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Performance Appraisal for Cooperative and Non-Cooperative Spectrum Sensing Techniques in Cognitive Radio

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Abstract

The drastic increase in wireless applications led to an obligation on the usage of available radio spectrums, which led to a demand for an optimistic spectrum management method. Cognitive Radio (CR) materialized as an optimistic technology that can handle spectrum scarcity by providing an efficient strategy to utilize the available bandwidth opportunistically. CR strategically allows the Secondary Users (SU's) to approach the available spectrum without causing intervention with the Primary Users (PU's). This layout is said to be Spectrum sensing (SS) and the unused spectrum that the SU occupies is called a Spectrum Hole. In this research paper, various SS techniques are elaborated that are used in both Cooperative and Non-Cooperative spectrum sensing methods and various parameters like the probability of detection, sensing time, probability of false alarm, probability of miss detection, the energy efficiency of various SS techniques are compared and a drive to a conclusion as to which of the technique would yield an optimal SS result.

Keywords
Cognitive Radio, Spectrum Hole, Spectrum Sensing, Secondary User, probability of detection, sensing time, probability of false alarm, probability of miss detection**.**

I. Introduction

In the past few decades, wireless technology has witnessed massive growth in almost every field of technology, which leads to an alarming increase in wireless applications. This leads to the immense constrain on the available spectrum and the need for new spectrums so that these wireless devices to communicate with each other [1]. Due to the fact that spectrum is a limited natural resource, it was crucial to effectively utilize the available resource. So the government came up with the idea of a fixed spectrum policy [2], where each radio spectrum user was allocated to a licensed user or Primary Users (PU). A study that was conducted by the Federal Communication Commission (FCC) divulge that depended on the geographical location and as well as certain hours of the day most of the spectrums were sparsely used while only a few frequencies were heavily used, which led to underutilization of the limited available radio spectrum. This obliged the evolution of Dynamic Spectrum Access (DSA) [3]. This technology made it possible to sense the unused spectrum (spectrum hole) and make it available to Secondary Users (SU) or unlicensed users without much interference to the PUs which lead to the concept of Cognitive Radio (CR) [4]. The CR is a smart device that can detect the spectrum hole (SH) and share the spectrum with other SU in an opportunistic manner without causing interference with the PU.

The CR works on the principle of the Cognitive Radio cycle, which comprises four steps [5] as shown in Fig1.

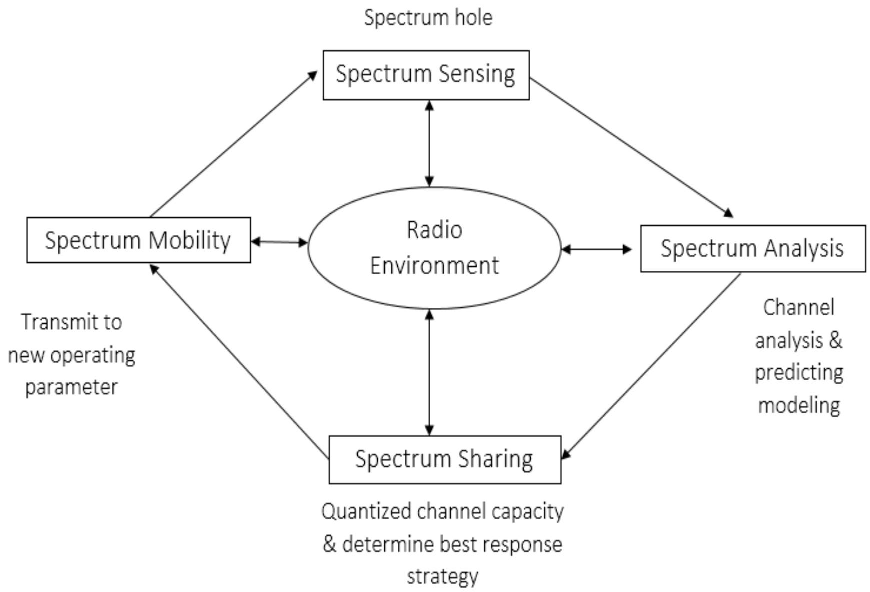

Fig. 1 Cognitive Radio Cycle

Spectrum Sensing: Detecting an unused or partially used spectrum is called spectrum sensing.

Spectrum Decision: elicited from the spectrum sensing result and users' requirements the best available spectrum is chosen for the data transfer.

Spectrum Sharing: A mechanism is needed to provide a fair spectrum scheduling policy among CR users and also coordinate the access to the network among all SU's as there may be many CR users trying to communicate at a particular time there.

Spectrum Mobility: If a PU is active again in the frequency occupied by the SU then the SU should switch over seamlessly to a suitable new frequency for further data transmission.

Spectrum sensing is the initial step in Cognitive Radio. In this paper, we are concerned only with spectrum sensing. The rest of the paper is organized into the following six sections. We start with the literature survey in Section II. We explain the measuring system in Section III, followed by Section IV, which gives a detailed explanation of spectrum sensing methods. Last but not least we decorate Section V which results and discussion followed by the conclusion in Section VI.

II. Literature Survey

Umme Salama et al [6] have analyzed that energy detection method using matched filter, as energy detection method has less complexity than other methods but it could not detect the weak PU signal in a noisy channel, so matched filter was employed. When the information regarding PU signals like modulation and packet format knows the matched filter could detect the PU signal easily which is not possible in all cases.

Spectrum sensing using a Matched filter detector was evaluated by Suresh Dannanan et al [7]. Whereat different SNR levels the detection probability and the false alarm probability were observed. It is inferred from the results that for SNR above 25 dB better probability of detection was achieved for a given false alarm probability and increasing the false alarm probability will automatically decrease the threshold value which leads to better detection probability and finally as SNR increases the corresponding threshold value decreases for a fixed false alarm probability.

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Cebrail et al [8] have developed an eigenvalue/covariance-based detection method with new scale adjustments and centering for larger eigenvalue distribution. By using an equation and a new threshold value for the covariance Eigen matrix the probability of detection (Pd) and false detection probability (Pfa) for Max-Min Eigenvalue (MME), Max Eigenvalue to Trace (MET), and Max Eigenvalue- Geometric Mean (ME-GM) is obtained. This method was able to detect even at low sample length and spectrum sensing time was reduced.

Cyclostationary feature detection for Spectrum Sensing was examined by Khadeeja Sherbin et al [9]. As cyclostationary detection uses underlying periodicity of the modulated signal for detection of signals, four modulation schemes QPSK, BPSK, FSK, and MSK were used. The cyclic profile of the received signal is searched. As CFD searches for a particular modulation scheme used by the primary user same frequency can be used for two PU. The output was more reliable and accurate and detection performance was high even at low SNR.

Fang Liu et al [10] proposed an adaptive double threshold stratagem for spectrum sensing for CR. The spectrum sensing segregated into several stages and depending on the sample number the threshold can be varied. So an adaptive double threshold scheme was proposed to reduce the number of samples. The optimal no of samples at each phase is calculated by using an iterative algorithm. When the energy value is between two thresholds, then CR moves to the next phase to collect the sample until a binary decision depending on the channel is made. This method requires fewer signal samples which drastically lessens sensing time and the throughput of the CR network is improved.

A novel cluster-based spectrum sensing in CR. Where data objects are bunched into clusters based on harmony. The similarities within the group will be large and the difference will be greater between the groups is called the hierarchical clustering method. In each cluster, a sensor node is selected for spectrum sensing instead of all the nodes as the similarities are very high and the information is shared among other clusters. Thus energy consumption is reduced [11,23].

Kae Won Choi [12] evaluated cooperative spectrum sensing under a random geometric primary user model. This network displays a certain limit on the degree of randomness in topography. A location-aware cooperative sensing algorithm is adopted which linearly blends the sensing results from all the SU’s through Fisher linear discriminant analysis. This reduces false alarms and increases the detection probability.

III. Measuring System

The frame structure of Cognitive Radio comprises sensing time (Ts) and data transmission time (Td). So the frame time (Tf) is a combination of Tf = Ts+Td. The spectrum sensing is formulated with two hypothesis

Null hypothesis (H0): Primary user or Licensed user is absent (i.e.) channel is vacant

H0: y (t) =n (t) ------ (1)

Where y (t) is the received signal and n (t) is the additive white Gaussian noise

Alternating hypothesis (H1): Primary user or licensed user is present (i.e.) channel is occupied

H1: y (t) = h*x (t) +n (t) ------ (2)

Where y (t) is the received signal and h is the channel gain. We consider x (t) as the primary signal, and n (t) is Additive White Gaussian Noise. H1 indicates the presence of the primary user in the

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channel. A threshold is fixed in line with the description of the service. If the received signal y (t) is lesser than the threshold null hypothesis H0 is presumed to be approved else alternative hypothesis H1 is approved. The sensing accuracy is calculated based on the Receiving Operating Characteristics (ROC) curve. This curve is a plot of the detection probability against the false alarm probability (or) miss detection probability against the false alarm probability. This probability is formulated as follows

Probability of detection (Pd): It is the probability that CR will detect and announce the existence of PU when PU is nearby and the spectrum is not allocated to other SUs.

Pd=Pr [Decision H1/H1] ------ (3)

Probability of miss detection (Pm): It is the probability that CR will miss a signal when it is present and the spectrum is allocated to other SUs. This is due to the noise present in the channel and this causes the energy level to exceed the threshold value, so the CR decides that the PU is present.

Pm= Pr [Decision H0/H1] ------- (4)

Probability of false alarm (Pf): This is caused due to interference. This happens when the energy of PU does exceeds the predefined threshold value and hence the CR decides that PU is present.

IV. Spectrum Sensing Methods

Spectrum sensing is a vital service on which the complete procedure of Cognitive Radio relay on. To ensure reliable operation, Cognitive Radio has to detect precisely the spectrum hole at the link level. This approach of constantly watching the spectrum is called spectrum sensing [13]. Spectrum sensing does the function of evaluating radio channel parameters such as transmission channel characteristics, interference level, noise level, spectrum availability, etc. Spectrum sensing is mostly done in the frequency or time domain.

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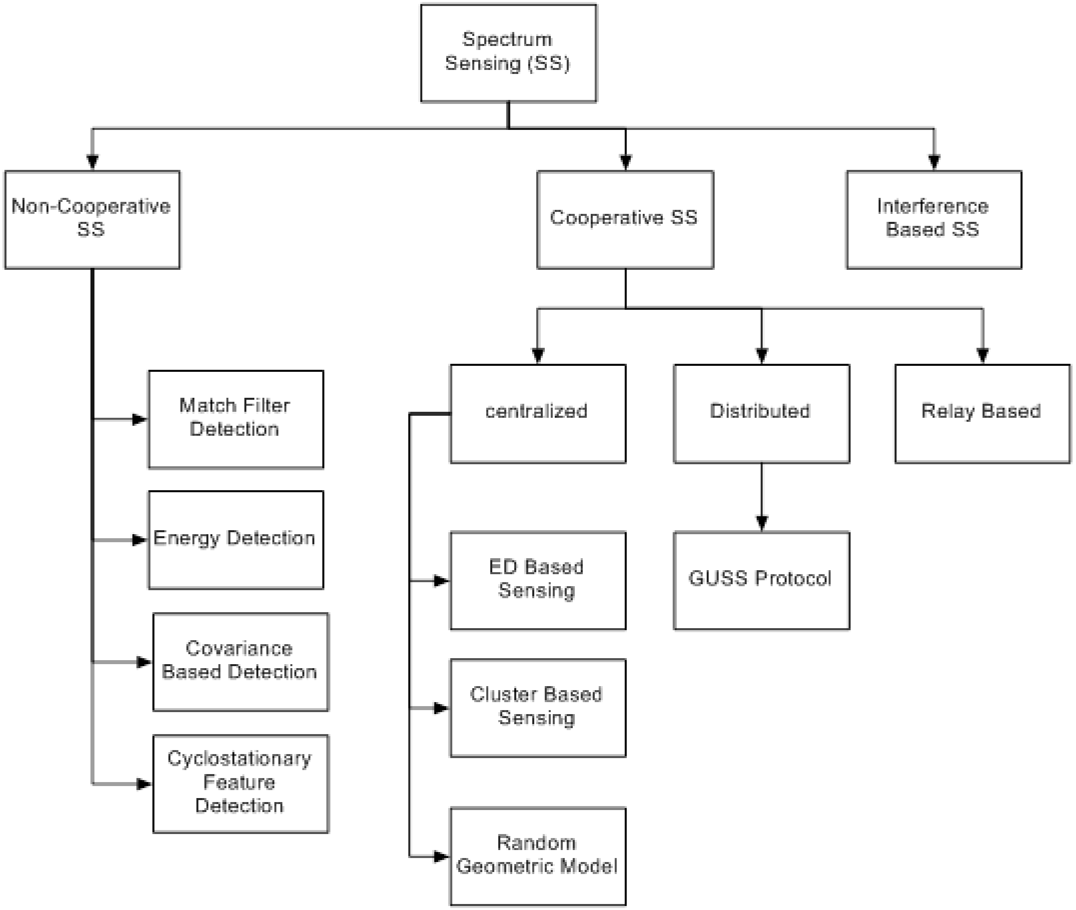

Fig. 2 Spectrum Sensing technique under study

Spectrum Sensing (SS) technique is further classified into three-technique they are Cooperative spectrum sensing, Non-cooperative spectrum sensing, and interface-based spectrum sensing as shown in Fig2. In this paper, we concentrate on cooperative and non-cooperative spectrum sensing techniques

4.1 Non-Cooperative spectrum sensing

It is also termed a transmitted detection method or local spectrum sensing. In this sensing method, there is no cooperation or sharing of information among the SU. So the CR user detects the absence and presence of PU through sensing by itself. The information obtained through sensing is used to find whether the channel is busy or ideal. There are several methods of non-cooperative spectrum sensing. The widely used sensing methods are Energy Detection, Match filter detection, Cyclostationary feature detection, and covariance-based detection [14]. In the Match filter detector and cyclostationary feature detection, a former tip is needed by the CR. So that CR can discover the existence of PU whereas no prior information is need when using Energy detection and Covariance based detection so these two methods are called blind detectors methods.

4.1.1 Match Filter Detection

It is a type of non-blind spectrum sensing. The prior details regarding the PU signal such as modulation rate, coding technique, frequency, bandwidth, pulse shaping, and frame format are known. If all these are known then a matched filter is the best process for finding the existence of PU and also for downsizing of SNR at the receiver [15]. The matched detector correlates the

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unknown received signal x (t) and compares the received signal with prior information captured from the same transmitter. Then the test static output is then measured with a threshold. If above the threshold then the signal is considered to exist.

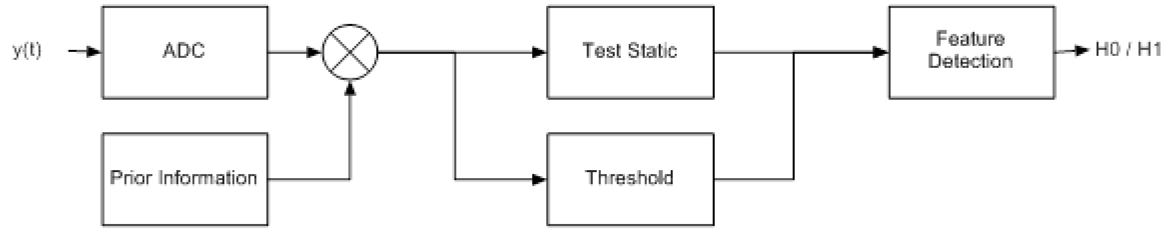

Fig. 3 Block diagram of Match filter detection

The above Fig. 3 represents the block diagram of match filter detection. The matched detector test statics is given by

$$T_{MF} = \frac{1}{N} + \sum_{n=1}^{N} y(n) x_p^*(n) --- (5)$$

Where N is the no of samples y is the vector of the samples and xp is the prior information samples. The test static is contrasted with the threshold to shape the sensing outcome as if

TMD< λMD   Primary User is absent. ------ (6)

TMD> λMD Primary User is present ------ (7)

λMD is the threshold that leans on the noise present at the obtained signal. Since this threshold is static and sometimes the received signal is affected by noise uncertainty it will lead to less accurate results. To overcome these issues dynamic selection of the threshold was encouraged, which lead to better sensing performance at the receiver end.

4.1.2 Energy Detection

This is a commonly used method in Non-Cooperative Spectrum Sensing. This is a non-coherent detection method in which advanced information regarding the primary user or licensed user signal not necessary [16]. The energy detector calculates the energy of the received signal and compares it with the threshold and if the energy is above the threshold then the PU is treated as present else the PU is treated missing. The energy of the samples is calculated by squaring the magnitude of the FFT average over the number of samples N. This is given by

$$T_{ED} = \frac{1}{N} \sum_{n=1}^{N} [y(n)]^2 ----(8)$$

The block diagram of energy detection is shown in Fig4. Where N indicates the sum of received samples and y (n) indicates the nth received sample.

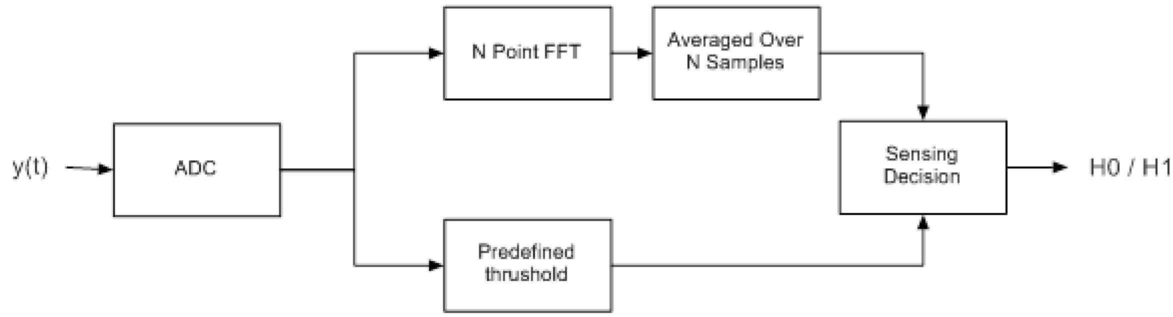

Fig. 4 Block diagram of Energy detection

The result is then analyzed with the pre-set threshold to acquire the sensing decision. The decision is based on the following

TED<λED PU is considered as absent ----- (9)

TED <λED PU is considered as a present -- (10)

λED is the threshold that relies on the noise variance in the channel. The choice of the threshold can be made statically or dynamically or adaptively which will drastically affect or enhance the detection performance. As a static threshold was affected by the noise variance researcher's preferred dynamic threshold. But the further method for improvement was achieved by a dynamic threshold method where the threshold is estimated dynamically by taking the preceding decision and other parameters like the probability of false alarm, probability of detection, SNR, and several samples are considered. Another advanced and well-known method was the double threshold method. When there is uncertainty like if the energy of the sample is small than a particular threshold then the band is said to be free, but if the energy of the sample is higher than the second threshold then the spectrum of interest is busy. The double threshold method reduces the collision probability its detection probability is less when the SNR is low and its probability of miss detection is high than one threshold method.

4.1.3 Cyclostationary Feature Detection

This approach utilizes the cyclostationary feature like required transmission capacity, frame format, periodicity, modulation type from receiver PU, and also mean, cyclic correlation, and autocorrelation. Generally, the PU signal contains features along with the data they carry. These attributes are due to the ingrained periodicity from the transporting wave, hopping sequence, modulation speed, transporting frequency, and similar parameters. This regular function is called the cyclostationary feature and these functions differentiate signal from all other signals [17]. However, each Primary signal has its different signature that implies its cyclostationary feature also will differ among each primary signal and from noise. A received signal y (t) is said to be cyclostationary if the mean and autocorrelation of the received signal is regular.

$$m_y(t) = E[y(t)] = m_y(t+T0) ----(11)$$

$$R_y(t,\tau) = R_y(t+T_0,\tau) ----(12)$$

E is the signal period is the expectation operator, Ry is autocorrelation function ζ is the offset timer. The autocorrelation of the received signal y(t) is given by

$$R_y(\tau) = E[y(t+\tau)y^*(t-\tau)e^{-j2\pi\alpha t}] --- (13)$$

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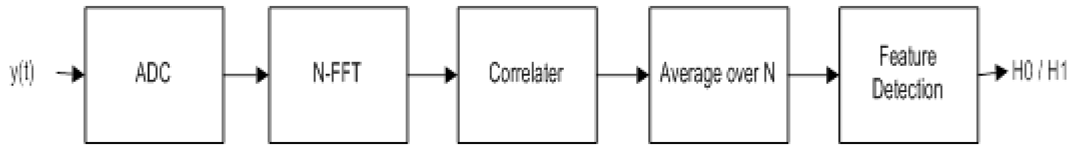

Fig. 5 Block diagram of Cyclostationary feature detection

Above block diagram Fig5. is cyclostationary feature detection where the received analog signal is digitized using an analog to digital converter and then computed to an N point Fast Fourier Transform (N-FFT) signal and these N-FFT values are correlated with themselves and then averaged over a number of samples N. The sensing decision is the obtained by the average of the outcome of feature detection.

4.1.4 Covariance Based Detection

This spectrum sensing compares the covariance of the obtained signal along with noise covariance. It is easy to detect signals from noise at a low SNR value [18]. The covariance-based detection technique uses a sampled covariance matrix and Singular Value Decomposition (SVD) of the received signal to detect if the PU is present or absent. Below Fig6 represents the block diagram of covariance-based detection. The covariance matrix of the acquired signal is determined by

$$R_y(N) = \frac{1}{N} \sum_{n=L-1}^{L-2+N_s} \hat{y}(n) \hat{y}^*(n) ---(14)$$

Then by using the SVD method the eigenvalue of the matrix is determined. This is done by applying SVD on the matrix Ry (N) which gives λ max and λ min eigenvalues. Then is static test is used to calculate the ratio of maximum eigenvalue to minimum eigenvalue, λmax/λmin was found which is then contrasted with a threshold to figure out either of two states H0 and H1. If the value is below a threshold, then we considered that the channel is not occupied by PU. Else if the test static is above the threshold, PU is considered to be present.

λmax/λmin < threshold   PU is absent ---(15)

λmax/λmin > threshold   PU is present ----(16)

Fig. 6 Block diagram of Covariance based detection

4.2 Cooperative Spectrum Sensing

Few factors make local spectrum sensing or Cooperative Spectrum Sensing ineffective, they are, affected by unpredictability of noise, shadowing, multi-pathway effect, and concealed PU problem [19]. To succeed these shortcomings Cooperative Spectrum Sensing (CSS) came into existence. CSS allows multiple SUs to cooperatively probe the spectrum and forward their review to the Central Controller or Fusion Center (FC). In the FC, the observed data are integrated and the verdict is made if the PU signal is present or not.

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The various topologies are used in CSS are classified [20] as follows, Decentralized Uncoordinated Technique, Centralized Coordinated technique, Decentralized Coordinated Technique.

Decentralized Uncoordinated Technique: Each Cognitive user will single-handedly probe the channel. If a CR user finds primary users within that channel, then the Cognitive user will quit the channel without notifying other CRs. These noncooperation techniques, in general, are error-prone when contrast with other cooperative techniques.

Centralized Coordinated Technique: This approach has a Cognitive Radio controller. When any one of the CR users digs out the existence of a PU then it will intimate to the CR controller. The controller will then notify all the CR users within its range.

Decentralized Coordinated Technique: This approach consists of developing a network of CR uses that can work without the controller. Where the cognitive users are gathered into clusters and auto coordinated themselves. This cooperative spectrum sensing needs a control channel through which it can coordinate with other users. Diverse algorithms are used in this technique among which gossiping algorithms or clustering schemes were used. Even though when cooperative spectrum sensing is immune to multipath fading, shadowing, plummeting to sensitivity requirement, penetration losses, restricted by power and cost. As shown in the above block diagram we mainly focus on the centralized spectrum sensing technique. There are mainly classified into ED-based sensing, Cluster-based CSS, and Random Geometry based detection methods.

4.2.1 ED based Sensing

This is one of the most simple detection methods as no information regarding PU is required. So it is often used method in cooperative sensing. The energy detector detects the existence of a PU signal based on the sensed energy, this is a non-coherent detection method. However, there are a few disadvantages to energy detection. 1. The channel sensing time is much longer to achieve a given detection probability. 2. The accomplishment of detection is subjected to the unpredictability of noise. 3. This cannot discriminate primary signal from CR user signals. So to overcome the above-mentioned disadvantage the CR users need to closely synchronize and should not transmit during the "quiet period" interval in cooperative sensing. The noise uncertainties causing deterioration could be limited by diversity gain of cooperation spectrum sensing.

To detect a signal in the energy detector, the test statics is central chi-square distributed as H0 and non-central chi-square distributed with N degree of freedom as H1 and the number of samples is N/2 from either in-phase (I) or quadrature (Q) components. By making use of the number of received samples N, SNR of the received signal γ, detection threshold λ, and noise power $\sigma 2$ the equation for detection probability Pd and false alarm probability Pf in a fading channel and for over an AWGN channel is designed.

4.2.2 Cluster based Sensing

Non-cooperative user selection has heaps of CR users who need to participate in sensing and convey their reports to the Fusion Center (FC) which will incur high overhead like delay, energy efficiency, and control channel bandwidth. To palliate this problem, the CR users are grouped into clusters for cooperative sensing, which is an impressive way to lessen the cooperation range and diminish overhead. The first step, in this method, is to form a cooperative cluster where all the members of the cluster are within the transmission range of each other. So that, they can communicate their decision with minimum error and bandwidth. In each cluster, the CR user with the substantial energy or channel gain is chosen as cluster head (CH), to cut the reporting time and error [21]. The CH collects the locally sensed data from each member of their cluster and forwards

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the result to FC. To pursue this, each SU is allocated with bandwidth to broadcast their decision, to other members of the cluster. Each SUs sends at least one bit of information about their decision to other SUs. The clustering technique is widely used ad hoc as it can reduce channel contention and packet collision which will lead to better network throughput under heavy load.

4.2.3 Random Geometric Model

The major problem in the existing detection method is that we consider only less PU exists in the network or we rule out the geology of the PU network. This type of model is feasible for large-scale networks with fixed PU [22]. In this, we propose an algorithm that displays some degree of randomness in its topography. This kind of topology can be used to describe small-scale mobile PU networks. The irregularity of the PU within the topology of the network is well defined by the random geometric networks. The SU aims to dig out the presence of PU-Rx (Primary User Receiver) inside the finding range by collecting the sensing outcome from other SU's. This detection is mostly used in far-reached ad-hoc mesh CR networks, wherein each SU finds out neighborhood spectrum availability by themselves. In this detection, local awareness is incorporated into the cooperative sensing algorithm. An SU will have a better and reliable sensing result if a PU-Rx exists within its detection range when compared to a distant SU. The sensing performance is improved when each SU fuses the sensing result by taking into consideration the difference in their reliability according to their distance from PU.

V. Results And Discussion

In this section, numerous simulations were carried out as shown in the figure. The scenario of the simulation were 1 primary use, 10 Secondary users, and one fusion center in case of cooperative spectrum sensing. The frequency range was between 50 to 950 MHz, 1 channel was equal to 10 MHz and the sampling frequency is considered to be 1400 MHz. The transmitted signal is a QPSK signal. In each spectrum sensing method we assess the performance of various spectrum sensing techniques using MATLAB Version 2014a. The stimulation parameters that were taken into focus were sensing time, spectrum sensing efficiency, probability of detection, probability of false alarm, and the probability of miss detection. The simulation result was then compared with various other sensing methods.

5.1 Non-Cooperative Spectrum Sensing

Fig 7 shows the simulation results of Non-Cooperative Spectrum Sensing. It is observed that Cyclostationary Detection shows better performance even in a noisy environment. This is mainly because this method uses the intrinsic property that is associated with each PU's signal, so this shows better performance than the other non-cooperative methods.

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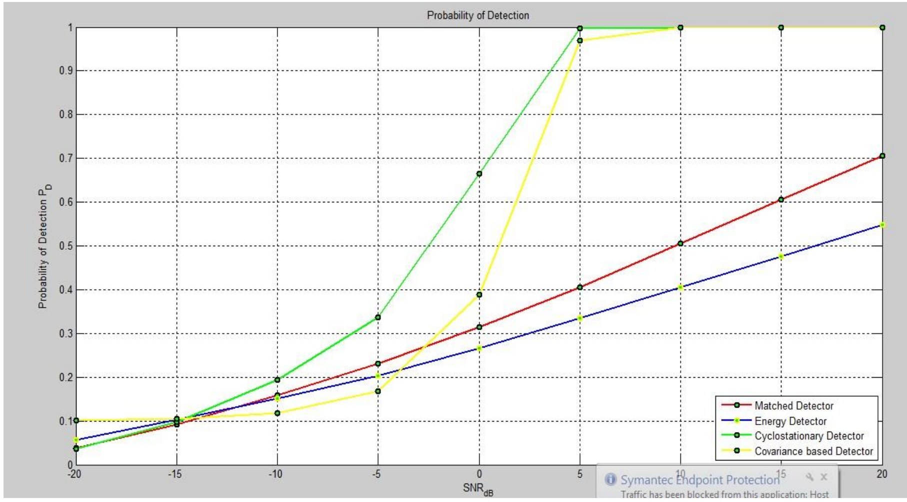

Fig. 7 Probability of detection PD Verses SNR.

Fig8 represents the Probability of Miss detection Vs SNR. It is evident from the output that cyclostationary detection has the least miss detection whereas ED-based has a large miss detected probability when compared with the other non-cooperative methods.

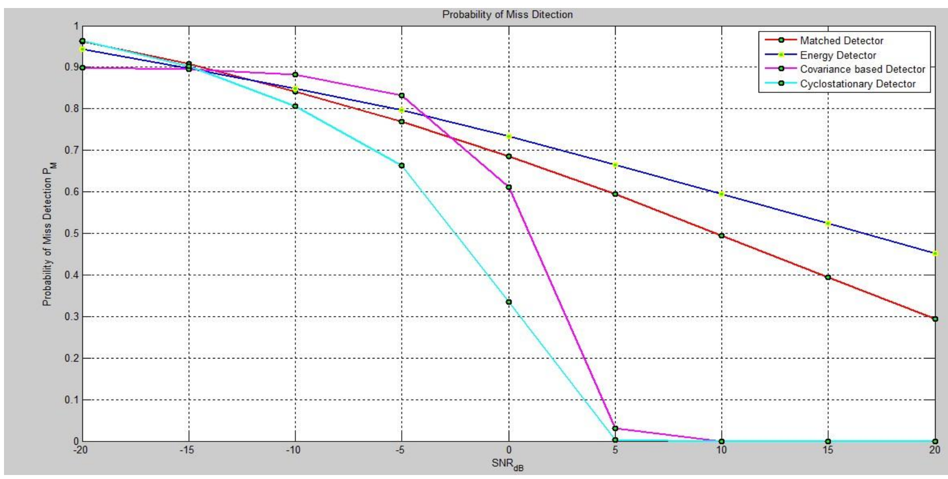

Fig. 8 Probability of Miss Detection P_M Vs SNR.

The Probability of Detection Vs Sensing time is shown in fig 9. The graphs show that the probability of detection increases as the sensing time is increased. The covariance-based detector gives better detection probability when sensing time is increased.

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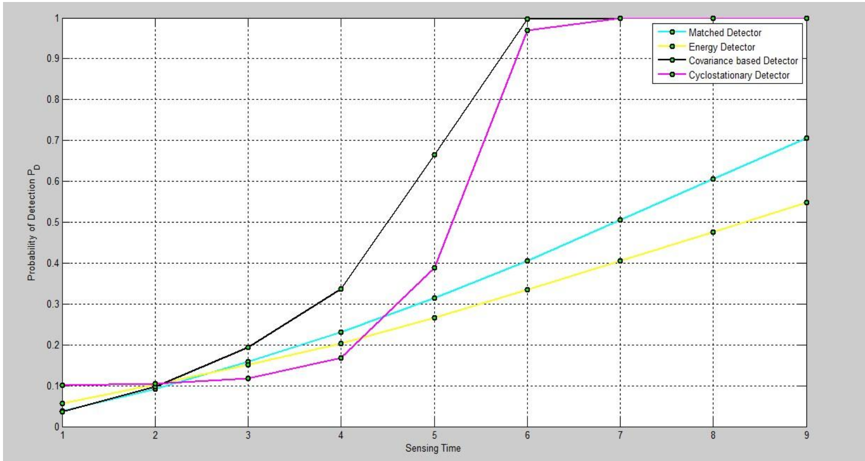

Fig. 9 Probability of Detection P_D versus Sensing time.

5.2 Cooperative Spectrum Sensing

Fig10 shows the ROC curves which are Probability of detection PD versus Probability of false alarm PF for Energy Detector, Random Geometry, and cluster-based CSS. The simulation result shows that cluster-based CSS has a higher probability of detection with less false alarm probability when compared with the other two methods. This is because in Cluster-based CSS the fusion center can select the best sensing node within the cluster as its cluster head which helped in obtaining better results.

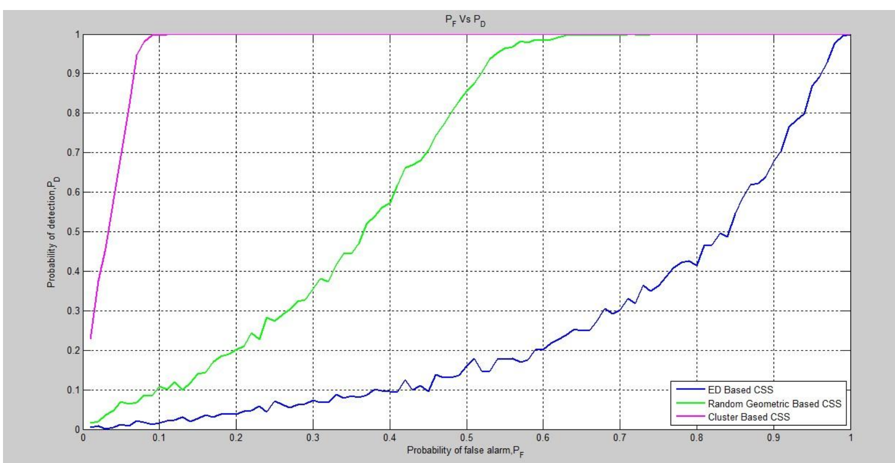

Fig. 10 ROC curve compression of ED, Random Geometry, and cluster based CSS

Fig 11. Shows the probability of detection PD against Sensing time. This graph depicts that ED-based CSS has a high detection probability in a lesser amount of time when compared with other CSS methods. This is because in Cluster and Random Geometry the SU are scattered in a wider area and information is to be forwarded FC to carry on the final result this makes ED-based CSS much easier to access.

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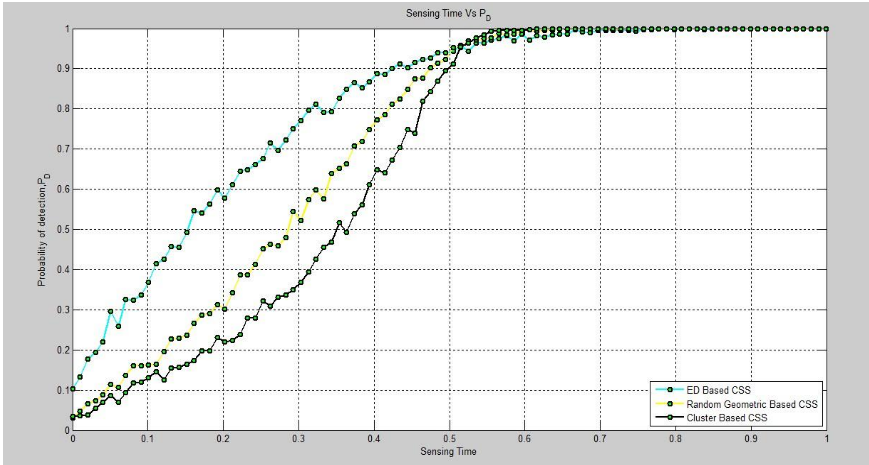

Fig. 11 Probability of detection P_D versus sensing time

Fig12 compares the probability of detection PD performance of various CSS methods against SNR when Pf=0.1 and SNR are varied between -20dB to 20dB. From the simulation result, we can conclude that the probability of detection is high for Cluster-based CSS even at a low SNR. This shows that even when the PU is at a very low signal power the cluster-based cognitive radio will be able to detect that signal.

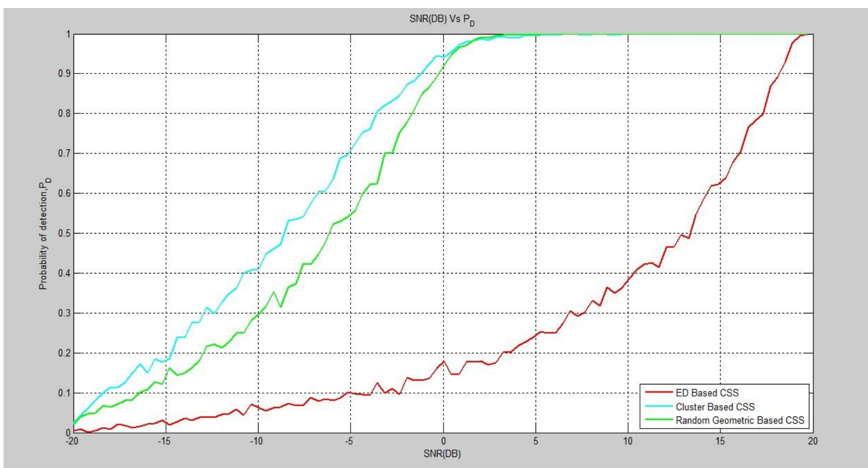

Fig. 12 Probability of Detection P_D versus Signal to Noise

Fig13 reveals that ED-based CSS works well at higher SNR were as collapse at a lower SNR, as it will not be able to differentiate noise and week signal at low SNR which is not the same in the case of Cluster-based CSS. As cluster-based CSS detection is high even at a low SNR.

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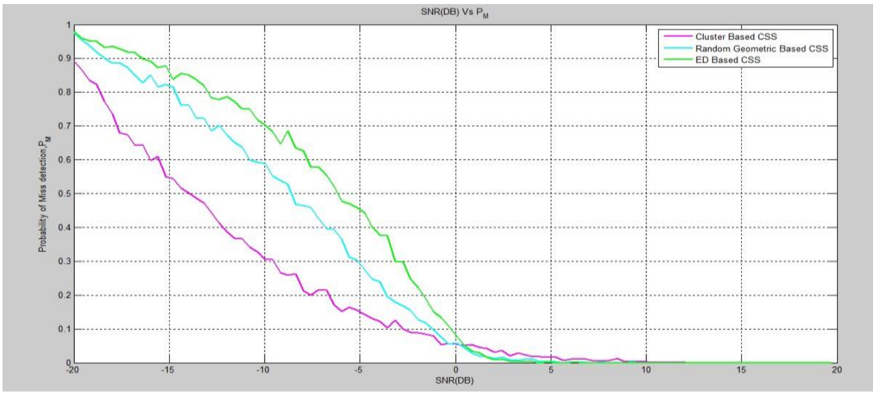

Fig. 13 Probability of Miss detection P_M Versus SNR

VI. Conclusion

In this paper, a comparison has been drawn on the various spectrum sensing methods in both cooperative and non-cooperative spectrum sensing and a conclusion is drawn based on the simulation results. From the results, it was evident that the cluster-based spectrum sensing technique which is a cooperative spectrum sensing-based method performed better when compared with ED and Random Geometry-based sensing technique. In non-cooperative spectrum sensing, cyclostationary spectrum sensing has better performance when compared to a Matched detector, ED, and covariance-based detection methods.

TABLE I: Performance evaluation for Cooperative and Non-cooperative SS

Spectrum sensing techniques	Sensing time	Probability of detection	Probability of false alarm	Probability of miss detection	Energy efficiency
Non-cooperative Spectrum sensing					
ED based	Less	Less	High	High	Less
Matched filter	Less	Less	High	High	Less
Covariance based	Moderate	Moderate	Moderate	Moderate	Moderate
Cyclostationary based	More	High	Low	Low	High
Cooperative spectrum sensing					
ED based	Less	Less	High	High	Low
Cluster based	High	High	Less	Less	High
Random Geometry	Moderate	Moderate	Moderate	Moderate	Moderate

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