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An Improved Energy Detection Scheme based on Channel Estimation

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Abstract

Energy detection is most commonly employed technique for spectrum sensing in cognitive radio networks due to its low computational and implementation complexities. However, the performance of energy detector deteriorate considerably under severe fading environment especially in low SNR region. The performance metrics used for energy detector are probability of detection, probability of false alarm and number of samples requirements. The detection threshold plays a significant role in PU signal detection and thus must be chosen appropriately to meet tradeoff between probability of detection and probability of false alarm under severe fading. In this paper, we have proposed adaptive threshold detection scheme for severe fading environment to work under low SNR. The simulated results are presented to validate the proposed scheme and it has been shown that proposed scheme is more robust against noise uncertainty under severe fading environment and performs better than conventional energy detection scheme to yield same detection performance.

Keywords: Channel State Information, Energy Detection, Threshold Adaptation

1. Introduction

The concept of cognitive radio is introduced to overcome the spectrum scarcity problem existing today. With the rapid development of wireless applications today, the demand for more frequency spectrum has been increased manifold. Since electromagnetic spectrum is natural and scarce source, it should be exploited efficiently and intelligently. So far, fixed spectrum allocation policy has been adopted worldwide in which the spectrum is auctioned to the given geographical location for stipulated time. But, the recent FCC report has revealed that this spectrum allocation policy does not work well as most of the allocated spectrum is being exploited sporadically. That is how the concept of cognitive radio technology has evolved. The technology allows unlicensed secondary user to exploit the frequency spectrum of licensed incumbent user when it is not being used by it[1]. To do so, many spectrum sharing schemes have developed so far. These schemes are broadly classified as *underlay scheme* & *overlay scheme*. In underlay spectrum sharing scheme, both licensed and unlicensed spectrum users can share the spectrum as long as the secondary user holds spectrum-sharing constraints imposed by primary user on it. Whereas, in overlay spectrum sharing scheme, secondary user is allowed to use licensed spectrum when primary user is not using it[2].

For spectrum sharing-scheme and to work efficiently, it is mandatory to know the presence or absence of the primary user before exploiting spectrum opportunities. To do so, spectrum sensing capabilities are embedded to the prototype of the next generation hand held devices. Various spectrum sensing schemes have been proposed so far to make cognitive radio technology a reality. These schemes are: energy detection, cyclostationary detection and matched filter detection[3]. Each detection method has its own pros and cons, and out of these, energy detection method is the simplest and oldest used technique. Radar is the one successful application based on energy detection method[4]. In this technique a threshold is selected to detect the presence or absence of the desired signal in a frequency band. Due to its simplicity and less complexity over match filtering and cyclostationary feature detection scheme, it is more popular and requires less number of

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samples for detection[5]. However, the fundamental problems associated with it are: (i) Susceptibility to noise levels, (ii) Inability to distinguish between modulated signal and noise and thus between incumbent user and secondary user (iii) Inability to detect the incumbent user's signal with low signal to noise ratio[6].

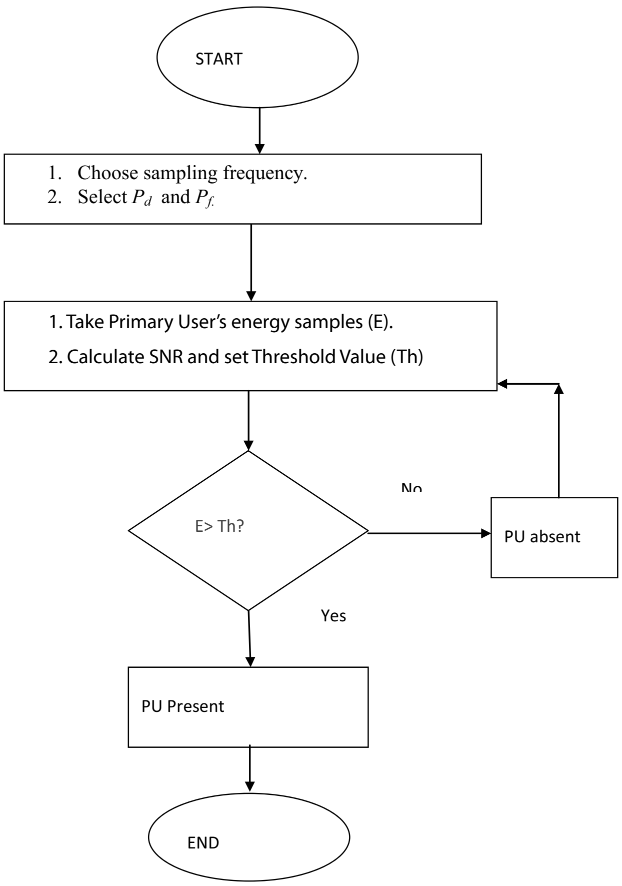

Figure 1. Conventional Energy Detection Scheme.

Despite these bottlenecks, energy detection outperforms in terms of its low sensing duration than other sensing techniques, which makes it a strong candidate for wideband spectrum sensing. Recently, many techniques have been proposed to enhance the performance of energy detector. For example, cooperative spectrum sensing[7] is used to improve the detection performance. Significant work is reported on double threshold method[8-10] also. In most of these work, signal to noise ratio at secondary transmitter is considered to adapt sensing threshold with assumption that it has full knowledge channel state information (CSI). From a practical point of view, it is never possible to have full knowledge about the channel conditions as it is time varying in nature and thus keep changing with time and geographical location. To deal with such conflicts, cooperative spectrum sensing schemes have also been proposed[12]. However, they have considered that channel CSI is known beforehand. In few recent reports threshold adaptation techniques have been proposed for imperfect channel conditions with significant probability of detection but they requires significantly long duration for spectrum sensing and large number of energy samples. This may lead to the reduction of transmission time and thus overall throughput of the system decreases[13].

In this paper, a novel threshold adaption scheme is proposed that could determine the presence of licensed incumbent user better than conventional adaptive threshold techniques with imperfect knowledge of channel CSI. The theoretical and simulated results are presented to demonstrate the effectiveness of the proposed scheme over conventional scheme. The rest of the paper is organized as follows. In Section II analytical model for conventional energy detector with imperfect channel CSI is presented. The improved energy detection scheme and sensing threshold adaption is proposed in section III. Simulated results for both detection schemes followed by conclusion is presented in section IV and V respectively.

2. Conventional Energy Detection Scheme

In conventional energy detection scheme the transmitted signal power of the incumbent user is sampled over a frequency channel for fixed time duration. It is assumed that channel is following block fading model with coherence time T_c. The samples of energy signal are taken and are compared with predefined threshold level to determine the presence or absence of incumbent user. Based on the outcomes, we can define two hypothesis i.e. H_0 and H_1. When total energy of the samples is greater than the preset threshold λ, it represents the presence of the incumbent user and therefore hypothesis is H_1, otherwise, the absence of incumbent user is represented with null hypothesis H_0.

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

Two different performance indicators namely, probability of detection (P_d) and probability of false alarm (P_f), are used to measure the performance of the energy detector. Where, probability of detection may be defined as the probability of detecting incumbent user signal accurately under fading channel. Whereas, probability of false alarm may be defined as the probability of detecting the presence of incumbent user when it is actually not present. According to the central limit theorem, for number of samples $> 30,$ the sampled signal can be approximated as a Gaussian distribution[10] and is defined below

$$\sum y^2(n) = \begin{Bmatrix} Normal(\mu_0, \sigma_0^2) & H_0 \\ Normal(\mu_1, \sigma_1^2) & H_1 \end{Bmatrix}$$

$$\sum y^2(n) = \begin{Bmatrix} Normal(N\sigma_n^2, 2N\sigma_n^4) & H_0 \\ Normal(N\sigma_n^2(\gamma+1), 2N\sigma_n^4(\gamma+1)^2) & H_1 \end{Bmatrix} \quad (2)$$

The test statics of energy detection scheme will be given by

$$\vartheta(y) = \frac{1}{N}\sum_{n=1}^{N} |y(n)|^2 \quad (3)$$

The flow diagram of conventional energy detection scheme is shown in Figure 1. Based on test statics, P_d and P_f may be given by

$$P_f = P_r[y > T_h | H_0] = \int_0^{\infty} P_1(x)dx \quad (4)$$

$$P_d = P_r[y < T_h | H_1] = \int_0^{\infty} P_0(x)dx \quad (5)$$

where P_0 and P_1 are probability density functions for test statics under H_0 and H_1. Thus, P_f and P_d are in terms of T_h and N may be given by

$$P_d(T_h, N) = Q\left(\left(\frac{T_h}{\sigma^2} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma+1}}\right) \quad (6)$$

$$P_f(T_h, N) = Q\left(\left(\frac{T_h}{\sigma^2} - 1\right)\sqrt{N}\right) \quad (7)$$

Where $Q(.)$ is complementary distribution function and N is number of samples. The receiver operating characteristic (ROC) that plots probability of missed detection with respect to the probability of false alarm for different values of thresholds (in rectangular box) and samples is shown in Figure 2. It is evident from the graph that energy detector performance deviate significantly by changing sensing threshold and number of samples for received signal to noise ratio. Thus in cognitive radio networks, the performance of energy detector in spectrum sensing process depends upon the sensing threshold, number of samples and signal to noise ration sensed at secondary receiver. Now, we shall prove the concavity of P_d and P_f on sensing threshold.

Proposition 1: For a given range of sensing threshold (T_h); $P_d(T_h)$ is increasing and concave on (T_h) and $P_f(T_h)$ is increasing and concave on (T_h).

Proof: Differentiating eq. (6) and eq. (7) with respect to T_h, we get

$$P_d'(T_h) = \frac{d}{dT_h}P_d(T_h) = \frac{1}{\sqrt{2\pi}\sigma^2}\left(\sqrt{\frac{N}{2\gamma+1}}\right)exp\left(\frac{-\left(\left(\frac{T_h}{\sigma^2} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma+1}}\right)^2}{2}\right) \quad (8)$$

$$P_f'(T_h) = \frac{d}{dT_h}P_f(T_h) = \frac{1}{\sqrt{2\pi}}\left(\sqrt{\frac{N}{\sigma^2}}\right)exp\left(\frac{-\left(\left(\frac{T_h}{\sigma^2} - 1\right)\sqrt{N}\right)^2}{2}\right) \quad (9)$$

For $T_h > 1$; $P_f'(T_h) > 0$ and $P_d'(T_h) > 0$. Therefore, both are concave on T_h T_h. The local maxima and local minima are given by the terms $\left(\frac{T_h}{\sigma^2} - 1\right)$ and $\frac{T_h}{\sigma^2} - \gamma - 1$ for P_f and P_d respectively[11]. Figure 3 is showing both values of local maxima and minima where the concavity is proved.

$$P_d = 0.5\, erfc\left[T_h - \mu_1 / \sqrt{2\sigma_1}\right] \quad (10)$$

$$P_f = 0.5\, erfc\left[T_h - \mu_0 / \sqrt{2\sigma_0}\right] \quad (11)$$

Where, γ is average signal to noise ratio of received signal and T_h is sensing threshold based on assumption that full channel CSI is known to the secondary transmitter beforehand and it may be given by

$$A = X\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right);\ B = X\left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_0}{\sigma_0^2}\right);\ X = \sigma_1^2\sigma_0^2$$

$$C = X\left(\frac{{\mu_0}^2}{\sigma_0^2} - \frac{{\mu_1}^2}{\sigma_1^2} - 2log\left(\frac{\sigma_1}{\sigma_0}\right)\right)$$

$$T_h = (-B + \sqrt{B^2 + Ac}) / A \quad (12)$$

A. Conventional ED under with Partial CSI

Since, wireless channel is time varying in nature, it is extremely difficult to estimate it accurately. Thus, the conventional detection scheme with fixed threshold leads to the erroneous results for given P_d and P_f. Here, we are defining β as a CSI parameter to indicate channel uncertainty conditions such as $\beta \propto {}^{1}/_{g_{ps}}$. Where, g_{ps} is channel gain between primary transmitter and secondary transmitter. Thus, higher the value channel CSI, weaker is the channel. When partial CSI information is available, the noise variance of the channel and detection threshold will get modified accordingly. The modified test statistics for conventional energy detection scheme will be given by

$$\sum y^2(n) = \begin{cases} Normal(\beta N\sigma_n^2, \beta^2\, 2N\sigma_n^4) & H_0 \\ Normal(N\sigma_n^2(\gamma+\beta^{-1}), 2N\sigma_n^4(\gamma+\beta^{-1})^2) & H_1 \end{cases} \quad (13)$$

The sensing threshold can be calculated by substituting modified test statics from (13) into (12).

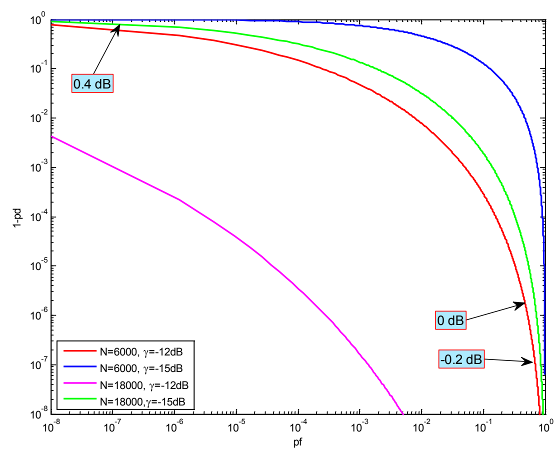

Figure 2. Receiver operating characteristic curve for different N and γ.

3. Proposed Detection Scheme with Partial CSI

Under fading channel conditions, detection threshold plays a very important role, as it deteriorate the detection performance severely if not chosen properly. In this paper, we present a dynamic optimal threshold selection algorithm to overcome the effect of improper channel CSI. The flow diagram of proposed energy detection scheme is shown in Figure 4. According to the channel inversion method, if the channel CSI factor is β, we adapt the threshold value to the minimum value such as $T_{h\,min} = {}^{T_h}/_{\beta}$ and to maximum value such as $T_{h\,Max} = \beta T_h$. Therefore, when channel CSI is high (deep fading) accordingly the threshold will be lower down by an amount of β and when channel CSI is low (low fading) accordingly the threshold will be enhanced by an amount of β. The (10) and (11) will be modified as

$$P_d = 0.5\, erfc\left[\frac{T_h/\beta - \mu_1}{\sqrt{2\sigma_1}}\right] \quad (14)$$

$$P_f = 0.5\, erfc\left[\frac{\beta T_h - \mu_0}{\sqrt{2\sigma_0}}\right] \quad (15)$$

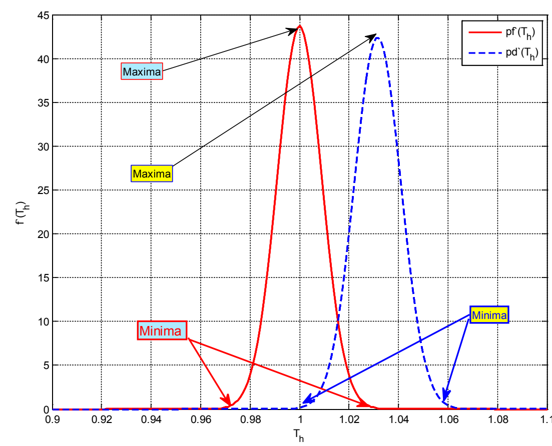

Figure 3. Local maxima and minima of derivates of probability of detection and probability of false alarm.

4. Numerical Results and Discussions

In this section, simulated results are presented to validate the theoretical results of the proposed scheme. The results are simulated in MATLAB environment. Figure 5 shows that under similar channel conditions proposed scheme has higher probability of detection than conventional scheme even in low SNR region. With an increase in SNR to secondary channel it improves further and achieve 100% detection of incumbent user in shared channel with improper information of channel CSI. Here, we have assumed channel CSI equals to 1.3 and number of samples equals to 10.

The probability of false alarm with channel CSI equals to 1.5 is shown in Figure 6. It is clear from the graph that our proposed algorithm is performing better than conventional and it reduces P_f P_f from 0.33 to 0.02 at SNR equals to 0 dB.

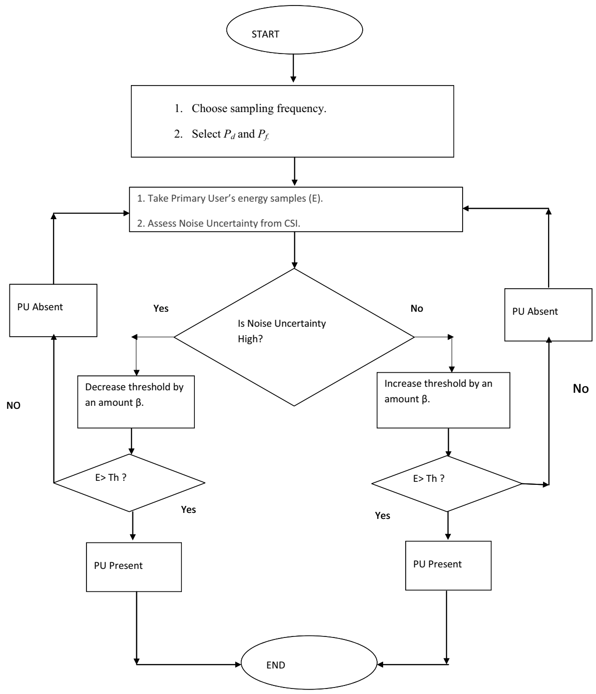

Figure 4. Proposed Energy Detection Scheme.

Figure 7 shows the number of samples requirement energy detector for P_d equals to 0.9 and P_f equals to 0.1. It is observed that proposed detection algorithm requires significantly less numbers of samples over conventional technique. From Figure 3, it is evident that at SNR equals to 0 dB, number of samples required are 23 for conventional scheme; whereas for our proposed scheme it requires only 9 samples for same probability of detection and false alarm.

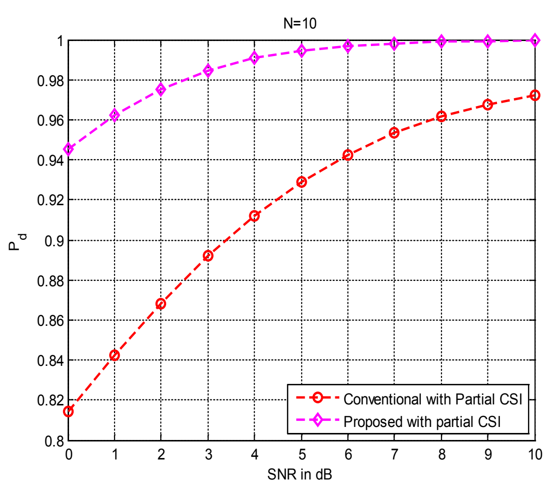

Figure 5. P_d verses SNR(dB).

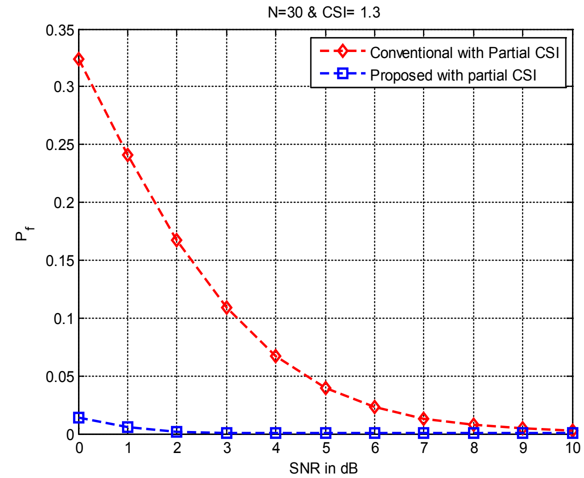

Figure 6. P_f verses SNR(dB).

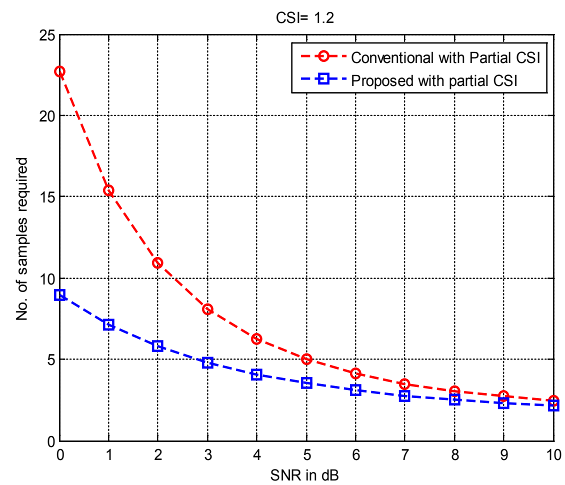

Figure 7. Samples requirement by Energy Detector.

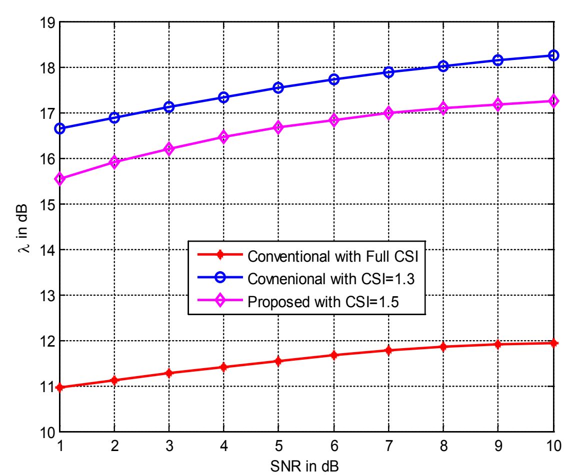

Figure 8. Threshold verses SNR.

Figure 8 is showing the comparison of the required value of threshold for conventional scheme as well as proposed scheme. It is observed that for conventional scheme with full CSI knowledge, threshold value is very less whereas for the same scheme with partial CSI knowledge, threshold increases significantly. As it may be seen that for our proposed schemes, threshold value is neither too high nor too low to discriminate incumbent signal user from background noise.

5. Conclusion

In this paper, a novel sensing threshold adaption scheme is proposed in which sensing threshold is selected based on channel sensing information. It is shown that for proposed scheme the probability of detection increase significantly and probability of false alarm decreases significantly over conventional scheme. Moreover, the number of samples required to sense the presence of incumbent primary user are also significantly less over conventional scheme.

6. Reference

1. Akyildiz IF, Lee WY, Varun MC, Mohanty S. Next generation/dynamic spectrum access/cognitive radio wireless networks: survey, computer networks. 2006; 50(1):2127-59.
2. Kozal ASB, Merabti M, Bouhafs F. An improved energy detection scheme for cognitive radio networks in low SNR region. Cappadocia: IEEE Symposium on Computers and Communications (ISCC). 2012; p. 684-89.
3. Rana V, Bala I, Jain N. Resource Allocation Models for Cognitive Radio Networks: A Study. International Journal of Computer Applications. 2014; 91(12):51-5.
4. Bala I, Bhamrah MS, Singh G. Analytical Modelling of Ad Hoc Cognitive Radio Environment for Optimum Power Control. International Journal of Computer Applications. 2014; 92(7):19-22.
5. Gorcin A, Qaraqe KA, Celebi H, Arslan H. An adaptive threshold method for spectrum sensing in multi-channel cognitive radio networks. Doha: IEEE 17th International Conference on Telecommunications (ICT). 2010; p. 425-29.
6. Qingchun R, Qilian L. Performance Analysis of Energy Detection for Cognitive Radio Wireless Networks. International Conference on Wireless Algorithms, Systems and Applications, WASA'07. 2007; p. 139-46.
7. Padmavathi G, Shanmugavel S. Performance Analysis of Cooperative Spectrum Sensing Technique for Low SNR Regime over Fading Channels for Cognitive Radio Networks. Indian Journal of Science and Technology. 2015 Jul; 8(16):1-5.
8. Tandra R, Sahai A. SNR Walls for Signal Detection. IEEE Journal of Selected Topics in Signal Processing. 2008; 2(1):4-17.
9. Yucek T, Arslan H. A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Communications Surveys and Tutorials. 2009; 11(1):116-30.
10. Bala I, Bhamrah MS, Singh G. Capacity in fading environment based on soft sensing information under spectrum sharing constraints. Online published. 2015; p. 1-13.
11. Boyd S, Vandenberghe L. Cambridge University Press: Convex optimization. 2004; ISBN: 978-0-521-83378-3.
12. Letaief KB, Zhang W, Cooperative Communications for Cognitive Radio Networks. In Proceedings of the IEEE. 2009; 95(7):878-93.
13. Bala I, Bhamrah MS, Singh G. Capacity in fading environment based on soft sensing information under spectrum sharing constraints. Online published. 2015; p. 1-13.