Optimization of Cooperative Spectrum Sensing in Cognitive Radio

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1 Abstract

Cognitive radio (CR) is a new paradigm in the area of wireless communication system for effective utilization of radio frequency (RF) spectrum. Cognitive Radio (CR) is used to maximize the available spectrum utilization. When the licensed user/primary user (PU) is not using the spectrum, at that time cognitive radio will allowed to use spectrum to communicate with other CR. Spectrum sensing is the key function of cognitive radio in which it is the procedure to accurately determine the licensed user's existence and identify the available spectrum. Cooperative spectrum sensing has been proven to be an effective method to improve the detection performance and mitigate the impact of multipath fading, hidden terminal problem and receiver uncertainty issues in local spectrum sensing.

In cooperative spectrum sensing, sharing of local spectrum sensing result between the cognitive radio/secondary users and the fusion centre (FC) is the most challenging process that determines the performance of cooperative sensing. The detection performance of cooperative spectrum sensing is depend on the quality of local spectrum sensing result and quality of the local sensing data received by the fusion centre (FC). The local sensing information sent by the CR users is collected at the Fusion centre (FC) by conventional soft decision fusion (SDF) or conventional hard decision fusion (HDF) techniques. Conventional soft decision fusion (SDF) has excellent performance but, it requires lots of overhead and bandwidth of the control channel for reporting while conventional hard decision fusion (HDF) scheme requires only one bit of overhead, but it has worst detection performance because of loss of information. Therefore, the number of bits sent for sensing reports to fusion centre (FC) and the global decision logic affect the system performance.

In order to reduce this overhead between CR users and the fusion centre (FC), we use 2-bit *softened* hard (quantized) combination scheme at fusion centre (FC). In conventional hard decision fusion scheme with only single threshold. Here, we have three thresholds λ_1, λ_2 and λ_3 in the 2-bit scheme which divide the entire range of the observed energy into 4 different regions of equal in size. In this frame work, each CR user senses the spectrum locally and sends its 2-bit information "quantized observation" as L_n(index of the quantization level) to indicate which region of its observed energy falls in to the fusion centre (FC) rather than sending the exact sensing observation to FC. The fusion centre makes a global decision according to index of energy level (L_n) and weight vector $\vec{w}$ of corresponding energy level. Here weight is given to energy level not to the CR user.

In this research work, use of teaching learning based optimization (TLBO) algorithm as a significant method is proposed to optimize the weighting coefficients vector of observed energy level of sensing information. The TLBO technique evaluate optimal weighting coefficient vector so that the probability of detection P_d is improved for given probability of false alarm P_f under the Neyman-Pearson criterion and minimize the false alarm probability P_f and overall probability of error P_e under the Min-Max criterion. The performance of the proposed TLBO based cooperative spectrum sensing (CSS) frame work is extensively analysed and compared with conventional HDF and SDF based CSS schemes as well as other optimization techniques i.e. genetic algorithm (GA) and particle swam optimization (PSO) based CSS through simulations. Simulation result shows that performance of TLBO based method is better than conventional HDF scheme i.e. AND, OR, MAJORITY etc. and close to conventional SDF scheme i.e. EGC with low overhead in the environment of different fading channel like AWGN, Rayleigh and Nakagami. Proposed TLBO based CSS scheme is effective and stable and also shows good convergence performance which confirms lower computation complexity of the TLBO compared to GA and PSO based method. Moreover, the strength of proposed method is also analysed under the false reporting node and imperfect reporting channel.

Finally, an analytical evaluation for performance of proposed method while taking into consideration of some realistic issues, such as multi-hope cooperative spectrum sensing and sensing-throughput trade-off is also presented in this research work.

2 Brief description on the state of the art of the research topic

2.1 Introduction

The spectrum congestion is now becoming a serious problem due to rapid growth in the field of wireless services. This problem arises due to the inefficient usage of the radio spectrum, where a large portion of the licensed spectrum is underutilized, According to The Federal Communications Commission (FCC) report 80% of allotted spectrum are idle at most of the time so current frequency assignment policy cannot meet the real time requirement so they consider opportunistic access to the licensed spectrum by SUs conditioned on no interference to the PUs or license user [1].

Cognitive radio (CR) is a talented technology to the next generation to overcome the inefficient usages of the licensed bands. It has the capability to select the unused spectrum and through adapting the parameters it access the channel with the other users' channels and vacant that channel with the arrival of the licensed user. Spectrum sensing is the key functionality to achieve this requirement [2], [3].The CR users are considered as secondary users (SUs) in cognitive radio network (CRN). So, spectrum sensing plays a very challenging task in cognitive radio networks (CRNs) to carry the improvement in spectrum utilization. Sometimes, CR receiver might not receive the PU transmitted signals due to hidden terminal problem and shadowing effect. Thus, the sensing performance will be degraded [4]. In [5], [6] [7], to overcome these drawbacks, cooperative spectrum sensing was used if PUs' presence is detected

Teaching learning based optimization (TLBO) based cooperative spectrum sensing is proposed to reduce probability of error and improve the detection performance of cognitive radio (CR) user. The TLBO based optimization process is implemented at the fusion centre to optimize the weigh vector for minimization of global probability of error and maximization the detection performance.

2.2 Background on spectrum sensing

The goal of the spectrum sensing is to decide between the two hypotheses, H_0: no signal transmitted and H_1: signal transmitted. In this regard, there are two probabilities that are most commonly associated with spectrum sensing: probability of false alarm P_f which is the probability that a presence of a signal is detected even if it does not exist and probability of detection P_d which is the probability for a correctly detected signal

$$x(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases} \tag{1}$$

Where x(t)the signal is received by secondary user and s(t) is primary user's transmitted signal, n(t) is the additive white Gaussian noise (AWGN) and h(t) is the amplitude gain of the channel. We also denote by γ the signal-to-noise ratio (SNR).

In AWGN channel environment the probability of false alarm, the probability of detection, and the average probability of missed detection are given, respectively, by [8]

$$P_d = P\{Y > \lambda | H_1\} = Q(\gamma, \lambda) \tag{2}$$

$$P_f = P\{Y > \lambda | H_0\} = \frac{\Gamma(TW, \lambda/2)}{\Gamma(TW)} \tag{3}$$

Where, λ is the energy detection threshold, γ is the instantaneous signal to noise ratio (SNR) of CR, TW is the time-bandwidth product of the energy detector, $\Gamma(.)$ is the gamma function, $\Gamma(.,..)$ is the incomplete gamma and $Q(.,..)$ is generalized Marcum Q-function.

The threshold of i^{th} CR according to Neyman-Pearson criteria is determined as

$$\lambda^* = 2\Gamma^{-1}(P_f, TW) \tag{4}$$

Replace the above threshold in probability of detection equation gives receiver operating charactertics(ROC) for given probability of false alarm which is given by following.

$$P_d = P\{Y > \lambda | H_1\} = Q(\gamma, \lambda^*) \tag{5}$$

2.4 Cooperative Spectrum sensing (CSS)

One of the main challenging issues of spectrum sensing is the hidden terminal problem when the CR user is shadowed or in deep fade. To diminish this issue, multiple cognitive radios cooperative work for spectrum sensing constitute a cooperative spectrum sensing environment which greatly improve the probability of detection in fading channels. In CSS, there is two main data combining method at fusion centre (FC). (1)Hard decision fusion (HDF) (2) Soft decision fusion (SDF) [9, 10]. In a general way, there is trade-off between overhead and accuracy in this method. The way the local decision sends to the fusion centre plays a main role in cooperative spectrum sensing. In this research work, we use *softened* hard (quantized) data fusion scheme for cooperative spectrum sensing at FC where optimal weigh vector is evaluated using TLBO. Cooperative false alarm probability and detection probability is given by [8].

$$Q_f = \sum_{k=n}^{N} \binom{N}{k} P_f{}^k (1 - p_f)^{N-k} = prob\left\{\frac{H_1}{H_0}\right\} \tag{6}$$

Also, Detection probability is given by;

$$Q_d = \sum_{k=n}^{N} \binom{N}{k} {P_d}^k (1 - p_d)^{N-k} = prob\left\{\frac{H_0}{H_1}\right\} \tag{7}$$

3 Definition of the problem

The research aim of this report is to find the techniques to improve the detection performance and reduce the total sensing error of cooperative spectrum sensing (CSS) in cognitive radio with low overhead in the presence of fading environment. From the deep literature review the facts have been identified that the sharing of local spectrum sensing result with neighbouring cognitive radio/secondary users or sensing result reported to the fusion centre (FC) is the most challenging process that determines the performance of cooperative sensing. Performance of cooperative spectrum sensing is heavily depend on the quality of local spectrum sensing result and the quality of the sensing information received by the fusion centre as well as global decision logic. Furthermore, having bandwidth-limited reporting channel does not allow to sending the whole observation to fusion centre using complicated protocols Hence, the sensing nodes must optimize the size(sensing bits) of their sensing result in an optimal manner rather than sending the exact sensing result to the fusion centre(FC). Furthermore, global decision logic at the FC is static in nature. Sometimes imperfect reporting channel and false report due to malicious secondary user also change the global decision logic which affects the entire performance so global decision logic must be dynamic for performance improvement.

Many evolutionary optimization techniques i.e. GA, PSO, ACO, ABC etc. are used to find optimal solution for performance improvement of CSS but they are not free from algorithm parameters i.e. there is no algorithm parameters are required for the functioning of the algorithm. This aspect is considered in this research work. In wireless communication, continues parameters setting of these algorithms are serious problem due to malicious secondary user and random nature of fading channel which affect the performance of the optimization technique. Correct tuning of the algorithm related parameters is very critical issue in the wireless communication which affects the performance of CSS. The improper tuning of algorithm related parameters either increases the computational time or find the local optimum solution so optimization technique used to find optimal solution should be free from algorithm parameter.

4 Objective and scope of work

- To investigate the effect of various data fusion scheme on the performance of cooperative spectrum sensing(CSS)
- To analyse the performance of cooperative spectrum sensing in the environment of different fading channel as well as imperfect reporting channel and false reporting node.
- To reduce the extra overhead and communication bandwidth of control channel through the optimal threshold(λ) and weight vector$(\vec{w})$.
- To improve the receiver operating characteristic (ROC) of CSS by improving the probability of detection (P_d) for a given probability of false alarm (P_f) under Neyman-Person criterion.
- To reduce the all over sensing error of Cooperative spectrum sensing by improving probability of error (P_e) under Min-Max criterion.
- To compare the performance of various optimization technique for the evaluation of optimal weight vector in cooperative spectrum sensing(CSS)
- To built an optimal cooperative spectrum sensing frame work.

5 Original contribution by the thesis

In this thesis, energy detection based cooperative spectrum sensing (CSS) techniques have been thoroughly examined and analyzed. This CSS techniques use *softened* hard (quantized) data fusion method at fusion center (FC) for global decision. The use of teaching learning based optimization (TLBO) algorithm as a substantial method is proposed to evaluate optimal weighting coefficient vector of sensing information. The main contributions of this thesis are summarized by following.

- TLBO based cooperative spectrum sensing frame work is proposed which optimize thresholds and the weighting coefficients vector of energy level of sensing information so that the probability of detection (P_d) is improved and the total probability of error (P_e) is minimized with low overhead.

- The performance of the TLBO based cooperative spectrum sensing method is analysed in the environment of different fading channel like AWGN, Rayleigh, and Nakagami and also for the case of false reports and an imperfect reporting channel.
- The performance of the TLBO based cooperative spectrum sensing is compared with conventional soft decision fusion schemes like EGC as well as hard decision fusion based cooperative spectrum sensing like AND rule, OR rule, Majority rule etc...
- An optimization problems that maximize the probability of detection (P_d) and minimize the probability of sensing error (P_e) is solved
- Analytical evaluation is carried out for the performance of TLBO based multi-hop cooperative spectrum sensing and sensing-throughput trade-off.
- The performance of TLBO based CSS method is compared with the other optimization technique i.e. GA, PSO based CSS for validation

6 Methodology of research, results / comparisons

6.1 Methodology of research

In this research work the qualitative and exploratory approaches have been used and followed the research methodology steps. During the first phase of literature review, we referred various research papers, journal and other articles on cooperative spectrum sensing in cognitive radio (CR). Our research work has been carried out using simulation. During this initial phase of literature review, we found researchers had done work on cooperative spectrum sensing but very few of them worked on optimization algorithm for cooperative spectrum sensing in centralize architecture. Major reasons for this gap are that the most of optimization algorithms have a difficulty in determining the optimum controlling parameters (parameter of algorithms) in wireless communication. If any parameter of algorithm is not properly set, It will affect the effectiveness of the algorithm and hence affect the performance of CSS and also very less work have been done for dynamic decision fusion techniques in cooperative spectrum sensing.

During next phase of our literature review, we found there will be research works on *softened* hard (Quantized) decision fusion based cooperative spectrum sensing. Therefore, our second phase of literature review was mainly focused on optimization of *softened* hard (Quantized) cooperative spectrum sensing. By studying and analysing various approaches, we found the estimation of optimal weight vector for local sensing data and formation of the global decision for centralized architecture is challenging task. We also found none of the researcher has worked on optimization techniques for CSS which is free from the algorithm parameters, i.e. there is no algorithm parameters are required for the functioning of the algorithm. As a result of both phases of literature review, we proposed the use of TLBO based cooperative spectrum sensing system model with two main objectives 1)Improve the receiver operating characteristic (ROC) of CSS and 2) Reduce the all over sensing error of CSS. The proposed system model and TLBO based algorithm are shown in figures 1 and 3 respectively. The detail of each is available in the further sub sections.

To fulfill this objectives, TLBO based cooperative spectrum sensing model has been optimized in two modes. In the first mode, 1) optimal weight vector is evaluated to improve the cooperative detection probability based on Neyman-Pearson criterion, 2) optimal weight vector is evaluated to reduce the all over sensing error based on Min-Max criterion.

The weight vector of proposed TLBO based cooperative spectrum sensing (CSS) frame work are evaluated through computer simulations and the convergence performance of TLBO based CSS is displayed. We validate the optimal solutions obtained by the TLBO based CSS through the comparison with other optimization techniques like GA, PSO etc. based CSS. Finally, concluding remarks has to be made and the research substances are documented

6.2 The Proposed System Model

The system model for the proposed TLBO based softened hard (quantize) CSS method is depicted in Figure 1. In this frame work, each CR user senses the spectrum locally and sends its 2-bit information "quantized observation" as $\mathrm{L_n}$(index of the quantization level) to indicate which region of its observed energy falls in to the fusion centre (FC) rather than sending the exact local spectrum sensing observation to FC. The fusion centre makes a global decision according to index of energy level ($\mathrm{L_n}$) and weight vector $\vec{\mathrm{w}}$ of corresponding energy level. Here weight is given to corresponding energy level not to the CR user.

In Soft combination based data fusion scheme, detection performance is obtained by allocating different weights to different CR users according to their SNR. In the conventional one-bit hard combination based data fusion scheme, there is only one threshold (λ) dividing the whole range of the observed energy into two regions. As a result, all of the CR users above this threshold are allocated the same weight regardless of the possible significant differences in their observed energies. *softened* hard(quantized) two-bit combination based data fusion scheme achieve the better detection performance and less complexity with two-bit overhead by dividing the whole range of the observed energy into four regions of energy and allocate a different weights to each region

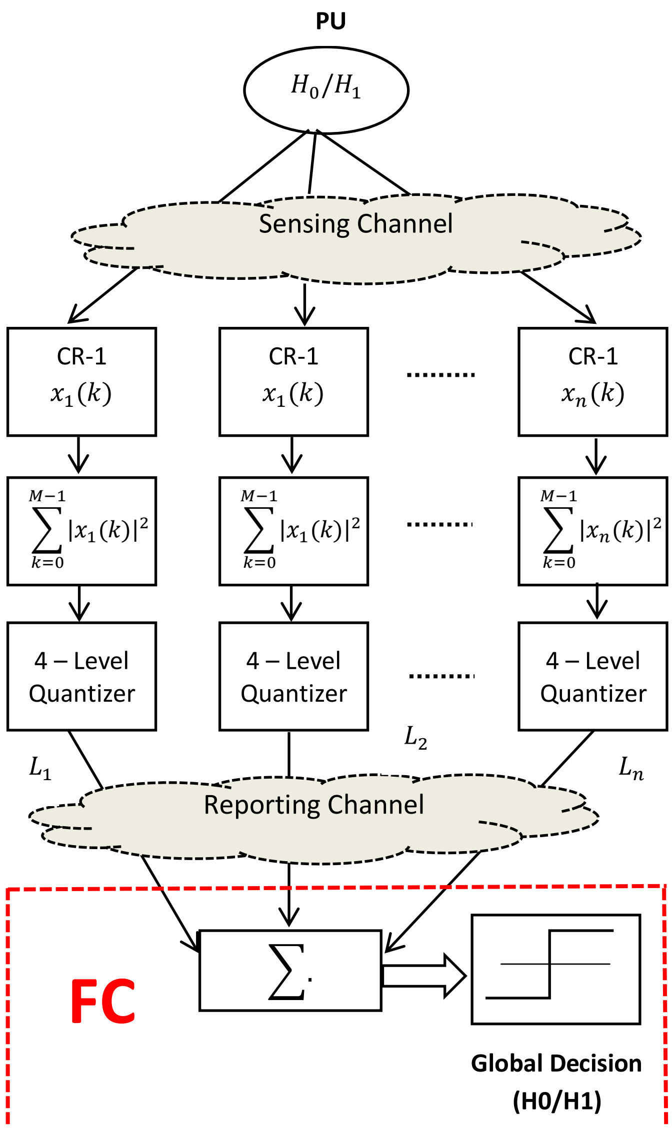

Figure 1: Proposed system Architecture

Figure 2 show this principle of the two-bit *softened* hard (Quantized) combination based data fusion scheme. In conventional one-bit scheme with only one threshold, Here, we have three thresholds λ_1, λ_2 and λ_3 in the 2-bit scheme which divide the whole range of the observed energy into four regions. Each cooperating secondary user senses the spectrum locally and sends its two bit information to indicate which region its observed energy falls in to fusion centre (FC) at the cognitive base station. The fusion center makes a global decision according to its 2-bit index value.

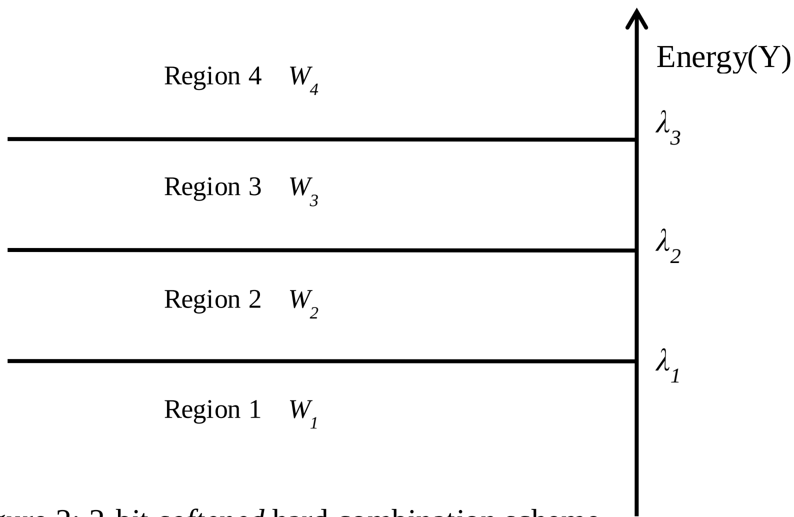

Figure 2: 2-bit *softened* hard combination scheme

Probability of having observation in respective region under hypothesis H_0 and H_1 for AWGN channel is following

$$P_{di} = \begin{cases} 1 - P_d(\lambda_k) & if\ k = 1 \\ P_d(\lambda_{k-1}) & if\ k = n \\ P_d(\lambda_{k-1}) - P_d(\lambda_k) & otherwise \end{cases} \tag{8}$$

In the proposed method, the global decision depends on the threshold values and the weight vector. For this 2-bit softened hard data fusion scheme, fusion centre receives the quantized measurements and counts the number of users in each quantization level which is given by following

$$\vec{N} = [n_1\ \ n_2\ \ n_3\ \ n_4] \tag{9}$$

The decision function is evaluated with the help of the weights and the number of users in the each energy level.

$$f(\overrightarrow{w}) = \begin{cases} 1 & if\ \vec{N}.\vec{W} > 0 \\ 0 & otherwise \end{cases} \tag{10}$$

Here the weighted summation is given by

$$N_c = \sum_{i=0}^{3} w_i . N_i \tag{11}$$

Where N_i = Number of observed energies falling in region i.

If the weighted summation of first two levels is higher than weighted summation of remaining level then true state is H_0 otherwise true state is H_1.

In *softened* hard combination based data fusion strategy, the probabilities of cooperative detection for a given false alarm are evaluated using [13, 14] which is given by following

$$P_d = \sum_{i=1}^{4} \sum_{j=1}^{4} P_r(N_1 = n_1, N_2 = n_2, N_3 = n_3, N_4 = n_4 | H_1) \tag{12}$$

$$P_d = \sum f(\vec{w}) \binom{N}{n_1} \binom{N - n_1 - n_2}{n_3} \binom{N - n_1 - n_2 - n_3}{n_4} (1 - P_{d1})^{n_1} (P_{d1} - P_{d2})^{n_2} (P_{d2} - P_{d3})^{n_3} (P_{d4})^{n_4} \tag{13}$$

The overall probability of error is can be represented as

$$P_e = P_f(\vec{w}) + 1 - P_d(\vec{w}) \tag{14}$$

It is observable that the probability of detection (P_d) and probability of error (P_e) is highly dependent on $(\vec{w})$. Therefore, the optimal solution is the weighting vector that maximizes the probability of detection and minimizes the total probability of error.

The most suitable optimality criterion for the decision is Neyman-Pearson optimality that maximizes the probability of detection and Min-Max criterion that minimize the total probability of error here the weight vector $(\vec{w})$ are optimized by TLBO method so our optimization problems are following

Optimization Problem 1: $Maximize\ P_d\ suject\ to\ \ P_f \leq \alpha,\ -5 \leq\ w_i \leq 5$

Optimization Problem 2: $Minimize\ P_e\ \ suject\ to\ -5 \leq\ w_i \leq 5$

6.3 TLBO based Weighting Method

A novel teaching-learning based optimization (TLBO) method is first proposed by prof. Rao [15, 16, 17] which is based on the process of teaching and learning. TLBO method is also population based evolutionary techniques which mimic the impact of a teacher on learners (student). The class of learner can be considered as a population and different design variables are different subjects. Learners' outcome is similar to the fitness value of the objective function. In the entire population the best solution is considered as the teacher. Working process of TLBO is divided into two stages. The first stage contain "teacher phase" and the second stage contain "learner phase." The "teacher phase" means learning through the teacher and the "learner phase" means learning by the mutual interaction between students.

In the teacher phase, learners learn through a teacher. A good teacher tries to raise the level of learners in terms of knowledge. However, in reality it is not only the input from the teacher which can raise the level of knowledge of learners but also from the learner. The capability of learners also plays very important role in this teaching learning process. Supposing there are m number of subjects (design variables) learned by n number of learners (population size, k = 1, 2… n). At any iteration i let T_i be the teacher and M_i be the mean of learners. T_i will try to increase mean M_i as per his or her capability. After the any iteration i there will be a new mean, say M_{new}. The solution is updated as per the difference between the existing and the new mean given by the following expression,

$$Difference\_Mean = r_i(M_{new} - T_F . M_i) \tag{15}$$

In the above equation T_F is a teaching factor that decides the value of mean to be change, r_i is a random number between [0, 1] which is given by following.

$$T_F = round[1 + rand(0,1)\{2 - 1\}) \tag{16}$$

The difference evaluated in equation (23) updated the existing solution to the following equation

$$x_{new,i} = x_{old,i} + Differene\_Mean \tag{17}$$

In learners' phase the learners raise their knowledge by two different approaches: one from the learning through teacher and the other through mutual interaction among the learners. A learner interacts randomly with each other through discussions in the group, active presentations, normal communications with each other, etc. It learns something novel if the other learner has additional knowledge than him or her. In this phase randomly two learners say x_i and x_j are selected where $i \neq j$. Learner alteration is represented by following is expressed as

$$x_{new,i} = x_{old,i} + r_i(x_i - x_j) \qquad if \quad f(x_i) < f(x_j) \tag{18}$$

$$x_{new,i} = x_{old,i} + r_i(x_j - x_i) \qquad if \quad f(x_i) > f(x_j) \tag{19}$$

$x_{new,i}$ is accepted if it gives a better function value. This entire process is repeated for the learners in the population. TLBO based weighted decision fusion algorithm is given in the following sub section. It is shown in [15] that teaching-learning based optimization algorithm is robust and efficient algorithm that produced better optimum solutions than other evolutionary optimization algorithm.

6.4 Weighted Decision Fusion Algorithm

Algorithm 1: Weight Optimization Using TLBO

Input: Channel, SNR, N, λ, Iteration, Population size
Output: P_d, P_e ,Optimal vector $\vec{w}$
Initialize the population size and Generation
While$(number\ of\ generation\ is\ not\ reached)$
$\{teacher\ Phase\}$
Find the mean of each design variable w_{mean}
Identify the best solution as teacher
$[w_{teacher} \rightarrow w\ with\ f(w)_{max}]$
For $i = 1\ to\ n$
Calculate $T_{F,i} = round[1 + rand(0,1)\{2 - 1\}]$
$w_{new,i} = w_i + rand(0,1)[w_{teacher} - T_{F,i}.w_{mean}]$
Calculate $f(w_{new,i})\ for\ w_{new,i}$
If $f(w_{new,i}) < f(w_i)$ **then**
$w_i = w_{new,i}$
End If $\{End\ of\ teacher\ phase\}$

$\{student\ Phase\}$
Select a learner randomly w_j such that $j \neq i$
If $f(w_i) < f(w_j)$ **then**
$w_{new,i} = w_{old,i} + rand_i(w_i - w_j)$
Else
$w_{new,i} = w_{old,i} + rand_i(w_j - w_i)$
End If
If $f(w_{new,i}) < f(w_i)$ **then**
$w_i = w_{new,i}$
End If $\{End\ of\ student\ phase\}$
End For
End While

Figure 3: Pseudo Code of TLBO algorithm

6.5 Simulation Results/Comparison

A simulation has been accomplished to access the performance of proposed TLBO based CSS. The receiver operating characteristics (ROC) curve shown in figure 4 which compare with the conventional SDF technique i.e. EGC and convention HDF technique i.e. AND, OR, MAJORITY rules etc., In this simulation we have set TW = 5, the channel is Rayleigh, number of particles S = 15 and iteration = 25. It is observable that the performance of TLBO based method is out perform with HDF technique and almost same to EGC with low overhead.

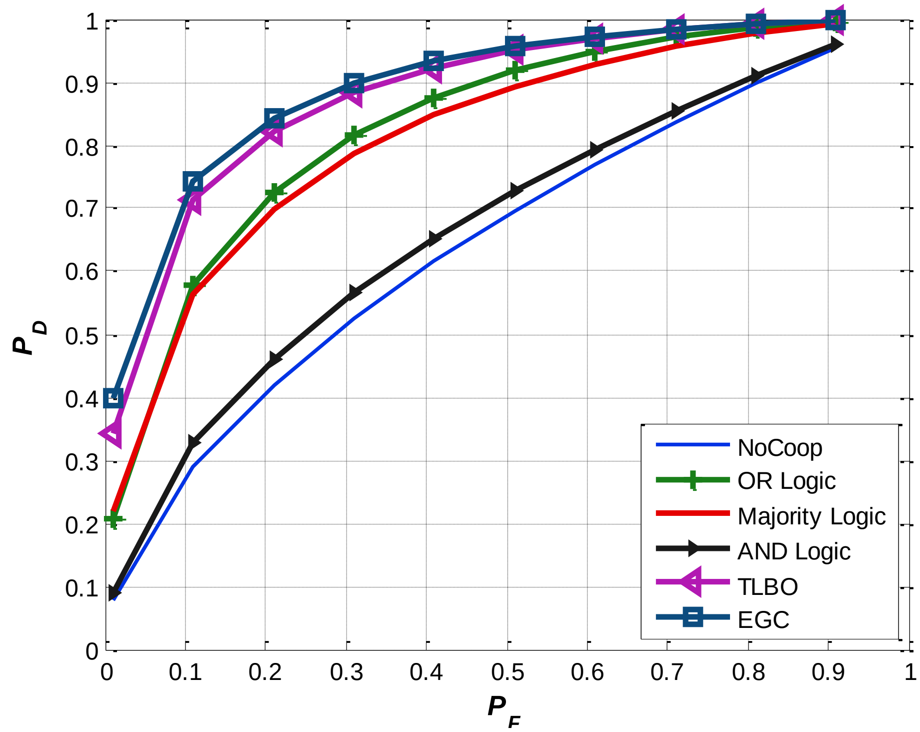

Figure 4: ROC curve of different decision logic

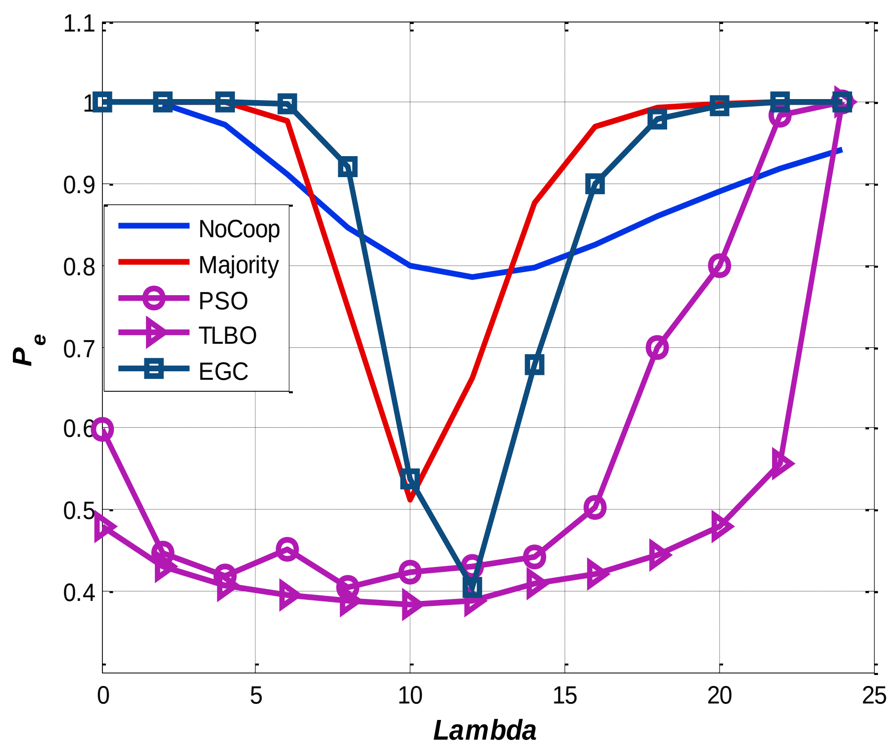

Figure 5: Comparison of P_e versus Lambda for different schemes

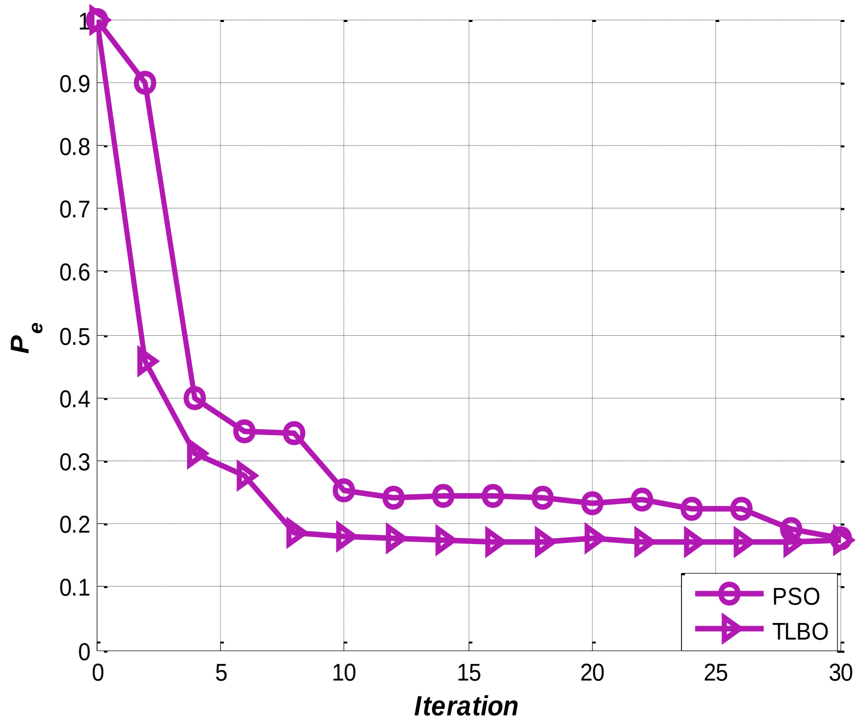

Figure 6: Iteration versus total sensing error P_e curve

Comparison of P_e versus λ for different schemes is shown in figure 5. It can be clearly observed, the TLBO-based method generates the best weighting coefficients vector leading to minimized probability of error for CSS compared to other schemes.

The convergence performance of TLBO based *softened* hard decision fusion scheme for a given $\lambda = 6$ is shown in figure 6 which is so fast for convergence that can ensure to meets real time requirements of cooperative spectrum sensing in cognitive radio.

7 Achievements with respect to objectives

The outcome of the proposed TLBO based cooperative spectrum sensing (CSS) model shows that the objectives of the research work have been acquired. The performance of proposed TLBO based CSS method is analyzed and compared with other conventional soft decision fusion (SDF) as well as conventional hard decision fusion (HDF) based method. Simulation result shows that proposed TLBO based method gives excellent detection performance and minimize the total sensing error with low overhead in the environment of different fading channel. The strength of proposed TLBO based CSS model for the case of false reports and an imperfect reporting channel and also for multi hop case is analyzed

8 Conclusion

In this research work, the detection performance for local spectrum sensing and cooperative spectrum sensing using OR-rule, AND-rule, MOJORITY-rule and EGC under the different fading channel are evaluated. A TLBO-based CSS framework is proposed to optimize the weight vector of local sensing result for cooperative spectrum sensing. From the simulation results, it can be concluded that the proposed method is efficient and stable and it outperforms with conventional GA and PSO based optimization method in that it can obtain higher probability of detection given the same probability of false alarm and minimize probability of error.

9 Publication

1) D.R.Keraliya, Dr.Ashalata Kulshrestha and S.D.Patel,(2015) "Optimization of Cooperative Spectrum Sensing in Cognitive Radio Networks" *in proceeding of IEEE international conference of communication and networks 2015*, 19-21Nov., pp. 237-242 IEEE Explore DOI 10.1109/ICCN.2015.46 **(available on IEEE explore)**

2) D.R.Keraliya and Dr.Ashalata Kulshrestha,(2016) "Optimization of Cooperative Spectrum Sensing using quantized data fusion scheme for cognitive radio" in International Journal of Advance Research in Engineering Science and Technology(IJAREST) Vol. 03, issue 1,pp 192-197. e-ISSN No.: 2393-9877, p-ISSN No.: 2394-2444.

3) D.R.Keraliya and Dr.Ashalata Kulshrestha,(2017) "Minimizing the Detection Error in Cooperative Spectrum Sensing Using Teaching Learning Based Optimization(TLBO)" in International Journal of Engineering Research and Technology(IJERT) Vol. 06, issue 02,pp 495-500, ISSN No.: 2278-0181.

4) D.R.Keraliya and Dr.Ashalata Kulshrestha and Hitesh Loriya,(2017) "Performance Analysis of Cooperative Sensing In Fading Channels for Wireless Communication" in International Journal of Advanced Research in Computer and Communication Engineering(IJARCCE) Vol. 06, issue 02,pp 275-279, e-ISSN No.:2278-102, p-ISSN No.:2319-5940.

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6) D.R.Keraliya and Dr.Ashalata Kulshrestha,(2017) "Optimization of Quantized Cooperative Spectrum Sensing Using Teaching Learning Based Optimization (TLBO) Algorithm" in Far East Journal of Electronics and Communication(FJEC) accepted with Paper ID: PPH-I-1617-423-EC**(SCOPUS Indexed Journal)**

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