



## ORIGINAL RESEARCH ARTICLE

## DEVELOPMENT OF ADAPTIVE SENSING ALGORITHM FOR MINIMIZING ENERGY AND BANDWIDTH CONSUMPTION IN COOPERATIVE SPECTRUM SENSING TECHNOLOGY

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## ARTICLE INFORMATION

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## ABSTRACT

Optimized consumption of energy and bandwidth is crucial for efficient utilization of the limited electromagnetic spectrum for telecommunication purposes. Cognitive radio is one of the dynamic spectrum management applications with numerous benefits related to the management of available spectrum. But it has the challenge of high energy and bandwidth usage when the cooperative scheme of spectrum sensing is applied for accurate sensing. In this paper, an adaptive spectrum sensing algorithm was developed to minimize energy and bandwidth consumption in cognitive radio spectrum sensing while ensuring accurate spectrum sensing. The adaptive algorithm was developed based on the signal-to-noise ratio conditions of the channel. Results reveal that the energy and bandwidth usage by the cooperative spectrum sensing can be significantly reduced without negatively affecting the performance and detection of the cognitive radio in varying noisy conditions

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**1.0 Introduction**

The electromagnetic radio spectrum is a limited treasured resource which exists naturally. Utilizing it efficiently for wireless communication has become a huge challenge due to the growth and advancement of wireless systems, services and devices in recent years (Goldsmith, 2005; Kakalou et al., 2018; Riya et al., 2018). This growth has increased the energy and bandwidth requirement of these devices and services to ensure optimum connectivity (Gupta, Verma and Dubey, 2016; Wang et al., 2018). Moreover, the conventional spectrum allocation policy does not permit full utilization of the radio spectrum. A dynamic rather than static usage of the spectrum must be encouraged to increase the availability of frequency spectrum (Lee et al., 2012; Sahu et al., 2018). This would aid channel capacity expansion since cell occupancy varies with traffic load. Cognitive radio which applies the concept of dynamic spectrum access is utilized to exploit the spectrum holes in order to ensure more efficient spectrum utilization (Riya et al., 2018). Cognitive radios are aware of their surroundings and bandwidth availability and are able to dynamically tune the spectrum usage based on location, nearby radios, time of day and other factors (Goldsmith, 2005).

Transmitter detection techniques (otherwise called single user detection techniques) especially the energy detection technique suffer severely from fading and path loss effects (Lee et al., 2012). This makes it unreliable in low signal to noise ratio conditions (Sahu et al., 2018). It therefore necessitates the inclusion of more cognitive radios to improve on the sensitivity and accuracy of report (Zou, 2010). This process of including more cognitive radios to improve detection accuracy can be referred to as cooperative spectrum sensing. The cooperative sensing technique was developed to boost the Quality of Service (QoS) of the network and to improve on the results obtained from single user detection techniques. But it has a major challenge of consuming additional energy and bandwidth thereby increasing communication overhead (Sobron et al., 2015; Kakalou et al., 2018).

There is therefore a need for a more efficient and adaptive sensing algorithm that can reduce the overall energy and bandwidth consumption of the cooperative sensing technique to the barest minimum without a negative toll on the performance of the cognitive radio system which is the aim of this study. The objectives worked on to achieve this aim include: simulating and studying the detection performance of the single user and cooperative sensing using an improved energy detection algorithm under varying signal to noise ratios, evaluating the effect of change in probability of false alarm on detection and then making the cooperative sensing adaptive based on the SNR threshold set.

This study is limited to cooperative spectrum scheme of cognitive radios with focus on energy and bandwidth optimization for improved performance of cognitive radio systems.

## **2.0 Related Studies**

Dynamic spectrum management (DSM) design when initially proposed had mainly been focused on maximization of data rates (Tsiaflakisa et al., 2007). However, reducing the total power had become a main target as IT power consumption has been identified as a significant contributor to global warming (Santhanam and Keller, 2018). Traditional DSM design was also extended towards a much wider power-efficient scope and how to tackle the corresponding optimization problems. The technique developed helped to save about 50% power alongside improved data rate performance.

Some research efforts have also been made to the energy efficiency of spectrum sensing sharing while ensuring simplicity and robustness using a Multi-rate Asynchronous Sub-Nyquist Sampling System (Sun, 2011). Further improvements were made to the algorithms employed in DSM. The coordination of power was decentralized in order to make it more distributed to minimize cost and complexity was a major focus of the research effort (Rognsvåg, 2008). The results showed admirable improvement in the capacity of the system as compared to Static Spectrum Management (SSM). Some other researchers proposed a sensing method which chose between single energy sensing and cooperative energy according to the received signal's Signal to Noise Ratio (SNR) from

the Primary User (PU). The simulation using conventional energy detection technique produced results which showed that the adaptive spectrum sensing produced efficiency and improvement in cognitive radio systems (Lee et al., 2012).

Some adaptive systems have also been developed such as the adaptive random access technique (Lee, 2015). In this technique, a heuristic approach was utilized to improve the sensing data collection. Some other adaptive systems have been developed which focused on detection sensitivity, not on the energy and bandwidth consumption (Sobron et al., 2015; Gupta et al., 2016)). One of these adaptive systems employed an adaptive threshold for each cognitive radio (CR) in cooperative spectrum sensing scheme based on the Neyman Pearson theorem (Huber and Strassen, 1973; Yan and Blum, 2001). Most of these systems which produced better performances for the cooperative spectrum sensing, but was placed more computational demand on the system (Rauniyar and Shin, 2018). Another study utilized a dynamic threshold for detection but used matched filters which require prior information of the PU signals with more complexity (Salahdine et al., 2016). A recent survey of sensing algorithms for cognitive radio networks (Kakalou et al., 2018) revealed that the majority of the sensing algorithms employed in research are energy based sensing algorithms due to the low implementation complexity and the fact that they do not require prior information of the PU signals. However, there is still a need for adaptively aimed reducing energy and bandwidth consumption specifically when cooperative spectrum sensing is utilized. This is the need which this paper addresses. It proposes a method to minimize the energy and bandwidth consumption at the fusion point during cooperative sensing while making consideration for low SNR conditions.

### **3.0 Methods**

#### **3.1 Proposed Adaptive Spectrum Sensing**

The adaptive spectrum sensing algorithm is proposed to solve the problem of increased energy and bandwidth consumption by the multiple cognitive radios in cooperative spectrum sensing. The algorithm is meant to be adaptive based on the secondary user's SNR status. If the secondary user has sufficient SNR to detect reliably, single user sensing is employed. Otherwise, cooperative sensing is utilized. This is done using a supervised mode of learning to ensure that the communication overhead is reduced considerably.

Each of the cognitive radios employed in the adaptive sensing algorithm utilizes the improved energy detection technique introduced by (Lopez-Benitez and Casadevall, 2012). This ensures higher sensitivity in the single user and cooperative sensing algorithms compared to the conventional sensing schemes.

The adaptive spectrum sensing works with two hypotheses:  $H_1$  (signal plus noise hypothesis) and  $H_0$  (noise only hypothesis) to indicate the presence and absence of the primary user respectively. If an  $H_1$  cell is being tested, the probability density function (PDF) of the received signal ( $y$ ) of a specific CR user can be expressed (as used in Lee et

al., 2012) as:

$$f_{Y_F}(y|H_1) = \frac{1}{\sqrt{2\pi M\sigma_F^2}} e^{-\frac{(y-\bar{S}_F)^2}{2}} \quad (1)$$

where

$$\bar{S}_F = \sum_{i=1}^M \bar{S}_F^i \quad (2)$$

$\bar{S}_F^i$  = mean value of the transmitted signal from the *i*th CR user.

$\bar{S}_C$  = mean magnitude value of primary user's transmitted signal.

$\bar{M}$  = total number of cognitive radios

$\sigma_F^2$  = standard deviation of primary user's transmitted signal.

$f_{Y_F}$  = probability density function (PDF) of the received signal (*y*)

And if an  $H_0$  cell is being tested, then the PDF of received signal (*y*) can be expressed as:

$$f_{Y_F}(y|H_0) = \frac{1}{\sqrt{2\pi M\sigma_F^2}} e^{-\frac{y^2}{2}} \quad (3)$$

After each CR user determines whether there is the primary user or not, the results are retransmitted to the fusion center over wireless channel. Then, the fusion center makes the final decision by combining the received signals from *M* CR users. When the  $H_1$  and  $H_0$  cells are being tested, the PDFs of the combined result  $Y_F(k)$  at the fusion center are expressed in line with Lee et al.(2012)in equation (1) and in equation (4) as follows:

$$f_{Y_F}(y|H_0) = \frac{1}{\sqrt{2\pi M\sigma_F^2}} e^{-\frac{y^2}{2}} \quad (4)$$

The detection probability for a given value of the decision threshold is defined as the probability of the event that the output decision variable corresponding to the  $H_1$  cell exceeds the decision threshold, which can be obtained as:

$$P_D = \int_Y^{\infty} f_{Y_F}(y|H_1) dy \quad (5)$$

$$P_D = \int_Y^{\infty} \frac{1}{\sqrt{2\pi M\sigma_F^2}} e^{-\frac{(y-\bar{S}_F)^2}{2}} dy \quad (6)$$

where

$P_D$  represents the detection probability of the  $H_1$  cell.

Let

$$z = \frac{y-\bar{S}_F}{M\sigma_F^2} \quad (7)$$

Then the detection probability can be expressed as:

$$P_D = \int_{\frac{\gamma - \bar{S}_F}{M\sigma_F^2}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \quad (8)$$

$$P_D = Q\left(\frac{\gamma - \bar{S}_F}{M\sigma_F^2}\right) \quad (9)$$

Where:  $Q(\cdot)$  denotes Q function.

Since the transmitted signal of primary user is random signal, the improved energy detection technique is utilized. Various techniques such as Equal Gain Combining (EGC), Maximum Ration Combining (MRC), Selective Combining (SC) and many more could be used to combine the signal from multiple antennas. In EGC, each signal branch weighted the same factor irrespective of the signal amplitude. EGC is simpler to implement than MRC and channel amplitude estimation is unnecessary. In this work each local sensing result is combining employing EGC due to the advantage of using the same factor in combining for each cognitive radio.

### 3.2 Algorithm for Adaptive Cooperative Spectrum Sensing

An improved energy detection (IED) algorithm (Lopez-Benitez and Casadevall, 2012; Olatunji et al., 2019) is utilized for each of the cognitive radios in the cooperative sensing scheme. The adaptive mechanism is then implemented based on the SNR status of the channel. The algorithm for this mechanism is presented as a flowchart in Figure 1. It should be noted that the procedure for the simulation of the IED is similar to the Conventional Energy Detection (CED), except that an additional check of the immediate past sensing event ( $T_{i-1}(y_{i-1})$ ) asides just the immediate signal energy check and the check for the average energy of the former sensing episodes ( $T_i^{avg}(T_i)$ ) is included.

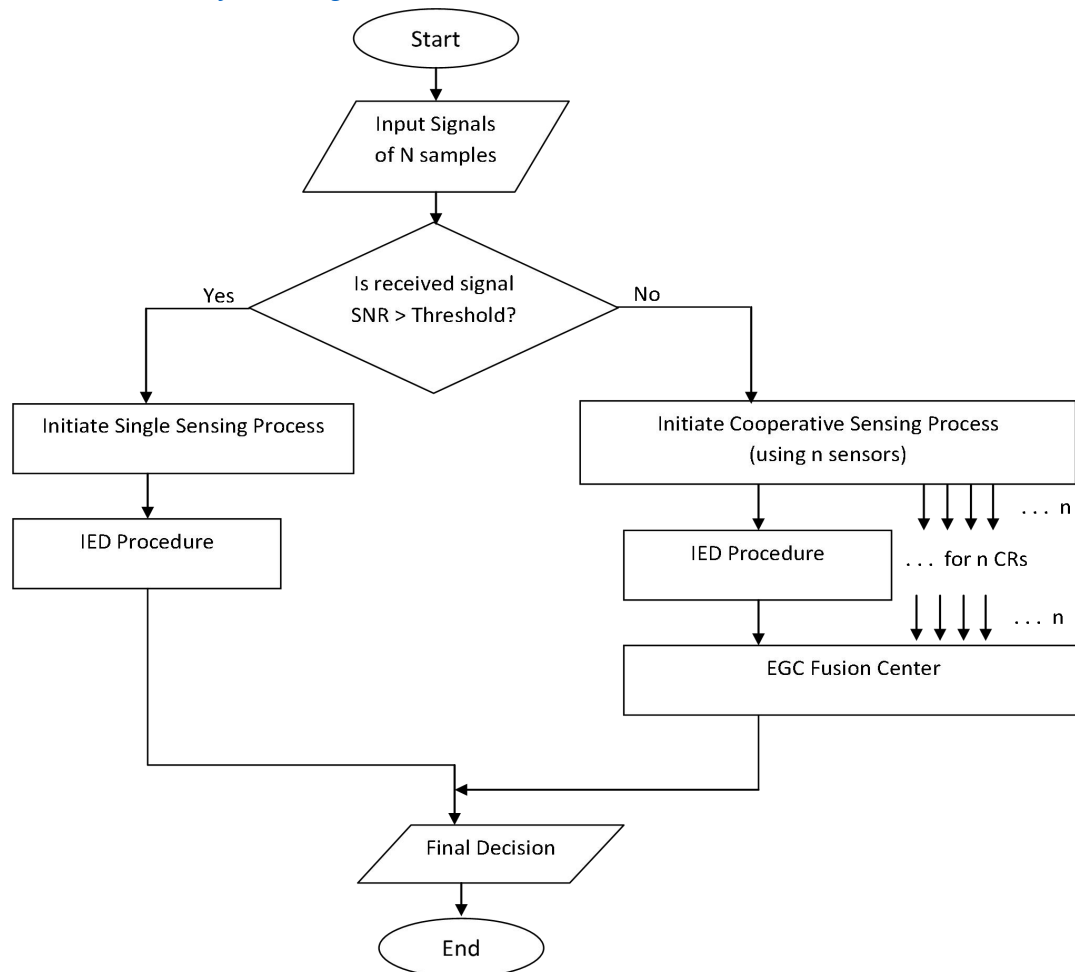


Figure 1: Flowchart for Adaptive Spectrum Sensing

The approach suggested to achieve this has been discussed earlier which entails making the number of cognitive radios employed for sensing adaptive based on the Signal to Noise Ratio (SNR). Therefore, when the SNR is poor, several cognitive radios are utilized to ensure accurate sensing, else just one cognitive radio is utilized for sensing the simulation was first done with one cognitive radio using the IED procedure to observe the performance under varying SNR conditions. The number is then increased to two and then five and later ten to observe the performance of cooperative sensing using IED scheme under varying SNR conditions.

### 3.3 Simulation

#### 3.3.1 Simulating the Received Signal

The simulations were carried out using MATLAB version R2017a. Receiver Operations Characteristics (ROC) analysis was used to study the performance of the energy detector in the simulations as a trade-off between the probability of detection (PD) and the probability of false alarm (PFA). Chi-square distribution was used to analyse the output which was assumed as Gaussian distribution for large samples. For a sampling episode, one hundred samples were simulated. The sample energy was varied from  $2.07 \times 10^8$  to  $2.005 \times 10^8$  dBm. Signal to Noise Ratio (SNR) values were varied from -15dB to 15dB with the PFA initially set to 5%.

### 3.3.2 Simulating Cooperative Spectrum Sensing

Ten cognitive radios were simulated for the cooperative sensing. Each cognitive radio is simulated to operate with the IED algorithm explained earlier in section 3.2. The simulation parameters are given in Table 1.

**Table 1:** Simulation Parameters

Parameter	Value
SNR variation	-15dB – 15dB
PFA	0.05
No. of cognitive radios	10
Operating frequency of PU	1 x 10 <sup>9</sup> Hz
Observation time	1 x 10 <sup>-4</sup>
Variance of the noise ( $\sigma^2_n$ )	1 x 10 <sup>-12</sup>
Variance of the received signal ( $\sigma^2_s$ )	( $\sigma^2_n \times 10^{-1}$ ) <sup>2</sup>
Operating power	40 mW

## 4.0 Results and Discussion.

### 4.1 Performance of the Cooperative IED under varying SNR conditions

The result presented in Figure 2 shows the performance of the IED scheme when only one cognitive radio is employed in sensing. The scenario represents a very noisy environment where the noise level has been raised. Yet it is still observed from the result that detections begin from about 13.6dB and increases rapidly to maximum detection probability within a range of about 1dB. This reveals the sensitivity of the IED scheme.

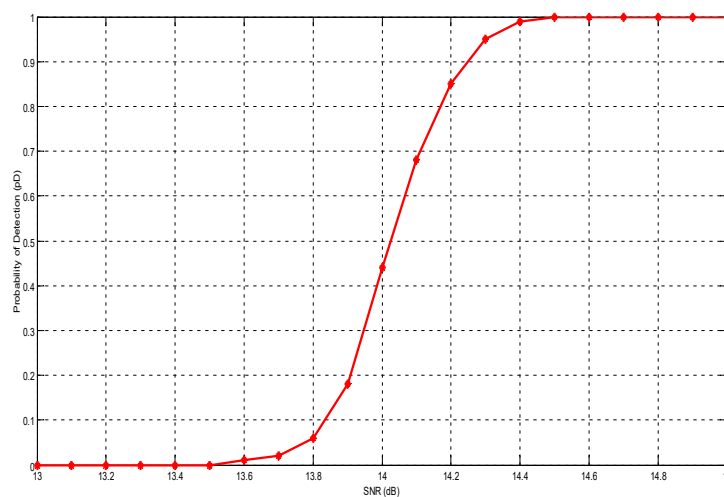


Figure 2: Spectrum Sensing using IED Scheme with a Single CR

Performance improves as the number of cognitive radios used in sensing is increased to ten as seen in Figure 3. The result compares the performance of cooperative sensing with single user sensing working with the IED algorithm. The result validates the fact that multiple sensors give a more accurate result since the individual reports of each of the cognitive radios are collated before the final decision is taken. Hence, cooperative sensing done with a greater number of cognitive radios had truer detections than those with a smaller number of cognitive radios. This therefore means that some of the

detections observed between 13.6dB and 14.5dB could have been false alarms. This is confirmed from the result using ten cognitive radios where the true detections began at 14.5dB. This therefore implies that the higher the number of cognitive radios employed in sensing, the better and more accurate the detection result.

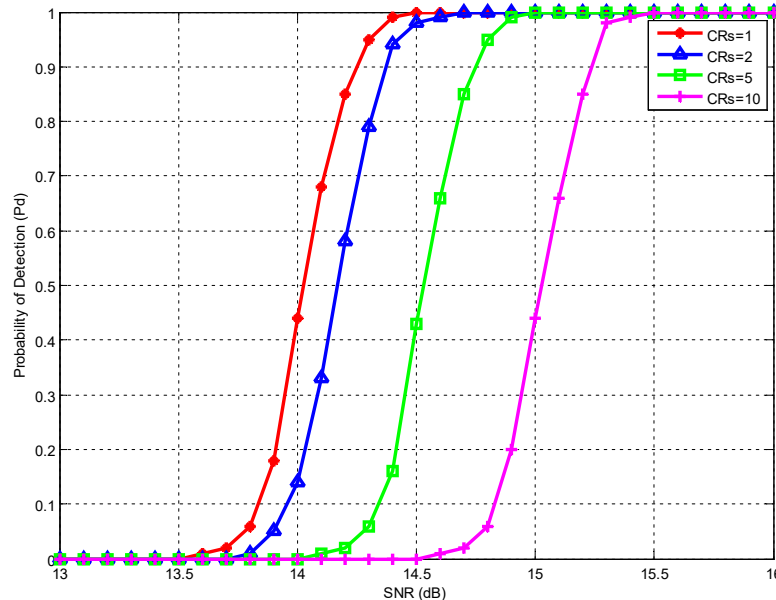


Figure 3: Performance of Cooperative Sensing using IED Scheme

It should also be noted that these performance simulations were performed with the probability of false alarm (PFA) fixed at 5%. Varying the PFA was also explored and outcome is presented in section 4.2.

#### 4.2 Effect of change in Probability of False Alarm (PFA) on Detection

The result presented in Figure 4 reveals the effect of changing the probability of false alarm.

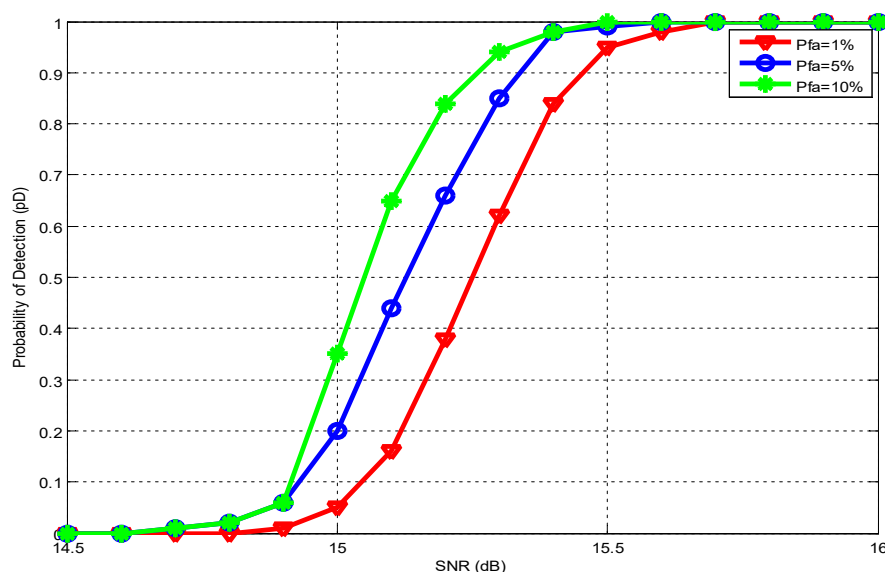


Figure 4: Cooperative Sensing using IED Scheme at various PFA



The result shows detections starting from 14.6dB when the probability of false alarm is set to 1% which is about the same point where detections begin when it is set to 5%. But detections did not commence until about 14.8dB when the probability of false alarm is increased to 10%. It is also observed that detections when PFA is 1% rise higher and at a faster pace than the higher values of PFA which is expected and logical. This reveals that the higher the probability of false alarm, the lower the detection probability.

#### Performance of the Cognitive Radios using the Adaptive Algorithm

The result in Figure 4 reveals that the detection using a single cognitive radio commences slightly before the cooperative spectrum sensing. This is expected, owing to the fact that a single sensor detection possesses less computations and may also be infiltrated with missed detections and false alarms. But the same detection was obtained for both schemes at about 15.5dB. Therefore, the adaptive cooperative spectrum sensing is activated when the SNR is poor (<15dB). When the SNR improves, a single cognitive radio was used. This gave accurate detections as shown in Figure 5.

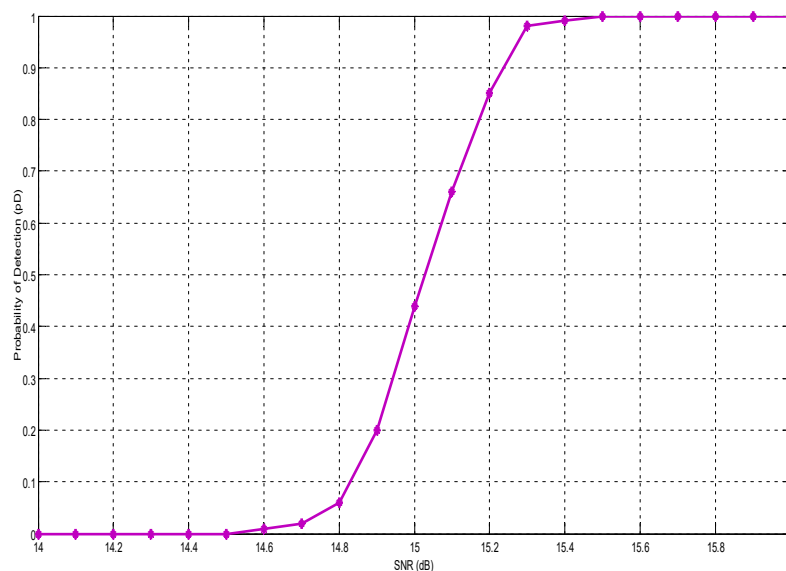


Figure 5: Adaptive Cooperative Sensing using Single and Multiple CRs

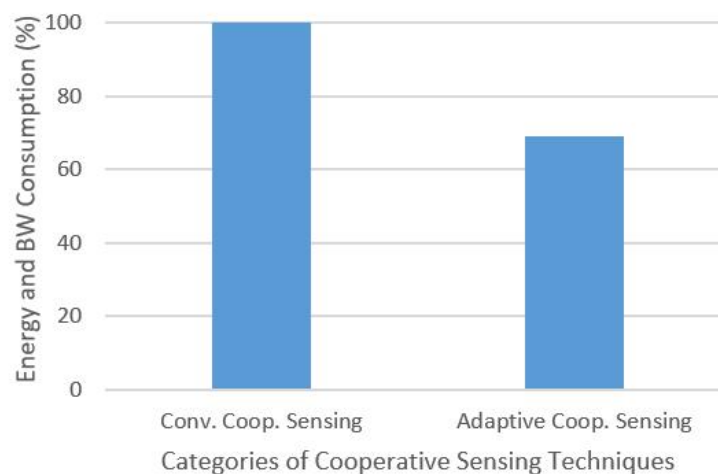


Figure 6: Comparison of Percentage Energy and Bandwidth Consumption for

### **4.3 Conventional and Adaptive Cooperative Sensing**

The outcome was compared to a conventional cooperative spectrum sensing system and a reduction of 31% in energy and bandwidth consumption was recorded. This is presented in Figure 6.

### **5.0 Conclusion**

The adaptive cooperative spectrum sensing developed using supervised learning helped set a threshold which is adaptive to the noise level. At this threshold, both cooperative and uncooperative spectrum sensing perform efficiently. The adaptive scheme activated the single sensing technique when the SNR condition was above this threshold. When the channel SNR conditions was equal to or lower than this threshold, cooperative sensing was activated. This cut the energy and bandwidth requirement by about 31%. The results imply considerable conservation of resources for further needs in the network. Only in poor SNR scenarios would full cooperative sensing be employed. This adaptive technique employed IED algorithm for the individual cognitive radios in the cooperative sensing scheme which ensured accurate spectrum sensing sensitivity. The adaptive cooperative spectrum technique developed proved to be energy and bandwidth efficient after testing. Future work would explore evaluating this adaptive scheme in other forms of fading channels such as Rayleigh and Nakagami with varying signal conditions. The outcome of this present research suggests, that the developed adaptive cooperative technique will be effective in such channels as well.

### **References**

- Goldsmith, A. 2005. *Wireless Communication*. Cambridge University Press, UK, pp. 1 - 27
- Gupta, M., Verma, G. and Dubey, RK. 2016. Cooperative spectrum sensing for cognitive radio based on adaptive threshold. *Proceedings - 2nd International Conference on Computational Intelligence and Communication Technology, (CICT 2016)*, Ghaziabad, India, 12-13 Feb., 2016., IEEE, pp. 444–448. doi: 10.1109/CICT.2016.94.
- Huber, PJ. and Strassen, V. 1973. Minimax Tests and the Neyman-Pearson Lemma for Capacities on JSTOR. *The Annals of Statistics*, 1(2): pp. 251–263.
- Kakalou, I., Papadopoulou, D., Xifilidis, T., Psannis, K.E., Siakavara, K., Ishibashi, Y. 2018. A survey on spectrum sensing algorithms for cognitive radio networks. *Proceedings - 7th International Conference on Modern Circuits and Systems Technologies, (MOCAS 2018)* Thessaloniki, Greece, May 7-9, 2018. IEEE, 1(3), pp. 1 - 4. doi: 10.1109/MOCAS.2018.8376562.
- Lee, DJ. 2015. Adaptive random access for cooperative spectrum sensing in cognitive radio networks. *IEEE Transactions on Wireless Communications*. IEEE, 14(2): 831–840. doi: 10.1109/TWC.2014.2360857.
- Lee, SM., Kim, YH. and Kim, J. 2012. Adaptive Spectrum Sensing Algorithm for Cognitive Radio System. *Information Science and Industrial Applications: Proceedings - International Conference, ISI, Cebu, Phillipines, May 29-31, 2012*: 34-45.
- Lopez-Benitez, M. and Casadevall, F. 2012. Improved energy detection spectrum sensing

for cognitive radio. IET Communications, 6(8): 785–796. doi: 10.1049/iet-com.2010.0571.

Olatunji, SA., Fajemilehin, TO. and Opadiji, JF. 2019. Reduction of Computational Time for Cooperative Sensing Using Reinforcement Learning Algorithm. African Journal of Computing and ICT, 12(2): 90 - 108.

Rauniyar, A. and Shin, SY. 2018. Cooperative spectrum sensing based on adaptive activation of energy and preamble detector for cognitive radio networks, APSIPA Transactions on Signal and Information Processing, 7: 1–7. doi: 10.1017/atsip.2018.5.

Riya, P., Pamoli, N. and Soumyasree, B. 2018. Design of Spectrum Sensing System', Lecture Notes in Electrical Engineering, 44(2): 537–544. doi: 10.1007/978-981-10-4762-6\_51.

Rognsvåg, JV. 2008. Autonomous Algorithms for Dynamic Spectrum Management in DSL Systems, 59. Institutt for elektronikk og telekommunikasjon. Available at: <https://brage.bibsys.no/xmlui/handle/11250/2369157>.

Sahu, AK., Singh, A. and Nandakumar, S. 2018. Improved adaptive cooperative spectrum sensing in cognitive radio networks', Proceedings - 2nd International Conference on Electronics, Materials Engineering and Nano-Technology, (IEMENTech. 2018) 4-5 May 2018, Kolkata, India. IEEE, pp. 1–5. doi: 10.1109/IEMENTECH.2018.8465199.

Salahdine, F., Ghazi, HE., Kaabouch, N., Fihri, WF. 2016. Matched filter detection with dynamic threshold for cognitive radio networks. Wireless Networks and Mobile Communications (WINCOM), 2015 International Conference on, IEEE, Oct 2015, 2015-10-23, France. ff10.1109/WINCOM.2015.7381345ff. fffhal-01371162.

Santhanam, A. and Keller, C. 2018. The Role of Data Centers in Advancing Green IT: A Literature Review. Journal of Soft Computing and Decision Support Systems, 5(1): 9–26.

Sobron, I., Diniz, PSR., Martins, WA., Velez, M. 2015. Energy detection technique for adaptive spectrum sensing. IEEE Transactions on Communications, 63(3): 617–627. doi: 10.1109/TCOMM.2015.2394436.

Sun, H. 2011. Compressed collaborative spectrum sensing in cognitive radio network. Engineering thesis and dissertation collection, Edinburgh Research Archive, University of Edinburgh.

Tsiaflakisa, P. Yi, Y., Chiang, M., Moonen, M. 2007. Dynamic Spectrum Management for Green DSL. Available at: [www.dslforum.org](http://www.dslforum.org) (citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.488.1537&rep=rep1&type=pdf)

Wang, C., Song, T., Wu, J., Miao, L., Hu, J. 2018. Energy-efficient cooperative spectrum sensing for hybrid spectrum sharing cognitive radio networks. IEEE Wireless Communications and Networking Conference, WCNC. IEEE, 2018-April, pp. 1 – 6. doi: 10.1109/WCNC.2018.8377191.

Yan, Q. and Blum, RS. 2001. Distributed signal detection under the Neyman-Pearson criterion. IEEE Transactions on Information Theory, 47(4): 1368 – 1377. doi: 10.1109/18.923720.