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ABC ALGORITHM BASED MINIMIZATION OF THE DETACTION ERROR IN COOPERATIVE SENSING

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Abstract

In the recent wireless communication trends, the radio frequency spectrum is the prime concern for effective utilization as there are many radio frequency channels simultaneously used by many users. Cognitive radio (CR) can be the most useful new technique to utilize the radio frequency spectrum effectively and efficiently. Multiple users of the cognitive radio can be detected by sensing the spectrum in cooperative mode and vacant spectrum space is detected from these cognitive radio networks (CRN) for new users. Information of these CR users jointly utilized and combined at the common receiver level either by conventional or soft combining technique. Hence most attention is required in sensing the used cooperative spectrum with a minimum of error. This paper focuses on the optimization technique called Artificial Bees Colony (ABC) under the MINI-MAX criterion to minimize the probability of the error of spectrum energy level weighting coefficient. ABC algorithm generates the weighting coefficients vector which in turn minimizes the probability of error during sensing. Comparative analysis of the performance of this proposed algorithm and traditional soft decision fusion (SDF) methods like Equal Gain Combining (EGC) and hard decision fusion (HDF) methods like Majority, AND, OR etc. is done in this paper and simulation results shows that proposed technique have a minimum of error in detection.

Keywords:

ABC, Cognitive Radio, Decision Fusion, EGC, Fusion Centre

1. INTRODUCTION

At a time, the majority part of the radio spectrum is not used when multiple users utilizing the spectrum for their need of communication. The Federal Communications Commission (FCC) reported that 80% of the licensed part of the spectrum remains unused most of the time. Hence there must be a change in the policy of the carrier assigned to the user [1]. The report generated by FCC for the graph of the frequency spectrum utilization is shown in Fig.1.

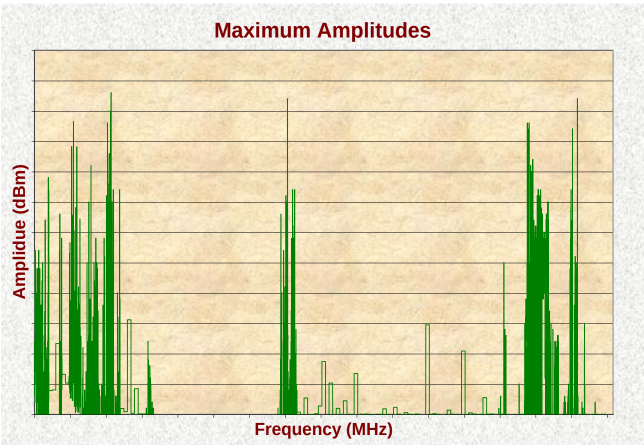

Fig.1. Utilization of Frequency Spectrum

From this report, it is oblivious that most of the frequencies are unutilized much of the time, but today's demand cannot be met by the new assignment strategy and hence frequency assignment policy should be changed.

By effectively utilizing this part of the idle spectrum allotted to license users without having interference to current users in that licensed spectrum, further requirements of the spectrum can be satisfied. In the latest trends of wireless communication, cognitive radio (CR) can play an important role by the combination of two technology i.e. radio technology and networking technology. By smart use of radios in the sense that it can identify the idle part of the spectrum, learn from that and take action accordingly to allocate spectrum to new users.

A cognitive radio network should be able to identify the presence of current users in the spectrum, as current users may have a fading effect due to propagation losses and the introduction of new users in that same spectrum. Using diversity gain, new users in the spectrum can cooperatively sense spectrum to use unused part of the spectrum by minimizing fading to the current users.

New user in cooperative spectrum system detect unused part of the spectrum and send this information to the central centre known as fusion centre (FC) [2] and the decision is taken regarding the presence or absence of current users using some specific rule. In soft fusion, new user gather all information and do not take any decision whereas in hard fusion [3], new user send decision information (commonly of one bit) to FC. Soft fusion based on Maximum Ratio Combining (MRC) and Equal Gain Combining (EGC) used to find out the weight vector with optimum value [4]. This paper is aimed at the quantized cooperative spectrum sensing scenario, where new users take the information of softened hard measurements and send it to FC for the evaluation of weight vector.

Here in this paper, Artificial Bees Colony (ABC) method is proposed in sensing cooperative spectrum to improve the probability of errors in detection. Optimization based on ABC is deployed at the fusion centre (FC) to optimize weight vector which in turn minimize overall probability error of detection. Results obtained using ABC method is more efficient and stable in comparison to that with results of conventional method like ECG, AND, OR and MAJORITY etc. This proposed method also has good performance in convergence which in turn has lower computational need.

In this paper, section 2 describes the spectrum sensing, and section 3 elaborates the proposed system model of the cooperative spectrum sensing along with the problem of optimization. Section 4 is related to the proposed ABC weighting method for minimizing the error of detection. Simulation results and analysis of that for the conventional methods and ABC method are compared for minimization of detection error are discussed in section 5.

2. SPECTRUM SENSING

Before allowing the new users to access a free licensed channel, it is necessary to sense the spectrum in the cognitive radio network. Spectrum sensing is aimed at deciding whether hypothesis H_0 (signal is not transmitted) or H_1 (signal is transmitted) is true. Here two probabilities exist for spectrum sensing which is P_f (false alarm Probability) and P_d (detection Probability). False alarm probability is the probability that even though a signal does not exist but it is detected and Probability of detection is the probability that signal existence is correctly detected [5]. Users and channels can be represented by the following ways

Users and channels can be represented by the following ways:

$$y(t)=\begin{cases} p(t) & HT_0 \\ g(t)e(t)+p(t) & HT_1 \end{cases} \tag{1}$$

where $y(t)$ is the signal strength received by new users, $g(t)$ is the gain of the existing channel, $e(t)$ is signal strength received by existing user and $p(t)$ is White Gaussian Noise which is additive (AWGN) in the channel.

As per [6], average false alarm probability P_f, average missed detection probability P_m and average detection probability P_d over the channel which is AWGN can be given by:

$$P_f = P\{Y>\lambda \mid H_0\} = (\Gamma(TBW,0.5\lambda)/(\Gamma(TBW)) \tag{2}$$

$$P_m=1-P_d \tag{3}$$

$$P_d=P\{Y>\lambda \mid H_1\} = Q(\gamma,\lambda) \tag{4}$$

Here, general Signal to Noise Ratio (SNR) is represented by Y, the threshold of energy detection is λ, considering cognitive radio network instantaneous SNR is γ, time-bandwidth product for the energy detector is TBW, the gamma function is given by $\Gamma(.)$, $\Gamma(.,..)$ is the not a complete gamma and generalized Marcum Q-function is $Q(.,..)$. Q function is given by:

$$Q_u(a,b)=\int_b^a \frac{x^u}{a^{u-1}} e^{\frac{x^2+a^2}{2}} I_{u-1}(ax)\,dx \tag{5}$$

By averaging the conditional P_d in the AWGN case over the SNR fading distribution, the average probability of detection can be obtained by:

$$p_d=\int Q_u(\gamma,\lambda)\, f_\gamma(x)\,dx \tag{6}$$

In some types of scattering environments, when composite received signals consist of large numbers of a plane wave, received signals have Rayleigh distribution [7]. For Rayleigh fading, γ may have an exponential distribution which is given by:

$$f(\gamma)=\frac{\gamma}{\bar{\gamma}}\exp\left(\frac{\gamma}{\bar{\gamma}}\right), \gamma \geq 0 \tag{7}$$

Here considering this case, probability of detection may be obtained in closed form after some manipulation by substituting $f(\gamma)$ in the expression of P_d.

$$P_{dRay}=e^{-0.5\lambda}\sum_{k=0}^{u-2}\frac{1}{k!}\left(\frac{\lambda}{2}\right)^k+\left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{u-1} \ldots\ldots\ldots$$

$$\left(e^{\frac{\lambda}{2(1+\gamma)}}-e^{-0.5\lambda}\sum_{k=0}^{u-2}\frac{1}{k!}\left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)^k\right) \tag{8}$$

In spectrum sensing, one of the major and challenging issue is the hidden terminal problem when the cognitive radio is in the shadow region or it is in the deep fade. Multiple cognitive radios may work together to resolve this problem in order to monitor bandwidth in the fading networks can be greatly improved by cooperative spectrum sensing technique. Here in this case, a receiver which is common for all will calculate the probability of false alarm and detection probability using an average probability for each cognitive radio. As per suggestion given in [8], false alarm probability is given by:

$$Q_f=\sum_{k=n}^{N}\binom{N}{k}P_f^k\left(1-p_f\right)^{N-k}=prob\left\{\frac{HT_1}{HT_0}\right\} \tag{9}$$

And detection probability is also given by;

$$Q_d=\sum_{k=n}^{N}\binom{N}{k}P_d^k\left(1-p_d\right)^{N-k}=prob\left\{\frac{HT_0}{HT_1}\right\} \tag{10}$$

For combining the signals in the spectrum sensing, one of the methods is hard fusion in that each cognitive user decides for the availability of the current user and transmits decision in only one bit to the central data fusion centre. Hence it consumes less bandwidth, it is advantageous for the bandwidth saving purpose. In binary based decision reporting to central fusion common node, the "AND", "OR", Half Voting, and "MAJORITY" rules of decision are commonly used. The second method used for signal sensing is the soft fusion method where cognitive radio users transmit sensed result of spectrum to the central fusion centre and user will not take any binary kind of decision locally. By following some sets of rules at central fusion centre, the decision is to be taken by using all result of new users. One of them is Equal Gain Combining (EGC) where equal weight is given to each sensing node and all are combined equally at the central fusion centre. Whereas in Maximal Ratio Combining (MRC) rule, all new user will be given different weight according to SNR sensed by them in network and these data combined at the central fusion centre as per different weight due to their different SNR sensed. Soft fusion gives better performance compared to hard fusion, but larger bandwidth need for reporting purpose in the control channel is the disadvantage [9]. This way compared to hard fusion scheme, it requires additional overhead data.

$$Q_{d,MAJORITY}=\sum_{k=0.5N}^{N}\binom{N}{k}P_d^k\left(1-p_d\right)^{N-k} \tag{11}$$

$$Q_{d,OR}=1-(1-P_d)^N \tag{12}$$

$$Q_{d,AND}=P_d^N \tag{13}$$

By setting k=1 and k=0.5N in Eq.(9) and Eq.(10), the performance of cooperative detection and false alarm can be evaluated for OR and Majority fusion rule respectively but if $k=N$ then it corresponds to AND rule.

3. PROPOSED SYSTEM MODEL

Our new proposed system model architecture in cooperative spectrum sensing is the quantized softened hard scheme is shown in Fig.2. In this, every new user which is considered to be added cooperatively will sense the spectrum themselves at the local level and information related to this sense measurement will be quantized and then send to the fusion centre of the cognitive based station as L_n (index of the quantization level). According to L_n and weight of respective energy quantization level, a fusion centre will take global decision.

Detection performances in the Soft combination-based data fusion method computed by taking different weights for different CR users as per their SNR level. This is different from the conventional method (one-bit hard combination fusion type) in which the whole range of the observed energy level is divided into only two regions by setting only one threshold level. The disadvantage of this conventional method is that all the CR users either above or below the threshold level will be assigned the same weights irrespective of the difference in observed energy level are significant.

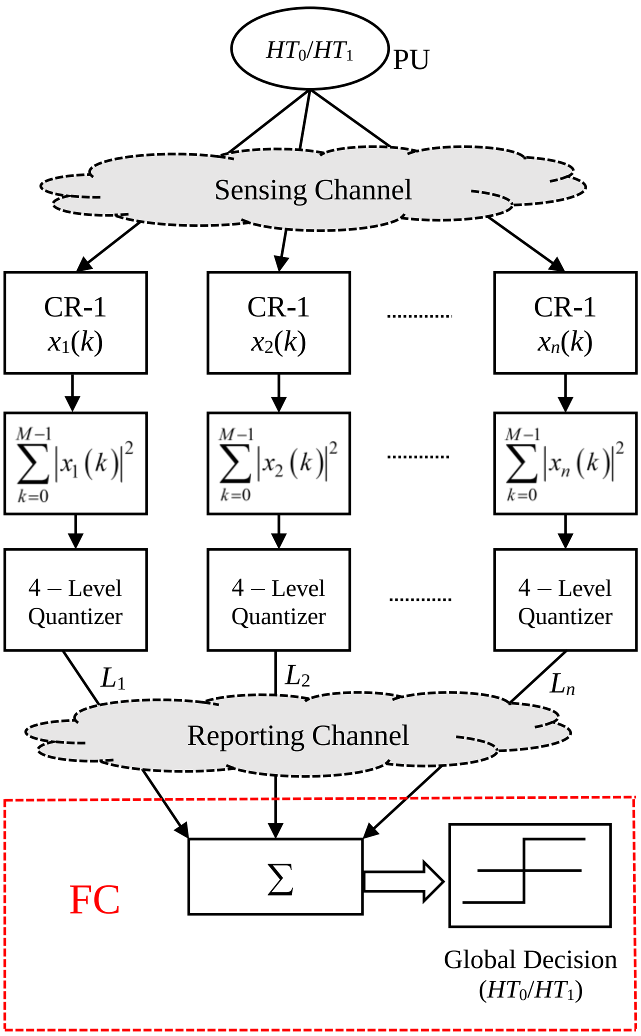

Fig.2. The architecture of new Proposed System

While in soften two-bit hard combination-based data fusion method, the whole range of the observed energy level is divided into four regions with different weights assigned to each region according to energy level in a particular region, this requires only two-bit overhead and hence have less complexity and better performance if detection compared to the one-bit method above seen. However, in a soft combination based fusion system, each CR user needs to send sense information data periodically to central fusion. In terms of overhead bits required to send to central fusion, one-bit conventional method is good but it suffers from the poor performance of detection due to information loss caused by the local hard decision. Soften hard (quantized) combination method is used here with two-bit overhead for each CR user where the complexity is less and have better detection performance.

Combination using two-bit soften hard data fusion method is shown in Fig.3 have total three thresholds levels as per two bits use which are L_1, L_2, and L_3. Here complete region of the energy observed by users is divided into four different sub-regions.

Using this method each new user wants to enter in to particular spectrum will sense the spectrum energy level at local and sends two-bit information which is quantized to show that which region out of four falls in energy. Fusion centre takes global decision based on the 2-bit value sent by CR users and also weight assigned to each region. In contrast to this if we divide the complete energy level range into only two sub regions then hard decision logic like OR, AND, and MAJORITY can be applied at fusion centre level. In this method, each cognitive user needs to send either 0 or 1 for L_n. But for more quantization level in the spectrum, softened hard decision logic can be used.

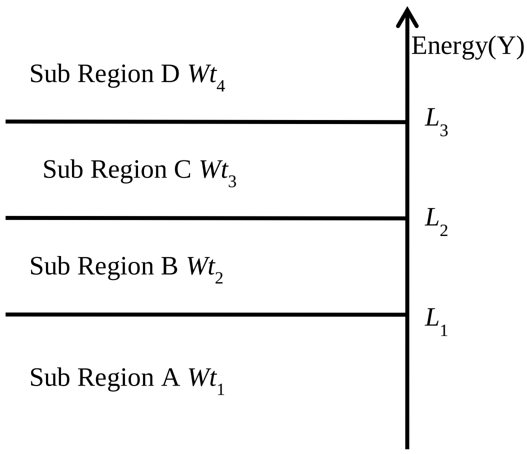

Fig.3. A Hard combination method using two-bit

For the probability that particular region has been observed with hypothesis HT_0 and HT_1 and AWGN channel, we can use the following expression [10].

$$p_{di}=\begin{cases} 1-P_d(\lambda_k) & if\ k=1 \\ P_d(\lambda_{k-1}) & if\ k=n \\ P_d(\lambda_{k-1})-P_d(\lambda_k) & otherwise \end{cases} \tag{14}$$

In proposed method, as discussed earlier weight vector and hence threshold value is the important measures for global level decision. As we have seen energy level in sub region decides weights and reporting nodes are not assigned any weight. Using this two-bit hard decision method (softened), fusion centre will receive a quantized measurement of energy level, and then it will count numbers of users in particular quantization level. Counts of users and weights can be represented using $\vec{N}=[n_1\ n_2\ n_3\ n_4]$ and $\overrightarrow{Wt}=[wt_1\ wt_2\ wt_3\ wt_4]$.

Based on the above weights and numbers of users in particular energy level, decision function can be evaluated by:

$$f\left(\overrightarrow{wt}\right)=\begin{cases}1 & if\ \vec{N}\cdot\overrightarrow{Wt}>0\\ 0 & Otherwise\end{cases} \tag{15}$$

Also, weighted sum is given by

$$N_c=\sum_{i=0}^{3} wt_i\cdot N_i \tag{16}$$

Here, N_i = Number of sensed energies in sub region i.

Now, N_c and threshold, N_T compared for the decision about presence or absence of the user. Current user signal is declared present if $N_c \geq N_T$, otherwise, absence is considered for the user.

For hard combination (softened) method with quantization, over a Rayleigh channel cooperative detection probability are derived as per [11] [12] is given as below.

$$P_d=\sum_{i=1}^{4}\sum_{j=1}^{4} P_r\left(N_1=n_1,N_2=n_2,...,N_4=n_4\left|HT_1\right.\right) \tag{17}$$

$$P_d=\sum f\left(\overrightarrow{wt}\right)\binom{N}{n_1}\binom{N-n_1}{n_2}\binom{N-n_1-n_2}{n_3}\binom{N-n_1-n_2-n_3}{n_4} \tag{18}$$
$$...(1-P_{d1})^{n_1}(P_{d1}-P_{d2})^{n_1}(P_{d2}-P_{d3})^{n_3}(P_{d4})^{n_4}$$

For probability of false alarm expression can be derived in similar way. Using all these, the overall probability of error is represented as [13]:

$$P_e = P_f + P_m \tag{19}$$

$$P_e=P_f+1-P_d \tag{20}$$

$$P_e=P_f\left(\overrightarrow{wt}\right)+1-P_d\left(\overrightarrow{wt}\right) \tag{21}$$

It is clear from the above expression that, probability of error is majorly dependent on vector $\left(\overrightarrow{wt}\right)$. Hence to minimize the total probability of error P_e, the focus should be on weighting vectors. Eq.(18) is used as the main objective functions in this paper for minimizing error probability, but for reducing searching space on that our proposed ABC algorithm works, $\overrightarrow{wt}$ should be within the range of $-5\leq wt_i\leq 5$.

So, optimization problem is to minimize P_e with limitation on wt_i as $-5\leq wt_i\leq 5$

4. WEIGHTING METHOD BASED ABC ALGORITHM

Artificial Bees Colony (ABC) algorithm was first developed in 2005 [14], which is a population-based search algorithm. The food foraging behavior of swarms of honeybees is utilized in this paper. In the basic form of this algorithm, neighborhood search and random search is combined which is used for functional as well as combinational optimization. After that scout bees visit for the fitness of site is done for the evaluation of that. Bees with the highest fitness are considered as selected bees and also sites visited by them are considered for neighborhood search [15]. Then, the algorithm searches in the neighborhood selected sites to assign more and more bees for search nearer to the best-considered sites. Detailed searches in the neighborhood region of the best sites are made by recruiting new more bees to follow earlier selected bees [16]. Along with scouting, the differential recruitment method is the major operation of the ABC algorithm. Bees not assigned any search in their population are now given random around search space scouting for new possible options.

The process of honey searching by the bees or targeted value is repeated continuously to meet the desired stopping criteria. At the end of each iteration, this colony is divided in two parts which are considered fittest representatives from a patch and those who have been sent out randomly in the search space.

ABC algorithm is the evolutionary types of unconstrained algorithm which mimic the natural process of bee colony and it is mainly focused on the exploitation process in which exploitation to be carried out by the onlookers, employed bees, and exploration by the scout bees in the search space [17] [18]. Mathematical formulation of this natural process is carried out in the form of equation which is described below in the algorithm. The computer simulation of this algorithm is implemented by coding of MALAB simulation tool. The Algorithm 1 shows pseudo-code for this ABC algorithm.

Algorithm 1: Weight Optimization with the help of ABC

Step 1: Initialization of the population of solution

Step 2: $x_i(i=1,2,\ldots SN)$

Step 3: *cycle*=1

Step 4: **While** cycle ≤ MCN **do**

- **a.** Generate new solution vi for the considered bees and then evaluate them
- **b.** Use the greedy process of selection for the considered bees
- **c.** Compute particular probability value p_i for the related solution x_i
- **d.** Generate the new solution v_i for the onlookers for the selected solution x_i depending on p_i and also evaluated them,
- **e.** Use greedy selection process for these onlookers
- **f.** Decide the particular solution for the scout, if exist, replace it with a new randomly produced solution x_i
- **g.** Keep a record of the best solution achieved so in these steps
- **h.** Then new Cycle = Cycle + 1

Step 5: **End while**

5. RESULT OF SIMULATION

For cooperative spectrum sensing using the ABC algorithm, simulation is carried out to assess the performance of the suggested algorithm. The Fig.5 shows the values of probability of errors for the different values of threshold λ for various conventional soft fusion methods discussed earlier along with the proposed ABC algorithm. Conventional methods included in tables use EGC, AND, OR, and MAJORITY rules for the fusion. Some parameters used for the simulation are like Time-bandwidth product is taken 5, and the channel considered is Rayleigh, the samples of the received signal are 2. ABC algorithm uses the number of particles S=15 and number of iterations are 30. Perfect reporting channels were assumed here with no false reporting.

The Fig.5 also compares the ABC-based systems with some standard structure systems for many values of the threshold. In the ABC-based method, it gives the highest vector weighting coefficients, which in turn leads to reducing the cognitive probability of error. While for the traditional hard decision functions like AND, OR and MAJORITY based sensing of the spectrum gives poor error performance which is due to insufficient secondary consumer data fusion over the network. C-ROC curve is also simulated to verify the performance of the proposed framework which is shown in Fig.6.

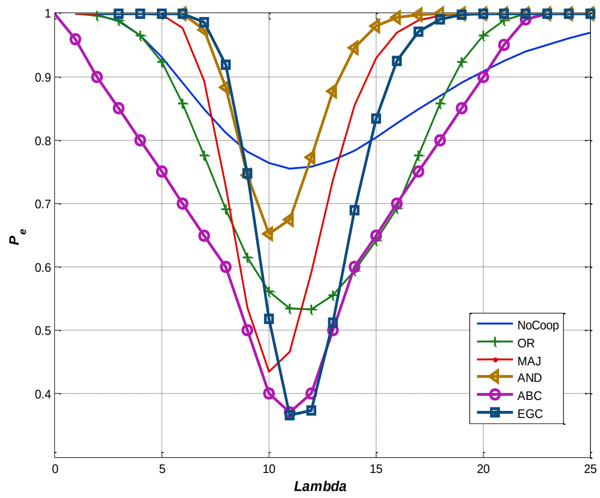

Fig.5 Result of Lambda Vs sensing error P_e

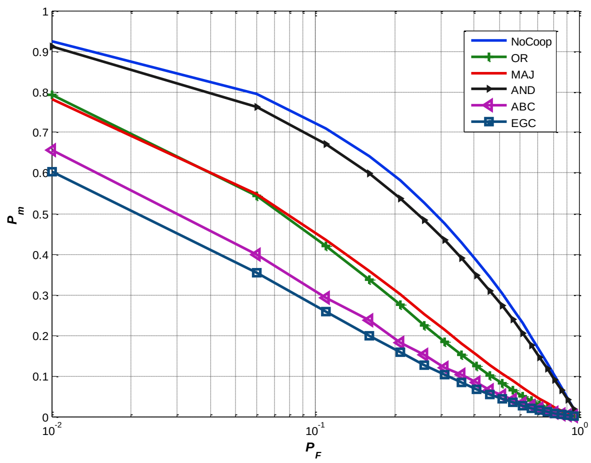

Fig.6. C-ROC curve for the proposed framework

In Fig.5 it is clear that by increasing the values of the threshold, the performance of ABC-based cooperative spectrum sensing is improved. Finally, it reaches to best value when the optimum value of the threshold is decided. Also, last two column of the table gives comparable performance for the proposed ABC framework and conventional soft decision fusion methods EGC with low overhead.

As shown in Fig.7, the probability of errors in ABC based method with λ=6 converges after around 30 iterations. This is at the so fast rate which in turn favors for the real-time requirements of cognitive radio cooperative spectrum sensing in terms of the computation complexity. Under 25 simulations the standard deviation of the obtained probability of error of detection can be neglected, hence it is clear that the ABC algorithm dependent scheme is quite suitable and stable which is real-time requirement of the wireless channel.

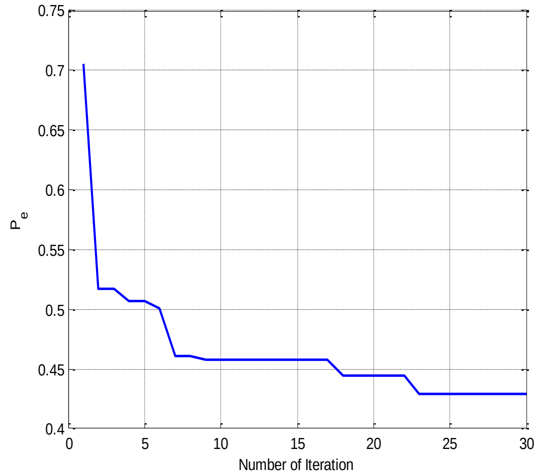

Fig.7. Performance of ABC based method

6. CONCLUSION AND FUTURE SCOPE

As per the simulation result, it is concluded that the proposed ABC-based cooperative spectrum sensing (CSS) method is more effective, stable, and robust. This method is superior in terms of performance than traditional and conventional hard decision fusion (HDF) based CSS. Also, performance is close to soft decision fusion (SDF) based CSS with low overhead. Its convergence fast for the output which is in favor of the lower computation time and less complexity of ABC based framework.

To extend this work as the scope of the future, some recommendations and potential research directions are given here. One can focus on the other parameter optimization like time of sensing, a user in cooperative channels, etc. The work of this paper can have a scope of expansion with multiple cognitive networks and user mobility which can be evaluated with that.

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