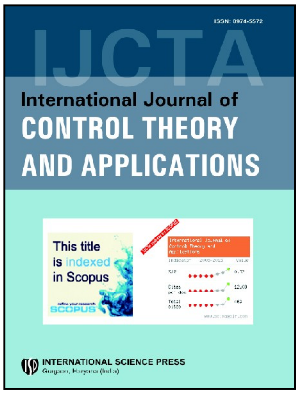

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 28 • 2017

Cooperative Spectrum Sensing Using Genetic Algorithm for Optimal User Detection in Cognitive Radio Networks

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Abstract: Cognitive Radio is an modern technology that is used to get the picture of spectrum and cope themselves to operate the secondary users who are unlicensed to share the spectrum with licensed primary users. Cooperative spectrum sensing allows unlicensed access whenever possible to the unexploited portions of the licensed spectrum by exploiting the spatial diversity among multiple secondary users. Due to cooperation overhead and correlated shadowing the performance of cooperative sensing gets derivate. If we select suitable members of secondary users who exhibit a small correlation with each other, we can establish balance between cooperation overhead and the performance for the sake of cooperation. Based on the false-alarm and missed-detection probabilities, the paper proposes the performance of the cooperative spectrum sensing detection under the correlated log-normal shadowing scenario. Adaptive genetic algorithm is used for the optimization of the number of secondary users required. The proposed method will find the optimum number of secondary users participating in cooperation. Finally, we presented the simulation results to prove the proposed scheme is effective.

Keywords: Genetic algorithm (GA), Cooperation overhead, Cooperative spectrum, Correlated shadowing

1. INTRODUCTION

Due to the huge data requirement for wireless applications spectrum congestion and scarcity may occur. It is found that most of the spectrum is underutilized with lot of white bands in the spectrum at different places or at different times [1, 2]. To overcome the haul of spectrum underutilisation Cognitive Radio (CR) is found as a potential technology [3]. Its primary duty is to find the unoccupied bands and allot them for the secondary user without causing any interference to the licensed user. The Federal Communications Commission (FCC) framed spectrum policy reforms for accessing unlicensed bands [4] for CR networks. Access to the unoccupied bands by avoiding interference to the licensed user is the standard framed by IEEE [5]. The Figure 1 shows the spectrum with white spaces.

In real time environment, the CR technologies are affected by the effects of shadowing and multipath fading [6] for accurate spectrum sensing. By means of single cognitive user we cannot achieve better detection.

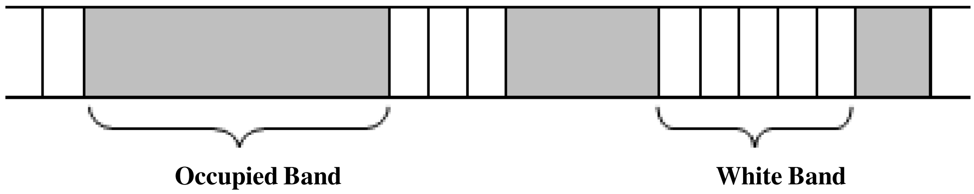

Figure 1: Occupied spectrum with white spaces

So, Cooperative spectrum sensing is one method used to improve the detection efficiency. These two effects can be effectively addressed by this method [7,8].

The figure 2 shows the modeling cooperative sensing network

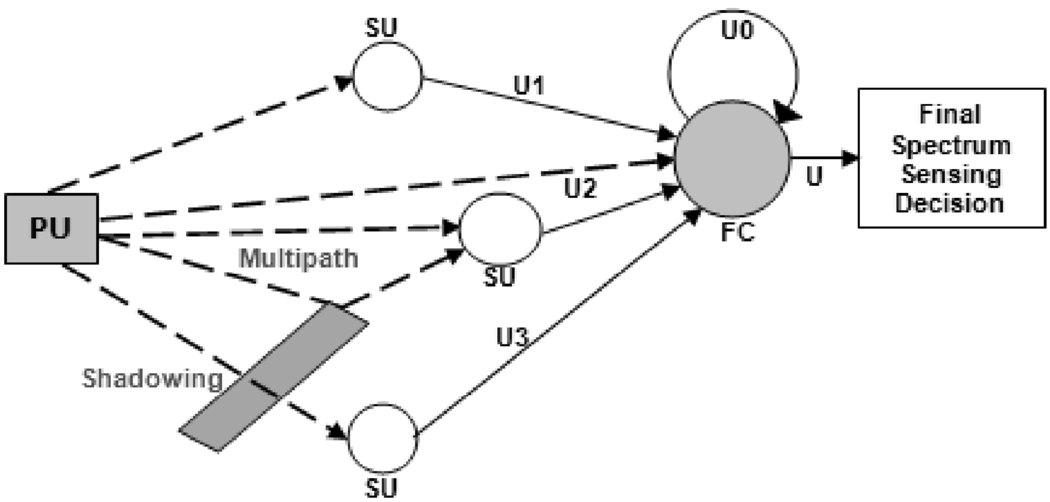

Figure 2: Modeling cooperative spectrum sensing network

In a given space the metrics will increase among the correlated users, if the amount of secondary users increases in the log-normal shadowing and this will tend to minimise the spectrum efficiency [7]. When the limit of secondary user participating in cooperation reaches maximum value, further addition of secondary user will improves the performance of the spectrum sensing marginally. The total transmission power and the control channels bandwidth grows linearly to the extent of secondary user take part in the cooperation [9]. But it is suggestible to make all the obtainable secondary users to participate in the cooperation.

The performance gets slowly reduced, if the mutual users are close enough by the means of shadowing correlation. To attain correlation between detection performance and cooperation overhead, a proper number of spatially separated secondary users should be properly selected. With both the probabilities of miss detection and false alarm bounded, the scheme for the selection of secondary user is proposed in [10]. This approach will reduce the shadowing correlation but high correlation between secondary users still exists in the selected set, which gives cooperation overhead high and the poor detection performance. So there is need for the design of optimal secondary user selection scheme.

This paper proposes an optimal number of secondary users set needed for the cooperation under correlated log normal shadowing. Optimal solutions cannot be attained that easy because it is a nondeterministic polynomial hard problem. From the extensive literature survey a huge range of complex optimization problems are analysed and this paper we used adaptive genetic algorithm [11, 12]. Series of experiments were conducted for the analysis of the performance of the secondary users in the proposed selection schemes.

2. COLLABORATIVE SPECTRUM SENSING

Consider a network with 'n' number of cooperative users arranged at a distance of r from the base transmitter. The frequency band may be accessed by the secondary network if r is greater than a certain length R. For some value of ä>0, the secondary network will be determined if $r = R + \delta$. Let us assume the size of the secondary network to be small compared to r, and then the secondary users will experience the effects of path-loss. Figure 3 shows System model of cooperative spectrum sensing with the Secondary users arranged in a fixed d x d square area (d is the length and breadth of the square).

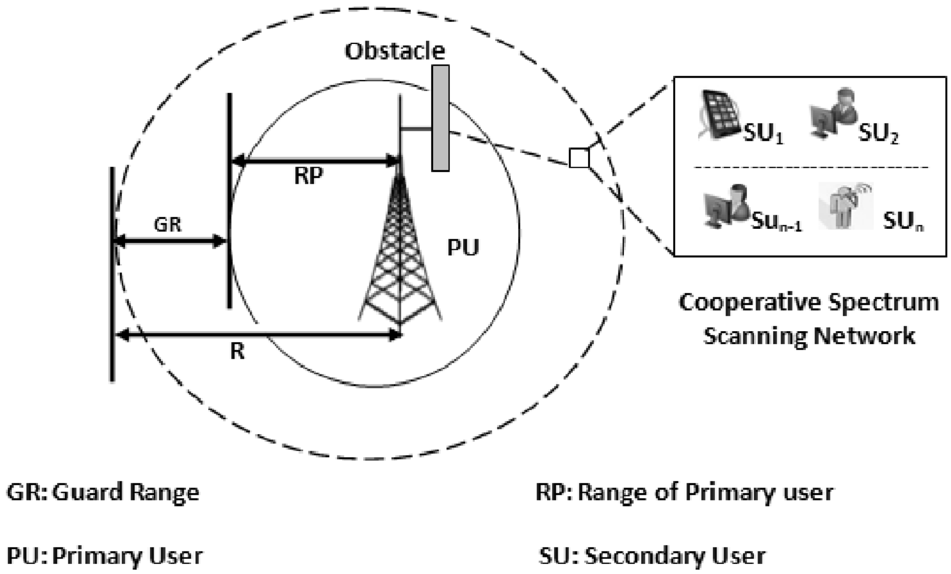

Figure 3: Secondary users arranged in a fixed d x d square area

We denote, on logarithmic scale yj, be the signal to noise ratio (SNR) of the primary user signal at jth secondary. Let us assume SNR estimation is perfect and under log normal shadowing, the distance-dependent path-loss is determined by means of Gaussian distribution with mean of μ(r) and variance of ó2 for yj. The cooperative spectrum sensing is a binary hypothesis and it is formulated as follows [13],

$$\begin{Bmatrix} y \sim N(\mu(R+\delta)X1, \sigma^2\Sigma), & H_1\,(white\,space) \\ y \sim N(\mu(R)X1, \sigma^2\Sigma), & H_0\,(occupied) \end{Bmatrix} \tag{1}$$

Where $y = [y1,...,yn]T$ is the vector which contains the estimated SNR levels and Σ is the normalized covariance matrix of y.

The probabilities of false alarm and missed detection are defined below,

$$\text{Pm.o.} = \text{P}\{\text{decision=H0}|\text{H1}\} \tag{2}$$

$$\text{Pf.a.} = \text{P}\{\text{decision=H1}|\text{H0}\} \tag{3}$$

The probability of false alarm (Pf.a) determines the probability of unsafe interference and it is set by the primary user. These values should be kept less than a threshold value β. Probability of missed detection (Pm.o) is the unoccupied spaces in the spectrum. Here, Pm.o. may be made randomly small with increasing n, while guaranteeing Pf.a. ≤ β. Lower bound on Pm.o. will be obtained by spatially-correlated shadowing the Neyman-Pearson detection rule for the equation (1) may be found as [13],

$$\frac{1^T \Sigma^{-1} yH_1}{1^T \Sigma^{-1} 1} > T \tag{4}$$

$$\frac{1^T \Sigma^{-1} yH_0}{1^T \Sigma^{-1} 1} < T \tag{5}$$

Where decision threshold T is $T = \mu(R) - Q^{-1}(\beta)$ (6)

Where β is the maximum acceptable level of probability of false alarm and $Q(x)$ is given as follows

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2} dt \tag{7}$$

The missed-opportunity probability for the rule of optimum detection in (4) and (5) can be calculated as,

$$Pm.o.(\delta) = 1 - Q\left(\frac{\Delta(\delta)}{\sigma}\sqrt{1^T \Sigma^{-1} 1} + Q^{-1}(\beta)\right) \tag{8}$$

Probability of missed opportunity is represented as in the below figure 4.

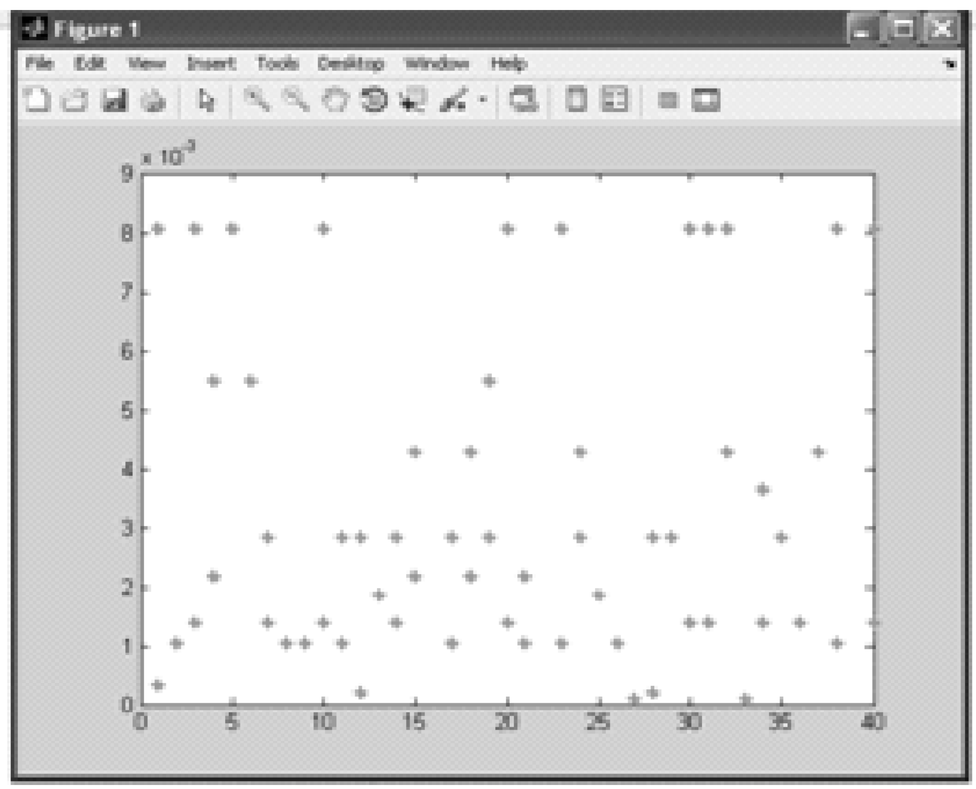

Figure 4: Probability of missed opportunity Vs number of users

where $\Delta(\delta) = \mu(R+\delta) - \mu(R) < 0$. The dependence of P_{mo} w.r.t 'n' is given as,

$$\lim_{n\to\infty} Pm.o.(\delta) = 0 \Leftrightarrow \lim_{n\to\infty} \sqrt{1^T \Sigma^{-1} 1} = \infty \tag{9}$$

As shown in the figure 2 let us assume that secondary users are arranged in a fixed space D having one dimensional distribution. For the sake of simplicity let us assume that there is equal distance d (i.e. d= D/(n-1)) between the two neighbouring users. The above discussed is a covariance matrix of the system [8] with n x n elements, defined as

$$\Sigma_{ij} = \rho^{|i-j|}, i, j = 1, 2, ...n \tag{10}$$

let
$$\rho = e^{-ad} = e^{\frac{-aD}{n-1}} \tag{11}$$

Depending upon the environment the constant 'a' will have [8], $a \approx 0.12$ in urban environments and $a \approx 0.002$ in suburban environments. Hence, Σ is a symmetric Toeplitz matrix which has tri-diagonal inverse,

$$\Sigma^{-1} = \frac{1}{1-\rho^2}\begin{bmatrix} 1 & -\rho & 0 & \cdots\cdots & 0 \\ -\rho & 1+\rho^2 & -\rho & \cdots\cdots & 0 \\ 0 & \cdots & \cdots & \cdots\cdots & 0 \\ \cdots & \cdots & \cdots & 1+\rho^2 & -\rho \\ 0 & \cdots & 0 & -\rho & 1 \end{bmatrix} \tag{12}$$

From the equation 12,

$$\sqrt{1^T \Sigma^{-1} 1} = \sqrt{\frac{(1-\rho)n + 2\rho}{1+\rho}} \tag{13}$$

Substituting the value of ñ from equation (11), we can write

$$\left.\begin{aligned} &\lim_{n\to\infty} \sqrt{1^T \Sigma^{-1} 1} = 0 \Leftrightarrow \lim_{n\to\infty} \sqrt{\frac{1-e^{-\frac{aD}{n-1}}}{2} + 1} \\ &= \sqrt{\frac{aD}{2} + 1} \end{aligned}\right\} \tag{14}$$

From the equation (9), the limit in the right hand side if finite for any finite distance D and the probability of missed opportunity is given below:

$$\lim_{n\to\infty} Pm.o.(\delta) = 1 - Q\left(\frac{\Delta(\delta)}{\sigma}\sqrt{\frac{aD}{2}+1} + Q^{-1}(\beta)\right) > 0 \tag{15}$$

The performance can be further developed by increasing D, keeping 'a' constant which is environment dependent. Under independent and identically distributed (i.i.d), shadowing, $\sqrt{1^T \Sigma^{-1} 1} = \sqrt{n}$. Comparing this with equation (14) and it implies that for an infinite number of collaborating users under exponentially correlated log-normal shadowing is equal to $\frac{aD}{2}+1$ users with i.i.d. measurements. By employing the optimum detection rule of equation (4) and (5), the equation (15) holds good. The equation (15) comprises of the lower limit of probability of missed opportunity under any rule of detection and for any number of collaborating users.

3. SECONDARY USER SELECTION USING ADAPTIVE GENETIC ALGORITHM

The optimal number of unlicensed users involved for cooperation in the sensing network by considering the tradeoff between the performance and overhead. This problem is solved by using adaptive genetic algorithm.

A. Secondary User Selection for Optimization Problems

We considered that there are 'n' number of states for each secondary user and ci ={ci,1,ci,2, ci,3,...,ci,n} correspond to the ith secondary user state set, where ci,j {0,1},j =1,2,...,n. When ci,j =1, the jth secondary user participates in cooperation in the ith state set and if ci,j =0 then the secondary user is assumed to be in sleep state. The total number of state set is 2n,

i.e., i =1,2,...,2n.

Let $m(c_i) = \sum_{j=1}^{n} c_{i,j}$ represents that the active secondary users in the i[th] state set.

Let PM(ci) and PF(ci) represent the probability of missed detection and probability of false alarm for all the active secondary users. As per the condition in the below equation for PF and PM

$$P_F \le \beta \text{ and } P_M \le \alpha \text{ Where } 0 < \alpha < 1 \text{ and } 0 < \beta < 1 \tag{16}$$

Minimum number of secondary users should take part in cooperation in order to reduce the cooperation overhead and meeting the constraint condition PF ≤ β and PM ≤ α. The optimization problem for secondary user selection can be done, considering the detection performance and correlated shadowing is given below,

$$\min_{ci,i=1,2\ldots2^n} \{m(c_i) + \alpha^{-1} P_m(c_i)\} \text{ sub. to } P_F(c_i) \le \beta, P_M(c_i) \le \alpha \tag{17}$$

PF(ci) and PM(ci) are calculated and 0 < α–1 PM ≤ 1 is added to discriminate the state where the number of secondary users are identical. PM value is usually very small. So, to increase the degree, weighting coefficient α–1 is used.

4. PROBLEM SOLUTIONS BASED ON ADAPTIVE GENETIC ALGORITHMS

In our proposed scheme the number of secondary user selection is based on the adaptive GA. GA consists of initial population, fitness function formulation, adaptive genetic operations and an elitism selection mode.

Let us assume that the state set ci ={ci,1,ci,2,...,ci,n}directly denote a binary value and it is called the chromosome, where ci,j, represents the jth gene on chromosome ci and j=1,2,….n. Each secondary users are mapped to a gene in the chromosome and participation of the secondary user in the cooperation is indicated by the binary value ('1' indicates it is participating in the cooperation and '0' means not participating).

A. Initial Population

The following procedure is followed to create initial population with K chromosomes and it will be a set of prospective answer for optimization challenges. Figure 5 gives the block diagram for basic operations in adaptive genetic algorithm.

Initial population of genes are generated in two ways. The procedures for generating are given below:

Method 1:

Init_gen()

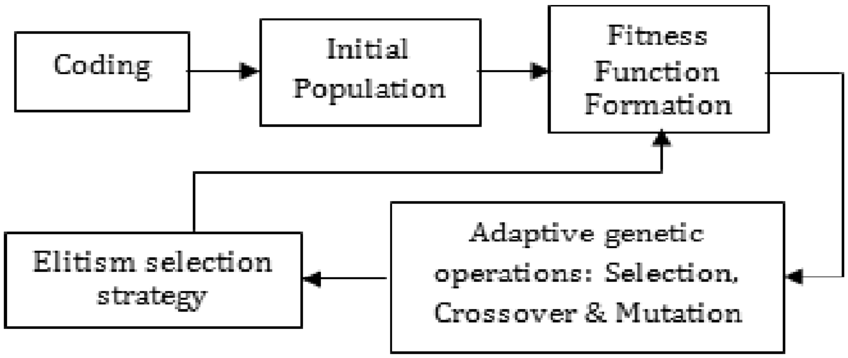

Figure 5: Basic operations in the adaptive Genetic Algorithm

{

Initially all secondary users in sleep state

ci = {0,0,.....0)1xN where i=1,2,.....K

Activate each gene one by one

Until PF(ci) ≤ β, PM(ci) ≤ α

do

cj=1 where j=1,2,....K select j in increment way

else

ci,N =1.........1 initialize all gens to 1

}

Method 2

After resetting the genes for each chromosome, randomly generate an integer Z value and set cZ =1 until PF(ci) ≤ β, PM(ci) ≤ α. The initial population is generated.

B. Fitness Function Formulation

The capability of an individual chromosome to evolve itself to sustain in a particular environment depends on the fitness function and this fitness function helps in GA optimisation. The fitness function for chromosome ci is defined and it is given by

$$Fit_1(c_i) = \begin{cases} T_1 - \left\{ m(c_i) + \alpha^{-1} P_M(c_i) \right\}, & P_M(c_i) \le \alpha \\ T_1 - \max\limits_{ck,k=1,2,..k} \left\{ m(c_i) + \alpha^{-1} P_M(c_i) \mid P_M(c_k) \le \alpha \right\}, & P_M(c_i) > \alpha \end{cases} \tag{18}$$

Where i =1, 2,..., K, K is the total number of chromosomes in population, and $T_1 \ge \max\limits_{ck,k=1,2,..k} \left\{ m(c_i) + \alpha^{-1} P_M(c_i) \mid P_M(c_k) \le \alpha \right\}$ is a constant. When PM(ci) d” á, the fitness of chromosome ci is higher when m(ci) value is smaller. If ci and cj are two chromosomes and the values of m(ci) = m(cj), then the better chromosome is the one which exhibits smaller probability of missed detection. The chromosome ci suffers from the worst fitness when PM (ci)>α, i.e.,

$$\min_{ci,i=1,2,..k} \left\{ Fit_1(c_i) \right\} = T_1 - \max_{ck,k=1,2,..k} \left\{ m(c_k) + \alpha^{-1} P_M(c_k) \mid P_M(c_k) \le \alpha \right\} \tag{19}$$

In selection operations the ci will be eliminated as per the probability of selection.

Adaptive Genetic Operations

The evolution process of Genetic operations has three actions namely: selection, crossover, and mutation. The selection strategy is made on the fitness level of the chromosomes. In the next generation, there would be higher probability of evolving more number of off springs if the chromosomes tend to possess high fitness value. The selection probability of chromosome ci is given in the below equation.

$$P_g(c_i) = \frac{Fit(c_i) - Fit_{\min}}{\sum_{i=1}^{k}\left(Fit(c_i) - Fit_{\min}\right)} \tag{20}$$

where Fit(ci) represents the chromosome ci's fitness value, and $Fit_{\min} = \min_{ci, i=1,2,..2^n} \{Fit_1(c_i)\}$ represents chromosome's minimal fitness value in the population.

In order to generate new offspring, if the genes gets exchanged from a pair of parent chromosomes we call this as a crossover. We have adopted two steps procedure; the first is mating in a random manner after selection process to obtain a new chromosome. In second step each chromosome undergoes two point crossover operations. Assume that chromosomes ci and cj are mated and then the adaptive crossover probability is given below

$$P_c\left(\left[c_i, c_j\right]\right) = \left\{\begin{array}{ll} k_1 \dfrac{Fit_{\max} - Fit'}{Fit_{\max} - Fit_{avg}}, & Fit' \le Fit_{avg} \\ k_1, & Otherwise \end{array}\right\} \tag{21}$$

where Fit' = max{Fit(c_i), Fit(c_j)}, the average fitness value of population is denoted by Fitavg, Fitmax represents the maximum fitness value, and the crossover probability by k_1.

By changing the genes of the chromosomes if any process inherits the features from their parents then we call this as mutation. The changes of chromosomes are made in such way that the results of searching probability should never leads zero. If the coding bits are negated, then mutation can be attained i.e., changing 0 to 1 and vice versa. The adaptive mutation probability is given as

$$P_m(c_i) = \left\{\begin{array}{ll} k_2 \dfrac{m(ci)}{n}, & 0 \to 1 \\ k_2 \dfrac{n - m(ci)}{n}, & 1 \to 0 \end{array}\right\} \tag{22}$$

Where k2 is the mutation probability.

The new population is created using crossover and mutation. By this there is a chance that the fitness chromosomes will be lost. To overcome this problem elitism selection strategy can be used. From the new population we can copy a small part of the chromosome that is fit in this strategy. This approach will speed up the convergence of GAs. A series of experiments were conducted and the performance results are analysed.

5. RESULTS AND DISCUSSIONS

The proposed scheme is simulated under the correlated log-normal shadowing conditions and the performance is evaluated. Below are the experimental parameters considered for simulation, illustration without loss of generality.

1. σ is set to 2.3dB and $\Delta(\delta)$ to –5.19dB, as specified in [11].
2. ε = 0.1204/m, assuming that the CRN is located in urban environments.
3. Let $\alpha = \beta = 0.01$.
4. P(H0) = P(H1) = 0.5, C0,1=C1,0=1and C0,0=C1,1=0.

(A) Confluence Performance Evaluation of Proposed Adaptive GAs

For the proposed adaptive GA, in a 30m x 30m square area for the confluence performance evaluation the secondary users are uniformly arranged. By doing this we could able to achieve better search performance for the secondary user selection. Apart from the random and conventional selection schemes the proposed selection scheme has performed much better and the same is shown in figure 6.

(B) Remarks from the result

1. The three selection schemes possessed equal number of cooperative users who are ought to be secondary users when we had small 'n' number of users in a fixed square area.
2. In a fixed square area, after reaching a particular level of threshold the cooperative users in the proposed scheme decreases even though the number in random selection tends to be steady.
3. For cooperation the selection of secondary users participation is maximum in the proposed scheme. So, a few secondary users are enough in the proposed scheme as 'n' continue to increase after a certain number to attain better detection performance.

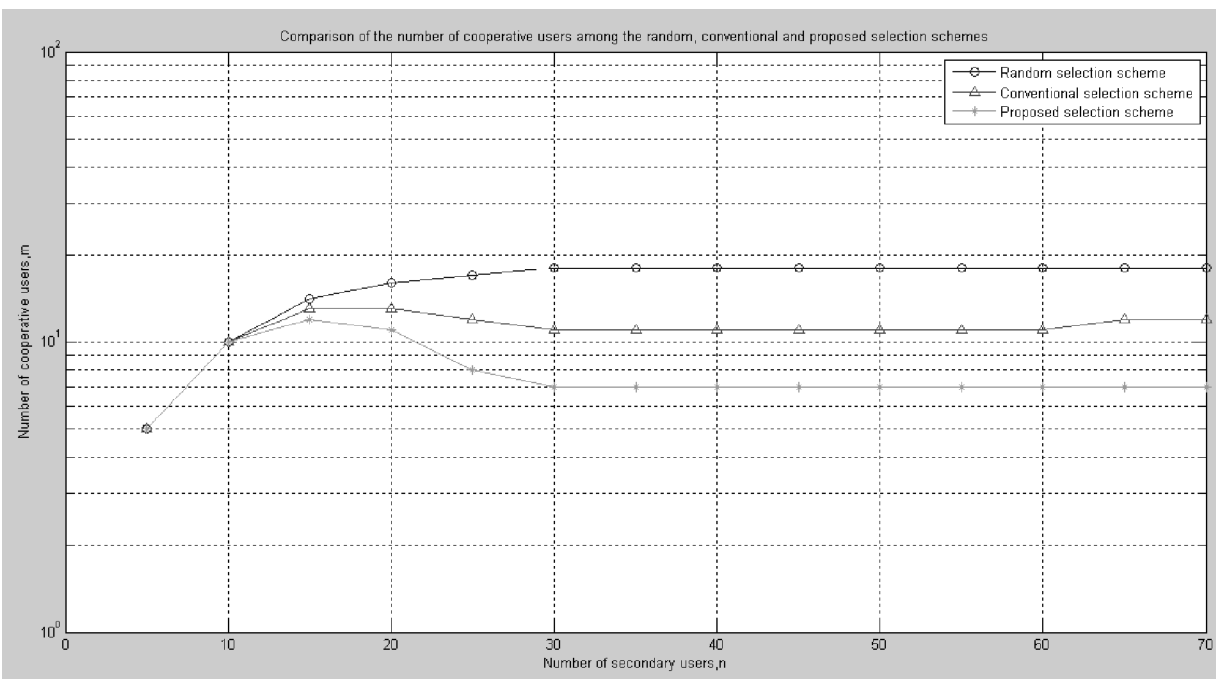

Figure 6: Comparison of various schemes

6. CONCLUSION AND FUTURE WORK

It is been found due to correlated shadowing and cooperation overhead, the performance has got deprived in the of cooperative sensing. The trade-off between the cooperation overhead and detection performance are considered in the proposed adaptive Genetic algorithm. The secondary user selection problem is formulated and the optimum solution is obtained by using adaptive Genetic algorithm. The simulation result shows that optimum numbers of unlicensed users are selected to participate in the cooperation under correlated shadowing situation. In a fixed square area, after reaching a particular level of threshold the cooperative users in the proposed scheme decreases even though the number in random selection tends to be steady. The future work of this is to extend the problem to use in the correlated channels.

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