



Optimized Complexity Problem Based on Combined Fully Blind Self Adapted Method using PSO for Cognitive Radio Spectrum Sensing

Rakesh Singh Rajput, Rekha Gupta, Aditya Trivedi

Abstract: The main purpose of this paper is to solve the complexity problem and improved existing methods such as energy detection, Maximum-Minimum Eigen value detectors (MME), MME with blind two stage detector and adaptive covariance threshold method. PSO algorithm stands for Particle Swarm Optimization is utilized to novelty the optimal sensing time at that there will be maximum detection of probability for the Primary user. In which, we compare the optimal-PSO algorithm with non-optimal method. The simulation of the paper is depend on the performance of probability of detection based on the false alarm rate on the different region of the signal to noise ratio. The proposed optimized method of detector shows a superior performance values when compared to three individual detectors. The performance metrics of proposed method are performed better than other three individual detector.

Index Terms: Blind sensing, energy detector, maximum-minimum eigenvalue(MME) detector, PSO.

I. INTRODUCTION

There are two types of users-Primary user and secondary user. Primary user has a license of the spectrum and secondary user has no license of the spectrum. When the spectrum of the PU is idle, SU can utilize the spectrum of primary user until the PU is inactive but if the PU becomes active then SU must immediately vacate the spectrum of the primary user [1]. The spectrum which is idle at a particular time is called a spectrum hole [2]. Cognitive Radio senses its radio frequency environment to detect the idle spectrum and to detect whether the PU is active or inactive. Cognitive Radio has a fixed time frame in which sensing of the environment and transmission of the data has been done [3]. Now, if the sensing time of the CR will be more, then there will be less time for data transmission which and there will be less throughput. On the other hand, if the transmission time will be more, then there is a possibility that CR will not detect the active user and there will be interference to the primary user, with which there will be low Quality of Service.

Hence, transmission time and sensing time has a tradeoff [4]. There should be some optimal sensing time at which CR can achieve maximum possible throughput provided there is a sufficient quality of service to the primary user i.e. there is no interference to the primary user. Particle Swarm Optimization (PSO) is used to find this optimal sensing time [5].

An adequate radio spectrum that can easily manage the ever-increasing mobile data traffic [6]. Many studies have also found out that several of the radio spectrums are also being under-utilized by the existing systems [7, 8]. Here, a radio enabled device can alter its transmission accepting parameters to adjust according to the prevalent or upcoming changes in the radio environment [9]. On other hand, there is inadequate radio spectrum that can manage all the wireless services while on the other hand, the existing systems are not properly utilizing the available radio spectrums [10, 11].

The rapid progress in wireless communication and a need for high data rate has increased the requirements of more spectrums. It has been found that, the licensed spectrum is not utilized to its full extent at all the time [9] due to inefficient fixed frequency allocation, whereas the cellular bands are overloaded. This has led the FCC to think about this underutilized spectrum and to allow the unlicensed users in licensed band, if they would not cause any interference to the licensed user. This initiative has focused on cognitive radio (CR) [12]. The main purpose of CR is to identify the unoccupied licensed spectrum for secondary usage without interfering with the primary user (PU), and with the awareness of the surrounding environment it can adapt its internal states with the corresponding changes in certain operating parameters such as transmit power, carrier frequency, modulation type etc. [13]. Due to these unique characteristics of CR and unreliable nature of wireless communication channel, cognitive radio networks (CRNs) acquire many research challenges, especially in aspects of security.

The other method used for detection is the ED (energy detection) method. In this method, the signal energy that is received is compared and assessed with the noise energy is still needed to be identified [14-17]. Here we took very prior algorithm in cognitive radio network. These algorithms are energy detection(ED) and MME (maximum-minimum Eigen value) and the two-stage combined detector 2EMC is modelled on the multistage spectrum sensing technique [17-19].

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* Correspondence Author

Rakesh Singh Rajput, Madhav Institute of technology and Science, Gwalior

Rekha Gupta, Madhav Institute of technology and Science, Gwalior
Aditya Trivedi, ABV Indian Institute of Information technology and Management, Gwalior

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This paper presented the optimization algorithm called Particle Swarm Optimization (PSO) is utilized to find the optimized sensing time value where detection value will be maximum which will be mandatory for Quality of Service to the Primary user. In this paper, we compare existing method ED, MME and 2EMC with optimized these methods along with PSO technique.

The performance comparison is presented based on the simulated value and graphs between different combinations which is presented in this paper.

II. LITERATURE REVIEW

It has been observed that the accuracy of detection of signal varies with changing sampling rate. The DFT filter bank utilized to adjustments the sampling rate depending on the expected SNR of every detector [20]. The ED uses this as the foremost detection stage and cyclo-stationary as the 2nd stage if nothing is identified during the 1st stage [21]. In case of the recommended algorithm, if the signal absence is declared in the first stage only then SNR is calculated and the second stage is based on that, or else the calculations of the first stage are taken into consideration [21-22]. The two-stage detector differs from the proposed algorithm in the sense that SNR based estimation is carried out firstly and then the cyclo-stationary or energy identification is done depending on the SNR based estimations [23]. While in a 2-stage fuzzy, the method of detection of logic is commenced. In the 1st stage, there are individual detections carried out by various CR's by means of the different methods for detection. The 2nd stage combines the sensing results obtained from the 1st stage and uses fuzzy logics to estimate the presence or lack of a signal [24]. Algorithms detecting multistage spectrums are classified into three categories. The first one is a sequential multistage spectrum, in which there is a serious connection between the different detection stages. The energy detection is implemented in the 1st phase, and a covariance absolute value (CAV) detector is utilized in the 2nd stage if energy detection estimate signal absence [25]. In the 1st-stage ED is utilized to kind the channels established on SNR values and cyclo-stationary detection is utilized for low SNRs in the channels [26]. Figure1 representation of the sequential multistage model for spectrum sensing

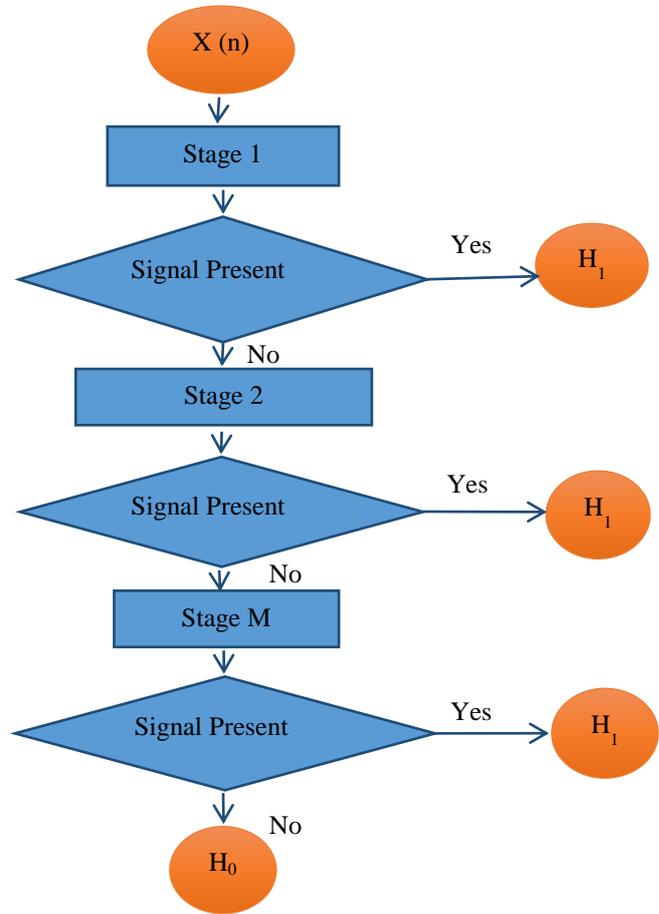


Figure 1. Sequential multistage model for spectrum sensing.

III. MOTIVATION AND CONTRIBUTION

This paper lists the points that have not been addressed by authors to the best of their knowledge regarding sequential sensing. The various points are as follows:

1. Development of a full blind multistage detection based on adaptive covariance threshold method. It has been observed that several multistage detectors have a blind stage but none of the have adaptive covariance threshold method. The proposal laid by this paper regarding the full blindness of adaptive covariance threshold detectors is as follows –
 - Using MME and 2EMC in the second stage detection in two different cases
 - Making use of noise detection wherein noise estimation is done by MME, 2EMC.
 - Proposed method compared with their existing method respectively.
2. The previous studies do not lay much emphasis on the impact of other parameters apart from SNR. This study paper analyses on how both of the bandwidth of signal and the bandwidth of observation are important and the impact on the performance of the ED, MME as well as the 2EMC.

- The combined kind of detector on the existing methods have been proposed through this paper is well tested with the help of simulation matrix and mathematical equation proof [28].

IV. SPECTRUM SENSING METHODS AND METHODOLOGY

Here, presented the system model with some of the theoretical features, which is utilized through the paper.

A. System Model

In our findings, we used a received signal $x(n)$ of SU users. Here the cognitive receiver's general discrete signal is shown as:

$$H_0: x(n) = \eta(n) \quad (1)$$

$$n = 0, 1, \dots, N - 1$$

$$H_1: x(n) = s(n) + \eta(n) \quad (2)$$

Here, $s(n)$ and $x(n)$ represents the primary signal of PU and received signal of SU respectively; (n) denotes the background noise; N denotes the size of the sample. Here the noise is assumed to be AWGN or Gaussian white noise that has a variance σ_0^2 and (n) could be a stochastic signal that represents channel features including multipath and fading. The samples of primary signal $s(n)$ can be demonstrated as a Gaussian random process with σ_s^2 variance. Therefore, the signal to noise ratio (SNR) is

$$SNR = \sigma_s^2 / \sigma_0^2. \quad (3)$$

The problem of spectrum sensing is said to be the binary hypotheses. Here H_0 represents the absence of the signal that is primary.

To accomplish the higher protection to PU, P_d should be high, whereas P_f should be as small as possible to maximize the throughput of SU. The probability of false alarm P_{fa} and probability of detection p_d is formulated as

$$\left. \begin{aligned} P_{fa} &= \Pr(H_1|H_0) \\ p_d &= \Pr(H_1|H_1) \end{aligned} \right\} \quad (4)$$

B. Detection Methodology

• Energy Detector

The samples of signal have being squared up and then added up to evaluate the energy of signal in the ED. Let's say, the energy of signal is estimated from the given values of N that is received signal.

Later, x_j and s_j represent the received-signal with noise signal respectively. Following the estimation of the energy signal is consequently contrasted against the components of the energy related to noise-only in the spotting band. Therefore, the below stated conclusion is stated as:-

$$X \rightarrow \begin{cases} \left(\sum_{j=1}^M |x_j|^2 \right) < \rho, H_0 \\ \text{otherwise,} & H_1 \end{cases} \quad (5)$$

The outcome of the ED is in the form of chi-square distribution, than may be estimated as being Gaussian distributed assuming that the $N \rightarrow \infty$ [27, 28], stay on the estimation, the P_d versus P_{fa} of the ED. The P_{fa} for the ED p_f^E achieved by

$$P_f^E = Q \left(\frac{\rho - N\sigma_z^2}{2\sqrt{2\sigma_z^2}} \right) \quad (6)$$

Here $Q(\cdot)$ is the Q function demonstrating the cumulative distribution function (CDF) of a Gaussian random process as well as σ_z^2 (noise variance).

$$\rho = \sqrt{2N}\sigma_z^2 Q^{-1}(P_f^E) + N\sigma_z^2 \quad (7)$$

Here $Q^{-1}(\cdot)$ representing inverse function of Q.

After calculating the ρ from equation (7), based on the ρ value calculate the probability of detection (p_d^E) using the following formula:

$$P_f^E = Q \left(\frac{\rho - N(\gamma + 1)\sigma_z^2}{2\sqrt{2N}(\gamma + 1)\sigma_z^2} \right) \quad (8)$$

As for the ED complexity, the multiplication operations of N are needed to square up the samples received, as well as $(N - 1)$ summations are required in summing them up altogether. Thus, the complexity of the ED, CE is achieved as

$$C^E = O(N) \quad (9)$$

• Maximum–Minimum Eigenvalue Detector

The Eigenvalues distribution of the co-variance matrix is offered an interactive process of research in the theory of random matrix [29]. In general, the theory of random matrix and in particular, the distribution of covariance matrix Eigen value, are broadly utilized to solve the problems related to wireless-communication [30-31].

Many techniques have been established based on the eigenvalues & eigenvectors of the received signal covariance matrix for spectrum sensing. In addition to MME methods include the signal energy with minimum and maximum eigenvalue for generalized likelihood ratio test. Elaborated elucidations of the procedures are incorporated. First step to compute the MME is covariance matrix (SCM) \hat{R}_x as

$$\hat{R}_x = \frac{1}{N} X X^H \quad (10)$$

With $(\cdot)^H$ representing the Hermitian. From equation (10) \hat{R}_x , is calculating and here L eigenvalues indicated $\lambda_1, \lambda_2, \dots, \lambda_L$, where $\lambda_1 > \lambda_2 > \dots > \lambda_L$, are achieved. Subsequently, a detection threshold (Λ) is measured as:

$$\Lambda = \left(\frac{\sqrt{N} + \sqrt{L}}{\sqrt{N} - \sqrt{L}} \right)^2 \left(1 - \frac{(\sqrt{N} + \sqrt{L})^{-\frac{2}{3}}}{(NL)^{\frac{1}{6}}} F_1^{-1}(1 - p_f^M) \right) \quad (11)$$

Where, P_{fa} for MME is (P_f^M) , and $F_1^{-1}(\cdot)$ represented the inverse Tracy–Widom distribution order 1.

$$X \rightarrow \begin{cases} \left(\frac{\lambda_L}{\lambda_1} \right) \leq \Lambda & H_0 \\ \text{otherwise} & H_1 \end{cases} \quad (12)$$

The p_d values for MME is indicating P_d^M and the computation is very complex. So make the process easier empirical formula is found in [19].

Consequently, the MME detection probability is found to be a concave function relating to β . As of [31], the below relations are being proven:

$$\underset{\beta}{\operatorname{argmin}} (p_a^M) = [0,1] \tag{13}$$

$$\underset{\beta}{\operatorname{argmix}} (p_a^M) = [0.5] \tag{14}$$

As affirmed in [19], to the MME computational complexity context, the governing two MME procedures are erecting the SCM, in equation. (13), as well as attaining the L Eigen values of the SCM by decomposition of singular value. To determine the SCM [19], evaluating the 1st row only that is required. It needs N number of multiplications as well as (N-1) summations. Thus, evaluating the 1st row of the SCM has the complication of O(N). The 2nd procedure of carrying out decomposition of singular value has the complexity of O(L³) [32]. Coalescing of the two procedures would have outcome of a MME complexity C^M as

$$C^M = O(N) + O(L^3) \tag{15}$$

• Maximum-Minimum Eigenvalue with Combined Detector Solution

Generally, MME surpasses ED as of the detection probability. This benefit of MME over ED with regard to the detection probability is traded off against the complexity of sensing. As given in equation (9) and (15) equations, the MME executes the sensing at an order of (L³) extra operations contrasted with the ED.

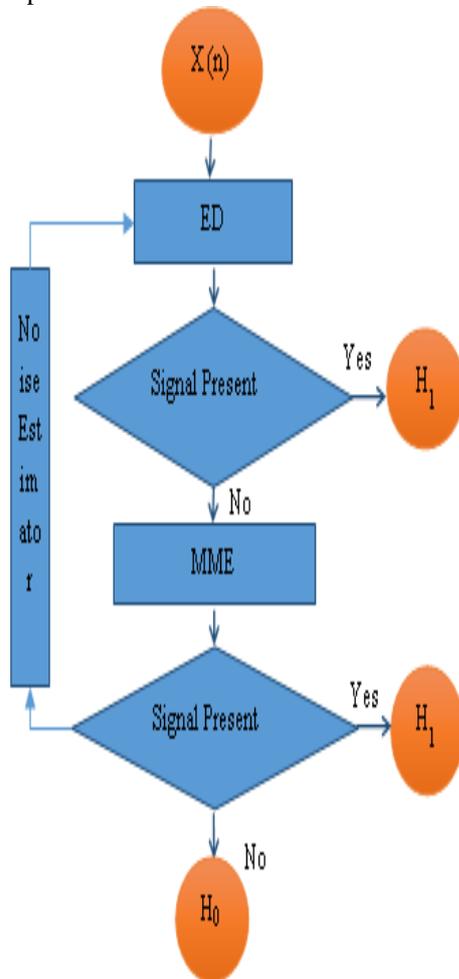


Figure 2 The model of the 2EMC detector.

From the detection process flow in the sensing of sequential multistage spectrum, the detection probability relationship in [21] and [22] is designated pd(γ) and may be universalized for a detector of M-stage as

$$p_d \gamma = p_a^1(\gamma) + \sum_{i=2}^M \left(p_a^i(\gamma) \prod_{j=2}^{i-1} (1 - p_a^j(\gamma)) \right) \tag{16}$$

Likewise, the false alarm probability for a 2-staged detector is establish to be within [33-34] as well as universalized for a detector of M-stage. Designate this universalized false alarm probability as p_f, that is

$$p_f = p_f^1 + \sum_{i=2}^M \left(p_f^i \prod_{j=1}^{i-1} (1 - p_f^j) \right) \tag{17}$$

A 2-staged ED–MME combined detector has been built up in this research paper that is elucidated in a detailed manner later. Henceforward, the combined detector thus developed is known as 2EMC that stands for 2-staged EMM combined detector [35-37]. Figure 2 representing the system model diagram of the 2EMC.

From equation (17), the Pfa for the 2EMC denoted p_f^C is obtained as

$$p_f^C = p_f^E + (1 - p_f^E) p_f^M = p_f^E + p_f^M - p_f^E \cdot p_f^M \tag{18}$$

As in equation (18), if a specific Pfa is represent for the ED below the limit of Pfa is fixed for the 2EMC, consequently the MME Pfa is found as

$$p_f^M = \frac{p_f^C - p_f^E}{1 - p_f^E} \tag{19a}$$

As in equation (19a), there are the combinations of p_f^M and p_f^E in infinite number to attain a particular value of p_f^C. If the p_f^E value happens to be too elevated, consequently the ED would be capable to spot signals of weaker manner and would be utilized more. The complexity of the 2EMC on the whole would be diminished. It would craft the MME less proficient since the false alarm probability would be too low, and it would not be able to spotting signals with less values of SNR. Whereas, for too low p_f^E values, the stage of ED needs high value of SNR to be capable of detecting, and mostly, it will entrust the decision over to the MME, which makes the ED less useful and consequently 2EMC further complex. To solve this problem, a halfway solution with equivalent Pfa of the ED and MME both are put into this method. Therefore, with the solution (18), the Pfa for both the stages are ascertained to be

$$p_f^E = p_f^M = 1 - \sqrt{1 - p_f^C} \tag{19b}$$

Based on (15), the pd of the 2EMC indicated as p_d^C is related to p_d^E and p_d^M as

$$p_d^C = p_d^E + (1 - p_d^E) p_d^M = p_d^E + p_d^M - p_d^E \cdot p_d^M \tag{20}$$

C. Proposed Particle Swam Optimization Method

Now optimized above these methods based on the particle swam optimization scheme can be summarized as: Particle Swarm Optimization (PSO) is an algorithm to solve optimization problems.

In Particle Swarm Optimization, there are lot of particles in the search space having some randomly assigned initial position and velocity. Each particle is known as an individual and population of all the particles is known as swarm. The main aim is to find the best solution for the given problem. A point in the search space will give the optimal solution. Every particle is moving with some speed in some direction in the search space. The velocity and position of the particles will be updated after every iteration. At any point of time, every particle has its own personal best position and a global best position of the swarm. Particles will move towards to the global best position of the swarm. Global best position of the population will be updated if any particle's position will be more close to the best solution. Now, this particle's position will become the global best position and all the particles will start moving towards this updated global position. This process will continue until all the particles converges at one point of the search space. The point at which all the particles converges is the optimal solution of the given objective function. The system of non-linear equations is equal to the optimization problem and PSO can be used to solve non-linear set of equations.

$$maxf(x) = \sum_{i=0}^n 0.5 * (qfuncinv(pfm)) ./ sqrt(L) + 1 \tag{21}$$

Thus the master function is similar to non-linear equations, and PSO can be applied to solve the optimization problem. The PSO algorithm is:

- (1) Set up the control parameters and iteration to $t=1$.
- (2) Initialize position $x_i = (x_1, x_2, x_3, \dots, x_n) \in S$, and the velocity $v = (v_1, v_2, v_3, \dots, v_n) \in S$ of each particle i
- (3) Update position of each particle at $p = (p_1, p_2, p_3, \dots, p_n) \in S$.
- (4) Evaluate objective (fitness) function of each particle body.
- (5) Update the personal best position $p_{id}(t)$ for each particle and swarm best position $p_{gd}(t)$.
- (6) If desired result, then output the best position (global solution).
- (7) Otherwise repeat step 3-6 by increasing the iteration $t = t+1$.

V. SIMULATION AND NUMERICAL RESULTS

This paper present the simulation of Energy-Detection (ED), ED with Maximum-Minimum Eigenvalue (MME), MME with combine detector (2EMC) and Modified these Spectrum Sensing Methods based on particle swam optimization algorithm. The results presented in this paper demonstrate the performance of the proposed PSO algorithm and comparison with presented sensing method without optimization. The method of spectrum sensing are proposed and compare to each other respectively such as ED with ED-PSO, MME with MME-PSO and 2EMC with 2EMC-PSO based spectrum sensing scheme are also simulated and compare the performance to each other respectively. In our experiments, we proposed to solve two probabilities that are concerned with detection which is P_d and false alarm as represented by P_f . Here, P_d is concerned with the algorithm probability that accurately detects if primary signals are

present or not under H_1 hypothesis. P_f relates to the false algorithm relating to the declaration of the primary signal. During the transmission mode of the PU, the SU has to leave the band. This results in false alarm low probability resulting in higher reusability of bands that are unoccupied. Similarly, if the probability detection is high then, PUs is detector better. In Table 1 show the simulation parameters

Table 1: Simulation parameter

Parameters	Values
Operating System	Windows
Matlab version	2015b
L	5, 20, 50
N	5,000, 1000
SNR_dB	-20, -14, -12, -10, -8
B	0.5:0.05:1
Algorithm	ED, ED-PSO, MME, MME-PSO and 2EMC-PSO

In the experiment, the number of samples (N) is a sensing interval, which is vary from 1,000 to 5000, the parameter L is taken as 5, 20 and 50.

Various simulations scenarios on the different SNR approaches were done. H_0 hypothesis is kept as constant independent of the size of the sample. The ratio of the false alarm is kept as invariant. The size of sample could have an influence on the probability of detection in hypothesis H_1 . When the performance of ED, MME and 2EMC are concerned without applied adaptive covariance threshold method, they are evaluated based single test statics $T(J)$ and threshold by considering the probabilities of false alarm and detection. It is denoted by using P_d and P_f . Experiments of Monte Carlo are done for about 5000 runs $L = 1000$. The detection performance curves vs. false alarm probability of energy detection and proposed energy detection with covariance threshold with different SNR (dB) in figure (3-4) respectively, where the primary and the binary phase shift keying BPSK signal is modulated with frequency carrier of $f_c = 40$ KHz. Here the sampling frequency $f_s = 100$ KHz and the sampling time is $t_s = 5$ ms.

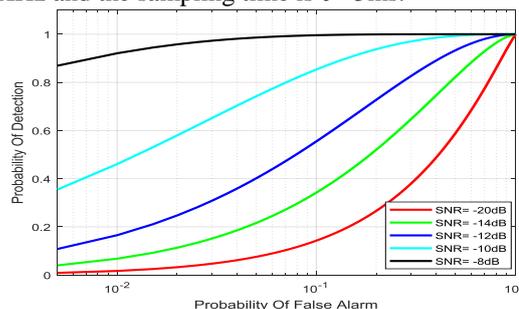


Figure 3: Detection performance vs. false alarm probability of ED with different SNR (dB) and sample Size ($N=5,000$).

It is seen that the performance is different based on the SNR values but as SNR value increases in the simulation with respect SNR probability of detection increased respectively. The performance of energy detection with covariance threshold method versus Pfa based on the SNR (dB) variation having higher values of pf as compared to the existing energy detection method. The performance of ED is deeply degraded at low probability of false alarm and high SNR.

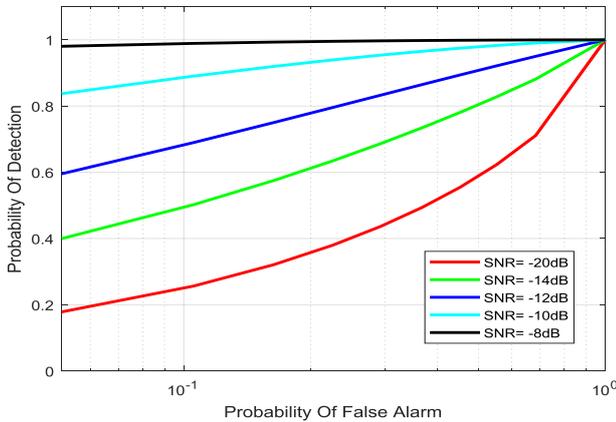


Figure 4: Detection performance vs. false alarm probability of ED-PSO with different SNR (dB) and sample Size (N=5,000).

As shown in the figure (3&4), the simulated energy detection with PSO performance higher at the value of SNR is -8 dB.

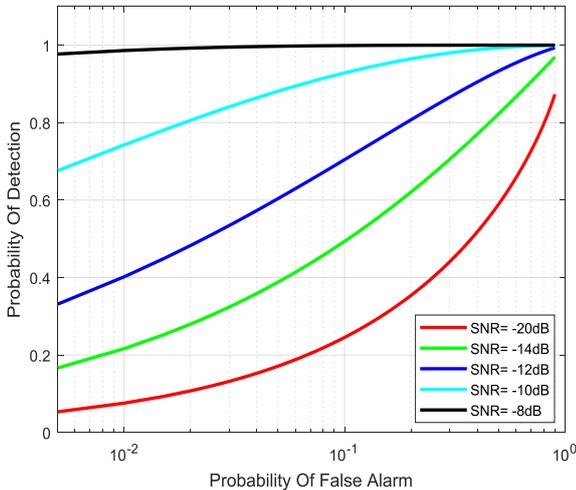


Figure 5: Detection performance vs. false alarm probability of MME with different SNR (dB) and sample Size (N=5,000).

Figure 5 and 6, shows the performance curves of detection. Here the MME and MME-PSO performance is calculated for different level of SNR where SNR is (-20, -14, -12, -10 and -8) as concerned with the constant probability of false alarm. The method of MME-PSO is better than the method of MME.

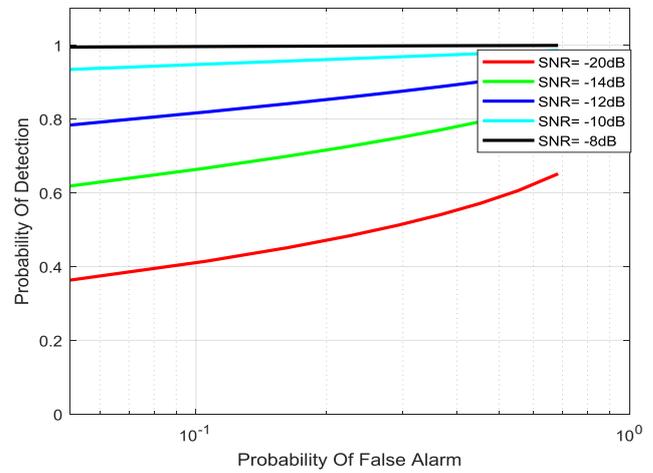


Figure 6: Detection performance vs. false alarm probability of MME-PSO with different SNR (dB) and sample Size (N=5,000).

The detection performance comparison curves vs. false alarm probability of 2EMC on the basis of the SNR (dB) in figure (7 & 8). It is seen that the performance is changing based on the SNR (dB) but the false alarm is constant. As we can conclude the detection probability is decreasing as SNR (dB) value is increasing but 2EMC-PSO have higher efficiency as compare to the 2EMC and MME.

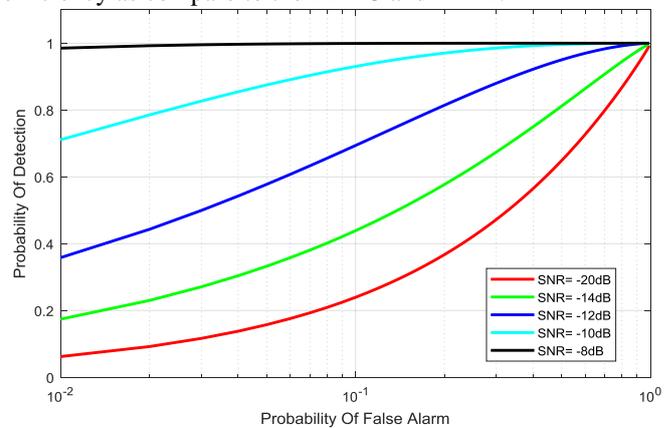


Figure 7: Detection performance vs. false alarm probability of 2EMC with different SNR (dB) and sample Size (N=5,000).

Moreover, for a variation in SNR, the detection probability performance is higher at (-8 & 10 dB) and worst performance at (-20 & 14 dB) SNR. As compare to above two method low SNR region is not acceptable. The main indication of the 2EMC method of spectrum sensing is to implement a probability detection (pd) over the high value of SNR and later on move to low SNR values where probability detection is very complex. In this algorithm first energy detection performed, if yes then assumed SNR value is high and signal presence. If not, then SNR value is low and signal is signal not existence, only noise is received. After that 2nd phase start of detection using MME algorithms, here probability for lower SNR are achieved highly with the high complexity.

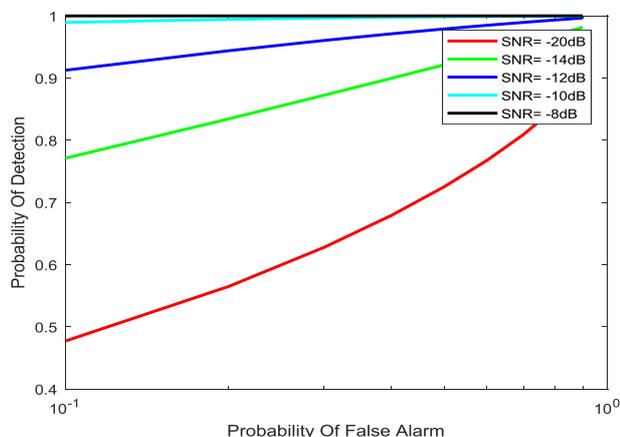


Figure 8: Detection performance vs. false alarm probability of 2EMC-PSO with different SNR (dB) and sample Size (N=5,000).

Figure 9, shows the Comparative curves of detection. Here the ED-PSO, MME-PSO and 2MME-PSO performance is calculated for SNR -12dB as concerned with the constant probability of false alarm. The method of 2MME-PSO is better than the other methods.

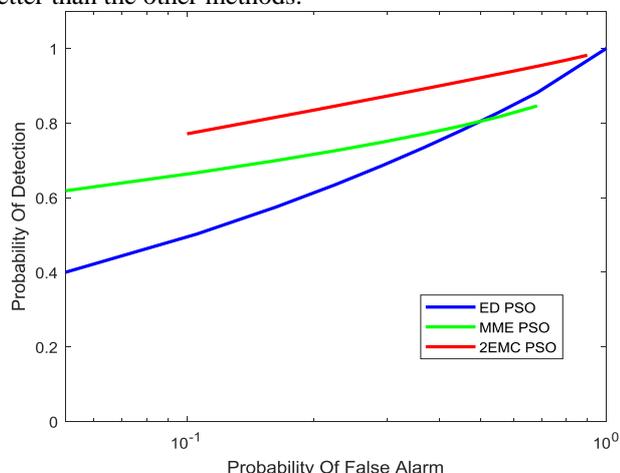


Figure 9: Comparative algorithms of detection performance vs. false alarm probability at low SNR value (-12 dB)

VI. CONCLUSION

In this experiment we proved that the scheme that we proposed based on the Particle Swarm Optimization with the help of experiments of Monte Carlo. Here we also showed that the existing algorithm with Particle Swarm Optimization would be highly efficient as compared to the existing published algorithms.

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AUTHORS PROFILE



Rakesh Singh Rajput received the B.E. degree in electronics and communication engineering from the Barkatullah University Bhopal in 1999 and completed Mtech from madhav institute of technology and science Gwalior in 2008. He is currently working towards the PhD degree in electronics and communication engineering from RGPV Bhopal.



Prof. Aditya Trivedi is a Professor in the Information and Communication Technology (ICT) Department at ABV Indian Institute of Information Technology and Management, He received his bachelor degree in Electronics Engg. from the Jiwaji University. He did his M.Tech. (Communication Systems) from Indian Institute of Technology (IIT), Kanpur. He obtained his doctorate (PhD) from IIT Roorkee in the area of Wireless Communication Engineering. His teaching and research interest include Digital communication, CDMA systems, Signal processing, and Networking.



Dr. Rekha Gupta is a Associate Professor in the Electronics department at Madhav Institute of Technology and Science, Gwalior. She received his bachelor degree in Electronics Engg. from the Madhav Institute of Technology and Science, Gwalior. She did his M.Tech. (Communication Systems) from Indian Institute of Technology (IIT), Roorkee. she obtained her doctorate (PhD) from RGTU, Bhopal in the area of Wireless Communication .