International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I4P212

Volume 70 Issue 4, 146-151, April 2022

Original Article

Performance Assessment of Equal Gain Combining Fusion Rule in Cognitive Networks

Aparna Singh Kushwah[1], Vineeta Nigam[2]

[1,2]*Department of Electronics, University Institute of Technology, RGPV, Bhopal, India*

[1]aparna.kushwah@gmail.com

Received: 22 February 2022 Revised: 31 March 2022 Accepted: 04 April 2022 Published: 26 April 2022

Abstract *- Optimal use of spectrum is based on the investigation of the primary signal present in the spectrum. Various methods are discussed in the literature for signal detection. The research presented is about the performance evaluation of the Equal Gain Combining fusion rule in cognitive radio. The analysis of equal gain combining is executed using MATLAB simulations. The energy detector is used for individual sensing at each Cognitive Radio. Computer simulations reveal that Equal Gain Combining shows considerable detections at low SNR levels. As the level of SNR is increases, the detection capability also increases without imposing any burden on the channel regarding channel-state information. Further, the effect of varying the Time-Bandwidth Product and the total cognitive radios participating in the sensing is also analyzed. Results show that the ideal value for the Time-Bandwidth Product (u) is 10. Results reveal that the optimal number of cognitive radios used for combined sensing is 5.*

Keywords *- Equal Gain Combining, Energy Detection, Probability of false alarm, Time bandwidth product.*

1. Introduction

Spectrum is a finite resource, so it should be efficiently allotted to the requesting users. In recent times there has been a need for an almost infinite spectrum to cater to the needs of the young generation. The available bandwidth should be distributed in such a way that every user gets time to access the channel. However, when the channels are statically assigned to a fixed number of licensed users, it is observed that these channels never remain busy at all times. Sometimes the channel is free and can be accessed by non-licensed users of the network. This fact is exploited by a cognitive radio to give service to more users, thereby increasing the overall system capacity. A cognitive radio intelligently senses the free slots in the band and uses them to transmit their signals [1]. But the main problem is keeping track of the free time of the channel. For this purpose, the users continuously sense the intended channel and report whenever there are blank spaces in the usage of the channel. The need to sense the channel gives rise to vast research in the field of spectrum sensing. A lot of methods are available to sense the channel. The task is to select the ideal method for spectrum sensing. Spectrum sensing is limited by a number of factors, viz., random nature of noise, shadowing (especially in urban areas), multipath fading, receiver sensitivity etc. [2].

Cognitive radio is a sensing device that is capable of adjusting its own operating features like operating frequency, modulation format etc., depending on the current traffic conditions [3]. Cognitive users are radios which are accessing the wireless channel. They are of two types- Primary user (PU) is the sole owner of the bandwidth, and Secondary users (SU) are self-seeker users who use the bandwidth allotted to the primary user when the primary user is not transmitting [4]. Wireless channels are used for sensing. Cognitive radio uses two types of channels- sensing and reporting channels. The sensing channels are used for sensing the presence of the PU. The reporting channels are used to send sensing decisions. Spectrum Sensing is the process of identifying the blank spaces in the spectrum and concluding whether the PU signal is available or not in the spectrum [5]. Spectrum Management is distributing the available spectrum among a large number of new users. Spectrum Sharing creates a scenario in which all the users can use the spectrum on a time-scheduling basis [6].

Cooperative Spectrum Sensing, also known by its acronym ‘CSS’ is a technique in which multiple cognitive radios sense the channel simultaneously and mutually decide whether the channel can be used by a SU or not [7]. All CRs provide their individual sensing information to a common hub termed a fusion center (FC). The FC merges the individual data to form a composite variable to describe the inherence of the PU in the channel. The Fusion center is the central processing unit of the spectrum sensing model. The FC uses different methods to combine the results of different cognitive radios to decide. These can be grouped into Hard and Soft fusion rules. Hard fusion is basically coarse sensing involving hard detection, while soft fusion is fine sensing with soft detection. Hard Fusion: When the CRs decide and send only 1 bit (0 or 1) independent decision about the availability of the PU signal. Mainly three hard fusion rules are defined- OR, MAJORITY-Logic and AND rule [8].

Soft Fusion: The CRs send their whole sensing data to the fusion center. In a fusion center, the signals are combined according to some algorithm. Some of the soft fusion rules defined in literature are maximal ratio, equal gain, selection combining and square law selection [9].

This study is focused on Equal gain combining as it is the best among the receiver combining techniques as it does not need to estimate the channel fading amplitudes. It is less complex. EGC is widely implemented in collaborative wireless networks to reduce the complexity of the system.

2. System Model

Soft fusion employs the concept of diversity provided by combining the sensing data of associated radio channels to form a more accurate sensing result. Multi-user sensing improves the detection sensitivity of the system without any overhead in terms of individual CR capability. A number of CR experiencing different channel fading have a better chance of detecting the PU. Their individual local sensing is combined at the Fusion Center.

For individual sensing, a simple energy detector is considered assuming nothing is known about the PU.

2.1 Energy Detector

As the name suggests is a sensor that observes the absolute energy contained in the signal received for a particular time duration. The computed energy is compared to a pre-determined threshold value. It consists of the following elements:

- Band Pass Filter (BPF): filters the frequency which does not fall within the limits of intended bandwidth.
- Squaring device: each term of the signal received for a certain time duration is squared using this block.
- Summing device: all these squared values are added to get the energy of the signal received.
- Integrating device: integrates the calculated energy for a particular time period to get the estimate of the original signal.

Decision device: estimate is compared with a pre-determined threshold value to judge in favor of one of the hypotheses.

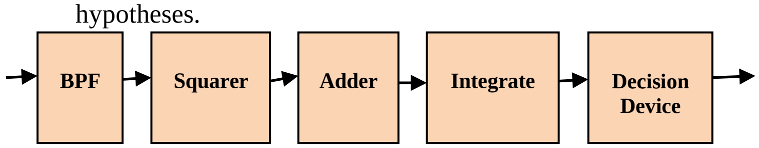

Fig. 1 Energy detector

2.2 Equal Gain Combining

Various algorithms can be used to form a composite signal received from diverse branches. Each branch is given the same weight factor despite its signal amplitudes. However, to avoid signal cancellation, co-phasing of all signals is done [10].

The FC combines the SNR (γ) of all the branches.

$$\gamma = \sum_{i=1}^{L} \gamma_i \qquad (1)$$

It is assumed that the noise levels are equal on all the branches.

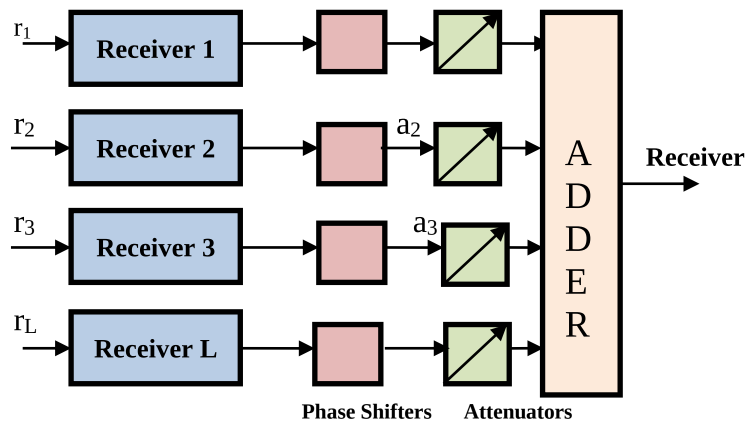

Fig. 2 Equal gain combining

3. Analytical Design of the System

The signal from the integrator in the energy detector is used as a test parameter to test for the validity of the two hypotheses, H_0 and H_1. The signal received r(t) is a combination of transmitted signal s(t) and noise signal n′(t):

$$r(t) = h'\, s(t) + n'(t) \qquad (2)$$

here
$$\begin{cases} h' = 0 \text{ in case } H_0 \text{ is true} \\ h' = 1 \text{ in case } H_1 \text{ is true} \end{cases}$$

Foremost the signal received is made band-limited by filtering with the help of a bandpass filter, the transfer function for which is given below.

$$H'(f) = \begin{cases} \dfrac{2}{\sqrt{N_0'}}, & |f - f_c| \le B \\ 0, & |f - f_c| \ge B \end{cases} \qquad (3)$$

The band-limited signal obtained from the BPF is processed using the squaring device and added to get the energy content of the signal received. Next, it is integrated to obtain the estimate of the signal received, which is then used to check the validity of one of the two hypotheses, H_0 and H_1.

For the simplification of analysis, the noise energy $E_{n'}$ is averaged over a time interval (0, T). So we get:

$$E_{n'} = \int_{0}^{T} n'^2(t)\, dt = \frac{1}{2B} \sum_{j=1}^{2u'} n'^2_j \qquad (4)$$

Where u′ = TB is the product of bandwidth and time. The test metric Y is formulated as

$$Y = \sum_{j=1}^{2u'} n'^2_j \qquad (5)$$

Now Y is modeled as the sum of 2u′ Gaussian random variable having zero mean and variance unity. In that case, Y will follow the central chi-square distribution (χ^2) with 2u′ degree of freedom. This same approach is applied when a signal is also present in conjunction with noise.

In that case, the decision metric Y will follow non-central chi-square distribution with 2u′ degree of freedom and non-centrality parameter (2γ) and can be stated with the following equation:

$$Y = \begin{cases} \chi^2_{2u'} & H_0 \\ \chi^2_{2u'}(2\gamma) & H_1 \end{cases} \qquad (6)$$

The PDF and CDF of Y are given by equations (7) and (8), respectively.

$$f_y(y) = \begin{cases} \dfrac{1}{2^{u'}\Gamma u'} y^{u'-1} e^{y/2} & H_0 \\ \dfrac{1}{2}\left(\dfrac{y}{2\gamma}\right)^{(u'-1)/2} e^{(2\gamma+y)/2} I_{u'-1}(\sqrt{2y\gamma}) & H_1 \end{cases} \qquad (7)$$

Where Γ(.) is the gamma function, and I(.) is the modified Bessel's function.

$$F_y(y) = 1 - Q_{u'}(\sqrt{\lambda}, \sqrt{y}) \qquad (8)$$

Here λ is a pre-determined threshold. By comparing the test metric Y with the threshold, it can check whether H_0 or H_1 is true.

$P(Y < \lambda) H_0$
$P(Y > \lambda) H_1$

The sensing performance of a cognitive network can be evaluated on the basis of certain probabilities. When the test metric crosses the threshold value, the CR senses the presence of PU. The probability is known as the probability of detection (P_d). Sometimes, the test metric may not give the correct information about the signal. Then two cases arise:

Case 1: when Y< λ, but the signal is present, this is calculated as the probability of missed detection (P_m).
Case 2: when Y > λ, but the signal is not present, this is calculated as the probability of false alarms (P_f).

The false alarm probability is derived from the PDF of Y

$$P_f = \int^{\infty} f_y(y)\, dy \qquad (9)$$

The detection probability is derived from the CDF of Y

$$P_d = 1 - F_y(y) \qquad (10)$$

After simplification, the expressions for P_d and P_f are

$$P_f = \frac{\Gamma(u', \lambda/2)}{\Gamma(u')} \qquad (11)$$

$$P_d = Q(\sqrt{2\gamma}, \sqrt{\lambda}) = 1 - P_m \qquad (12)$$

4. Simulation Details

Simulation Setup is created in order to simulate the above model for EGC employing energy detection at each CR. The implementation is executed in MATLAB following the Monte Carlo method. The performance is measured in terms of different probabilities. The setup included 1 PU, 5 SUs and an FC. Each SU tests 1000 samples for sensing the PU signal. The simulations are run for a range of SNR (-20 dB to 20 dB) as each CR may sense the channel at a different SNR. The channel is assumed to be disturbed by AWGN noise.
Fig. 3 shows the simulation model used

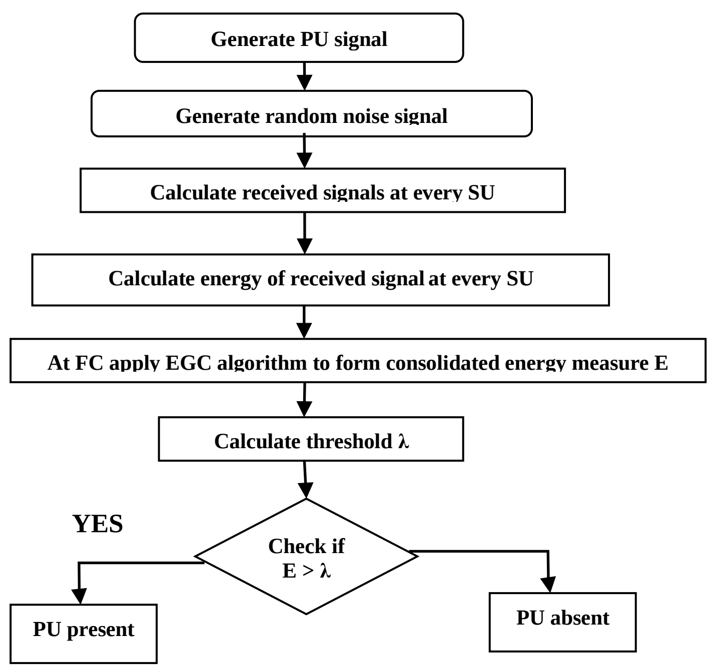

Fig. 3 Flowchart for Simulation

5. Results & Analysis

Computer simulations for 10000 iterations are done, and the results are presented in this paper as plots between P_d and SNR. Simulation results prove that equal gain combining shows good performance at a small number of false alarms Fig. 4 shows the variation of P_d relative to SNR, assuming different values of P_f. The different curves show that EGC attains higher values of P_d at very low values of $P_{f,}$ even at a low value of SNR. Comparing the curves for $P_f = 0.01$ and $P_f = 0.75$, it is obvious that detection probability increases at the cost of an increase in false alarms.

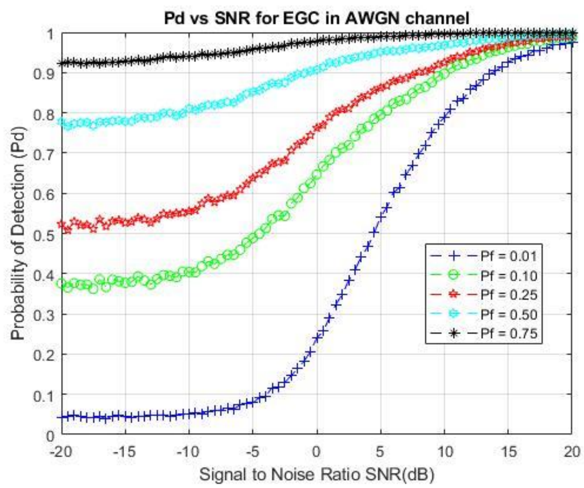

Fig. 4 P_d vs SNR for EGC at various values of P_f in AWGN channel

The detailed observations on the values of P_d are compiled in Table 1 below. Values of P_d corresponding to a set of P_f and SNR values are recorded from the computer simulation.

Table1. P_d at Different SNRs for different values of P_f

P_f →	0.01	0.1	0.25	0.5	0.75
SNR ↓ (dB)			P_d ↓		
-20	0.0435	0.3673	0.5190	0.7710	0.9238
-15	0.0450	0.3739	0.5253	0.7812	0.9308
-10	0.0498	0.4135	0.5613	0.8081	0.9405
-5	0.0913	0.4915	0.6389	0.8511	0.9573
0	0.2363	0.6474	0.7544	0.9120	0.9789
5	0.5406	0.8005	0.8684	0.9528	0.9950
10	0.7919	0.8990	0.9278	0.9707	0.9967
15	0.9263	0.9644	0.9725	0.9869	0.9997
20	0.9761	0.9890	0.9909	0.9962	0.9998

The values listed in Table 1 verify that the sensing performance of EGC increases with the increasing value of SNR. At around 20 dB, which is considered to be an ideal value for data and voice transmission, the probability of detection attains a perfect value (approximately 0.9761). It is noticed that as P_f is increased from 0.01 to 0.75, the detection probability also increases from 0.9761 to 0.9998. There is an increase of approximately 23.7 % in the overall detections. However, the false alarms indicating the fake presence of the PU signal increased by 65%.

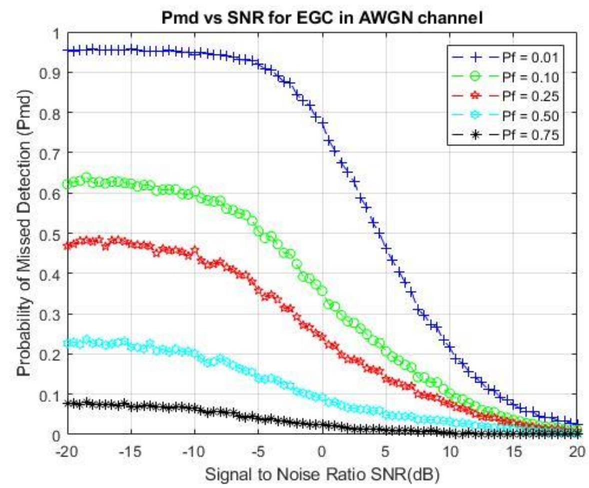

Fig. 5 P_{md} vs SNR for EGC at different values of P_f in AWGN channel

Fig. 5 demonstrates the variation of missed detections in relation to SNR. Curves show that the P_{md} is low in the case of lower values of $P_{f,}$ indicating fewer detections are missed during sensing, thereby showing good sensing accuracy. An_d decreases with the increasing value of SNR.

From Fig. 4 and Fig. 5, it can be verified that EGC gives fairly good sensing performance results even when the channel is disturbed by AWGN noise.

The effect of a time-bandwidth product on the detection ability of a CR is also analyzed. The value of P_f is kept fixed at 0.0001. Fig. 6 shows that the bandwidth-time product has an impact on the values of P_d with respect to SNR. It shows that as we increase the value of u from 10 to 2000, the value of detection sensitivity deteriorates. For u = 10 and u =50, the P_d achieves a satisfactory value at around -5 dB, but as the value is changed to u = 100, P_d decreases and continues to decrease for u = 500. It is clear from the plot that the optimum value for u is 10, as depicted in the simulations.

The sensing performance also depends on the total number of cooperating sensors used in the sensing in EGC. Fig. 7 shows how P_d changes as we increase the number of CRs used for sensing. P_f is again fixed at 0.0001, assuming very less false alarms. It is observed that the performance is enhanced by using EGC as compared to the case when only 1 CR was sensing the channel. For CR = 10, P_d does not show any considerable increase. But with CR = 15, the curve falls, showing a decrease in detection probability. So it can be said that the optimal value is 5 CRs for good detection capability without any overhead.

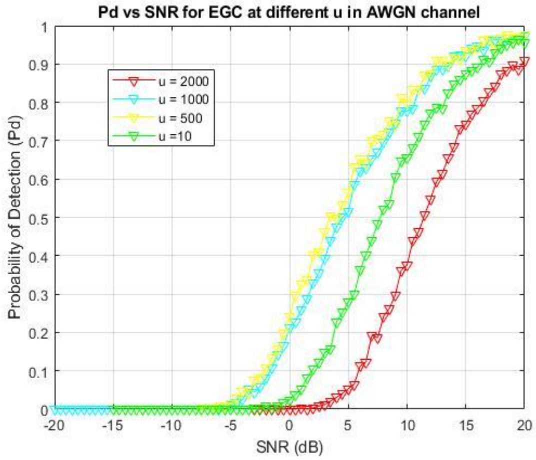

Fig. 6 P_d vs SNR for EGC at different values of u at P_f = 0.0001 in AWGN channel

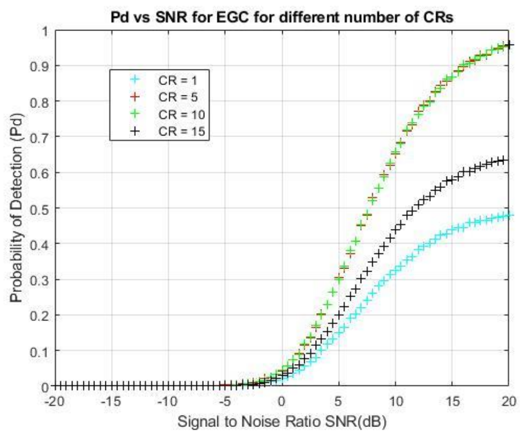

Fig. 7 P_d vs SNR for different numbers of Cognitive Radios at P_f = 0.0001 in AWGN channel

5. Conclusion

In this paper, the Equal Gain combining soft fusion rule is implemented, assuming energy detection spectrum sensing at all the cognitive radios. The mathematical modeling and the simulation details are explained, thereby verifying the simplicity and utilization of EGC. The detection probability achieves high values in the case of EGC even at lower values of SNR. The results show that the ideal value for the time-bandwidth product u is 10. Above this value of u, the performance degrades. Also, the ideal number of CRs used for sensing is 5. Increasing the number of CRs will not outperform the sensing decisions to a large extent. The false alarms are assumed to be very less by fixing P_f = 0.0001 in both cases. EGC is free from estimating the channel state information, unlike other diversity combining algorithms like Maximal Ratio Combining. Overall, EGC shows excellent performance in all cases.

6. Acknowledgements

The authors give thanks for this work being supported by the University Institute of Technology, RGPV, Bhopal

References

[1] Simon Haykin, Cognitive Radio: Brain-Empowered Wireless Communications, IEEE Journal On Selected Areas In Communications, 23(2) (2005).
[2] D. Taguig, B. Scheers, and V. LeNir, Data Fusion Schemes for Cooperative Spectrum Sensing in Cognitive Radio Networks, Military Communications and Information Systems Conference, (2012).
[3] Tevfik Y¨ucek and H¨useyin Arslan, A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications, IEEE Communications Surveys & Tutorials, 11(1) (2009).
[4] Pankaj Verma, Brahmjit Singh, On the decision fusion for cooperative spectrum sensing in cognitive radio networks, Wireless Networks, (2016).
[5] Hano Wang, Gosan Noh, Dongkyu Kim, Sungtae Kim and Daesik Hong, Advanced Sensing Techniques of Energy Detection in Cognitive Radios, Journal of Communications and Networks, 12(1) (2010).
[6] Dong-Jun Lee, Adaptive Cooperative Spectrum Sensing using Random Access in Cognitive Radio Networks, IEEE 24th International Symposium on Personal, Indoor and Mobile Radio Communications: MAC and Cross-Layer Design Track, (2013).
[7] J. Tong, M. Jin, Q. Guo and Y. Li, Cooperative Spectrum Sensing: A Blind and Soft Fusion Detector, IEEE Transactions on Wireless Communications, 17(4) (2018) 2726-2737.
[8] G. Sharma, R. Sharma, Performance comparison of hard and soft fusion Techniques for Energy Efficient CSS in Cognitive Radio, International Conference on Advanced Computation and Telecommunication (ICACAT), (2018).
[9] Srinivas Nallagonda, S. Kumar Bandari, Sanjay Dhar Roy and Sumit Kundu, Performance of Cooperative Spectrum Sensing with Soft Data Fusion Schemes in Fading Channels, Annual IEEE India Conference (2013).
[10] Doha Hamza, Sonia Aïssa and Ghassan Aniba, Equal Gain Combining for Cooperative Spectrum Sensing in Cognitive Radio Networks, IEEE Transactions on Wireless Communications, 13(8) (2014).
[11] Sanjeewa P. Herath, Nandana Rajatheva, Analysis of Equal Gain Combining in Energy Detection for Cognitive Radio over Nakagami Channels, (2008)..
[12] Goutam Ghosh, Prasun Das and Subhajit Chatterjee, Cognitive Radio and Dynamic Spectrum Access –A Study, International Journal of Next-Generation Networks (IJNGN), 6(1) (2014).
[13] Abdullah Yaqot and Peter Adam Hoeher, Efficient Resource Allocation in Cognitive Networks, IEEE Transactions on Vehicular Technology, 66(7) (2017).

[14] Yan Cai, Yiyang Ni, Jun Zhang, Su Zhao and Hongbo Zhu, Energy efficiency and spectrum efficiency in underlay device-to-device communications-enabled cellular networks China Communications. (2019).
[15] Ishu Gupta, Ashish Hari and O. P. Sahu, Hardware Implementation of Energy Detection Scheme in Cognitive Radio Networks, International Conference on Computing, Power and Communication Technologies (GUCON) , (2018).
[16] A. S. Tellambura, et al., Energy detection based cooperative spectrum sensing in cognitive radio networks, IEEE Transactions on Wireless Communications, 10(4) (2011) 1232-1241.
[17] Nan Zhao, Fei Richard Yu, Hongjian Sun and Arumugam Nallanathan, Energy-efficient cooperative spectrum sensing schemes for cognitive radio networks, EURASIP Journal on Wireless Communications and Networking 2013, Springer.
[18] Hano Wang, Jason Noh, Dongkyu Kim, Sungtae Kim, Datsik Hong, Advanced Sensing Techniques of Energy Detection in Cognitive Radios, Journal of Communication and Networks, 12(1) (2010).
[19] Omar Altrad and Sami Muhaidat, A new mathematical analysis of the probability of detection in cognitive radio over fading channels, EURASIP Journal on Wireless Communications and Networking, (2013).
[20] Risheek Kumar, Analysis of Spectrum Sensing Techniques in Cognitive Radio, International Journal of Information and Computation Technology. 4(4) (2014) 437-444.
[21] Qin Qin, Zeng Zhimin, Guo Caili, A Study of Data Fusion and Decision Algorithms Cooperative Spectrum Sensing, Sixth International Conference on Fuzzy Systems and Knowledge Discovery, IEEE. (2009).
[22] Nisha Yadav and Suman Rathi, A Comprehensive Study of Spectrum Sensing Techniques in Cognitive Radio, International Journal of Advances in Engineering and Technology, (2011).
[23] Ian F. Akyildiz, Brandon F. Lo and Ravikumar Balakrishnan, Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey, Physical Communication, ScienceDirect, Elsevier.(2010).
[24] W. Ejaz, N. ul Hasan, S. Lee and H. S. Kim, I3S: Intelligent Spectrum sensing scheme for cognitive radio networks, EURASIP Journal of Wireless Communications and Networking, Springer. (2013).
[25] Bin Shen, Taiping Cui, Kyungsup Kwak, Chengshi Zhao and et al., An Optimal Soft Fusion Scheme for Cooperative Spectrum Sensing in Cognitive Radio Network, IEEE Communications Society, WCNC proceedings. (2009).