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Minimizing the Detection Error in Cooperative Spectrum Sensing using Teaching Learning Based Optimization(TLBO)

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***Abstract*— Cognitive radio (CR) is a new paradigm in wireless communication system which is use for efficient utilization of radio frequency (RF) spectrum or RF channel for future wireless communication. Cooperative spectrum sensing is a key technology in cognitive radio networks (CRNs) to detect spectrum holes by combining sensing result of multiple cognitive radio users. This sensing information from CR users combines at the Fusion center (common receiver) by soft combination or conventional hard combination techniques. Sensing error minimization is an important aspect of cooperative spectrum sensing that needs attention. In this paper, the use of teaching learning based optimization (TLBO) under MINI-MAX criterion is proposed to optimize the weighting coefficients vector of energy level of spectrum sensing information so that the total probability of error is minimized. The TLBO algorithm investigates the best weighting coefficient vector which minimizes total probability of error. The performance of the TLBO based method is analysed and compared with conventional soft decision fusion schemes like EGC as well as hard decision fusion method like AND,OR, Majority etc. Simulation results show that the proposed scheme minimizes the detection error compared to conventional soft decision fusion schemes**

Keywords*— Cognitive Radio, Cooperative Spectrum Sensing, GA, Soft Decision Fusion, TLBO

I. INTRODUCTION

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 on the PUs or license holders [1]. In a cognitive radio network, to avoid the interference imposed on the licensed users, the SUs should be capable of identifying the presence or absence of the primary user (PU) signal. The PU signal is always subjected to deep fading effects due to propagation loss and secondary-user (SU) interference. To minimized the fading effects, we can use from the diversity gain that can be used by employing several SUs to cooperatively detect the spectrum.

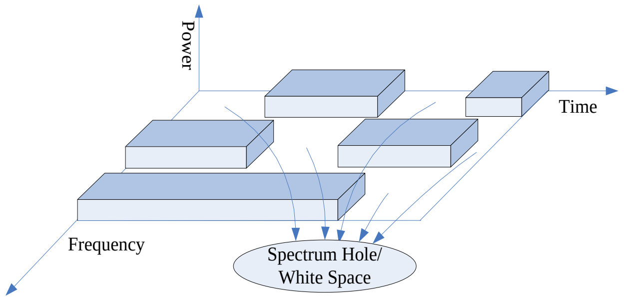

Fig.1. Utililization of spectrum Holes

In cooperative spectrum sensing system, SUs send their spectrum sensing information to fusion center (FC), which makes a global decision whether any PU is present or absent according to some rule. If SUs send all information received to FC without making any decision, it is called soft fusion [2]. On the other hand, if SUs send their decision information to FC (general one-bit decision), it is called hard fusion [3]. In [4], maximal ratio combining (MRC) and equal gain combining (EGC), based soft fusion method were used to calculate the optimal weighting vector. In this paper, we focus on a scenario of quantized cooperative spectrum sensing, in which a softened hard measurements from SU are send to fusion center where optimal weighting vector is evaluated. Teaching learning based optimization (TLBO) scheme for cooperative spectrum sensing is proposed to reduce probability of error for improvement of detection performance. The TLBO based optimization process is implemented at the fusion center to optimize the weighting coefficients vector and to minimize global probability of error. Simulation results and analysis shows that the proposed schemes are efficient and stable as compare to conventional convention soft decision fusion i.e EGC and conventional hard decision fusion like AND, OR, MAJORITY etc. The proposed scheme also shows good convergence performance which verifies lower computation complexity of the TLBO.

The paper is organized as follows. We present the spectrum sensing in Section II. In Section III, we proposed the system model related to cooperative spectrum sensing and optimization problem, Section IV are for the TLBO based weighting method for minimization of detection error. Simulation results in section V are given to compare our proposed technique with conventional scheme for minimization of detection error.

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II. SPECTRUME SENSING

Spectrum sensing is a key element in cognitive radio networks as it should be firstly performed before allowing CR users to access a vacant licensed channel. 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 average probability of false alarm, the average probability of detection, and the average probability of missed detection are given, respectively, by [5]

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

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

$$P_m = 1 - P_d \tag{4}$$

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 generalised Marcum Q-function defined as follow

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

The average probability of detection may be derived by averaging the conditional P_d in the AWGN case over the SNR fading distribution by following

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

When the composite received signal consists of a large number of plane waves, for some types of scattering environments, the received signal has a Rayleigh distribution [5]. Under Rayleigh fading, γ would have an exponential distribution given by

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

In this case, closed-form formula for probability of detection may be obtained (after some manipulation) by substituting $f(\gamma)$ in the above equation by

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

One of the main challenging issues of spectrum sensing is the hidden terminal problem for the case when the cognitive radio is shadowed or in deep fade. To mitigate this issue, multiple cognitive radios can be cooperative work for spectrum sensing so cooperative spectrum sensing can greatly improve the probability of detection in fading channels. In cooperative spectrum sensing common receiver calculates false alarm probability and detection probability with the help of average probability of each CR. The false alarm probability is given by [10],

$$Q_f = \sum_{k=n}^{N} \binom{N}{k} {P_f}^k (1 - p_f)^{N-k} = prob\{H_1/H_0\} \tag{9}$$

Also, Detection probability is given by;

$$Q_d = \sum_{k=n}^{N} \binom{N}{k} {P_d}^k (1 - p_d)^{N-k} = prob\{H_0/H_1\} \tag{10}$$

In hard combing based fusion scheme, each cognitive user decides on the presence or absence of the primary user and sends a one bit decision to the data fusion center. The main benefit of this method is that it needs limited bandwidth [6]. When binary decisions are reported to the common node, three rules of decision can be used, the "AND", "OR", Half Voting and "MAJORITY". While in soft combing based fusion scheme, CR users forward the entire sensing result to the fusion centre without performing any local decision and the decision is made by combining these results at the fusion centre by using appropriate combining rules such as equal gain combining (EGC) in which each sensing node gives equal weightage and at fusion center they are all combined equally, maximal ratio combining (MRC) in which weightage is given based on SNR of sensing data of secondary user and at the fusion center they all are combined with different weightage based on their SNR. Soft combination provides better performance than hard combination, but it requires a larger bandwidth for the control channel for reporting [7]. It also generates more overhead than the hard combination scheme [6]

$$Q_{d,MAJORITY} = \sum_{K=N/2}^{N} \binom{N}{k} {P_d}^k (1 - p_d)^{N-k} \tag{11}$$

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

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

Cooperative detection as well as false alarm performance with OR fusion rule and MAJORITY fusion rule can be evaluated by setting $\text{k} = 1$ and $\text{k} = \text{N}/2$ in expression (9, 10) while AND rule corresponds to the case of $\text{k} = \text{N}$.

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III. PROPOSED SYSTEM MODEL

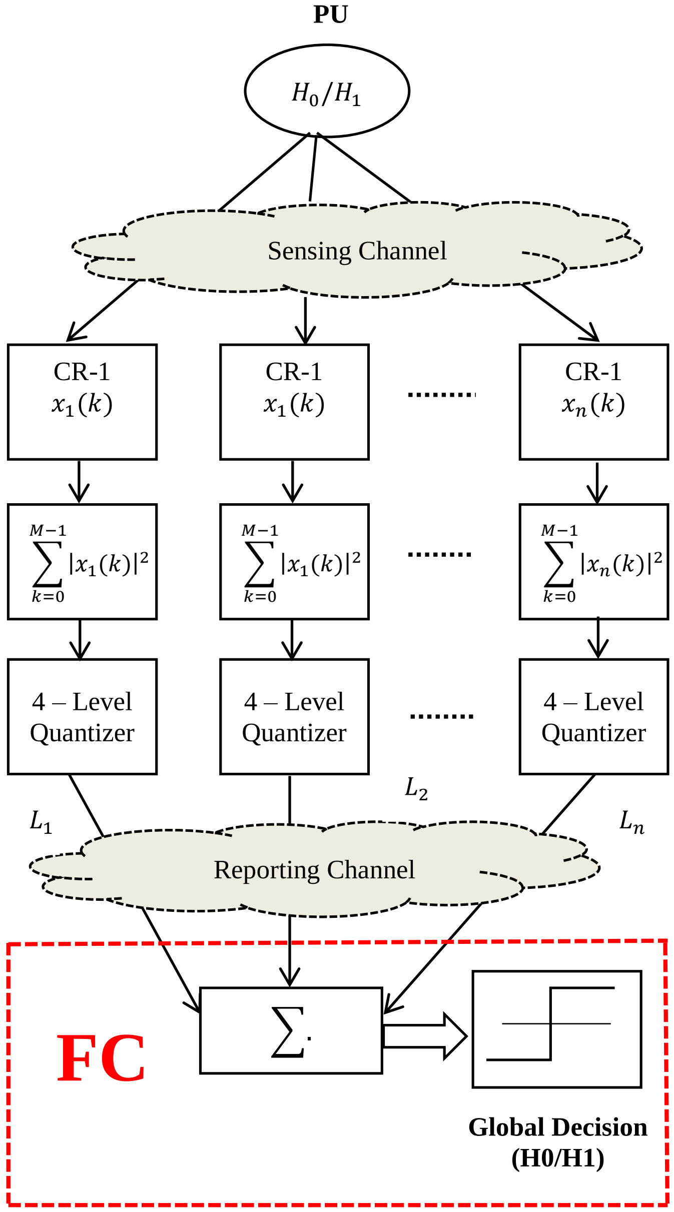

Fig.2. Proposed system Architecture

The system model for the proposed softened hard (quantize) cooperative spectrum sensing method is depicted in Figure 2. Each cooperating secondary user senses the spectrum locally and sends its 'quantized' local measurement as L_n(index of the quantization level) to the fusion center at the cognitive base station. The fusion center makes a global decision according to L_n and weight of corresponding energy level quantization level.

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 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* two-bit hard 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, and allocate a different weights to this region.

Although the Soft combination based data fusion scheme has the best detection performance, soft combination schemes require lots of overhead for each CR user to transmit the sensing result periodically. In contrast, the conventional hard combination scheme requires only one bit of overhead for each CR user, but suffers performance degradation because of information loss caused by local hard decisions. Here we will use *softened* hard (Quantized) combination scheme with two-bit overhead for each CR user, which achieves a good detection performance and less complexity.

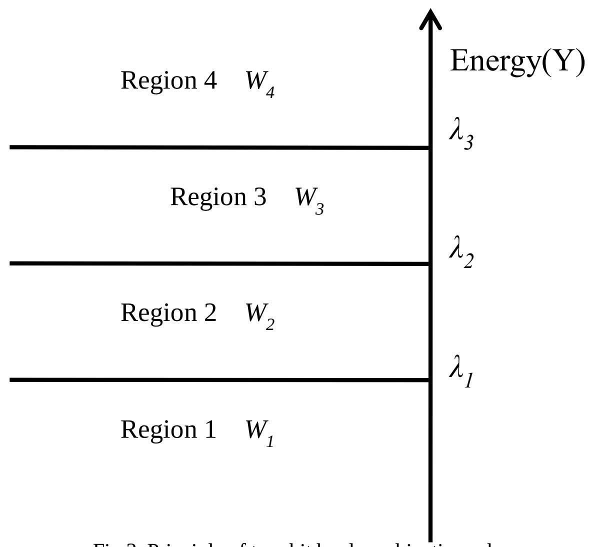

Fig.3. Principle of two-bit hard combination scheme

Figure 3 shows the principle of the *softened* two-bit hard combination based data fusion scheme. Different from the conventional one-bit scheme with only one threshold, here we have three thresholds λ1, λ1 and λ3 for two-bit scheme which divide the whole range of the observed energy into 4 regions. Each cooperating secondary user senses the spectrum locally and sends its two bit information "quantized data" to indicate which region of its observed energy falls in. The fusion center makes a global decision according to its 2-bit value measurement and weight allocated to each region. If the we divide the observed energy into two level, hard decision logic, such as OR, AND and MAJORITY logic can be applicable for global decision logic at the fusion center. Here each cognitive user either send only 0 and 1 for L_n.However, for the case of more quantization level softened hard decision logic can be used

The probability of having observation in respective region under hypothesis H_0 and H_1 and AWGN channel are following

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

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In the proposed method, the global decision depends on the threshold values and the weight vector. Here the weights are assigned to the energy level not the reporting nodes. For this 2-bit *softened* hard combination based data fusion scheme, fusion center receives the quantized measurements and counts the number of users in each quantization level which is given by following.

$$\vec{N} = [n_1\ n_2\ n_3\ n_4]\ and\ \vec{W} = [w_1\ w_2\ w_3\ w_4]$$

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

$$f(\overrightarrow{w}) = \begin{cases} 1 & if\ \vec{N}.\vec{W} > 0 \\ 0 & otherwise \end{cases} \tag{15}$$

Here the weighted summation is given by

$$N_c = \sum_{i=0}^{3} w_i . N_i \tag{16}$$

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

Then $N_c$is compare with the threshold, N_T If $N_c \geq N_T$, primary signal is declared present; Otherwise, it is declared absent

In *softened* hard (quantized)combination based data fusion strategy the probabilities of cooperative detection under a Rayleigh channel are derived using [2] which is given by following.

$$P_d = \sum_{i=1}^{4} \sum_{j=1}^{4} P_r(N_1 = n_1, N_2 = n_2, N_3 = n_3, N_4 = n_4 | H_1) \tag{17}$$

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

Similarly equation can be for probability of false alarm. Then, the overall probability of error is can be represented as

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

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

$$\mathrm{P_e} = \mathrm{P_f}(\vec{\mathrm{w}}) + 1 - \mathrm{P_d}(\vec{\mathrm{w}}) \tag{21}$$

It is observable that the probability of error is highly dependent on $(\vec{\mathrm{w}})$ vector. Therefore, the optimal solution is the weighting vector that minimize the total probability of error P_e. In our paper, equation (18) is used as objective functions that minimize the probability of error. However, to reduce the search space on which TLBO algorithm works, the $\vec{\mathrm{w}}$ used in this paper should satisfies the conditions $-5 \leq w_i \leq 5$

So, optimization problem:

$$Minimize\ P_e\ subject\ to -5 \leq w_i \leq 5$$

IV. TLBO BASED WEIGHTING METHOD

One of the most recently developed meta heuristics based algorithms is teaching-learning-based- optimization (TLBO) algorithm [8]. TLBO has many similarities to evolutionary algorithms(EAs) like an initial population, moving on the way to the teacher and classmates is comparable to mutation operator in EA, and selection is based on comparing two solutions in which the better one always survives.

Teaching-learning-based optimization (TLBO) algorithm is also population based evolutionary process which mimics the influence of a teacher on learners (student) [8]. The class of learner is similar to population and different design variables are considered as different subjects. Learners' achievement in result is analogous to the fitness value of the objective function. In the entire population the best solution is considered as the teacher. The process of working of TLBO is divided into two parts. The first part is a "teacher phase" and the second part is "learner phase." The "teacher phase" means learning from the teacher and the "learner phase" means learning through the interaction between learners (student).

In the teacher phase the learning process of learners through a teacher is repeated. A good teacher puts an effort to boots up the level of learners higher in terms of knowledge. However, in reality it is not only the inpurt of a teacher which can boost up the level of knowledge of learners. The capability of learners also plays very significant 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' achievements. T_i will try to move mean M_i to a its own level best. After the teaching of T_i there will be a occurrence of new mean, say M_i. The solution is modified according to the difference between the existing and the new mean to the following expression.

$$Difference\_Mean = r_i(M_{new} - T_F.M_i) \tag{22}$$

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 again a heuristic process and decided randomly with equal probability as given below

$$T_F = round[1 + rand(0,1)\{2-1\}) \tag{23}$$

The difference calculated in the equation (23) modified the existing solution to the following equation

$$x_{new,i} = x_{old,i} + Differene\_Mean \tag{24}$$

In learners' phase the learning process of learners through interaction among themselves is imitated. A learner interacts randomly with other learners with the help of group discussions, presentations, and formal communications. A learner can learn more unless the other learner has more knowledge than her or him. In this phase randomly two learners say x_i and x_j are selected where $i \neq j$.Learner modification is then expressed as follows

$$x_{new,i} = x_{old,i} + r_i(x_i - x_j) \quad if\ \ f(x_i) < f(x_j) \tag{25}$$

$$x_{new,i} = x_{old,i} + r_i(x_j - x_i) \quad if\ \ f(x_i) > f(x_j) \tag{26}$$

$x_{new,i}$ is accepted if it gives a better output value. This entire process is repeated for the learners in the population. The pseudo code of the TLBO algorithm is given in Fig. 4. It is shown in [9–10] that teaching-learning based optimization algorithm is robust and efficient algorithm that produced better optimum solutions that those meta heuristic algorithms considered for comparison.

Algorithm 1: Weight Optimization Algorithms Using TLBO

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

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

Fig.4. Pseudo code for TLBO algorithm

V. SIMULATION RESULT

A simulation has been done to assess the performance of proposed TLBO algorithms based cooperative spectrum sensing. Figure 5 demonstrate the probability of error in term of different value of threshold λ for TLBO based as well as other conventional soft decision fusion technique i.e. EGC and convention hard design fusion technique i.e. AND, OR, MAJORITY rules etc., We have considered time-bandwidth product $TW = 5$, the channel is Rayleigh, the number of received signal samples $M = 2u$. In TLBO, we have used the number of particles $S = 15$ and $iteration = 50$. We have assumed perfect reporting channels and there is no false reporting.

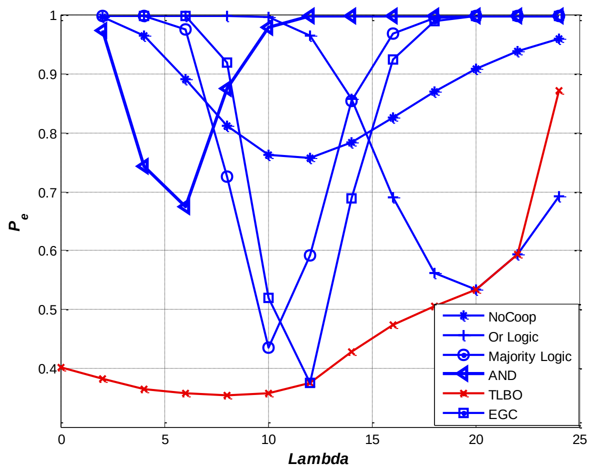

Fig.5. Comparison of Pe versus Lambda for different schemes

As it can be clearly observed, the TLBO-based method generates the best weighting coefficients vector leading to minimized probability of error of cognitive radio system. On the other hand, conventional hard decision fusion (HDF) based spectrum sensing provides the worst error performance resulted from insufficient data fusion from secondary user (SU) in the network.

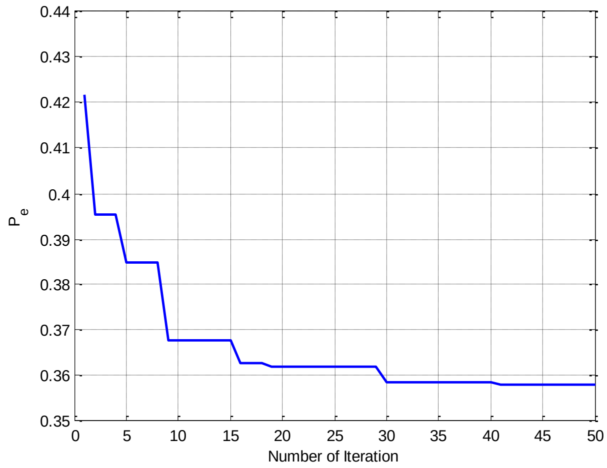

Fig.6. Performance of TLBO-based method

The convergence of TLBO based scheme for a given $\lambda = 6$ is shown in figure 6. It can be seen that the probability of error converges after around 30 iterations, which is so fast that it can ensure the computation complexity of the proposed method meets real time requirements of cognitive radio cooperative spectrum sensing. The standard deviation of the obtained probability of detection under 25 simulations can be negligible, which means that the TLBO-based method is quite stable.

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REFERENCES

[1] S.Haykin, "Cognitive radio: Brain-empowered wireless communications," IEEE J. Sel. Areas Commun., vol. 23, no. 2, pp. 201–220, Feb. 2005
[2] Ma, G. D. Zhao, and L. Ye, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," IEEE Transactions on Wireless Communications, vol. 7, no. 11, pp. 4502- 4507, 2008.
[3] D. C. Oh, H. C. Lee, and Y. H. Lee, "Linear hard decision combing for cooperative spectrum sensing in cognitive radio systems," IEEE 72nd Vehicular Technology Conference, Ottawa, Canada, pp. 1-5, Sep. 2010
[4] B. Shen and K. S. Kwak, "Soft Combination Schemes for Cooperative Spectrum Sensing in Cognitive Radio Networks," ETRI Journal, vo. 31, no. 3, 2009.
[5] Wei Zhang, Member, IEEE, Ranjan K. Mallik, Senior Member, IEEE, and Khaled Ben Letaief, Fellow, IEEE "Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks", IEEE transactions on wireless communications, vol. 8, no. 12, December 2009.

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ISSN: 2278-0181
Vol. 6 Issue 02, February-2017

[6] J. Ma and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," in Proc. IEEE Global Telecomm. Conf., 2007, pp. 3139–3143
[7] Zhi Quan, Shuguang Cui, H. Vincent Poor, and Ali H. Sayed, "Collaborative wideband sensing for cognitive radios," IEEE Signal Processing Magazine, Vol. 25, No. 6, pp. 63–70, 2008
[8] R. V. Rao, V. J. Savsani, D. P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems," Computer-Aided Design, vol. 43, no. 3, pp. 303- 315,2011
[9] Togan V," Design of planar steel frames using teaching-learning-based optimization".Elsevier Journel Engineering Structure, vol 34, pp.34:225–232,2012
[10] Togan V," Sizing truss structures using teaching-learning-based optimization".Elsevier Journel Structure, vol 47, no.2, pp.34:225–232, 2013