Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 163 (2019) 19–29

Procedia Computer Science

www.elsevier.com/locate/procedia

16th International Learning & Technology Conference 2019

Artificial Intelligence Based Cooperative Spectrum Sensing Algorithm for Cognitive Radio Networks

M. Mourad Mabrook[a], Hussein A. Khalil[b] , Aziza I. Hussein[c],

[a]*Faculty of Navigation Science & Space Technology, Beni-Suef University, Egypt*
[b]*Faculty of Engineering, Electrical Dept., Sohag University, Egypt*
[c]*Electrical & Computer Eng. Dept., Effat University,Jeddah, KSA*

Abstract

Cognitive Radio (CR) technology is regarded as a key network technology used to manage the limitation of the available spectrum in wireless communication networks. Spectrum Sensing (SS) is the core process in CR engine based on detecting the free channels and sharing it among other users. In wideband spectrum, many algorithms are proposed to sense the available free channels. Cooperative sensing is mainly considered as an effective solution of signal fading and shadowing problems in CR networks.

From another side, CR networks can utilize Artificial Intelligence (AI) techniques for dynamically sensing and decision making processes. In this paper, a blind adaptive spectrum sensing algorithm based over centralized cooperative sensing platform is proposed. Then, an Adaptive Neuro-Fuzzy Interference System (ANFIS) technique is applied in decision-making process to achieve the optimum and accurate decisions.

The simulation process and the output results showed that, the proposed technique outperforms both a standalone sensing techniques and other cooperative sensing with conventional decision making algorithms regarding to the probability of false alarms, probability of detection and probability of missed detection especially in low Signal to Noise Ratio (SNR). The results obtained by the proposed algorithm based on ANFIS decision making technique outperformed the other conventional decision making techniques.

Keywords: Adaptive cognitive radio; Adaptive-Neuro-Fuzzy; Multi-Coset Sampling; Cooperative sensing

1. Introduction

Recently, cognitive radio technology has received a great attention as a novel technique of efficiently utilizing the available working spectrum [1]. The cognition cycle functionalities include spectrum sensing process, spectrum sharing process, spectrum management algorithms, and spectrum mobility techniques [2]. However, sensing the unused channels in the wideband spectrum is the core function of CR networks. This process is so called spectrum sensing process.

1877-0509
10.1016/j.procs.2019.12.081

There are many classifications defining spectrum sensing techniques, some sensing techniques are based on either time domain or frequency domain approach. From another side, the necessity of spectrum sensing approach is another classification based algorithm [7]. From the perspective of spectrum bandwidth, spectrum sensing is divided into a narrowband sensing or wideband spectrum sensing schemes [8].

Narrowband sensing gives only the status of one channel at a time either it is free of users [H_0] or occupied with a primary user [H_1]. Energy Detection method (ED) which is based on the power level of the sensed channel, matched filter detection algorithm in addition to cyclostationary feature detection techniques are the most common used narrowband spectrum sensing techniques.

From the other perspective, wideband sensing technologies are able to sense the whole spectrum including many channels at once to detect the vacant channels. Wideband sensing can be categorized based on the digital processing rate of the used Analog to Digital Converter (ADC) into two main approaches [9]:

I. Wideband sensing based on Nyquist sampler: acquires the input digitized signals at or above the Nyquist sampling rate, such as the following techniques; Multiband joint detection technique, Sweep-tune detection algorithm Wavelet detection method, and Filter-bank detection technique

II. Wideband sensing based on Sub-Nyquist sampler: processes signals with a lower rate of data sampling than the Nyquist data sampling rate. It is commonly categorized into two fundamental categories. The first category is wideband Compressed Sensing (CS) based techniques. Then, the second category is Multi-Channel Sub-Nyquist spectrum sensing Algorithm involving the following techniques; Modulated Wideband Converter (MWC), Analog to information converter (AIC), Multi-rate sub-Nyquist sampling algorithms and Multi-Coset sampling (MC). Therefore, in this work, the proposed system is based on Sub-Nyquist wideband sensing techniques.

However, in practice there are many sources of noise and interference such as fading of multi-path channels, receiver uncertainty and shadowing problems affecting the performance and accuracy of detection [3]. To qualify the influence of such issues, the sensing process based on cooperative model is considered as an efficient way to improve sensing quality by utilizing space diversity techniques [3]. Cooperative sensing is achieved by importing the sensing decisions from multi-users and take the final decision based on all the sensed data from all the cooperated users. Three main categories of cooperative sensing based on the way of sharing data among cooperative users are known as centralized [4] based cooperative sensing, distributed based cooperative sensing [5] and relay-assisted based [6] cooperative sensing approaches.

2-Wideband Spectrum Sensing Model.

In this work, the proposed model is mainly based on wideband Multi-Coset (MC) sub-Nyquist method based on choosing number of (m) samples from a regular grid that is achieved depending on a lower sampling rate (f_s) than the Nyquist sampling rate. As a result of a permanent and frequent need to determine the free channels with the variation of the sparsity levels of wideband signals, adaptive type of MC algorithm is required [10]. However, in practice, the dynamic variation of the Primary users' active channels result in time-varying sparsity levels which are difficult to estimate [10]. Thus, it is necessary to propose an adaptive wideband sensing technique which enables the sensing processor to select the suitable number of compressed estimates quickly without a pre knowledge of the actual sparsity levels.

From another hand, the proposed system has to be able to sense the change of the free channels in a blind category, which means there is no information about the sparsity level of the input signal in the wideband spectrum and without any pre knowledge of the wideband channels' characteristics or the parameters of the noise. Therefore, this work is based on an adaptive blind Multi-Coset Sub-Nyquist wideband algorithm [11].

Figure (1) shows the main block diagram of the Periodic Non-uniform Multi-Coset Sampler which represents core of the adaptive MC sampling algorithm. The implementation of the non-uniform multi-coset sampler is mainly based on utilizing (P-branches), each branch contains instant delay (t_i) followed by a uniform ADC has a sampling rate (f') acting as a non-uniform periodic sampler. ($f' = \alpha \cdot f_{max}$), where, α is a compression ratio= (P/L) whereas, (L) is the total number samples.

The clock generator generates clocks based on the number of selected integers (C_i) from the total (L) samples with delays instants (T_i), (i) is considered to a specific branch. In order to agree Landau's lower bound [12], where, the number of data sequences (p) is considered to be greater than the maximum number of the occupied channels with Primary Users (PUs) to give enough number of equations which are able to solve the unknown parameters.

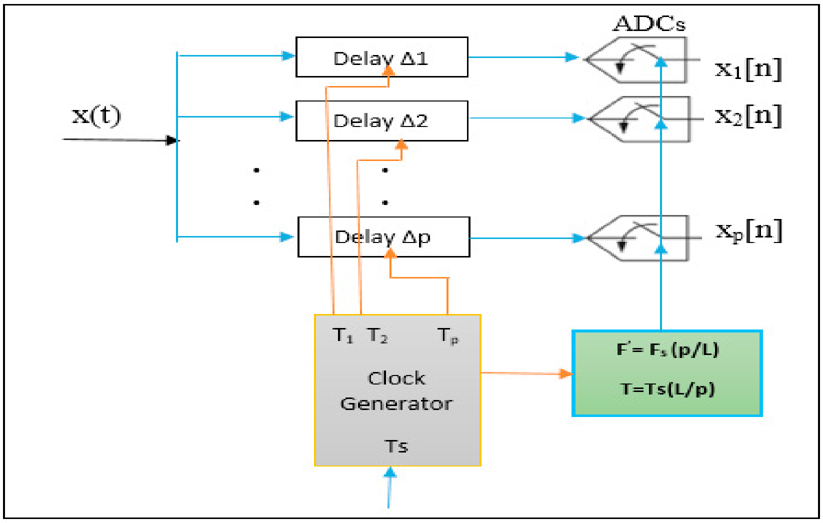


Fig. 1 Block diagram of Periodic Non-uniform Multi-Coset Sampler

3-The Problem statement and the Proposed Signal Model.

The transmitted wideband signal is assumed to be a finite-energy, continuous time, real valued and sparse in frequency domain. Therefore, the transmitted signal can be presented in the form of equation (1)

$$x(t) = \sum_{i=1}^{N_{sig}} s_i(t) \quad (1)$$

Where, Si(t) is a bandpass input process with a maximum bandwidth, (N_{sig}) transmitted signals from different users simultaneously.

From the other perspective, the received signal is faded and shadowed due to the multiple sources of noise, fading and other obstacles. Then, the received signal is denoted by $r_{ij}(t)$, for i' th number of transmission signals ($1<i<N_{sig}$), received at the j' th cognitive user ($1 \leqslant j \leqslant Nrec$) [16]. . Then, the received signal $r_{ij}(t)$ is denoted based on the channel impulse response $h_{ij}(t)$ by equation (2)

$$r_{ij}(t) = s_i(t) * h_{ij}(t) \quad (2)$$

In this paper three main types of shadowing and fading affecting the original transmitted signal within the wideband channels are studied as follows:

3.1 Rayleigh faded signal

The fading phenomena is defined as the deviation of the attenuation which affects the propagated signal over a certain medium due to multiple reflections occurred while travelling the signal from the transmitter to the receiver [17]. However, Rayleigh fading is regarded as a statistical model of the influence of the propagation environment on a radio signal that occurs while no direct line of sight propagation between the source and destination. Rayleigh distribution is modelled as the envelop of channel response $h_i(t)$ with the following distribution:

$$p_h(r) = \begin{cases} \frac{r}{\sigma^2} e^{-r^2/2\sigma^2} & r \geq 0 \\ 0 & otherwise \end{cases} \tag{3}$$

Where, (r) is the received signal envelope's amplitude whereas, (σ^2) is the received signal's time-average power before the envelope detection.

3.2 Rician faded signal

It is a type of radio propagation resulted from partial cancellation of the radio signal by itself as a result of receiving the signal through several different paths exhibiting multipath interference. Where, the line of sight path contains the strongest signal at the receiving part than the multipath signals [18]. Equation (4) denote the envelope of a Rician density function.

$$f(r) = \frac{r}{\sigma^2} e^{-\left\{\frac{r^2 + k_d{}^2}{2\sigma^2}\right\} \cdot I_0 \left\{\frac{r k_d}{\sigma^2}\right\}} \tag{4}$$

Then, for this distribution function f(r) the transmitted signal S(t) is presented in the form of:

$$s(t) = \sum_{i=1}^{N-1} a_i \cos(\omega_c t + \omega_{di} t + \varphi_i) + k_d \cos(\omega_c t + \omega_d t) \tag{5}$$

Where, (ω_d) is the Doppler shift along the direct path of the line-of sight. Whereas, (ω_{di}) are the Doppler shifts along the indirect multi-paths. The constant (k_d) denotes the strength of the line of sight, (I_0) is the 0^{th} order the first kind of modified Bessel function.

3.3 Shadowed Signal

Shadowing effect is defined as the average path loss of the transmitted signal due to the motion of the signal over large distances. Thus, the Path Loss (PL) is measured in (dB) and can be presented as

$$PL = PL_0 + 10\gamma \log \frac{d}{d_0} + X_\sigma \tag{6}$$

Where, (d_o) is the reference distance related to a point located far from the antenna (about 1 km), (PL_o) is the path loss to this reference point which can be measured using path loss in free space parameters, (ϒ) is the value of exponent path loss parameter which based on antenna height, the environment of propagation and the operating frequency. ($X\sigma$) is measured in (dB) and denotes the Gaussian random variable with a variance (σ^2). Then, the received shadowed signal is expressed as:

$$r_{ij}(t) = 10^{-PL_{ij}/20} \cdot s_i(t) \tag{7}$$

Where, (PL_{ij}) denotes the loss of the path from the transmitter (i) to the receiver (j).

Then, the received signal at each user is exposed to one or more types of fading or shadowing. Figure (2) shows that the SU_2 is located in the shadow region. Therefore, SU_2 can't detect the presence of the PU that results in higher probability of missed detection (P_{md}). Therefore, using cooperative sensing is the effective way to overcome these channel fading and shadowing problems.

4- The proposed Cooperative Sensing Model.

Cooperative sensing techniques allow communication among different Secondary Users (SUs) to share their sensing results to detect the active channels accurately. The proposed cooperative model of a wideband spectrum sensing is based on the centralized scheme of cooperative spectrum sensing [13-15]. In centralized category of cooperative sensing, the Fusion Center (FC) is the core of receiving sensing decisions from all SUs. Then, FC processes the results received from all SUs to evaluate the final decision.

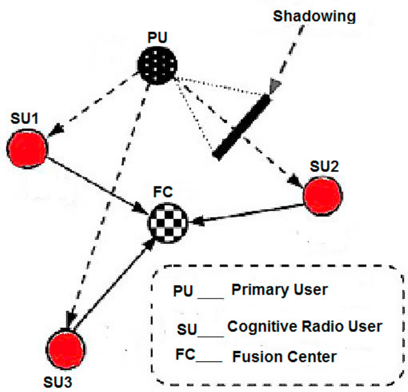


Fig. (2) Cooperative sensing scenario [19]

The proposed Scenario consists of five cognitive radio users (SU1,SU2,SU3,SU4,SU5) as presented in figure (3) . All SUs are sensing the primary sparse signals presented by x(t) to detect the free channels within a wideband spectrum. The sensed wideband spectrum is assumed to have a bandwidth of 0.5 GHz, Assuming the channel bandwidth =20 MHz then there are (L= 25) channel segments indexed from [0:24]. The proposed adaptive Multi-Coset sampling technique is applied by each SU to detect the free channels from its perspective. There are many types of noise and interference affecting the signal sensed by each user based on the environment surrounding their locations.

As indicated in figure (3), assuming that (S_{rxx}) is an output vector of the estimated active channels by SU1 which includes a very small Additive White Gaussian Noise (AWGN) with (sigma≤1/500) which can represent the ideal case due to no very un-affected noise levels. Whereas, the output vector of SU2, S_{rxx1}, is affected by Rayleigh faded channel with maximum Doppler shift frequency (F_d = 5 Hz). Then, SU3 is affected by AWGN with (sigma=0.01) results in the output vector S_{rxx2}. Then, the output vector S_{rxx3} is achieved by applying rician fading to the channel of SU4. Finally, SU5 is affected by another AWGN channel with (sigma =1/50) which is much larger than AWGN affecting the first and third users. The output of the 5 vectors $S_{rxx1:5}$ for one trial is shown in table 1.

Table (1) Active channel indexes for each SU

Detection	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.	Ch. index.
Srxx	1	4	5	7	10	12	20	21	24	
Srxx1	2	5	6	13	14	17	18	21	22	23
Srxx2	1	4	5	7	12	20	21			
Srxx3	2	3	5	6	8	11	12	13	21	22
Srxx4	1	4	5	7	12	20	21			

As indicated in table (1), there are 9 detected active channels by SU1 with indexes[1,4,5,7,10,12,20,21,24] whereas, SU2 with a Rayleigh faded channels detected 10 active channels with the following indexes [2,5,6,13,14,17,18,21,22,23]. SU3 exposed to AWGN and sensed only 7 active channels with indexes [1,4,5,7,12,20,21]. Rician fading affecting SU4 which detect the following 10 active channels [2,3,5,6,811,12,13,21,22]. Finally SU5 affected by AWGN sensed only 7 active channels with the following indexes [1,4,5,7,12,20,21]. So, the number and the index of the detected active channels based on the surrounding environment noise types and levels as explained in table (1).

The accuracy of active bands detection is estimated based of the probability of detection (P_d) that gives the probability of a CR user clarifying the existence of the PU when the PU is actually occupying the spectrum.

The second parameter is the Probability of false alarms (P_{fa}) that gives the probability of a CR user clarifying the existence of a PU while the spectrum is actually free. The last parameter is the probability of missed detection (P_{md}) that indicate there is no PU whereas, it is indeed exist causing interference between PU and SU and it is very important parameter for the performance metrics [20].

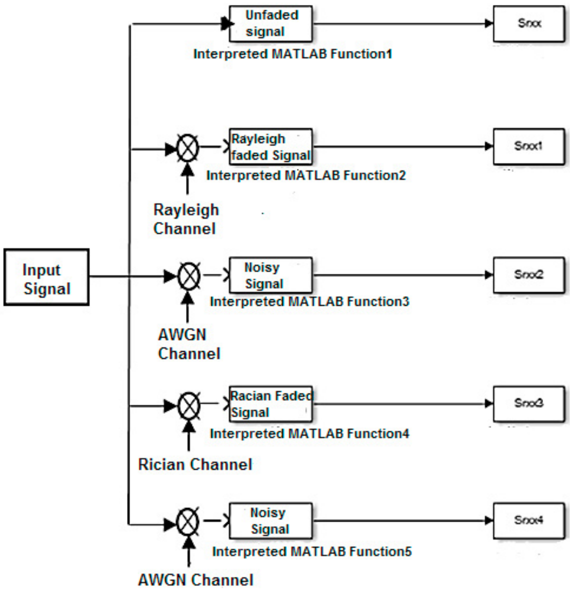


Fig.3 Simulink Block diagram of the cooperative proposed technique

5. The proposed Artificial Intelligence (AI) based Detection Technique

In order to achieve the optimum and the most accurate detections with a maximum probability of detection and minimum probability of missed detection and false alarms, many proposed techniques are used to combine and share the individual detection results from each SU to the fusion center. AND, OR, Majority rules are commonly used to get the final decision at the fusion centre [21]. In this work, the selection technique at the fusion centre is based on one of the AI techniques titled The Adaptive Neuro-Fuzzy Inference System (ANFIS) which is considered as a combination of the Artificial Neural Networks (ANN) with Fuzzy Logic (FL). The FL behaves the human logic and ANN represents as human brain [23-27]. AI has minimal process time than other techniques with more accurate results [22-25].

For the Fuzzy inference system, consider a system consists of five senders, Secondary users, as inputs (SU1, SU2, SU3, SU4, SU5) and one output (y). The fuzzy rules are constructed based on Mamdani type with bell membership function [22-23]. Figure 4 presents the ANFIS network containing five layers [24-26] as follow:

1) Input layer contains adaptive nodes of membership function.
2) Rules layer's output is regarded as fire strength of each node and it contains fifteen rules.
3) Normalization layer output is normalized fire strength.
4) Consequent layer's output is the product of normalized firing strength and the consequent polynomial of fuzzy rules.
5) Output Layer is defuzzification layer. It is summation of the output of layer (4).

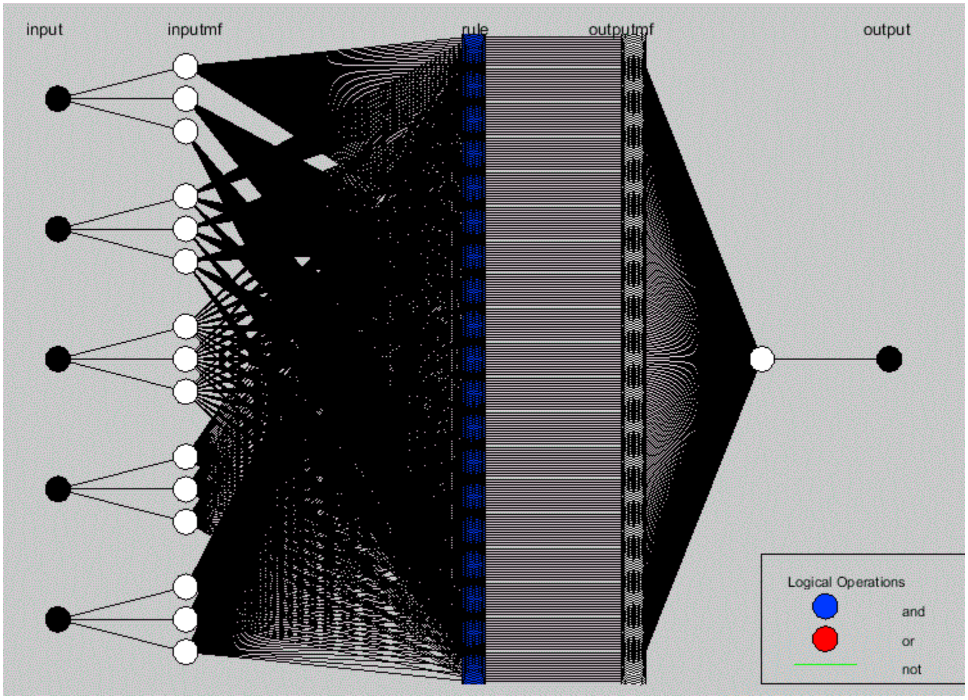


Fig 4: ANFIS network architecture

ANFIS model design is a trade-off problem between complexity and accuracy. Large numbers of rules lead to the highly accurate system on the other hand; the implemented system is higher cost [25-27] and complexity.
ANFIS architecture depends on a learning algorithm with a changing rules and /or membership functions to follow input/output training data. The initial architecture of the network requires to select the number of rules, which depends on the network pre-known data [22-24]. Measurements of the system could be used to determine the range of rules number (maximum and minimum) [26-27].

6. Simulation & Results of the Detection Process

ANFIS system was trained on fifty training data with 300 Epochs. Pre-known data achieved form Simulink model of five SUs with different conditions. System inputs are the detected channels by the SUs and the system output is the optimally available channels. Figure 5 depicts training error in y-axis and number of epochs in the x-axis. However, training and testing of the ANFIS system is reflecting an error of 10%. The error was in targeted zero channel index with a non-sensed output number such as ($-9\text{x}10^{-3}$) which is logic zero. So, the overall detection system could be considered with 1 % of detection error.

Fig 5. Training error in y-axis and number of epochs in x-axis

For system verification, the detected channel power of the signal was taken into consideration. Figure 6 contains the power of the sensed channels (P_{MU}) based on Music-Like algorithm of AI detected channels through five different trials. It shows highest P_{MU} values over other channels index.

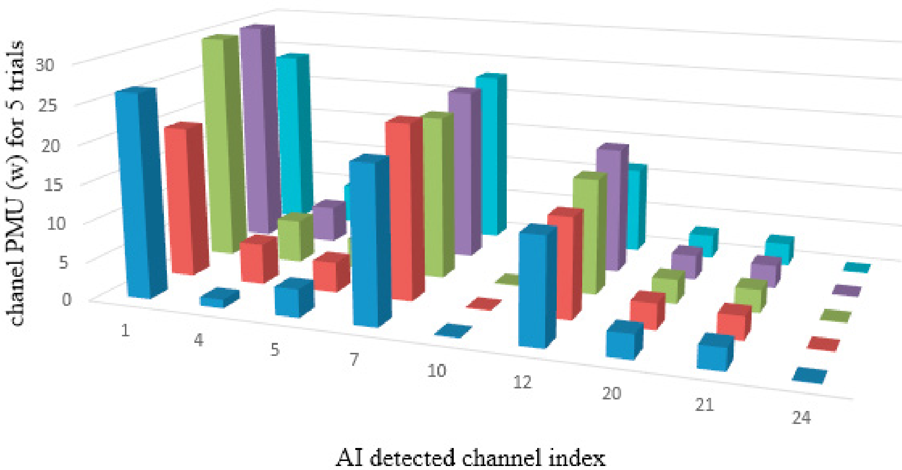
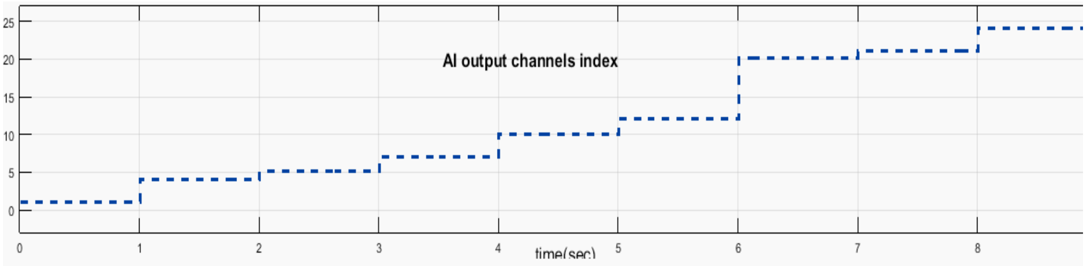


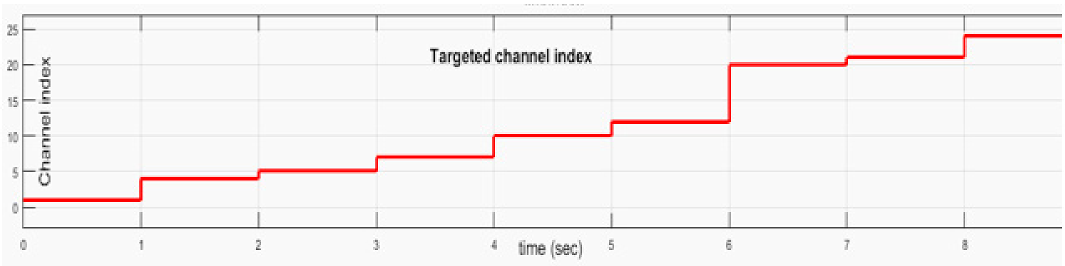
Fig 6. PMU for ANFIS detected channels for different trails of testing

Figure (7), reviews ANFIS detected channel indexes verses desired optimal values. It reflects the typical values of the practical detection system with high detection accuracy. Figure (7.a) shows ANFIS detection output while Figure (7.b) is for optimally desired indexes.

Compared to the common individual detection of each user with the proposed ANFIS based cooperative algorithm, it is obviously observed that the proposed ANFIS results achieve more accurate results with higher probability of detection (P_d) and less (P_{md} and P_{fa}) than individual decesions as presented in Figure (8).



(a)



(b)

Fig.7. (a) ANFIS detected channel indexes, (b) optimally desired indexes

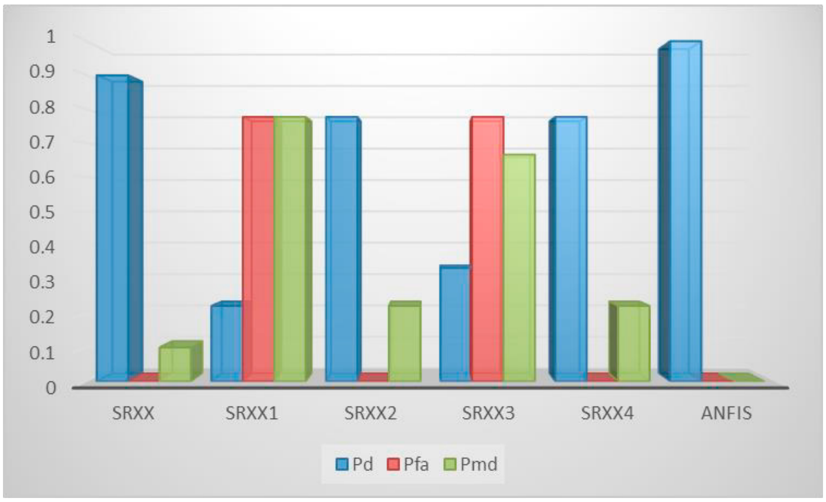


Fig.8 Pd, Pfa,Pmd for CR users and proposed ANFIS

In comparison with the other common cooperative techniques such as AND, OR techniques, figure (9) proved that the ANFIS based cooperative technique outperforms the other common cooperative detection techniques based on P_d,P_{fa} and P_{md}. Although P_d is almost 100% using OR algorithm, but the P_{fa} is about 20% and the overall probability reaches 80%. From another hand, using AND rule results in low P_d about 60% and high P_{md} reaches about 40%. Whereas, using the proposed ANFIS results in optimum P_d reaches 100% and P_{md},P_{fa} reaches 0% which leads to Total average probability of 100%. Thus, ANFIS algorithm outperformed the other common cooperative rules as presented in Figure (9).

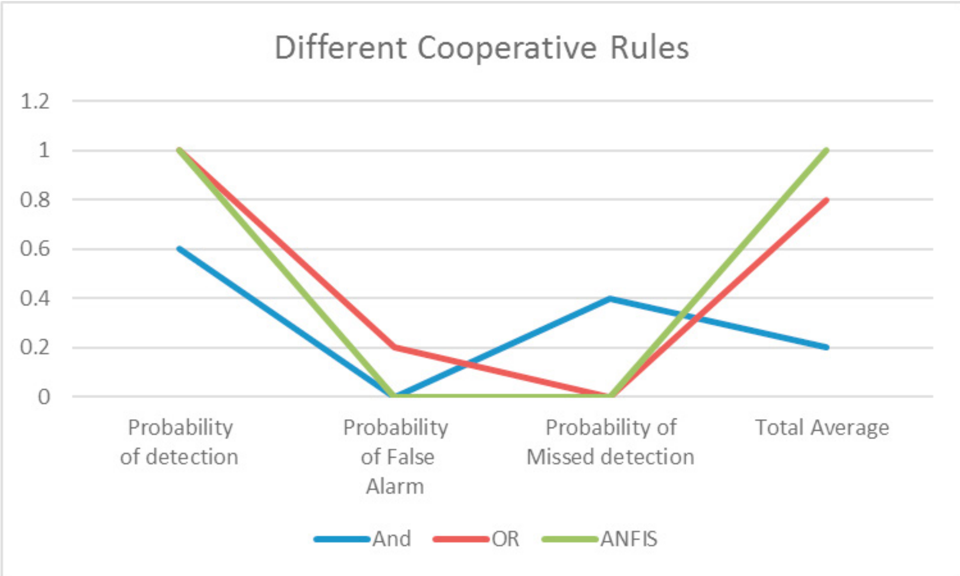


Fig.9 Pd, Pfa,Pmd for different cooperative rules (AND, OR, ANFIS)

7. Conclusion

Wideband spectrum sensing techniques achieved great importance in cognitive radio networks. Therefore adaptive blind Multi-Coset sampling based wide spectrum sensing technique is used in this paper. In order to overcome the effect of noise and fading problems, centralized cooperative sensing scheme is developed. The proposed system consists of five SUs each user utilize adaptive MC algorithm to detect the free channels then, centralized cooperative sensing scheme is applied to collect the detection results of each user. After that, AI detecting technique based on ANFIS structure is implemented including five inputs and fifteen rules. The channel power levels P_{MU} was calculated for ANFIS detected channels and it was the highest among others over five senders. The error was theoritically calculated about 10% but practical wise was 1 % after 300 epoch of training. Simulation results proved that the proposed cooperative model based on ANFIS detection is a perfect detection system compared to other common conventional detection rules.

References

[1] M.Mourad Mabrook, Aziza I. Hussein, “Major spectrum sensing techniques for cognitive radio networks: A Survey”, International Journal of Engineering and Innovative Technology (IJEIT), Volume 5, Issue 3, September 2015.

[2] I. F. Akyildiz, W.-Y. Lee, K. R. Chowdhury: "CRAHNs: Cognitive Radio Ad Hoc Networks", Ad Hoc Networks, Elsevier, Vol. 7, No. 5, , pp. 810-836, July 2009.

[3] Ian F.Akyildiz Brandon F.Lo Ravikumar Balakrishnan, “Cooperative spectrum sensing in cognitive radio networks: A survey”, Physical Communication Elsevier, Volume 4, Issue 1, pp. 40-62, March 2011.
[4] J. Unnikrishnan, V.V. Veeravalli, Cooperative sensing for primary detection in cognitive radio, IEEE Journal of Selected Topics in Signal Processing 2, pp. 18–27, 2008.
[5] Z. Li, F. Yu, M. Huang, A cooperative spectrum sensing consensus scheme in cognitive radios, in: Proc. of IEEE Infocom, 2009.
[6] W. Zhang, K. Letaief, "Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks"— [transaction letters], IEEE Transactions on Wireless Communications 7 (12), pp. 4761–4766, 2008.
[7] Mansi subhedar and Gajanan Birajdar,”Spectrum Sensing Techniques in Cognitive Radio: a Survey”, Int. Journal of Next Generation Networks, vol. 3, No.2, 2011.
[8] Ian F. Akyildiz, Brandon F. Lo, Ravikumar Balakrishnan, " Cooperative spectrum sensing in cognitive radio networks: A survey", Physical Communication 4, pp. 40–62, , 2011.
[9] H. Sun, A. Nallanathan, et. al., “Wideband spectrum sensing for cognitive radio networks: a survey,” IEEE Wireless Communications, vol. 20, no. 2, pp. 74–81, 2013.
[10] HONGJIAN SUN et al., “WIDEBAND SPECTRUM SENSING FOR COGNITIVE RADIO NETWORKS: A SURVEY”, IEEE Wireless Communications, pp. 74-81, April 2013.
[11] M. Mourad Mabrook, Ghazal Fahmy, Aziza I. Hussein, Mahmoud A.Ghany, “Adaptive blind wideband spectrum sensing for cognitive radio based on Sub-Nyquist sampling Technique”, IEEE ICM Conference, Cairo, pp. 141-144, 17-20 December 2016.
[12] M.Mishali and Y.Eldar,” Blind Multiband Signal Reconstruction: Compressed sensing for analog signals” IEEE Trans. Signal Processing, vol. 57, pp: 993-1009, 2009.
[13 Kabeer Ahmed, et al., “Comparative study of centralized cooperative spectrum sensing in cognitive radio networks”, 2nd International Conference on Signal Processing Systems, IEEE explore, 2010.
[14] Nima Noorshams, “Centralized and decentralized cooperative spectrum sensing in cognitive radio networks: A novel approach”, IEEE 11th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2010.
[15] G. Padmavathi and S. Shanmugavel, “Performance Analysis of Centralized Cooperative Spectrum Sensing Technique for Cognitive Radio Networks”, Asian Journal of Scientific Research, 2014.
[16]] Deborah Cohen, Alon Akiva, Barak Avraham, Yonina C. Eldar, “Centralized Cooperative Spectrum Sensing from Sub-Nyquist Samples for Cognitive Radios”, IEEEICC2015- cognitive radio and Networks Symposium.
[17] A. Ghasemi and E. S. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environments,” IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN), pp. 131– 136, Nov. 2005.
[18] Matthias Patzold. Mobile Fading Channels. John Wiley, 2002, England.
[19] Fazlullah Khan, Kenji Nakagawa , “Comparative Study of Spectrum Sensing Techniques in Cognitive Radio Networks”, World Congress on Computer and Information Technology (WCCIT), 2013.
[20] Amir Ghasemi, " Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-offs", IEEE Communications Magazine, pp. 32-39, April 2008.
[21] M. Mourad Mabrook, Ghazal A. Fahmy, Aziza I. Hussein , M. A.abdelghany, “Novel Adaptive non-uniform Sub-Nyquist Sampling Technique for Cooperative Wideband Spectrum Sensing”, IEEE ICENCO conference, Cairo, pp. 20-25, 28-29 December 2016.
[22] Siddique, Nazmuland Hojjat Adeli. Computational intelligence: synergies of fuzzy logic, neural networks, and evolutionary computing: John Wiley & Sons. 2013.
[23] Siddique, Nazmul. Neuro-Fuzzy Control. Intelligent Control: Springer International Publishing. 2014.
[24] H. A. Taha Hussein, M. E. Ammar amd M. A. Moustafa Hassan “Three Phase Induction Motor’s Stator Turns Fault Analysis Based on Artificial Intelligence” IJSDA, 6(3), 2017.
[25] AA Hassan, MR Sayed and MA Moustafa Hassan. Power system quality improvement using flexible ac transmission systems based on adaptive neuro-fuzzy inference system. WSEAS Transactions on Power Systems. 2013; 8: 1-13.
[26] Hussein Taha Hussein, Mohamed Ammar, Mohamed Moustafa Hassan “Induction Motors Stator Fault Analysis based on Artificial Intelligence” IJEECS.2.(1),2016
[27] Azar, A. T. (2010a). Adaptive Neuro-Fuzzy Systems. In A. T. Azar (Ed.), Fuzzy Systems. Vienna, Austria: INTECH. doi:10.5772/7220