Comparative Analysis of Blind Detectors in a Cluster-Based Cooperative Spectrum Hole Detection

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ABSTRACT: Prevention of authorized users from interference determine the accurate detection of Spectrum Hole (SH) is of great importance in a Spectrum Shearing Network (SSN). However, multipath fading and shadowing affect the accurate detection of SH resulting in interference. Cluster-Based Cooperative Spectrum Hole Detection (CBCSHD) used to address this problem depends on detector and number of clusters. Hence, comparative analysis of blind detectors in CBCSHD is carried out to evaluate its performance with various blind detectors and number of clusters. The CBCSHD is carried out using six Cognitive Users (CUs) that jointly carry out detection of SH and each of the CUs performs local sensing using Eigenvalue Detector (EVD), Energy Detector (ED) and Cyclostationary Detector (CD). The CUs form clusters to reduce reporting overhead between CUs. The local sensing results from individual user are combined at the Cluster Head (CH) using majority fusion rule. The performance of each of the detectors in CBCSHD is evaluated using Probability of Detection (PD) and Sensing Time (ST). PD values of 0.7661, 0.7160 and 0.6229 are obtained at SNR of 4 dB for ED, CD and EVD, respectively, while ST values of 3.0707, 3.7163 and 4.0907 s are obtained for ED, CD and EVD, respectively. The results obtained show that ED has the highest detection rate, followed by CD, while EVD shows the worst detection rate.

KEYWORDS: Eigenvalue Detector (EVD), Energy Detector, Cyclostationary Detector, Cognitive User (CU), Spectrum Hole (SH) and Cluster.

[Received Nov. 24, 2021; Revised May 15, 2022; Accepted May 26, 2022] Print ISSN: 0189-9546 | Online ISSN: 2437-2110

I. INTRODUCTION

Recent development in the communication applications has necessitated a paradigm shift in the effective usage of network resources to maximize the throughput and reduce interference. However, there is low frequency spectrum usage as demand for wireless communication services increases due to traditional fixing of spectrum access to only the authorized user. In a fixed spectrum access policy, the moment a particular spectrum has been assigned to a user, no other users can access it, thereby protecting the authorized users from interference. However, spectrum usage is a function of time and most of the assigned spectrum is not utilized over a considerable period resulting in under exploitation of the assigned spectrum. Therefore, fixed spectrum access policy is no longer a viable approach to meet up with the rapid growing demand of frequency spectrum to support emerging wireless applications (Jayanta *et al*., 2014; Saeid *et al*., 2013; Ojo *et al*., 2021; Samrat and Ajitsinh, 2016; Josip *et al*., 2022). Spectrum Sharing (SSH) technique known as Cognitive Radio (CR) has emerged as a promising technique to tackle the underutilization of the assigned spectrum through a Dynamic Spectrum Access (DSA).

Therefore, DSA is promising solution to the poor utilization of frequency spectrum by allowing unauthorized user to exploit the assigned spectrum when it becomes idle without interfering with the authorized users. SSH is a technique that senses the assigned spectrum over a certain frequency band to identify any unused spectrum known as Spectrum Hole (SH). The technique opportunistically provides communication links through the unused spectrum while avoiding the occupied ones [Nikhil and Rita, 2017; Dong *et al*., 2015; Adeyemo *et al*., 2019; Meenakshi *et al*., 2016; Kormal and Tanuja, 2016; Pawel *et al*., 2022]. Authorized User (AU) and Cognitive User (CU) are the two users that involved in SSH technique. AU owns the privileges to the assigned spectrum, while, CU is Unauthorized User (UAU) that makes use of the spectrum when it is idle. The SSH improves spectrum utilization by enabling CU to access the assigned spectrum without interfering with the AU [Ojo *et al*., 2020; Runze *et al*., 2019; Ojo and Fagbola, 2015; Jingwen *et al*., 2018; Hayking, 2005].

However, the performance of SSH is a function of accurate detection of SH through a phenomenon known as Spectrum Sensing (SS). In SS, AU scans through the assigned spectrum to identify unused spectrum required by the CU. This is achieved either by using only one CU known as Non-Cooperative Sensing (NCS) or group of CUs known as Cooperative Sensing (CS) [Abbas *et al*., 2021; Noor, 2017; Gevira, 2016; Chhagan and Rajoo, 2019]. NCS suffers from

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doi: http://dx.doi.org/10.4314/njtd.v20i1.1300

receiver uncertainty which occurs when CU is outside the transmission range of the AU as a result of effect of multipath propagation. The CS, on the other hand, solves the challenges of NCS and achieves a reliable detection rate. Also, CS allows CUs to jointly carry out spectrum sensing to improve the detection rate even at a very low AU signal [Shraddha, 2018; Arijit and Nityananda, 2017; Abolade *et al*., 2020].

The CS is characterized with bandwidth inefficiency and high hardware complexity due to several reporting overhead among CUs. In order to mitigate the challenges of CS, Cluster-based Cooperative Spectrum Hole Detection (CBCSHD) in which a certain number of CUs form a group, known as a cluster has been proposed by several authors in the literature using different detectors. The three most commonly used detectors are Energy Detector (ED), Eigenvalue Detector (EVD) and Cyclostationary Detector (CD) due to their independence of AU signals. The three detectors are blind detectors that do not require any prior information about the authorized user, therefore, synchronization between the AU and CU is not required. This makes the detectors to be widely used in detecting the presence or absence of Spectrum Hole (SH) in SSH technique. However, accurate detection of SH using CBCSHD is a function of detector used [Ojo *et al*., 2021; Moshin and Haewoon, 2019; Syed *et al*., 2016; Yang *et al*., 2015, 23, 24, 25]. There have been several existing works on CBCSHD using different blind detectors in DSA, but their comparison has not been adequately evaluated.

Ojo *et al*. (2021a) proposed an energy efficient cluster based cooperative sensing in a multiple antenna CR network using ED. In the paper, multiple copies of AU signal were combined using a modified equal gain combiner. Output of the combiner was then made to pass through ED to determine the presence or absence of SH during local sensing. The global sensing result was obtained by combining the results from individual clusters using majority fusion rule. The results of the paper showed a better performance than the existing cooperative sensing with reduced hardware complexity, better detection rate and bandwidth efficiency. However, the technique failed to analyze the effect of detector and number of clusters on the performance of CBCSHD. Also, Ojo *et al*. (2021b) worked on autocorrelation based white space detection in energy harvesting CR network to address the problem of cooperative sensing in SSH technique. Local sensing was carried out using CD by extracting the autocorrelation function of the received signal at the CU. Multiple CUs were used to form cluster and the sensing results from individual CU were combining at the cluster head using OR fusion rule. While the global sensing result was obtained by combining the sensing results from individual clusters using majority fusion rule. The method gave better performance than the existing CS with better detection rate and great reduction in hardware complexity. However, the technique could not analyze the effect of detectors and number of clusters on the performance of CCSHD.

Cluster based cooperative sensing in CR network using eigenvalue detector with superposition approach was proposed by Mohsin and Haewoon (2019) to reduce the reporting overhead and leading to reduction of the sensing time. Local sensing was carried out using eigenvalue detector and the results were combined at the individual cluster using OR fusion rule. The reporting time slot of cognitive users and cluster head were rescheduled using superposition approach. The simulation results of the paper revealed that, the method reduced the sensing time and high detection rate. However, the method failed to provide information about the effect of detector and the number of clusters on the performance. Furthermore, in Yashaswini *et al*. (2022), Optimization of inter fusion rule threshold for energy efficient in a cluster based CSS over the composite Nakagami and Rician fading channels was proposed to improve energy efficiency through optimal inter fusion rule for various number of clusters. Inter fusion rule was optimized in cluster based CSS over the composite fading channel mentioned. The mathematical expressions obtained were simulated to verify the performance. The result revealed that the optimized fusion rule is 5.06% more energy efficient than the existing fusion rule. However, the technique could not analyze the effect of detectors and number of clusters on the performance of CCSHD.

In summary, previous works on CBCSHD failed to provide information about the effect of detector and the number of clusters on the performance. Therefore, this paper analyzes the performance of blind detectors in CBCSHD. The contributions of this paper are as follows:

1) the effect of different detectors on the performance of CBCSHD, to reveal the appropriate blind detector that gives highest detection rate with lower sensing time have been revealed.

2) The suitable number of clusters to obtain higher detection rate with low sensing time for each of the detector considered has also been unveiled.

The remaining part of this paper is organized as follows; section 2 presents the methodology which consists of local sensing using different sensing detectors and formation of cluster, while, the simulation results of the effect of detectors and number of clusters are presented in section 3. The conclusion of the paper is presented in section 4. In this paper, the multiple copies of AU signals are combined using Equal Gain Combiner (EGC) which combines signal by multiplying the received signal with equal weight irrespective of signal strength before summing. EGC is adopted in this paper due to its lower hardware complexity when compared to other combiner such maximal ratio combiner and better performance than the selection combiner. Also, kappa-mu shadowed fading channel is adopted in this paper due to its ability to model both the multipath fading and shadowing.

II. METHODOLOGY

In this paper, multiple CUs are used to carry out local sensing and the results of local sensing decision from individual CUs are sent to the Clustered Heads (CH) of the respective clusters for making a global cluster decision. The sensed decision from individual clusters is communicated among one another to make a final decision. The ED, EVD and CD are blind detectors used for the local sensing.

A. Local Sensing using Energy Detector (ED)

The multiple copies of the transmitted AU signal over kappa-mu shadowed fading channel are received by multiple

CU antennas and combined using Equal Gain Combiner (EGC). The output of the combiner is applied to only one ED as shown in Figure 1 and h_ri is the channel gain of kappa-mu shadowed fading channel. Output of ED is then compared with the decision threshold to decide on the presence or absence of SH and when the output of ED is greater than the set threshold, the decision is SH absent due to ongoing transmission of AU, otherwise SH is present, that is, the spectrum is idle. The threshold is set at Probability of False Alarm (PFA) of 0.05 (5%) and 0.1 (1%).

The signal received r(i) at individual CU antenna is given as

$$r(i) = E(i) + N(i) \tag{1}$$

where: $E(i)$ is the AU signal power on each path

$N(i)$ is the noise present on individual path

According to [3], the output of ED with EGC 'E_{EGC}' is given as

$$E_{EGC} = \sum_{n=1}^{N} \left| \frac{1}{NL}\left(\sum_{i=1}^{L} r_n(i)\right)^2 \right|^2 \tag{2}$$

where: $r_n(i)$ is the received signal at various CU antenna

L is the number of branches received

Therefore, by substituting Eqn. (2) into Eqn. (1), the output of ED 'E_{EGC}' which is the received signal gives

$$E_{EGC} = \sum_{n=1}^{N} \left| \frac{1}{NL}\left(\sum_{i=1}^{L} E(i) + N(i)\right)^2 \right|^2 \tag{3}$$

The decision on the presence or absence of SH is then based on the test statistic given as

$$E_{EGC} > \sigma \tag{4}$$

where: σ is the decision threshold

The decision threshold based on probability of false alarm derived in [3] is obtained in Eqn. (5) and used to set decision threshold

$$PFA_{EGC} = \frac{\Gamma\left(\frac{\sigma}{2\sum_{n=1}^{N}\sum_{i=1}^{L}\delta_i^2(n)}, \ {}^{N}\!/_{2}\right)}{\Gamma({}^{N}\!/_{2})} \tag{5}$$

where: Γ is the gamma function,

$\delta_i^2(n)$ is the noise variance.

Therefore, to determine the Probability of Detection (PD) under ED, the energy of the received signal is obtained using Eqn. (3) and compared with the set threshold. Eqn. (5) is used to obtain threshold at PFA of 5%. If the energy obtained in Eqn. (3) is greater than the threshold obtained in Equation (5), then SH is absent due to ongoing AU transmission, otherwise SH is present. Therefore, the PD for the local sensing 'PD_L' is expressed as

$$PD_L = \Pr(E_{EGC} > \sigma) \tag{6}$$

B. *Local Sensing using Eigenvalue Detector*

The received signal '$R(i)$' from CU antennas is expressed as

$$R(i) = \sum_{i=1}^{G}\sum_{j=1}^{L} E_j(i) + N_j(i) \tag{7}$$

where: G is the number of antenna

L is the number of branches received by individual antenna

$E_j(i)$ is the LU signal

$N_j(i)$ is the noise present on the AU link

$$\boldsymbol{R} = \begin{bmatrix} E_{1,1} & E_{1,2}\ldots\ldots & E_{1,L} \\ E_{2,1} & E_{2,2}\ldots\ldots & E_{2,L} \\ \vdots & \vdots & \vdots \\ E_{G,1} & E_{G,2} & E_{G,L} \end{bmatrix} + \mathrm{R} = \begin{bmatrix} E_{1,1} & E_{1,2}\ldots\ldots & E_{1,L} \\ E_{2,1} & E_{2,2}\ldots\ldots & E_{2,L} \\ \vdots & \vdots & \vdots \\ E_{G,1} & E_{G,2} & E_{G,L} \end{bmatrix} \tag{8}$$

According to Syed *et al*. (2016), covariance matrix '$\boldsymbol{R_C}$' of the received AU signal is expressed as

$$\boldsymbol{R_C} = \frac{1}{G}(\boldsymbol{R})\boldsymbol{R}^T \tag{9}$$

where: $\boldsymbol{R^T}$ is the transpose of the signal received.

Using the characteristic equation of a square covariance matrix, the maximum (α_{max}) and minimum (α_{min}) eigenvalues are obtained from Eqn. (9) as

$$det(\boldsymbol{R_C} - \alpha I) = 0 \tag{10}$$

Solving Eqn. (9) and substituting into Eqn. (10) gives

$$det\begin{bmatrix} E_{C1,1} - \alpha & E_{C1,2}\ldots\ldots\ldots & E_{C1,L} \\ E_{C2,1} & E_{C2,2} - \alpha \ldots\ldots & E_{C2,L} \\ & & \vdots \\ E_{CG,1} & E_{CG,2} & E_{CG,L} - \alpha \end{bmatrix} = 0 \tag{11}$$

α with highest value is maximum eigenvalue, while, α with lowest value is the minimum eigenvalue. Therefore, test statistics 'γ' for the detector is expressed as

$$\gamma = \frac{\alpha_{max}}{\alpha_{min}} \tag{12}$$

The Probability of Detection at the local sensing using EVD 'PD_{LEVD}' is then expressed as

$$PD_{LEVD} = \Pr(\gamma > 1) \tag{13}$$

C. *Local Sensing using Cyclostationary Detector*

The existing Cyclostationary Detector (CD) is characterized with computational complexity due to Hilbert transform and windowing used to extract the cyclostationay feature of AU signal. The net effect of computational complexity is high power consumption and long sensing time. In order to overcome the computational complexity, the cyclostationary feature of the AU signal is extracted using autocorrelation function, which is the similarity between the received signal and its shifted version. Since AU signal is always a periodic signal, while the noise is always aperiodic signal because all modulated signals are periodic [Yang *et al*., 2015]. Therefore, based on this fact, the autocorrelation of the AU signal is determined and compared with the threshold of zero. The various copies of the received AU signal over kappa-mu shadowed fading channel are received and combined using EGC technique with CU antennas. The combined signal is shifted by time φ and the similarities between the signal and its shifted version is determined using autocorrelation function as shown in Figure 2. The value of autocorrelation obtained is then compared with the threshold of zero to decide on the presence or absence of SH. The autocorrelation function "$R(u)$" of the combined signal is expressed as

$$R(u) = \int_{-U}^{U} r(u) \times r(u-\varphi)du \tag{14}$$

where: u is the period of oscillation

$r(u)$ is the combined signal which is the output of EGC

$r(u-\varphi)$ is the shifted version of the combined signal.

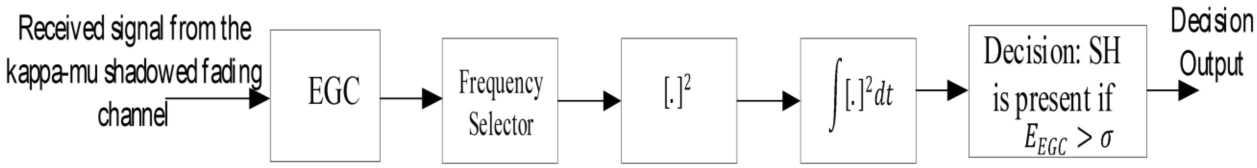

Fig. 1: Block diagram of local sensing using ED with EGC

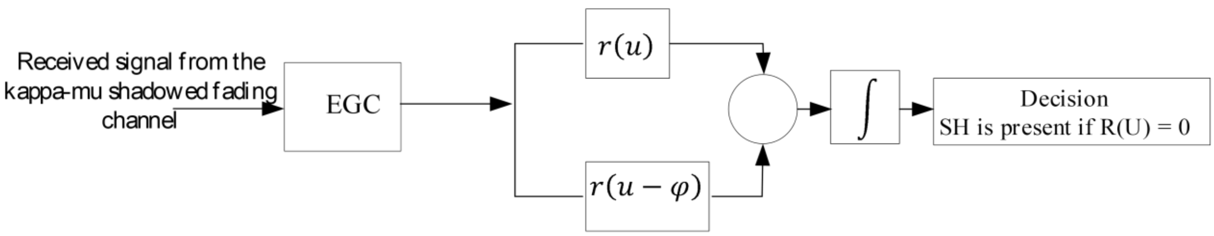

Fig. 2: Block diagram of local sensing using CD with EGC

However, the signal output of EGC 'δ_{EGC}' is expressed by Ojo *et al*. (2021) as

$$\delta_{EGC} = \frac{1}{NL}\left(\sum_{u=1}^{L} r(u)\right)^2 \tag{15}$$

where: $r(u)$ is the signal power on each branch;
L is the number of branches and
N is the noise present on individual branch.

Using the signal output of EGC, the autocorrelation of the combined signal is expressed as

$$R(u) = \frac{1}{NL}\int_{-U}^{U}\left(\sum_{u=1}^{L} r(u)\right)^2 \times \left(\sum_{u=1}^{L} r(u-\varphi)\right)^2 du \tag{16}$$

Therefore, SH is absent if the value of autocorrelation in Eqn. (16) is not equal to zero due to ongoing transmission of AU signal, otherwise, SH is present due to idleness of the spectrum. The probability of detection 'PD_{LCD}' for the local sensing using CD is expressed as

$$PD_{LCD} = \Pr\,(R(u) > 1) \tag{17}$$

D. *Formation of Cluster in CCSHD*

In this paper, Z number of clusters are considered, each cluster contains M number of CUs and a CH. The distance between respective CU and a CH is determined using radius of cluster 'F_C' expressed by Noor (2017) as

$$F_C = \frac{\vartheta-1}{\vartheta+1}X_P \tag{18}$$

where: X_P is the distance between the LU and CH.

However, according to Noor (2017)

$$\vartheta = 10^{\frac{0.1}{\tau}} \tag{19}$$

where: τ is the path loss exponent

The urban environment is considered, therefore, by solving Eqn. (19) using the average value of path loss exponent for the urban environment, the cluster radius for urban environment $F_{C/urban}$ is expressed as

$$F_{C/urban} = 0.037X_P \tag{20}$$

Eqn. (20) is the distance between the respective CU and CH for the urban environment.

At each cluster, majority fusion rule is used to decide on the presence or absence of SH at the CH due to its ability to strike balance between the AU protection and spectrum management efficiency. By using the global probability of majority fusion rule and the result of local sensing obtained in Eqns. (6), (13) and (17) for the different detectors considered, the probability of detection '$PD_{CL,major}$' at the clusters is obtained as

$$PD_{CL,major} = 2^{K-1}(L+2)(PD_L)^K(1-PD_L)^{L-K} \tag{21}$$

where: PD_L is the PD for the local sensing at individual CU in a cluster, L is the total number of CU, K is the number of CU that decides the presence of SH.

E. *Global Probability of Detection*

Probability of Detection (PD) describes the chances of making the right decision on the presence of SH and the higher the value of PD, the better the performance of the system. The global PD is the final decision by combining the sensing results from individual clusters. Therefore, at the global decision, OR fusion rule is used to combine the sensing results from clusters due to its increase in the AU protection. Using the global probability of OR fusion rule and the PD at each cluster, the global PD is obtained according to Ojo *et al*. (2021) as

$$PD_{GL,OR} = 1 - \left(1 - PD_{CL,major}\right)^L \tag{22}$$

$$PD_{GL,OR} = 1 - (1 - 2^{K-1}(L+2)(PD_L)^K(1 - PD_L)^{L-K})^L \tag{23}$$

III. SIMULATION RESULTS AND DISCUSSION

Probability of Detection (PD) and Sensing Time (ST) are the performance metrics used to evaluate the effect of the three detectors, that is, ED, EVD and CD on the CCSHD technique. Figure 4 presents PD versus SNR for ED, EVD and CD. PD values of 0.7661, 0.7160 and 0.6229 are obtained at SNR of 4 dB for ED, CD and EVD, respectively, while at SNR of 16 dB, PD values of 0.9783, 0.8878 and 0.7941 are obtained for ED, CD and EVD, respectively. Figure 5 depicts the effects of cluster on PD for ED, CD and EVD at SNR of 20 dB. The highest PD value obtained for ED is at PFA of 0.1. Figures 4

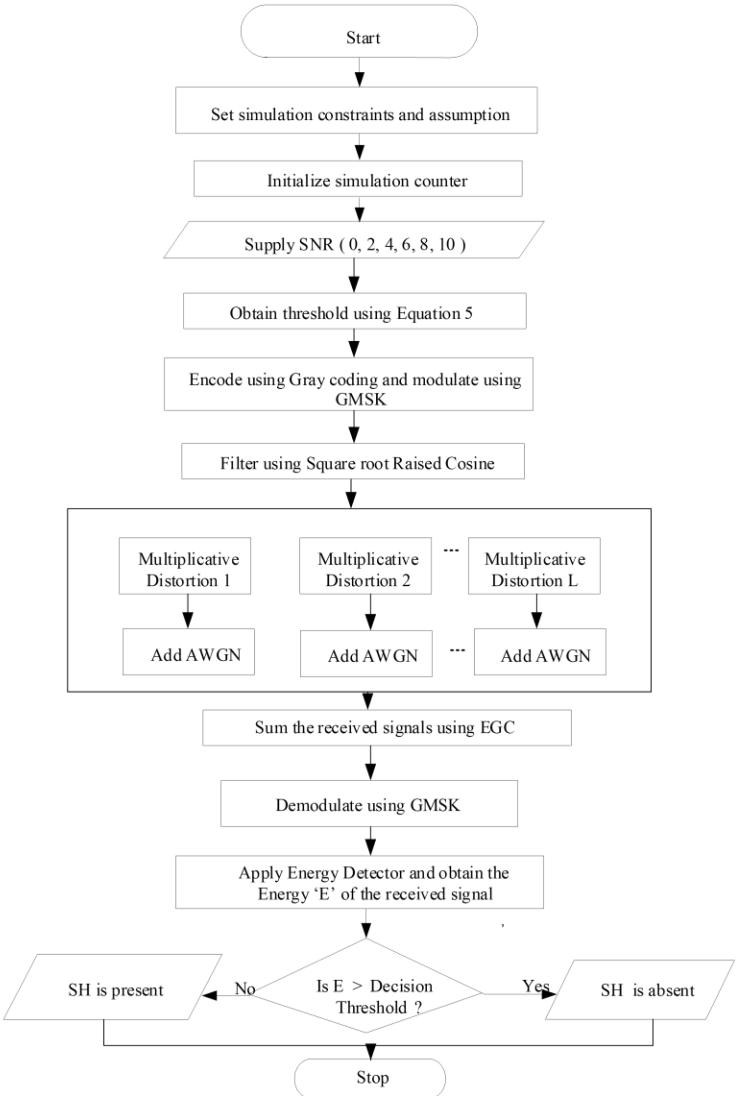

Figure 3a: Flowchart for Detecting SH using ED

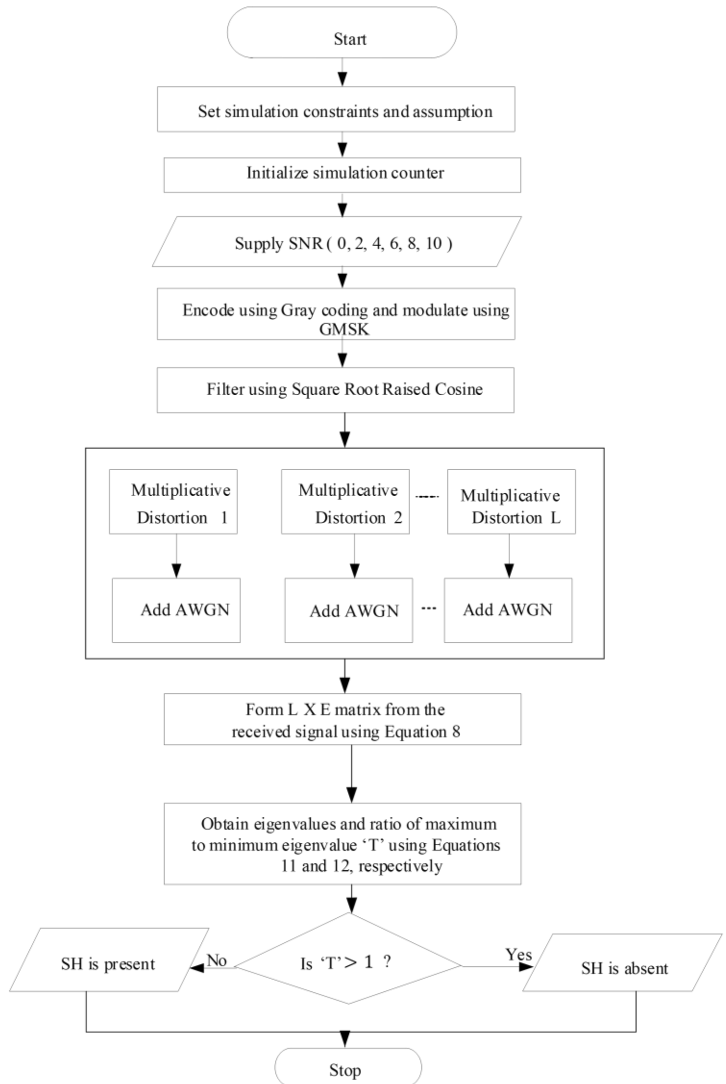

Fig. 3b: Flowchart for Detecting SH using EVD

and 5 revealed that ED has better detection rate with highest PD values than each of CD and EVD due to combining nature of AU signal that improves AU signal strength, which in turn increases the detection rate since the performance of ED increases with increase in signal strength.

Also, EVD shows the worst performance with lowest PD values compared to other techniques due to difficulty in differentiating between AU signal and noise when obtaining maximum and minimum eigenvalues. Figure 4 also shows that, for all the detectors considered, PD values increase with increase in SNR and this is due to ability of detectors to easily differentiate between the signal and noise at high signal strength. Furthermore, it can be deduced from Figure 5 that, for all the detectors considered, detection rate increases with increase in the number of clusters and this is due to decrease in the reporting overhead as the number of clusters increases. Reduction in reporting overhead in turn increases the detection rate as a result of decrease in reporting error as the number of reporting overhead reduces.

Figure 6 depicts ST versus SNR for ED, CD and EVD at L of 4. The ST values of 3.0707, 3.7163 and 4.0907 s are obtained at SNR of 4 dB for ED, CD and EVD, respectively, while at SNR of 16 dB, the corresponding ST values obtained are 2.6177, 3.1591 and 3.4931 s. It can be deduced from Fig. 6 that, ED has the lowest ST, followed by CD, while EVD has the highest ST and this is due to computational complexity in obtaining ratio of maximum to minimum eigenvalues compared to other detectors. Also, the ED that gives the lowest value of ST justifies the simplicity of the detector and this makes it to be widely used in detecting SH, most especially, when the strength of signal to be detected is very high. Figure 7 presents the effects of cluster on ST for ED, CD and EVD at SNR of 20 dB. The ST values of 2.5211, 3.2011 and 3.5102 s are obtained at three number of clusters for ED, CD and EVD, respectively, while with five number of clusters, the corresponding ST values obtained are 1.5201, 1.5842 and 2.1231 s. Figures 6 and 7 revealed that ED has better sensing rate with lowest ST value than each of CD and EVD, thus depicts the simplicity of ED when compared with other detectors.

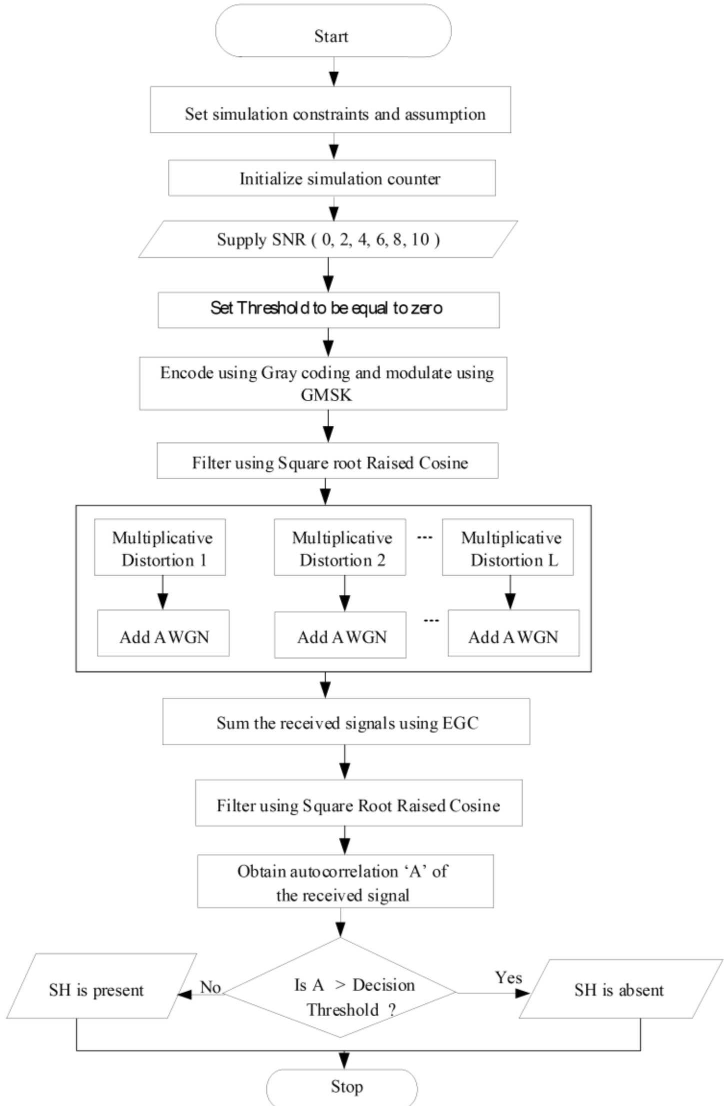

Figure 3c: Flowchart for Detecting SH using CD

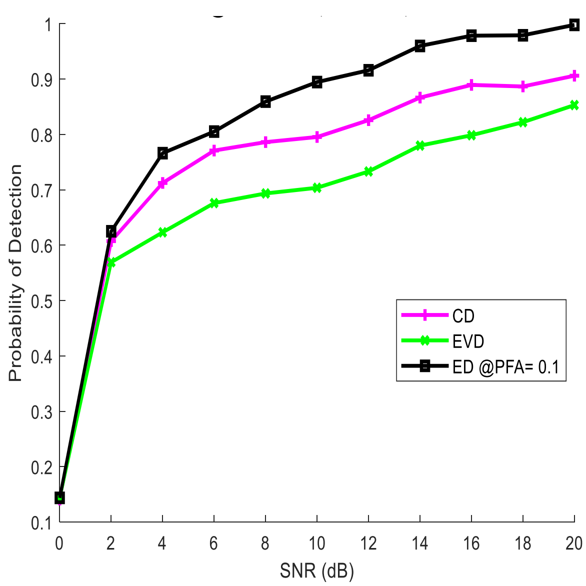

Figure 4: PD versus SNR for ED, CD and EVD using CBCSHD

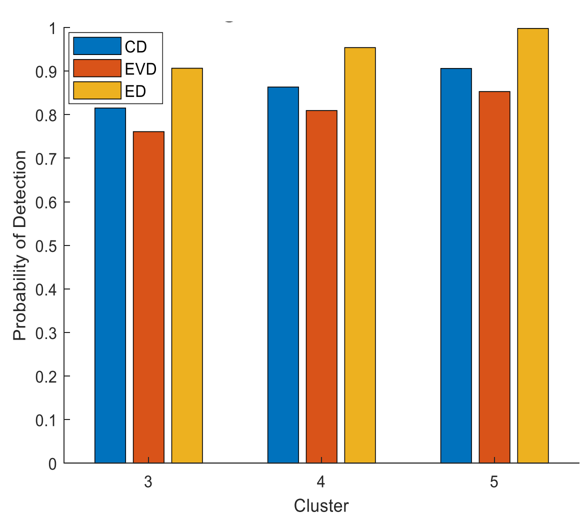

Figure 5: PD versus Cluster for ED, CD and EVD using CBCSHD

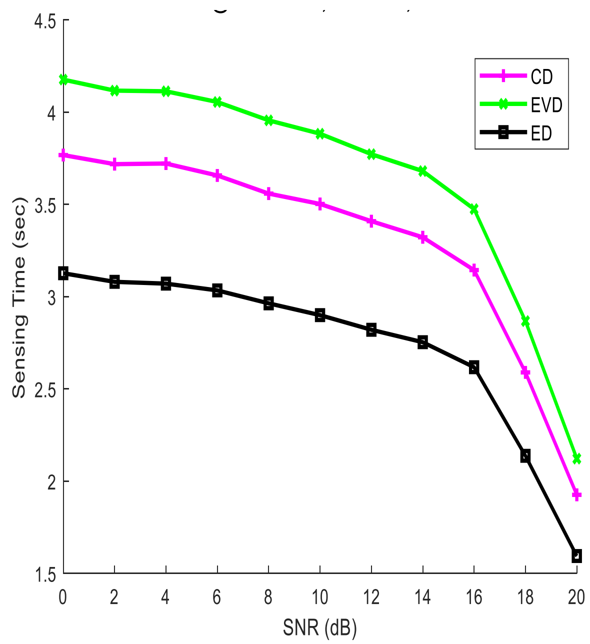

Figure 6: ST versus SNR for ED, CD and EVD using CBCSHD

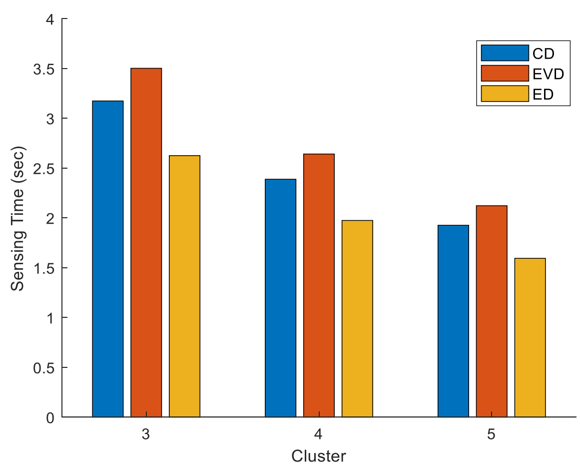

Figure 7: ST versus Cluster for ED, CD and EVD using CBCSHD

Furthermore, it can be deduced from Figure 7 that, for all the detectors considered, ST values decrease with increase in the number of clusters and this is due to reduction in hardware complexity as the number of clusters increases.

IV. CONCLUSION

In this paper, comparative evaluation of blind detectors such as ED, EVD and CD in CBCSHD has been carried out. Probability of Detection (PD) and Sensing Time (ST) are the performance metrics used in evaluating the effect of the detectors and number of clusters in CBCSHD. Cluster formation is achieved using multiple clusters with multiple CUs. The decisions from local sensing are combined at the various clusters using majority fusion rule. The global sensing result is obtained by combining the sensing results from individual cluster using OR fusion rule. It can be deduced from the results obtained that ED has highest detection rate with lowest sensing rate than each of EVD and CD. The better detection rate of ED is due to combining nature of AU signals, resulting in higher signal strength thereby enhancing detection rate. Therefore, it can be concluded that in a system with higher AU signal strength, ED is better as a detector than EVD and CD. The effects of the number of clusters are also observed on the CBCSHD and the results obtained revealed that the system has better performance at higher number of clusters. The PD and ST values obtained when the number of clusters is 5 are in agreement with IEEE 802 standard on CR which states that detection rate must be high as 0.9 (90%) to avoid interference, while keeping sensing rate as low as 2s. Consequently, ED has been shown to have the best performance with highest detection rate and lowest sensing time. Therefore, ED with higher number of clusters is recommended to be used in CBCSHD. The CD is more preferable than EVD when designing CBCSHD system and EVD is not advisable to be used at all. However, when using ED, the system must be designed in such a way to keep the signal strength as high as possible.

AUTHOR'S CONTRIBUTION

S. I. Ojo conducted the research, while **Z. K. Adeyemo** supervised the process and added technical inputs. **R. O. Omowaiye** assisted in paper preparation.

REFERENCES

Abbass, N.; H. H. Hussein; A. C. Jad; M. Ali and Y. Koffi-Clément. (2021). Spectrum Sensing for Cognitive Radio: Recent Advances and Future Challenge, Sensor. MDPI, 5 :1-29. doi.org/10.3390/s21072408

Abolade, R.O; S.I Ojo; I.A Ojerinde; J.S Adetunji and A.T. Lawal. (2020). Modification of Maximal Ratio Combining Technique for Detection of Spectrum Hole in a Cognitive Radio Network. International Journal of Wireless and Microwave Technologies, **7**(2): 9-21. doi:10.5815/ijwmt.2020.02.02

Adeyemo, Z.K.; S.I. Ojo; R.O. Abolade and O.B. Oladimeji. (2019). Modification of a Square-Law Combiner for Detection in a Cognitive Radio Network. International Journal of Wireless and Microwave Technologies, 4(2): 32-45. doi10.5815/ijwmt.2019.02.04.

Arijit, N. and Nityananda, S. (2017). A distributed solution for cooperative spectrum sensing scheduling in multiband cognitive radio networks, *Journal of Network and Computer Applications*, 94(3): 67-76.

Chhagan, C. and Rajoo, P. (2019). Cooperative Spectrum Sensing Using Eigenvalue-Based Double-Threshold Detection Scheme for Cognitive Radio Networks, Journal of Advances in Intelligent Systems and Computing 13(8): 189-194.

Dong, X. J.; Y.B. Chen; G.Y. Yang; X.S. Pang and J.X. Yang. (2015). The optimization of improved energy detector in Cognitive Radio network. International Conference on Computer Information Systems and Industrial Applications, Yunnan Minzu University, pp 87-93. doi: 10.2991/cisia-15.2015.23.

Gevira, O. O. (2016). Design of an optimal eigen value-based spectrum sensing algorithm for Cognitive Radio, Master thesis submitted to University of Nairobi, pp 12-47.

Haykin, S. (2005). Cognitive Radio Brain-Empowered Wireless Communications, *IEEE Journal on Selected Area in Communication* 3(23): 201-210.

Jayanta, M.; K.B. Deepak and K.S. Manoj. (2014). Cyclostationary Based Spectrum Sensing in Cognitive Radio: Windowing Approach. International Journal of Recent Technology and Engineering, **3**(1): 95-99. doi: 10.1049/ic:20080398.

Jingwen, T.; J. Ming; G. Qinghua and L. Youming. (2018). Cooperative Spectrum Sensing: a blind and Soft Fusion Detector. IEEE Transactions on Wireless Communications, 17(4):27262737. doi: 10.1109/TWC.2018.2801833.

Josip, L.; R. Ivana and B. Dinko. (2022). Analysis of the Impact of Detection Threshold Adjustments and Noise Uncertainty on Energy Detection Performance in MIMO-OFDM Cognitive Radio Systems. MDPI: Sensors 2022, pp 1-29. doi.org/10.3390/s22020631.

Komal, P. and Tanuja D. (2016). Review on: spectrum sensing in Cognitive Radio using multiple antenna. International Journal of Innovative Science, Engineering and Technology 3(4):313-318. doi:10.1155/2010/381465.

Meenakshi, S.; C. Prakash and S. Nityananda. (2016). A brief review of cooperative spectrum sensing: issues and challenges. IEEE Transaction on Wireless Communication 16(3):1-4. doi:10.1109/ICADW.2016.7942523.

Mohsin, A. and Haewoon, N. (2019). Optimization of spectrum utilization on cooperative spectrum sensing. Journal of sensor network **19**(8): 1-13. doi: 10.3390/s19081922.

Nikhil, A. and Rita M. (2017). Cooperative spectrum sensing using hard-soft decision fusion scheme. International Journal of open Information Technologies **5**(5):36-39. doi: 10.1109/IACC.2017.0057.

Noor, S. (2017). Combined soft hard cooperative spectrum sensing in Cognitive Radio networks. Ph.D dissertations submitted to University of Windsor, pp 1-79. doi: 10.1109/T-WC.2008.070941.

Ojo, S. I.; Z. K. Adeyemo; D. O. Akande and A. O. Fawole. (2021a). Energy-Efficient Cluster-Based Cooperative Spectrum Sensing in a Multiple Antenna Cognitive Radio Network. International Journal of Electrical and Electronic Engineering & Telecommunications, 10(3):176-186. doi: 10.18178/ijeetc.

Ojo S. I.; Z. K. Adeyemo; F. K. Ojo; A. A. Adedeji and F. A. Semire. (2020). Enhancement of Equal Gain Combiner for Detection of Spectrum Hole in a Cognitive Radio System. Universal Journal of Electrical and Electronic Engineering 7(5):289-298. doi: 10.13189/ujeee.2020.070503.

Ojo, S. I; Z. K. Adeyemo; R. O. Omowaiye and O.O Oyedokun. (2021b). Autocorrelation Based White Space Detection in Energy Harvesting Cognitive Radio Network. Indonesian Journal of Electrical Engineering and Informatics 9 (4):834-845. doi: 10.52549/ijeei.v9i4.3179.

Ojo, F.K. and Fagbola, F.A., (2015). Spectrum Sharing in Cognitive Radio Work Using Good put Mathematical Model for Perfect Sensing, Zero Interference and Imperfect Sensing Non-Zero interference, *international Journal of Wireless Communication and Mobile Computing,* 3(6): 58-59.

Pawel, S.; M. Krzysztof and T. Jerzy. (2022). Cognitive Radio Networks for Urban Areas, Building the Electromagnetic Situation Awareness in MANET. MDPI: Sensors 2022, PP 1-19. doi: 10.3390/s22030716.

Runze, W.; D. Lixin; X. Naixue; S. Wanneng and Y. Li (2019). Dynamic Dual Threshold Cooperative Spectrum Sensing for Cognitive Radio Under Noise Power Uncertainty. International Journal of Computing and Information Science, 22(9): 2-18. doi.org/10.1186/s13673-019-0181-x.

Samrat, C. S. and Ajitsinh, N. J. (2016). Centralized cooperative spectrum sensing with energy detection in Cognitive Radio and optimization. IEEE International Conference on Recent Trends in Electronics Information Communication Technology, India, PP 1002-1006. doi: 10.1109/RTEICT.2016.7807980.

Saeid, S.; T. Abbas and S. Joseph. (2013). Spectrum Sensing Using Correlated Receiving Multiple Antennas in Cognitive Radio. IEEE Transactions on Wireless Communications, 12(11):57555758. doi: 10.1109/TWC.2013.100213.130158.

Shraddha, E. J.; E. P. Deepak and E. S. Pawan. (2018). Eigen value Detection for Spectrum Sensing in Cognitive Radio Network over Nakagami Fading Channel. International Journal of Advanced Research in Electronics and Communication Engineering**,** 7(6): 1-4. doi: 10.1109/TCOMM.2009.06.070402.

Syed S. A.; L. Chang; L. Jialong; J. Minglu and M. K. Jae. (2016). On the Eigenvalue Based Detection for Multi-Antenna Cognitive Radio System. International Journal of Mobile Information Systems 5(3):18.doi.org/10.1155/2016/3848734.

Yang, L.; Z. Zhangdui; W. Gongpu and H. Dan. (2015). Cyclostationary Detection Based Spectrum Sensing for Cognitive Radio Networks. International Journal of Communications, 10(1):74-8. doi.org/10.1155/2022/7941978.

Yashaswini, S.; S. Ritu and K. K. Sharma. (2022). Optimization of inter fusion rule threshold for energy efficient in a cluster based CSS over Nakagami and Rician fading channels. International Journal of Electronics: Taylors and Francis, pp 1-6. doi.org/10.1080/00207217.2022.2117853.