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Research article

Cyclostationary and energy detection spectrum sensing beyond 5G waveforms

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Abstract: The cyclostationary spectrum (CS) method is one of the best at what it does because it effectively detects idle spectrum with low signal-to-noise ratios (SNR). In order to distinguish the signal in a noisy environment, gather more data that aids in a better analysis of signals, and use spectral correlation for dependable framework modelling, CS achieves optimal performance characteristics. High intricacy is seen as one of the CS's shortcomings. In this article, we suggest a novel CS algorithm for 5G waveforms. By restricting the computation of cyclostationary characteristics and the signal autocorrelation, the complexity of CS is reduced. To evaluate the performance of 5G waveforms, the Energy Detection (ED) and CS spectrum sensing algorithms based on cognitive radio (CR) are presented. The results of the study show that the suggested CS algorithm did a good job of detection and gained 2 dB compared to the conventional standards.

Keywords: cyclostationary; fifth generation; 5G; 6G; cognitive radio; CR; spectrum sensing

1. Introduction

The exponential increase in wireless applications with better quality of service (QoS) in the B5G radio system will demand a rigorous prerequisite, apart from low latency and the ability to handle massive devices and enhance mobile broadband. The requirements of the different sectors will be different and require complex technology to accomplish them. Hence, there will be more challenges to deploying a B5G radio network. There are advanced methods such as m-wave, M-MIMO and reconfigurable intelligent systems (RIS), which can be integrated with B5G to enhance the QoS. The utilization of RIS in M-MIMO will perform accurate analysis of the users with low power consumption and high spectral efficiency, and also reduce the complexity as no A/Ds are required [1]. It is also seen that the channel state information will play an important role in MIMO, and it will become more complex for the single antenna user equipment [2]. The authors in [3] proposed a novel algorithm that can efficiently determine the channel state of the framework with minimal complexity. The utilization of the cellular framework has been tremendously increasing, but the availability of the spectrum is becoming more and more congested. Hence, it is important to explore the new spectrum band. The congestion in the spectrum is also due to the static spectrum sharing regulation of the Federal Communication Commission (FCC) [4]. It is observed that the spectrum is not utilized in an efficient manner, and more than 70% of the spectrum is wasted [5]. The spectrum remains idle in many applications; it is not accessed 24/7 by the users. The idle spectrum cannot be shared with other devices. The low spectral access of the bandwidth can be solved by using cognitive radio (CR) [6]. CR is based on the spectrum sensing (SS) algorithms, which can identify idle bandwidth and allocate the idle spectrum to other devices and subscribers. The CR detects the spectrum from primary users (Pu), also known as licensed users, and shares the spectrum with the secondary user (Su), also known as an unlicensed user [7]. The allocation of spectrum from Pu to Su should take place without any interference, and the quality of service (QoS) should not be compromised. In order to identify idle bandwidth, the Pu should be continuously monitored and analyzed [8]. In the latest decade, it has been seen that CR-based spectrum sensing algorithms such as energy detection (ED) [9], matched filter detection (MF) [10] and cyclostationary detection (CS) [11] have been comprehensively investigated. The primary task of the SS algorithm is to locate idle spectrum. The idle spectrum is identified by estimating the energy of the device and comparing it with a predefined threshold value. If the energy of the device is greater than or equal to the defined threshold, it indicates the availability of the spectrum, and vice versa [12]. In the conventional SS algorithms, the sharing of spectrum from PU to Su takes place in the absence of the Pu. If Pu becomes active, then the spectrum should be reallocated to the Pu user, and Su should also get the spectrum from any idle Pu to continue its applications. Spectrum sensing is the process of identifying the existence or absence of Pu in a certain frequency group. In GSM (Global System for Mobile Communications), spectrum sensing is a crucial aspect of cognitive radio technology, which enables SU to use the frequency when it is not being used by PU. Random sampling is one approach used for spectrum sensing in GSM. In this approach, a secondary user randomly samples the conventional signal and equates it with the threshold to detect the presence or absence of primary users. Random sampling is a simple and effective technique, but it can be affected by noise and fading, which can lead to false alarms or missed detections [13]. Intelligent agent (IA) approaches have been proposed to address the limitations of random sampling. IA-based spectrum sensing uses autonomous agents that can learn from the environment and adapt to changing conditions. The agents can gather information about the spectrum usage patterns and make decisions based on that information. IA-based approaches can improve spectrum sensing performance by reducing false alarms and missed detections [14]. Modeling cognitive radio in GSM scenarios using Petri nets could involve developing a Petri net model that captures the dynamic behavior of the cognitive radio system as it interacts with the GSM network. This could involve exhibiting cognitive radio's sensing and decision-making processes, as well as its interactions with the GSM network's control channels and radio resources. Overall, cognitive radio has the ability to enhance the proficiency and reliability of wireless communication structures. Using Petri nets to model these systems can help researchers better understand the complex dynamics involved and identify opportunities for optimization and improvement [15]. The authors in [16] proposed a hybrid spectrum sensing technique that combines random sampling with a Q-learning algorithm to improve the performance of spectrum sensing in noisy environments. The Q-learning algorithm is used to learn the optimal sampling rate and threshold level for spectrum sensing. The signal was sampled using both homogeneous and random sampling, then it was rebuilt. The article in [17] used a synthetically generated signal to evaluate its condition in the GSM channel. At various SNRs, the outcomes in regards to detection curves are demonstrated. In [18], a Petri net-based model for cognitive radio networks is designed, which includes both the Cr and the PU. The model is then used to evaluate the efficiency of the Cr network in terms of throughput and delay. The authors in [19] designed a colored Petri net-based model for Cr with several Su. The model is used to evaluate the efficiency of the Cr in terms of throughput and collision probability. In [20], Petri net-Cr is implemented to study the spectral performance of the framework. The proposed framework contains both the Cr and the Pu. The simulation outcomes of the work reveal that the proposed algorithm obtained enhanced spectral efficiency with no interference between the users. Due to the high adaptability of the conceptual scheme, additional frameworks are explored for various PU and SU functions under different circumstances. The authors in [21] projected a Petri-Net-centered framework to improve the efficiency of the Su functioning in GSM-900. Further, the framework also decreases the interference between PU and SU. In [22], the dynamic threshold detection-based ED is implemented to enhance the spectral efficiency of the system. In two stages, the ED algorithm, also known as the "double stage ED algorithm", identifies the spectrum. The threshold is set in the first stage by estimating the amount of noise in the signal, and in the second stage, Ed is used to detect the idle spectrum. The numerical outcomes confirmed that the presented Ed performed better than the conventional Ed. The authors designed a novel Ed algorithm to detect idle Pu [23]. The performance of the detector is enhanced by evaluating the effect of noise present in the signal in different scenarios. It is concluded that the presented Ed performed optimally in terms of detection. The authors in [24] designed and investigated the efficiency of ED on fading and non-fading channels. It is noted that the efficiency of Ed depends on the criterion of threshold selection. The simulation outcomes reveal that the choice of an optimal threshold gave the system a high detection performance. The performance of Ed is severely affected due to the unwanted presence of noise variance in the signal. In [25], the authors introduced an ED algorithm where the presence of noise is nullified. The outcome of the work reveals that the presented Ed outperforms the conventional Ed. In [26], the authors implemented a MF based on dynamic threshold selection. As the characteristics of noise are random in nature, it is clear that dynamic threshold selection is one of the most important tasks. The outcome of the work demonstrates that the proposed MF algorithm outperforms the prevailing MF algorithm. The authors in [27] introduced a hybrid algorithm based on the combination of Ed and MF. The experimental outcomes reveal that the presented algorithm successfully reduces the false alarm rate, thus enhancing the accurate detection performance of the MF algorithm. In [28], the article presented a complete description, analysis and use of the CR in cellular framework. The article also discussed the limitations of MF implementation in advanced radio. It is concluded that MF can play a significant role in the utilization of the spectrum in an advanced radio framework. In [29], the authors introduced a novel MF-SS algorithm for the OFDM waveform. The analysis of MF is computed by applying it to OFDM with and without the cyclic prefix (CP). The results show an improvement in Pd and Pfa parameters. The parallel technique-based CS algorithm is implemented to enhance the utilization of the white holes. It should be noted that the presented method outperformed existing standards by 92% [30]. In [31], the availability of Pu is identified by implementing a CS-SS for the FBMC and OFDM frameworks. The authors have considered an AWGN channel for the analysis of the projected CS-SS. When compared to conventional standards, the proposed algorithm obtained a gain of 2 to 3 dB. It is also noted that the use of pilot signals increases the complexity of the framework. In [32], it is seen that the combination of MIMO and OFDM frameworks enhances the throughput and spectrum access of the system. The simulation outcomes demonstrate enhanced detection and performance. In [33], the authors applied an Ed to the OFDM structure, and the different parameters such as Pd, Pfa and BER were estimated. When compared to conventional electric, the proposed work achieved a gain of 2 dB. In [34], the article presented a novel algorithm to enhance the detection performance of the Pu. The proposed algorithm, which is based on the genetic algorithm, improves the framework's throughput. The article in [35] presented a novel ED algorithm based on mean energy estimation. The experimental work demonstrates a gain of 30% as compared with the conventional ED-SS method. In [36], the authors designed a CS-SS algorithm for the generalized frequency division multiplexing (GFDM) waveform. GFDM is considered an ideal candidate for 5G radio. The proposed work detects an idle Pu at a low SNR as compared with the existing approaches. The presented article is based on the principle of PU and SU initial decoding strategies [37]. It is seen that the interference is reduced and detection is achieved at low SNR. In [38], it is noted that an optimal selection of threshold plays a major role in the detection process. The article presented a dynamic threshold-based ED-SS algorithm to identify idle users at low SNR. Finally, the introduction of dynamic threshold in ED-SS yielded a gain of 1 dB to 2 dB when compared to static threshold schemes. In Table 1, we discussed the advantages and disadvantages of the spectrum sensing algorithms.

The contributions of the article are given below:

- To the best of our knowledge and available literature, the advanced SS algorithms for FBMC and NOMA are presented for the first time.
- The different parameters such as BER, PD, PFA and PSD are estimated and compared with the multi-carrier-waveforms. It is noted that CS outperforms MF and ED.
- We proposed novel ED and CS algorithms based on dynamic threshold detection for the advanced waveforms. It is seen that the spectral efficiency of NOMA is better than that of OFDM and FBMC.

Table 1. Merits and demerits of the spectrum sensing algorithms.

S. No	Techniques	Remarks
1	Conventional ED	Easy and straightforward to apply. Results in interference When PU is not present, the spectrum is allocated to SUs. High required SNR. The detection duration is small. Low-power, durable detectors. Spectrum loss No advance channel information is necessary.
2	Convention CS	The algorithm intricacy is high Results in interference When PU is not present, the spectrum is allocated to SUs Low required SNR. The detection duration is high. Intermediate robust detectors It results in spectrum loss No advance channel information is necessary.
3	Conventional MF	The algorithm intricacy is high Results in interference When PU is not present, the spectrum is allocated to SUs Low required SNR. The detection of the signal is superior than the CS but not better tha the ED Average detectors are required It results in spectrum loss No advance channel information is necessary.
4	Proposed method	The proposed algorithm outperforms the conventional algorithm with low intricacy. The interference between users is reduce by using a SIC method. The detected spectrum is allocated to the SU in both availability and non-availability of PU. The proposed algorithms obtained a gain of 2 dB SNR as compared with the conventional methods. The signal is accurately determined based on dynamic threshold. The accessing of the spectrum is high. No advance channel state information is required.

2. Proposed system model

2.1. Energy Detection (ED)

The conventional ED-SS is based on the principle of static threshold selection. The primary aim of the ED is to identify the spectrum of Pu, which can be allocated to the Su [39]. The Pu spectrum is identified by estimating the predefined threshold and comparing it with the received energy signal of the framework [40]. The hypothesis for the estimation of the spectrum is given by:

$$h_0: z(n) = n_{o(n)} \tag{1}$$

$$h_1: z(n) = x(n) + n_{o(n)} \tag{2}$$

The Eqs (1) and (2) indicates the absence and presence of Pu. Where $z(n)$ is the received signal, $x(n)$ is the transmitted signal and $n_{o(n)}$ indicate the presence of noise in the signal.

The estimation of the threshold (E_{Th}) is given by:

$$E_{Th} = \sum_{n=1}^{M} (x[n])^2 \tag{3}$$

Further, the threshold for h_0 *and* h_1 is evaluated with mean (μ), noise variance (σ_{no}) and transmitted power signal σ_x, given by:

$$E_{Th} = M(M\ \sigma_{no}^2, 2\ \sigma_{no}^4)\ :\ h_0 \tag{4}$$

$$E_{Th} = M(M\ (\sigma_x^2 + \sigma_{no}^2, 2\ N(\sigma_x^2 + \sigma_{no}^2)^2): h_1 \tag{5}$$

According to Eqs (4) and (5), a signal is sometimes misrepresented as a detected signal, which is known as a false alarm (PFA). The Pd and Pfa are important characteristics to define the performance of ED, given by:

$$P_{fa} = Prob\ (E_{Th} > \lambda_{Th}): h_0 \tag{6}$$

$$P_d = Prob\ (E_{Th} > \lambda_{Th}): h_1 \tag{7}$$

Further, the Eqs (6) and (7) can be express as:

$$P_{fa} = Q(\frac{\lambda_{Th} - M\sigma_{no}^2}{\sqrt{2\sigma_{no}^4}}) \tag{8}$$

$$P_d = Q(\frac{M(\sigma_x^2 + \sigma_{no}^2)}{\sqrt{2N(\sigma_x^2 + \sigma_{no}^2)^2}}) \tag{9}$$

Where Q represent a gaussian function. Considering Eq (8), the threshold is given by:

$$\lambda_{Th} = \sigma_{no}^2(\frac{1}{Q}\left(P_{fa}\right)\sqrt{2M} + M) \tag{10}$$

The structure of ED is given in Figure 1.

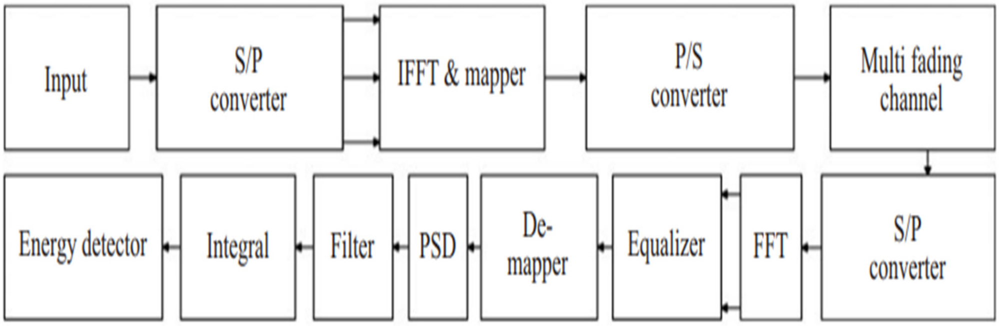

Figure 1. Structure of ED.

2.2. Cyclostationary (CS)

It is one of the most significant spectrum sensing algorithms that can be considered for advanced radio. The identification of spectrum at low SNR with independence from noise makes it a promising and effective algorithm. It exploits the periodicity properties of the signal by estimating the mean and autocorrelation of the signal. Another substantial characteristic of CS is the identification of Pu without a significant interference between Pu and Su. In recent years, the CS algorithm has been applied to detect the spectrum in various conditions [41]. The CS signals are estimated by utilizing the cyclic autocorrelation and spectrum correlation density functions. The first step in CS is to transform the signal into second-order CS by utilizing several operations such as sampling, filtering and encoding, defined as [42]:

$$E\{y(+)\} = E\{y(t+t_o)\} \tag{11}$$

$$R_y(t,\tau) = R_y(t+t_o,\tau) \tag{12}$$

From Eq (11), it is noted the signal is periodic in nature with fundamental period t_O. The Eq (12) can be expressed with the cyclic frequency (β):

$$R_y(t,\tau) = \sum_\beta R_x^\beta(\tau)\exp(i2\pi\beta t) \tag{13}$$

The Fourier coefficient of Eq (13) can be written as:

$$R_y^\beta(\tau) \triangleq \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_y(t,\tau)\,\tau)\exp(-i2\pi\beta t)\ dt \tag{14}$$

The $R_y^\beta(\tau)$ is represented as cyclic auto-corelation function at:

$$\beta = \{M/T_o\} \tag{15}$$

The spectral correlation density function of Eq (15) is estimated as:

$$S_y^\beta(f) \triangleq \lim_{T\to\infty}\int_{-\infty}^{\infty} R_y^\beta(t-\tau)\exp(-i2\pi\beta t) \tag{16}$$

3. Simulation results

We evaluated the performance of the CS and ED spectrum sensing algorithms for 5G and beyond waveforms in the proposed article. The computer simulation is used to estimate the performance of the CR algorithms. The parameters used in the simulation are listed in Table 2.

Table 2. Parameter used in computer simulation.

S. No	Parameters
1	Waveforms: OFDM, FBMC and NOMA
2	Spectrum Sensing Algorithms: ED, CS and MF
3	Channel: Rician
4	256-QAM
5	Samples: 500

The accurate detection capabilities of the cognitive radio are analyzed for the NOMA waveform shown in Figure 2. It is seen that the CS-SS method achieved a detection at -4.8 dB as compared with the 5 and 6.7 dB detection obtained by the MF and ED algorithms, respectively. So, we can say that the CS method is better than the MF and ED methods. This makes the NOMA a good 5G spectral access waveform.

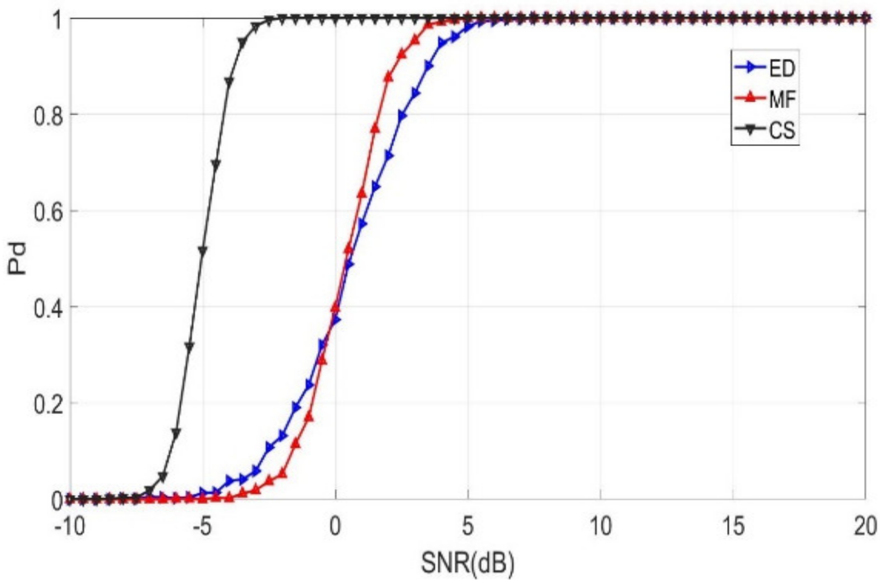

Figure 2. NOMA detection.

In Figure 3, the detection of signal characteristics is analyzed for the OFDM waveform. The CS achieved a detection at an SNR of 5.1 dB, compared to the MF's 6.3 dB and the ED's 10.1 dB. Hence, it is concluded that the CS obtained a gain of 1.2 and 5 dB as compared with the MF and ED.

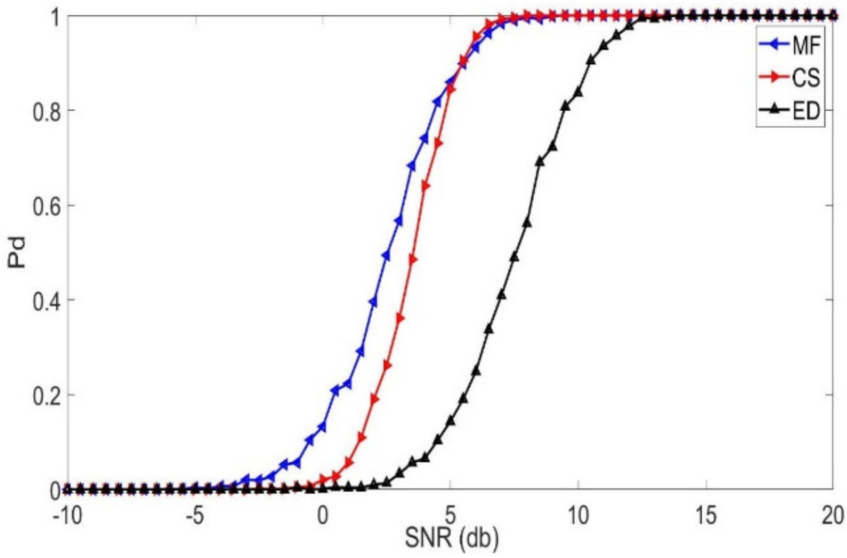

Figure 3. OFDM detection.

The detection performance of the SS algorithm for FBMC is given in Figure 4. The CS algorithm obtained a detection at an SNR of 4.1 dB as compared with 5.2 dB (MF) and 10.1 dB (ED). Hence, CS outperforms the MF and ED by the gains of 1.1 and 6 dB, respectively, as compared with the MF and ED.

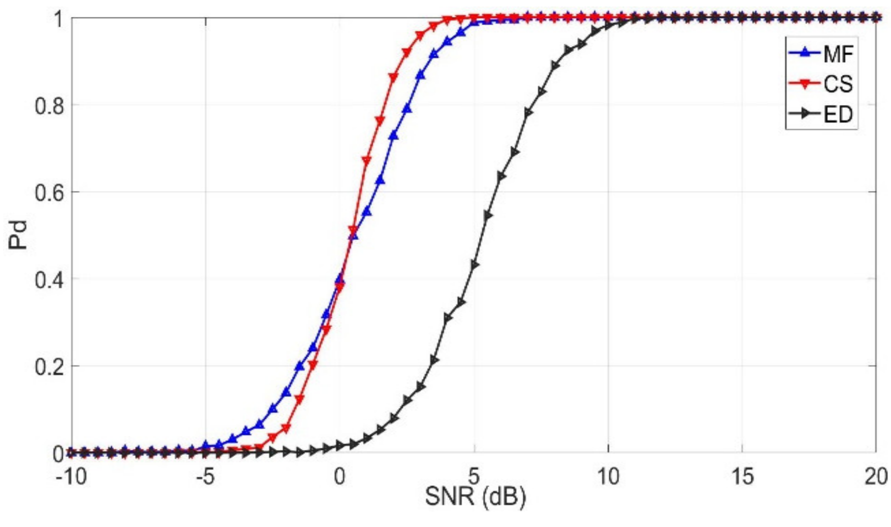

Figure 4. FBMC detection.

In Figures 2–4, it is seen that the CS obtained the best performance for OFDM, FBMC and NOMA waveforms. The CS also offers effective performance in noisy environments as compared with the existing SS algorithms. The primary objective of the CR is to detect the presence of an idle spectrum in an efficient manner. However, the noise is sometimes detected as a signal, which is referred to as PFA. In this work, we have evaluated the performance of SS algorithms under false alarm conditions. The performance of false alarms for the OFDM waveform is given in Figure 5. The pd and Pfa are estimated by determining the presence or absence of the signal for different threshold values. It is seen that ED misrepresents noise as the signal at an early stage (pfa = 0.4 and Pd = 1). In the same scenario, however, MF and CS detected at pfa = 0.2 and 0.1, respectively. Hence, it is concluded that CS gave a robust performance as compared with the prevailing standard.

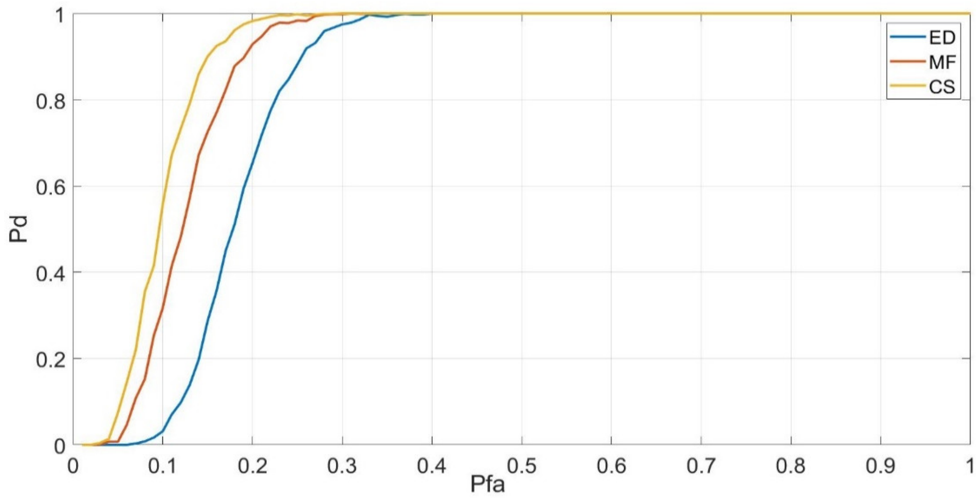

Figure 5. OFDM-PFA.

In Figure 6, it is seen that the CS is detecting the idle spectrum at a higher Pfa as compared with the MF and ED for the FBMC waveform. For the MF, ED and CS, the Pd is 1 for different values of Pfa. However, the MF and CS show a similar characteristic, which is better than the ED method. Hence, it is concluded that the detection of signal performance is gracefully degraded for the ED scheme.

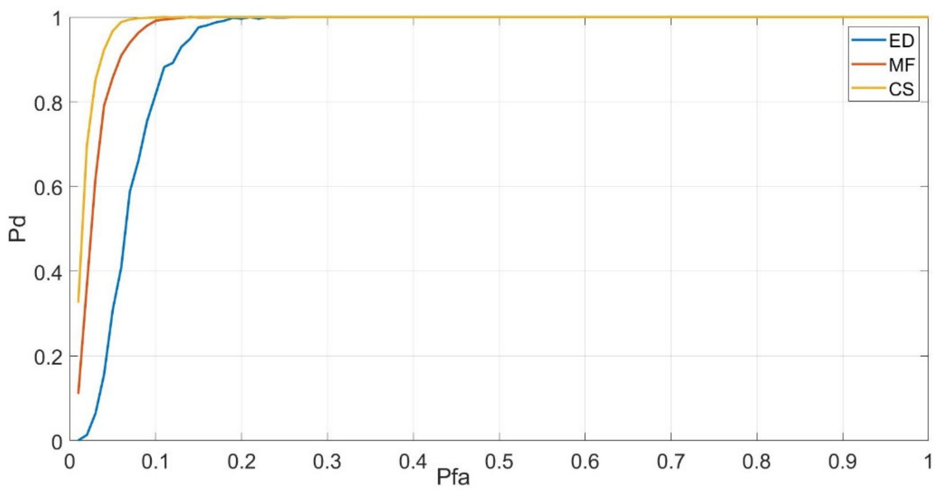

Figure 6. FBMC PFA.

The characteristics of the false alarm for the NOMA are given in Figure 7. It is seen that the noise is easily misrepresented as a signal for the ED method. The CS and MF performances, on the other hand, are stable and efficient. It is concluded that the probability of a signal being missed in CS and

MF is low when compared to current standards. It is noted that when the Pd is 1, the signal is detected, and when the Pfa is 1, the noise is misrepresented as a signal. Hence, it is noted that the CS and MF for NOMA and FBMC gave an approximately similar detection performance for different PFAs, outperforming the OFDM system.

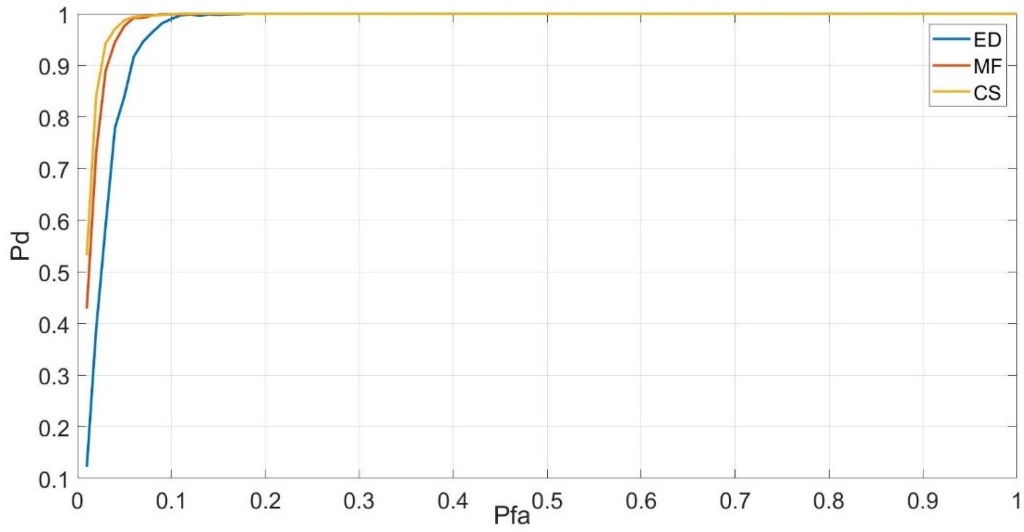

Figure 7. NOMA PFA.

It is important to analyze the throughput of the system for spectrum sensing techniques. The BER curves for the NOMA are given in Figure 8. The BER of 10^{-3} is obtained at SNRs of 2.8 dB for CS, 3.3 dB for MF and 6 dB for ED. It is seen that the CS algorithm enhances the throughput of the system and obtains a gain of 0.5 and 3.2 dB for a BER of 10^{-3} as compared with the MF and ED.

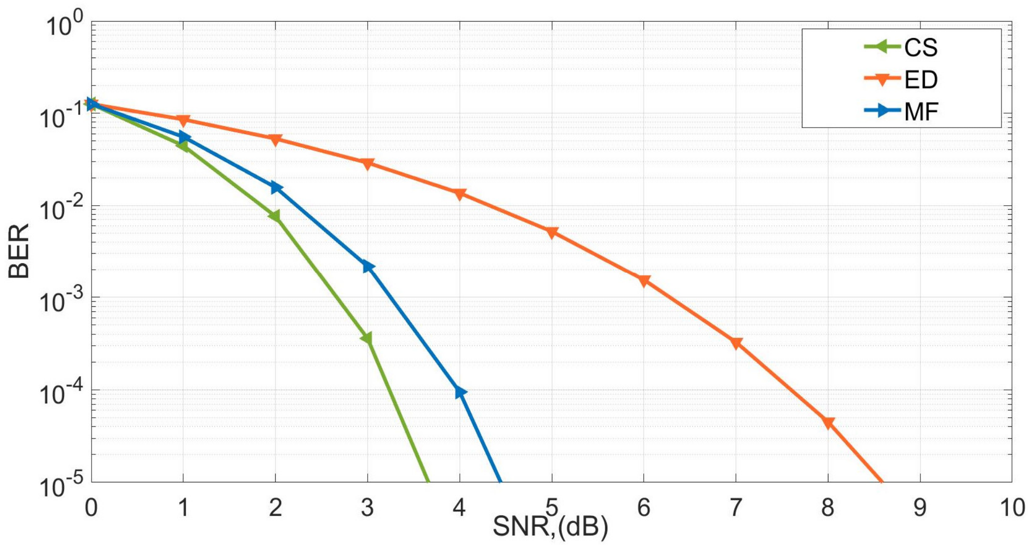

Figure 8. BER of NOMA.

The BER curves for the FBMC are evaluated in Figure 9. The BER of 10^{-3} is obtained at an SNR of 3.8 dB for CS, 4.2 dB for MF and 7 dB for ED. CS performed admirably, achieving gains of 0.4 and 3.2 decibels. Hence, it is concluded that CS outperforms the MF and ED methods.

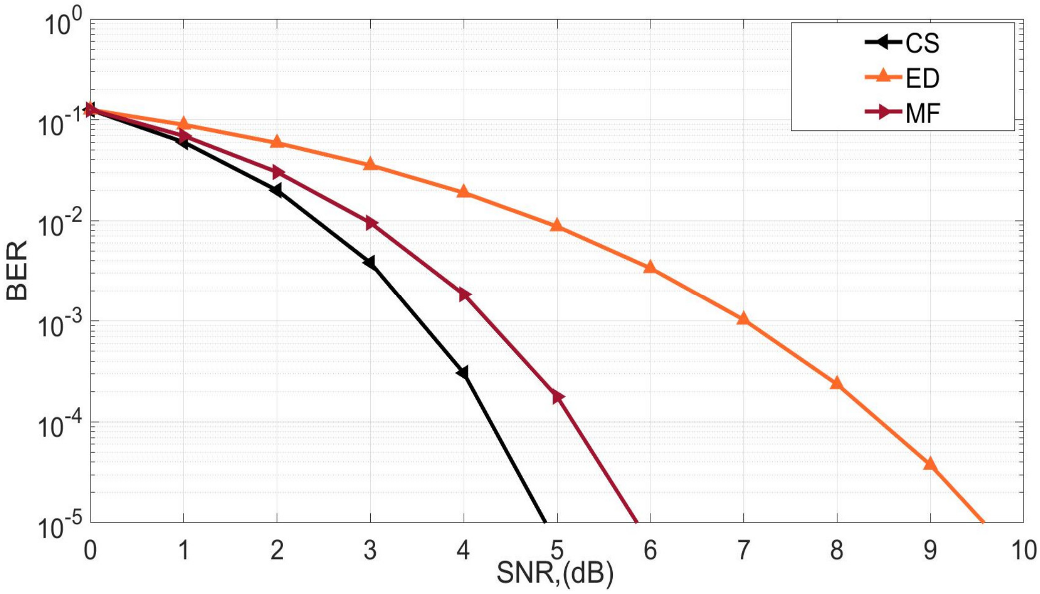

Figure 9. BER of FBMC.

The BER of OFDM is given in Figure 10. It is noted that CS, MF and ED obtained a BER of 10^{-3}, respectively. At SNRs of 5, 6.1 and 9 dB. Hence, it is noted that the CS outperforms the prevailing standard by obtaining a gain of 1.1 and 4 dB.

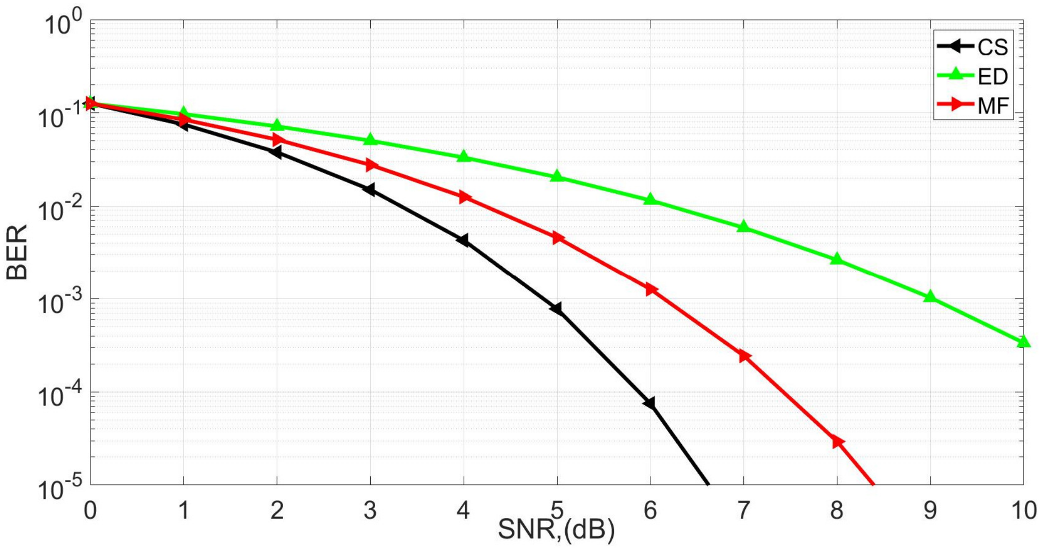

Figure 10. BER of OFDM.

The BER characteristics of OFDM, FBMC and NOMA indicate that the performance of the CS is better than the MF and ED algorithms. It is also noted that the performance of MF is very close to that of CS, obtaining a gain approximately equivalent to CS in most of the cases. It is also concluded that the NOMA is most compatible with the SS algorithms as compared with the FBMC and OFDM.

In Figure 11, we have analyzed the performance of PSD for the OFDM, FBMC and NOMA. It is seen that the bandwidth leakage of OFDM is -100, FBMC is -79 and NOMA is -150. As a result, when compared to the FMBC and OFDM waveforms, NOMA obtained an efficient spectral access.

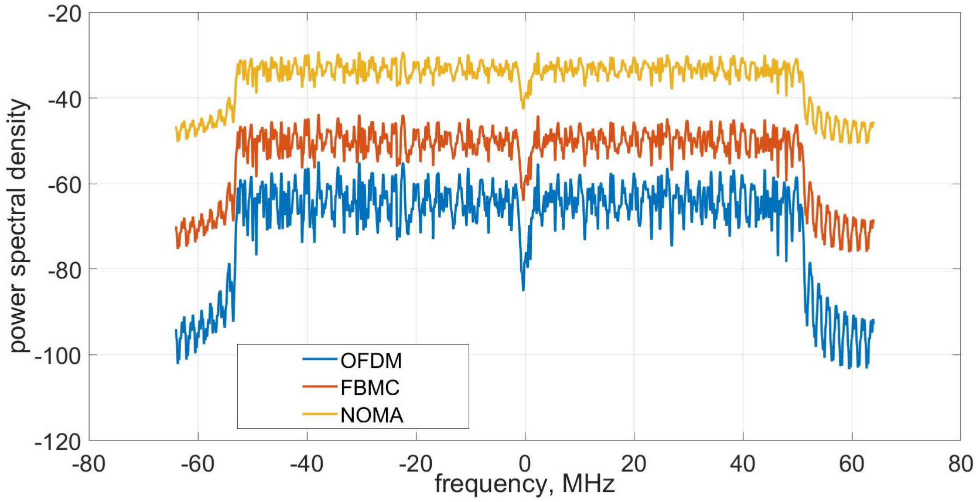

Figure 11. PSD performance.

In this part, the computational complexity of the sensing techniques is given in Figure 12. The complexity is the quantity of operations—like addition and multiplication—necessary to get the best possible detection. The proposed algorithm, ED, MF and CS complexity in the work provided is given by NM, $2KN$, $2Nn(k+1+n)$ and $2Nn(2k+Nn-1)$ respectively.

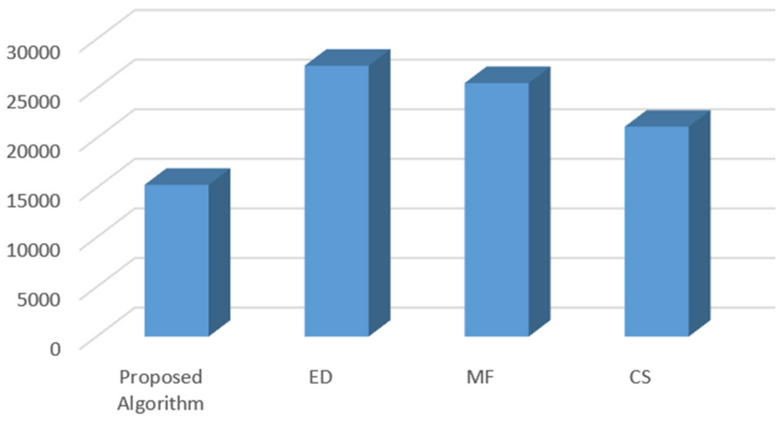

Figure 12. Complexity.

4. Conclusions

In this work, we presented a CS algorithm for waveforms used in 5G and beyond, including NOMA, FBMC and OFDM. By applying CS, MF and ED algorithms to the 5G waveforms, metrics including Pd, Pfa, BER and PSD are assessed and comprehensively analyzed. The static results from the Matlab-2016 simulation on the Rayleigh channel are shown to assess how well the Cr algorithms perform for various multi-carrier waveforms. The proposed CS, MF and ED obtained a detection at an SNR of 5.1, 6.3 and 10.1 dB respectively. It is noted that the CS achieved a gain of 1.2 and 5 dB as compared with the MF and ED. Further, it is seen that the intricacy of the proposed algorithm is lower than that of the ED and MF. The proposed CS had good detection and throughput performance even at low SNR. It is noted that the proposed CS outperforms the conventional spectrum sensing algorithms. Further, in the future, the proposed algorithm can be used for spectrum sensing in channels with non-flat characteristics.

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Conflict of interest

The authors declare there is no conflict of interest.

References

1. M. H. Alsharif, M. S. Hossain, A. Jahid, M. A. Khan, B. J. Choi, S. M. Mostafa, Milestones of wireless communication networks and technology prospect of next generation (6G), *Comput. Mater. Continua*, **71** (2022), 4803–4818. https://doi.org/10.32604/cmc.2022.023500
2. A. Fascista, A. De Monte, A. Coluccia, H. Wymeersch, G. Seco-Granados, Low-complexity downlink channel estimation in mmWave multiple-input single-output systems, *IEEE Wireless Commun. Lett.*, **11** (2021), 518–522. https://doi.org/10.1109/LWC.2021.3134826
3. N. Garcia, A. Fascista, A. Coluccia, H. Wymeersch, C. Aydogdu, R. Mendrzik, et al., Cramér-Rao bound analysis of radars for extended vehicular targets with known and unknown shape, *IEEE Trans. Signal Process.*, **70** (2022), 3280–3295. https://doi.org/10.1109/TSP.2022.3183853
4. P. Cai, Y. Zhang, Intelligent cognitive spectrum collaboration: convergence of spectrum sensing, spectrum access, and coding technology, *Intell. Converged Networks*, **1** (2020), 79–98. https://doi.org/10.23919/ICN.2020.0006
5. A. Kumara, M. Gupta, A review on activities of fifth generation mobile communication system, *Alexandria Eng. J.*, **57** (2018), 1125–1135. https://doi.org/10.1016/j.aej.2017.01.043
6. A. Ali, W. Hamouda, Advances on spectrum sensing for cognitive radio networks: theory and applications, *IEEE Commun. Surv. Tutorials*, **19** (2017), 1277–1304. https://doi.org/10.1109/COMST.2016.2631080
7. S. Li, S. Xiao, M. Zhang, X. Zhang, Power saving and improving the throughput of spectrum sharing in wideband cognitive radio networks, *J. Commun. Networks*, **17** (2015), 394–405. https://doi.org/10.1109/JCN.2015.000070
8. J. Zhang, L. Liu, M. Liu, Y. Yi, Q. Yang, F. Gong, MIMO spectrum sensing for cognitive radio-based internet of things, *IEEE Internet Things J.*, **7** (2020), 8874–8885. https://doi.org/10.1109/JIOT.2020.2997707

9. L. Arienzo, D. Tarchi, Statistical modeling of spectrum sensing energy in multi-hop cognitive radio networks, *IEEE Signal Process Lett.*, **22** (2015), 356–360. https://doi.org/10.1109/LSP.2014.2360234
10. A. Brito, P. Sebastião, F. J. Velez, Hybrid matched filter detection spectrum sensing, *IEEE Access*, **9** (2021), 165504–165516. https://doi.org/10.1109/ACCESS.2021.3134796
11. A. Bollig, A. Lavrenko, M. Arts, R. Mathar, Compressive cyclostationary spectrum sensing with a constant false alarm rate, *EURASIP J. Wireless Commun. Networking*, **2017** (2017), 135. https://doi.org/10.1186/s13638-017-0920-5
12. A. Kumar, M. K. Sharma, K. Sengar, S. Kumar, NOMA based CR for QAM-64 and QAM-256, *Egypt. Inf. J.*, **21** (2020), 67–71. https://doi.org/10.1016/j.eij.2019.10.004
13. A. Maali, H. Semlali, S. Laafar, N. Boumaaz, A. Soulmani, Effect of random sampling on spectrum sensing for cognitive radio networks, *TELKOMNIKA Telecommun. Comput. Electron. Control*, **19** (2021), 1137–1144. https://doi.org/10.12928/telkomnika.v19i4.20399
14. S. Yalcin, An artificial intelligence-based spectrum sensing methodology for LoRa and cognitive radio networks, *Int. J. Commun. Syst.*, **36** (2023) e5433. https://doi.org/10.1002/dac.5433
15. U. Mir, L. Merghem-Boulahia, D. Gaïti, Multiagent based spectrum sharing using petri nets, in *Trends in Practical Applications of Agents and Multiagent Systems*, (2010), 537–546. https://doi.org/10.1007/978-3-642-12433-4_63
16. Z. Chen, R. C. Qiu, Cooperative spectrum sensing using Q-learning with experimental validation, in *2011 Proceedings of IEEE Southeastcon*, (2011), 405–408. https://doi.org/10.1109/SECON.2011.5752975
17. S. Serrano, M. Scarpa, A. Maali, A. Soulmani, N. Boumaaz, Random sampling for effective spectrum sensing in cognitive radio time slotted environment, *Phys. Commun.*, **49** (2021), 101482. https://doi.org/10.1016/j.phycom.2021.101482
18. C. Spiegel, A. Viessmann, A. Burnic, C. Kocks, A. Waadt, E. Scheiber, et al., A petri nets based design of cognitive radios using distributed signal processing, *Procedia Earth Planet. Sci.*, **1** (2009), 1474–1479. https://doi.org/10.1016/j.proeps.2009.09.227
19. D. Boukredera, K. Adel-Aissanou, Modeling and performance analysis of cognitive radio networks using stochastic timed colored petri nets, *Wireless Pers. Commun.*, **112** (2020), 1659–1687. https://doi.org/10.1007/s11277-020-07121-8
20. A. Viessmann, A. Burnic, C. Spiegel, G. H. Bruck, P. Jung, Petri net based controller concept for cognitive radios in wireless access networks, *J. Commun.*, **2** (2007), 29–38. Available from: http://www.jocm.us/uploadfile/2013/0927/20130927023542527.pdf.
21. M. Scarpa, S. Serrano, A full Secondary User model for Cognitive Radio in a GSM-900 scenario, in *2019 International Conference on Computing, Networking and Communications (ICNC)*, (2019), 344–349. https://doi.org/10.1109/ICCNC.2019.8685497
22. X. Zhang, Y. Ma, Y. Gao, W. Zhang, Autonomous compressive-sensing-augmented spectrum sensing, *IEEE Trans. Veh. Technol.*, **67** (2018), 6970–6980. https://doi.org/10.1109/TVT.2018.2822776
23. D. M. M. Plataa, Á. G. A. Reátiga, Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold, *Procedia Eng.*, **35** (2012), 135–143. https://doi.org/10.1016/j.proeng.2012.04.174

24. Y. Arjoune, Z. E. Mrabet, H. E. Ghazi, A. Tamtaoui, Spectrum sensing: enhanced energy detection technique based on noise measurement, in *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, (2018), 828–834. https://doi.org/10.1109/CCWC.2018.8301619
25. K. kockaya, I. Develi, Spectrum sensing in cognitive radio networks: threshold optimization and analysis, *EURASIP J. Wireless Commun. Networking*, **2020** (2020), 255. https://doi.org/10.1186/s13638-020-01870-7
26. J. Luo, G. Zhang, C. Yan, An energy detection-based spectrum-sensing method for cognitive radio, *Wireless Commun. Mobile Comput.*, **2022** (2022), 3933336. https://doi.org/10.1155/2022/3933336
27. F. Salahdine, H. E. Ghazi, N. Kaabouch, W. F. Fihri, Matched filter detection with dynamic threshold for cognitive radio networks, in *2015 International Conference on Wireless Networks and Mobile Communications (WINCOM)*, (2015), 1–6. https://doi.org/10.1109/WINCOM.2015.7381345
28. G. Alnwaimia, H. Boujemaab, Enhanced spectrum sensing using a combination of energy detector, matched filter and cyclic prefix, *Digital Commun. Networks*, **6** (2020), 534–541. https://doi.org/10.1016/j.dcan.2019.08.009
29. Y. Arjoune, N. Kaabouch, A comprehensive survey on spectrum sensing in cognitive radio networks: recent advances, new challenges, and future research directions, *Sensors*, **19** (2019), 126. https://doi.org/10.3390/s19010126
30. A. Kumar, P. NandhaKumar, OFDM system with cyclostationary feature detection spectrum sensing, *ICT Express*, **5** (2019), 21–25. https://doi.org/10.1016/j.icte.2018.01.007
31. A. D. L. Lima, L. F. Q. Silveiraa, S. Xavier-de-Souzaa, Spectrum sensing with a parallel algorithm for cyclostationary feature extraction, *Comput. Electr. Eng.* , **71** (2018), 151–161. https://doi.org/10.1016/j.compeleceng.2018.07.016
32. M. K. Al-Haddad, H. T. Ziboon, Cyclostationary feature detection scheme for FBMC and OFDM cognitive radio, *Int. J. Intell. Eng. Syst.*, **13** (2020), 399–407. https://doi.org/10.22266/ijies2020.0831.35
33. J. Lorincz, I. Ramljak, D. Begusic, Algorithm for evaluating energy detection spectrum sensing performance of cognitive radio MIMO-OFDM systems, *Sensors*, **21** (2021), 6881. https://doi.org/10.3390/s21206881
34. P. Nandhakumar, A. Kumar, Analysis of OFDM system with energy detection spectrum sensing, *Indian J. Sci. Technol.*, **9** (2016), 1–6.
35. K. Danesh, S. Vasuhi, An effective spectrum sensing in cognitive radio networks using improved convolution neural network by glow worm swarm algorithm, *Trans. Emerging Telecommun. Technol.*, **32** (2021), e4328. https://doi.org/10.1002/ett.4328
36. C. Vlădeanu, O. M. K. Al-Dulaimi, A. Marţian, A modified double-threshold spectrum sensing algorithm based on adaptive-threshold mean energy detection, in *2021 International Symposium on Signals, Circuits and Systems (ISSCS)*, (2021), 1–4. https://doi.org/10.1109/ISSCS52333.2021.9497419
37. N. A. El-Alfi, H. M. Abdel-Atty, M. A. Mohamed, Sub-Nyquist cyclostationary detection of GFDM for wideband spectrum sensing, *IEEE Access*, **7** (2019), 86403–86411. https://doi.org/10.1109/ACCESS.2019.2925047

38. C. B. Barneto, T. Riihonen, M. Turunen, L. Anttila, M. Fleischer, K. Stadius, et al., Full-duplex OFDM radar with LTE and 5G NR waveforms: challenges, solutions, and measurements, *IEEE Trans. Microwave Theory Tech.*, **67** (2019), 4042–4054. https://doi.org/10.1109/TMTT.2019.2930510
39. S. A. Mousavifar, C. Leung, Energy efficient collaborative spectrum sensing based on trust management in cognitive radio networks, *IEEE Trans. Wireless Commun.*, **14** (2014), 1927–1939. https://doi.org/10.1109/TWC.2014.2377017
40. A. Martian, M. J. A. Al Sammarraie, C. Vlădeanu, D. C. Popescu, Three-event energy detection with adaptive threshold for spectrum sensing in cognitive radio systems, *Sensors*, **20** (2020), 3614. https://doi.org/10.3390/s20133614
41. J. Wang, R. Gao, D. Ye, Z. Zhang, Blind detection of cyclostationary signals based on multi-antenna beamforming technology, *IET Commun.*, **15** (2021), 2439–2447. https://doi.org/10.1049/cmu2.12282
42. A. Bagwari, G. S. Tomar, S. Verma, Cooperative spectrum sensing based on two-stage detectors with multiple energy detectors and adaptive double threshold in cognitive radio networks, *Can. J. Electr. Comput. Eng.*, **36** (2014), 172–180. https://doi.org/10.1109/CJECE.2014.2303519