensitivity of SU	-38 dBm
Maximum signal power PU	23.3 dBm when active, and (Sensitivity-7dBm) when inactive
Noise	Additive White Gaussian
Position of Base Station	Center of the area (10x10sq km)
Weightage of SUs during data fusion	1
Weightage of BS during data fusion	2

According to equation (7) provided in section III B(iv), if we use the fixed values of probability of false detection [3], then weightage *b* for BS is found out to be almost twice that of the SUs (4.54 and 2.19 respectively). Hence we take the values 2 and 1 respectively as shown in Table I. The PUs and SUs are deployed randomly throughout the area under consideration and one channel is assigned to each PU. The channel characteristics viz. EIRP, frequency, bandwidth vary from channel to channel [4]. For the sake of simplicity, we assume Gaussian noise. The fading is assumed to have exponential variation as discussed above. In Fig 5, the number of SUs is varied keeping the number of PUs fixed at 80 at first and compare the number of free channels detected by our algorithm (marked as BS+SU) with the number of free channels, input in the simulation (defined during setting up the simulation and marked as "Input Dataset" in the graphs) and free channels detected by the BS only. The same is done in figure 6 with number of PUs kept fixed at 120 in the simulation. In both figures, it is observed that number of false detections is minimized by our algorithm. Further may be seen due to our optimized SU selection that the variation of the number of PUs has negligible effect on the results.

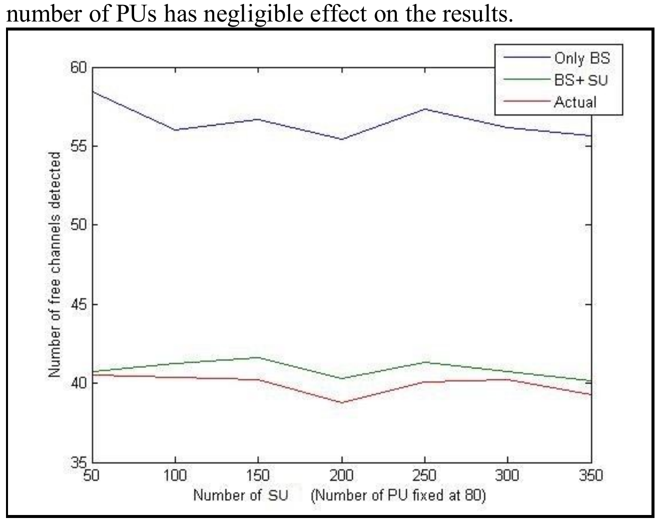


Fig 5. Minimization of false detection by our algorithm

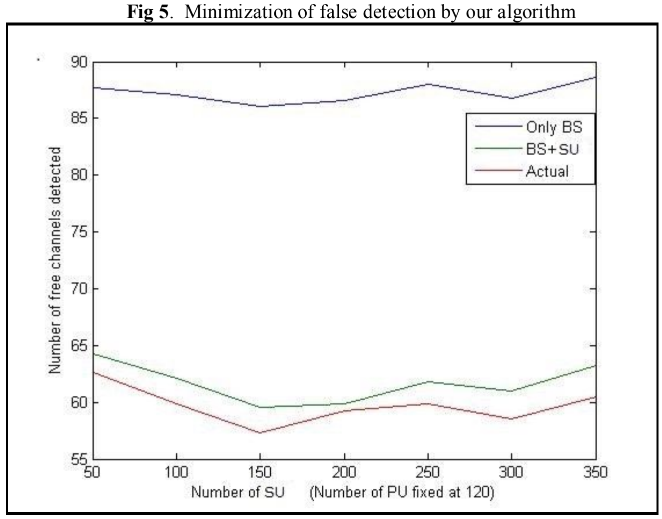
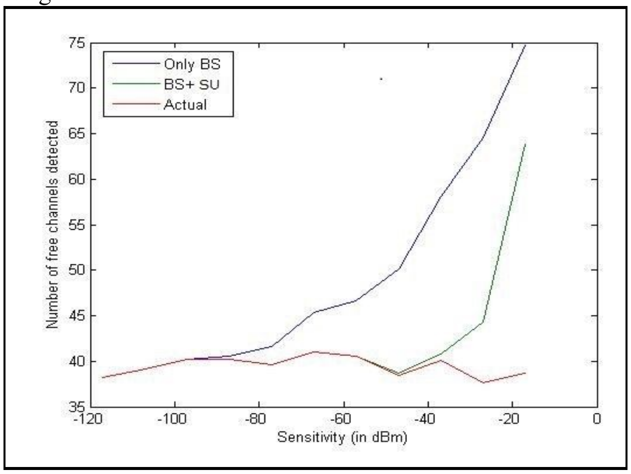


Fig 6. Minimization of false detection by our algorithm

In Fig 7, we vary the threshold level i.e., check the range of receiver sensitivity, over which the proposed algorithm works well. In IEEE 802.22 standard, it is mentioned that the threshold level should be at -117 dBm for centralized sensing. From figure 6, it may be observed that if we use our algorithm then the sensitivity of the receiver can be increased to -50 to -60 dBm depending on the input conditions (here it is around -

56 dBm), which is a significant decrease in the required sensitivity level resulting in simpler and low cost receiver design.



Using the fixed values of probability of detection instead of using probability of miss, and then weightage *b* for BS is agian found out to be almost 2 times that of the SUs (4.54 and 2.19 respectively). So we take the weightage of the SU to be 1 and BS to be 2. Now the PUs and SUs are again deployed randomly throughout the area under consideration and one channel is assigned to each PU. The channel characteristics which are EIRP, frequency, bandwidth vary from channel to channel [4]. For simplicity, the environmental noise is assumed to be Gaussian noise. The fading and path loss is assumed to have exponential variation as discussed above. In Fig 4 and 5, the number of SUs is varied keeping the number of PUs fixed at 80 and 120 and the number of free channels detected by our algorithm (marked as BS+SU) is compared with the actual number of free channels in the spectrum (defined during setting up the simulation and marked as "Actual" in the graphs) and free channels detected by the BS only. We observe that number of false detections is minimized by our algorithm. Further also it may be seen due to our optimized SU selection that the variation of the number of PUs has negligible effect on the results.

The threshold level is varied here also to check the range of receiver sensitivity over which the proposed algorithm works well. It may again be observed that if we use our algorithm then the sensitivity of the receiver can be increased to -50 to -60 dBm depending on the actual scenario (here it is around -56 dBm), which is a significant increase in the sensitivity level resulting in simpler and low cost receiver design.

V. CONCLUSION AND FUTURE WORK

Our work encompasses the basic periphery of sensing framework, in conformation to 802.22 standard. It also provides space for further analytical developments on the pillars of our framework. Like, our proposed algorithm may be extended for multiple BSs scenarios. Moreover, we have chosen Gaussian noise model only as the noise model in our simulations. Simulations can be done for other practical noisy environments. Also, we have not used any common control channel in our work which may be included for further work. In addition to above examples, the allocation algorithm can be optimized to obtain better performance as well. Here in our work we have used energy based sensing which is easy to implement. We can use cyclostationary and matched filtering techniques to get more accurate sensing results though they are more complex to implement. We can implement all the three sensing techniques to compare the advantages and disadvantages of each of them.

V. ACKNOWLEDGEMENT

We would like to thank Dr. Amitava Mukherjee, Senior Manager, IBM India Pvt. Ltd and Prof. Mrinal Kanti Naskar, Dept. of ETCE, Jadavpur University, for their constructive guidance which helped us to develop the work.

REFERENCES

[1] Unnikrishnan, Jayakrishnan, and Venugopal V. Veeravalli. "Cooperative spectrum sensing and detection for cognitive radio." *Global Telecommunications Conference, 2007. GLOBECOM'07. IEEE*. IEEE, 2007.

[2] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[3] S.Shellhammer et al. "Spectrum Sensing Simulation Model." , 6th June 2006.

[4] Stevenson, C., Gerald Chouinard, Zhongding Lei, Wendong Hu, S. Shellhammer, and Winston Caldwell. "IEEE 802.22: The first cognitive radio wireless regional area network standard." *Communications Magazine, IEEE* 47, no. 1 (2009): 130-138.

[5] Selén, Yngve, Hugo Tullberg, and Jonas Kronander. "Sensor selection for cooperative spectrum sensing." In *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, pp. 1-11. IEEE, 2008.

[6] Akyildiz, Ian F., Won-Yeol Lee, Mehmet C. Vuran, and Shantidev Mohanty. "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey." *Computer Networks* 50, no. 13 (2006): 2127-2159.

[7] U.S. FCC, ET Docket 08-260, "Second Report and Order and Memorandum Opinion and Order, in the Matter of Unlicensed Operation in the TV Broadcast Bands Additional Spectrum for Unlicensed Devices Below 900 MHz and in the 3 GHz Band," Oct. 18, 2006.

[8] Pawelczak, Przemyslaw, Keith Nolan, Linda Doyle, Ser Wah Oh, and Danijela Cabric. "Cognitive radio: Ten years of experimentation and development." *Communications Magazine, IEEE* 49, no. 3 (2011): 90-100.

[9] Ghasemi, Amir, and Elvino S. Sousa. "Collaborative spectrum sensing for opportunistic access in fading environments." In *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, pp. 131-136. IEEE, 2005.

[10] Cabric, Danijela, Shridhar Mubaraq Mishra, and Robert W. Brodersen. "Implementation issues in spectrum sensing for cognitive radios." In *Signals, systems and computers, 2004. Conference record of the thirty-eighth Asilomar conference on*, vol. 1, pp. 772-776. IEEE, 2004.

[11] Unnikrishnan, J.; Veeravalli, V.V. "Cooperative Sensing for Primary Detection in Cognitive Radio", *Selected Topics in Signal Processing, IEEE Journal of,* On page(s): 18 - 27 Volume: 2, Issue: 1, Feb. 2008.

[12] Yuan, Yuan, Paramvir Bahl, Ranveer Chandra, Thomas Moscibroda, and Yunnan Wu. "Allocating dynamic time-spectrum blocks in cognitive radio networks." In *Proceedings of the 8th ACM international symposium on Mobile ad hoc networking and computing*, pp. 130-139. ACM, 2007.

[13] M.Subehdar, G.Birajdar, "Spectrum sensing techniques in cognitive radio networks: a survey"in: International Journal of Next-Generation Networks (IJNGN) Vol.3, No.2, June 2011, pp. 37-51.