Telecommunication Systems (2024) 85:347–363
https://doi.org/10.1007/s11235-023-01079-1

A review of spectrum sensing in modern cognitive radio networks

Muhammad Umair Muzaffar[1] · Rula Sharqi[1]

Accepted: 5 November 2023 / Published online: 24 November 2023

Abstract

Cognitive radio network (CRN) is a pioneering technology that was developed to improve efficiency in spectrum utilization. It provides the secondary users with the privilege to transmit on the licensed parts of the spectrum if the licensed user is not utilizing it. The cognitive radio must, however, relinquish the spectrum when the primary user decides to reoccupy it. By exploiting the unused portion of the spectrum, a cognitive radio helps in making the use of the radio spectrum more efficient. Furthermore, the most important capability that a cognitive radio (CR) must possess is spectrum sensing. A CR must be able to correctly determine the status of the target spectrum with the help of spectrum sensing. This is a very challenging task and several methods have been investigated over the years. In this work, the state of the art of different spectrum sensing techniques for a variety of CRNs is presented. Both conventional and modern spectrum sensing techniques for different types of primary user signals are discussed in this work for Narrowband and Wideband signals. Legacy techniques such as energy detection are most commonly used due to their simplicity in implementation. However, this comes at the cost of poor performance at low SNR (signal-to-noise ratio) values. This issue is countered by methods that use statistical information of the primary signal to make a more informed decision on spectrum occupancy. Several techniques that make use of the power of machine learning algorithms are also discussed which show clear improvement in performance. The primary challenge in such techniques is selection of the best features. The most commonly used features are also discussed. Furthermore, spectrum sensing techniques that consider the 5G signal as the primary user signal of the network are discussed. It is observed that there is a significant need for research in additional spectrum sensing techniques for 5G cognitive radio networks.

Keywords Cognitive radio · Spectrum sensing · Machine learning · 5G communication

1 Introduction

The finite resource of the electromagnetic spectrum is facing the problem of scarcity with the advent of modern communication tools and devices. The introduction of more accessible and faster communication platforms has further resulted in many users competing to gain access to this precious resource. This has caused a shortage of available frequency slots for users to access which has led to the demand of a new technology that could help overcome this spectrum occupancy problem and allow several users to access the spectrum.

✉ Muhammad Umair Muzaffar
mm416@hw.ac.uk

Rula Sharqi
R.Sharqi@hw.ac.uk

1 School of Engineering and Physical Sciences, Heriot-Watt University, Dubai, UAE

In the past two decades, cognitive radio (CR) has developed as a potential contender to improve the efficiency of spectrum occupancy by creating a device capable of modifying its parameters according to the state of the spectrum while maintaining certain performance requirements. To achieve all of this, a CR must be aware of spectrum occupancy by performing an important task: spectrum sensing. Additionally, the increase in computing power has resulted in a boom in applications of machine learning in different engineering disciplines. Numerous applications of machine learning in spectrum sensing have been proposed and studied and a lot of research is ongoing.

This work presents a comprehensive review of different spectrum sensing techniques that have been proposed until now. Conventional techniques applied to both Narrowband and Wideband communications systems are considered. These include simple energy-based detection techniques which compute the energy of the received signal and based on a threshold decide on spectrum occupancy. More advanced techniques that use the statistical properties of signals, the entropy of the signal, etc. are also discussed and their performance is observed. In addition, this work places particular emphasis on work done related to machine learning based techniques for spectrum sensing. To the best of our knowledge, this is the only survey paper that reviews the different spectrum sensing techniques in a 5G cognitive radio network where all primary users are 5G based. For all of these techniques mentioned, the effects of noise and the performance at different SNR (signal-to-noise ratio) are discussed. Some techniques also consider multiple cognitive radios in a network that cooperate together to make a more informed decision on spectrum occupancy. Such techniques are also discussed for each spectrum sensing type.

The rest of the paper is organized as follows: Sect. 2 provides a background of Cognitive Radios and common terminology. Section 3 discusses the concept of spectrum sensing and provides an extensive review of the current techniques and the most relevant work related to spectrum sensing. Finally, the paper is concluded with an insight into where future work may be focused on.

2 Background

Recent years have seen an eruption in the applications and use of communication technologies, especially wireless communications, which has produced escalating pressure on the electromagnetic spectrum. This increased utilization of a naturally occurring finite resource has resulted in congestion and scarcity of the free spectrum. Spectrum is defined as *the range of frequencies that are used for transmission of data* by modern communication techniques.

Spectrum access is traditionally controlled by a governing body in a geographical area. The government body, such as FCC in the United States, charges users to obtain a license for access to a band of the spectrum. In return, the user gets complete uninterrupted access to that band. Traditionally, the wireless spectrum is divided into well-defined blocks and has been treated as a static quantity [1]. Licensed users, henceforth called *primary users (PU)*, have the sole right of access to these blocks. In addition, the PU is not obligated to always occupy its licensed spectrum. For some periods during the day, the occupancy of the licensed portions of the spectrum is even less than 5% [2].

However, with the boom in mobile communications and resulting exponential increase in the users of the spectrum, the finite resource has become overcrowded and lacking. A recent research was conducted to determine the spectrum occupancy in the spectrum ranging from 3.45 GHz to 3.65 GHz. It concluded that average band occupancy in some locations was around 25% while it was as low as 0.2% in other locations [3]. From this information, it can be inferred that despite having legacy rights of access to the spectrum, the primary licensed user does not access the spectrum at all times resulting in the formation of *spectrum holes: unused licensed bands within a geographical area of time* [4].

Cognitive Radio (CR) was initially proposed as the answer to the spectrum scarcity issue by Mitola and Maguire [5] where they introduced the concept of allowing a communication device to change its transmission patterns after determining the state of the target frequency channel in order to meet certain performance requirements. The FCC of USA defines CR as a device that is able to dynamically adjust its transmission parameters and operation after sensing it's operational spectral environment [6]. Cognitive Radio (CR) is often called the secondary user (CR) of the spectrum. Under this concept, the CR is given the right to use the unutilized portion of the spectrum only when it is vacated by the primary user.

The sole responsibility to avoid interference lies on the secondary user (CR) and, therefore, it must scan the spectrum to identify a spectrum hole. If it is found, the CR must then possess the capability to transmit to the empty frequency band until the primary user restarts its transmission. To achieve this, the secondary user must have cognitive capabilities, hence the name cognitive radio. This implies that CR must sense the spectrum and adjust its radio transmission parameters accordingly [7]. The network in which a CR operates is called a Cognitive Radio Network (CRN). A typical CRN setup is shown in Fig. 1.

2.1 Users of a cognitive radio network (CRN)

As discussed earlier, there are two types of users in a cognitive radio network:

1. Primary User (PU): PU is the licensed user of the spectrum band and has the absolute right to access the spectrum at any time in a geographical area. Traditionally, one PU was granted rights to access a spectrum band. However, modern communication technologies enable multiple PUs to use the same spectrum simultaneously such as devices connected to a WiFi network. This type of network is called a *multiple primary user cognitive radio network*.
2. Secondary User (SU or CR): SU is licensed to access bands of the spectrum when the licensed PU or multiple PUs are not accessing them. To achieve this, the SU is expected to have the cognitive capabilities to sense the spectrum. Most modern systems have multiple secondary users present in an area trying to access the spectrum holes as they become available. The terms SU and CR are used interchangeably in this work.

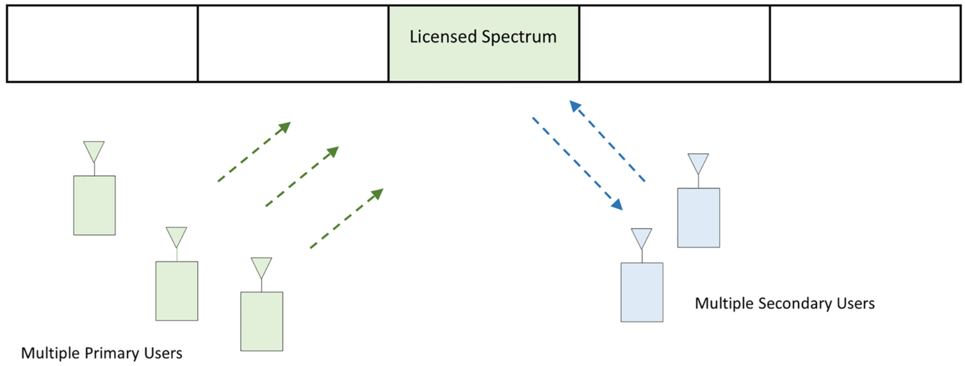

Fig. 1 Cognitive radio network

2.2 Performance metrics of a cognitive radio network (CRN)

To quantify the performance of a CR network and to determine the interference between PU and CR, the following metrics are used:

1. Detection Probability (P_d): the probability with which the CR correctly determines that the spectrum is occupied.
2. The missed detection probability (P_m): the probability with which the CR incorrectly determines that the spectrum is vacant while it is occupied.
3. False Alarm Probability (P_f): the probability with which the CR incorrectly determines that the spectrum is busy while it is not.
4. Receiver operating characteristics curves (ROC): is a plot of the False Alarm Probability (P_f) with the Detection Probability (P_d) for different Signal to Noise Ratio (SNR) values.

The performance of a CR network is usually measured at different Signal to Noise ratio (SNR) values. In communication systems, SNR is defined as the ratio of primary user signal strength to the noise signal strength. It is normally measured in decibels (dB). When the SNR values are high, the performance of a CRN is generally good. As the SNR decreases, degradation is typically observed. As the SNR value is decreased further, there comes a time when the CR is unable to sense the PU signal. This is known as the SNR wall and its value depends on the architecture of the CRN and the spectrum sensing technique being used [8].

2.3 System model

The CR needs to sense the spectrum for the presence or absence of the PU signal. To do this, it must read the incoming signal (over a given frequency range) for a window of time. If we assume that the PU signal was being transmitted at the time, the discrete time signal received by the CR for a window of W samples, is:

$$y[k] = c[k]x[k] + n[k], k = 1, \ldots, W \tag{1}$$

where $y[k]$ is the received signal at the CR, $x[k]$ is the transmitted signal, $n[k]$ is the Gaussian distributed white noise with the two-side power spectral density of $N_0/2$ and $c[n]$ is the channel coefficient. k is the discrete time index and W is the observation window length. The transmitted signal $x[k]$ is the PU signal and can have different types of modulation, such as LTE, 5G, etc.

The received signal, $y[n]$ is corrupted by different types of channel impairments such as Rayleigh Fading. A wide range of channel impairments are considered in the research narrated in this work. Since the task of the CR is to perform spectrum sensing only despite the existence of these impairments, the CR is not expected to perform any corrective actions to remove their effects. This is because any processing done by the CR to remove the channel effects will be computationally expensive and will result in a loss of precious time as the CR must take spectrum occupancy decisions urgently and act upon them. The observation window size can be varied, and the performance of the spectrum sensing algorithm can be determined for each window size. Increasing the window size will result in more PU signal samples being used to determine the existence of the PU signal but at the same time will increase the time required to perform spectrum sensing.

2.4 Cooperative cognitive radio networks (CRNs)

In most wireless communication scenarios, the CR experiences severe multipath fading and shadowing effects while trying to sense the spectrum to detect the presence of PU signal. This could lead to unwanted interference to the actual PU transmission since the CR is unable to detect the PU signal due to the channel state and severe fading in the path of transmission. This is known as the hidden-node problem [9]. Due to this problem, a CR does not detect the severely attenuated PU signal while the signal is, in fact, present. If there was another CR nearby which did not experience severe fading, it would have been able to detect the presence of the PU signal. If both CRs were cooperating in some way, a more informed decision on spectrum occupancy could have been made. Hence, cooperative spectrum sensing (CSS) is proposed as a solution to this problem.

In CSS, there are multiple CRs spatially located that incorporate their sensing information to decide on the existence of PU or multiple PUs. Using this method minimizes the uncertainty in the PU detection that arises when a single standalone CR acts as a CR. By cooperating, multiple CRs can make a more informed and accurate detection resulting in a performance improvement known as cooperative gain [8].

The most commonly proposed type of architecture in a cooperative CRN is centralized around a fusion center. All CRs transmit their sensing information to a centralized base station called the fusion center (FC). After compiling the information from all CRs, the FC takes a final decision regarding the existence of a spectrum hole using fusion schemes, a few of which are listed below:

1. Soft Combining: Each CR transmits its sensing information to the FC which then combines the information using different techniques. If the channel information is known, the information from each CR is weighted proportionally to their channel gain and summed up. This is called maximal ratio combining (MRC). In equal gain combining (EGC), on the other hand, they are weighted equally [8, 10].
2. Hard Combining: Each CR makes a local decision on spectrum occupancy and transmits the decision to the FC. The most frequently used fusion rules are AND, OR, and majority voting to make a final spectrum occupancy decision [8, 10].

Once a decision on the absence of the PU is made, the FC can either broadcast the information to all CRs or it can directly control the CR traffic by deciding on which CRs get priority to transmit.

3 Spectrum sensing

The primary job of the CR in a CRN is to perform spectrum sensing. It is defined as the process of gaining an understanding of the state of spectrum occupancy and identifying the existence of spectrum holes in a geographical area before a transmission is initiated. It is a critical task, and the performance of the CR network depends on it.

Theoretically, the spectrum sensing problem is defined as a hypotheses test based on the presence of the primary user signal:

$$\begin{aligned} H_0 &: \ No\ Primary\ User\ Signal \\ H_1 &: \ Primary\ User\ Signal\ Present \end{aligned} \qquad (2)$$

The actual method in which the hypothesis test is applied for spectrum sensing changes depends on the different CR network types and the spectrum sensing techniques used.

The performance metric probabilities of a CR network can be defined using the Hypothesis test:

1. The detection probability (P_d): probability of correctly deciding on H_1 given that H_1 is true.
2. The missed detection probability (P_m): probability of incorrectly deciding on H_0 given that H_1 is true.
3. The false alarm probability (P_f): probability of incorrectly deciding on H_1 given that H_0 is true.

The purpose of any spectrum sensing technique is to maximize the detection probability and keep the false alarm probability below a threshold. Thus, spectrum sensing is an optimization problem with the objective of achieving a target detection probability P_d while maintaining the false alarm P_f below a value.

This paper covers a wide range of spectrum sensing techniques that have been proposed over the years. Broadly, the techniques can be divided in two main categories: Narrowband and Wideband Sensing. Multiple techniques within each of these categories are discussed and assessed based on their advantages, drawbacks, and limitations. Figure 2 provides a summary of the different types of spectrum sensing methods listed according to their categories.

As discussed earlier, spectrum sensing techniques can be broadly divided into two categories: Narrowband and Wideband spectrum sensing. Narrowband spectrum sensing analyzes one frequency band at a time while wideband sensing senses several frequency bands at the same time in search of a vacant frequency band to initiate transmission.

Most of the early research on spectrum sensing for CRNs was done on narrowband. Examples of narrowband spectrum sensing techniques include energy detection, cyclostationary detection, matched filter detection, etc. In energy detection, the CR measures the energy of the spectrum to decide on the presence of PU while statistical detection utilizes statistical patterns in the PU signal. A detailed review of commonly used narrowband sensing techniques is discussed in Sect. 3.1.

Modern communication protocols and standards require high data transmission rates resulting in bigger bandwidth requirements. Thus, CRs need to sense wide frequency ranges of the spectrum to find a vacant band. Consequently, wideband spectrum sensing techniques have been proposed [10, 11]. The common approach to sensing is to divide the wideband into several narrow bands and perform sensing sequentially or in parallel. However, due to the long sensing

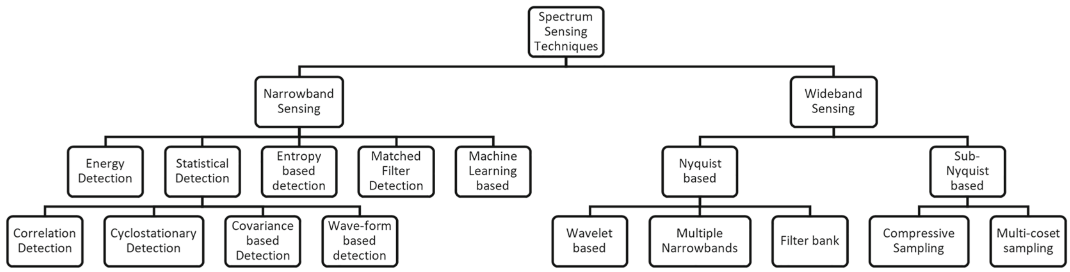

Fig. 2 Types of spectrum sensing

time and high sampling rates, Sub-Nyquist techniques have been proposed to reduce latency due to sensing. A detailed review of all relevant wideband spectrum sensing is discussed in Sect. 3.2.

3.1 Narrowband spectrum sensing

Narrowband spectrum sensing methods are the oldest and most common techniques as they conventionally sense one frequency band at a time. All the early work on spectrum sensing in CRs was focused on narrowband spectrum sensing and several techniques were developed. In this section, most popular methods for narrowband spectrum sensing will be discussed.

3.1.1 Neyman-pearson theorem and likelihood ratio test

Spectrum sensing was earlier defined as a Hypothesis test in (2) which essentially makes it an optimization problem. This means that various optimization techniques can be used to find the optimal results. A famous tool for hypothesis testing is the Neyman-Pearson Theorem which uses the likelihood ratio test to obtain the maximum detection probability for a fixed false alarm. If x is the received signal, applying the Neyman-Pearson Theorem to (2), the likelihood ratio test concludes that the hypothesis H_1 (PU present) is true when $L(x)$, or the likelihood, is greater than λ as shown in the equation below [12, 13]:

$$L(x) = \frac{p(x|H_1)}{p(x|H_0)} > \lambda, \tag{3}$$

where p(x| H_1) is the conditional probability of receiving x given a true H_1 and p(x| H_0) is the conditional probability of receiving x given a true H_0. λ is the threshold and its value is determined by the required false alarm probability. If the received signals for both hypotheses are assumed to be Gaussian distributed due to the large sample size, the maximum likelihood estimate (MLE) is used to estimate the unknown mean and variance. Using the estimated parameters, the likelihood ratio test is then applied [13]. This method is called the generalized likelihood ratio test (GLRT). LRT is the ideal algorithm for spectrum sensing. However, its requirement for exact information on the signal statistics such as the noise variance makes it difficult to implement since they are not easily calculated [14]. Additionally, the assumption that the received signals will be Gaussian distributed may not always be true. This will result in incorrect estimates of the parameters culminating in degraded performance. However, if all the assumptions are true for a particular set of primary user signals, the LRT will provide superior performance than any other technique.

3.1.2 Energy detection

Energy detection is by far the most prevalent technique for spectrum sensing [15]. The foremost reasons for its popularity are that it is very simple to implement and that it does not require any prior knowledge of the PU signal. The decision on spectrum holes is made by comparing the energy detector output with a predetermined threshold. All zero-mean constellation signals can be detected with great efficiency using energy detection [16]. A primary user signal corrupted by Additive White Gaussian Noise (AWGN) noise is the simplest possible energy detector PU signal [7]. At the receiver, the discrete-time received signal is defined in (1). The energy of any received signal that is a zero mean Ergodic signal is calculated by squaring and adding the discrete samples of the received signal [17, 18]. Instead of receiving the complete signal, energy can also be computed for an observation window size of W samples. The concept of windowing, by selecting fewer samples than the complete signal length, is commonly used for spectrum sensing.

The energy of the received signal can also be calculated in the frequency domain using Fast Fourier Transform (FFT). The signal is first sampled and then input to a FFT block. This converts the signal to a discrete frequency-domain signal, $X(m)$ where m is the discrete frequency index. The energy of the signal is computed using Parseval's theorem and a decision on the hypothesis is made after comparing the energy value against the threshold λ.

Although the energy detector is easy to implement, it is not without disadvantages. One key downside is that the energy detector is very good at detecting those PU signals which have energy levels above the set threshold. This causes issues for cases where the PU signal has low energy levels that may be below the set threshold.

Additionally, choosing the optimal threshold is difficult since it requires knowledge of noise power to achieve a desired detection probability while maintaining the false alarm probability below a specific level. Unfortunately, it is difficult to accurately find the noise power, so an estimated noise power is used instead. However, this has an adverse effect on the performance of the energy detector. Furthermore, noise power varies with respect to time which increases error in the noise estimation [16–18]. A double threshold energy detection technique is proposed by Jinbo et al. [19] to overcome the issue of noise uncertainty. If the energy of the received signal is less than the lower threshold, the spectrum is considered vacant. If the energy received is greater than the higher threshold, it is assumed that the PU signal is present. No decision is made if the energy falls between the two thresholds. Another major drawback of energy detection algorithms is that they suffer from poor performance at low SNR where the signal and noise energies are comparable [20].

As mentioned earlier, noise power estimation is a challenge in energy detectors. To avoid estimating, different approaches have been proposed. Shen et al. [17] perform measurements in all the sub-channels to determine the occupied bands. This is known as the Bayesian estimation method. The occupied channels are then determined by maximizing the likelihood of estimated samples. From these measurements, those with the highest power are assumed to be occupied by the primary users. In this way, the drop in performance of the CRN caused by a lack of knowledge of noise power is substantially reduced. Kim et al. [18] propose a histogram-based method to determine the threshold between the two categories of signals. Samples of signals belonging to both hypotheses are collected and plotted as histograms. Using the plots, a threshold λ is selected to meet the required false alarm and detection probabilities. Thus, there is no need to estimate the noise power since the received signal at the CR is not modeled statistically. This is because the histogram method is independent of the probability distribution of the PU signal.

Typical energy detection algorithms employ a different received signal model at the CR as described which considers corruption of the transmitted PU signal by AWGN only and not the one defined in (1). In most cases, No fading or shadowing effects of the channel are considered. Multipath fading causes noticeable degradation in the performance of an energy detector for different channel models [21]. Rayleigh fading is the most common fading channel model used to estimate the performance of CR in fading environments. The performance of the energy detector is improved by using Cooperative Spectrum Sensing (CSS). Atapattu et al. [22] propose both Soft and Hard combining where a fusion center (FC) receives transmissions from all CRs and decides on spectrum occupancy. In the soft-combining approach, the fusion center uses different fusion techniques such as Maximal Ratio Combining (MRL) to determine the primary user signal presence. In the hard-combining approach, each CR locally decides on the presence of the primary user before transmitting to the fusion center. The decision is then sent to the FC which uses OR, AND or Majority rules to decide on the spectrum occupancy. More CRs in the network will result in a more informed decision on the occupancy of the spectrum.

An adaptive double threshold CSS energy detection technique is proposed by Yu et al. [23] in which the two thresholds are adaptively changed based on the historical energy measured and the SNR computed by each CR present in the cooperating network. This results in an overall improvement in the detection probability.

Table 1 summarizes the performance of different energy detection techniques. The type of channel used is also mentioned where known. As can be seen from the table, AWGN is the preferred channel model used to determine the performance of the energy detection algorithms. The performance of the CR is shown for different SNR values.

3.1.3 Statistical detection

Statistical detection is a broad field of spectrum sensing which uses statistical properties of the PU signal to aid in the spectrum sensing process. Parameters such as Correlation and Covariance may be used at the CR to make a more informed decision on spectrum sensing. Different types of statistical detection methods are discussed below:

Correlation detection

Noise, by definition, is uncorrelated whereas most signals possess inherent correlation that can be utilized for sensing the spectrum. Correlating the received signal with a copy of itself is called autocorrelation and it can be used as a tool for sensing the spectrum. When only $x(t)$ is received at the CR, the correlation value $R_x(\tau)$ is maximum when $x(t)$ is correlated with a delayed copy of itself. However, when only noise is received, autocorrelation will have almost zero value since noise samples are uncorrelated. Using this knowledge, a decision on the type of received signal is made. Neyman-Pearson theorem becomes the optimal detector if the PU signals correlation is known to the CRN [12, 24].

Cyclostationary detection

If a signal or its statistics such as the first or second moment are periodic, the signal is called a cyclostationary signal. In [7], gaps in the spectrum were identified by calculating the cyclic autocorrelation function, CAF, of the received signal at the CR. After obtaining CAF, the Cyclic Spectral Density

Table 1 Spectrum sensing using energy detection

References	Authors	Channel	SNR (dB)	Detection Prob (%)	False Alarm (%)
[17]	Shen et al.	AWGN	−15	< 50	< 1
			−10	100	< 1
		Rayleigh Fading	−15	< 30	< 1
			−10	≈ 70	< 1
[18]	Kim et al.	Undefined	−10	95.7	7
				99.3	17
				100	27
[19]	Jinbo et al.	Undefined	−15	< 35	< 7
			−10	< 40	≈ 17
[20]	Atapatuu et al.	Rayleigh Fading	−5	25	20
				55	50
[23]	Yu et al.	AWGN	−10	100	5

(CSD) is computed by applying Discrete Fourier Transform to the CAF. The CSD has peak values when the frequency of the PU is equal to the cyclic frequency. If there is no PU signal present in the received signal, no peaks will be observed. By comparing the CSD value with a threshold and using the property that only PU signal will have peaks in the CSD, the detection probability can be maximized.

One advantage of cyclostationary-based detection over energy detection is that it performs better than energy detectors even under severe fading channel conditions [7]. Additionally, they also provide better detection performance than energy detection techniques [10].

Covariance based detection

The covariance-based detection method of spectrum sensing makes use of the received PU signals covariance matrix and singular value decomposition (SVD) to detect the presence of PU signal [10]. Using the SVD, the eigen values of the covariance matrix are determined and the ratio of the maximum Eigen value to the minimum Eigen value is used to detect the presence of the signal by comparing it with a known threshold [25]. The covariance matrix of the received PU signal is computed [26] and SVD is applied to the covariance matrix to obtain the maximum and minimum eigenvalues which are then used to perform the Hypothesis test defined in (2). Covariance-based detection outperforms energy-based detection since it relies on noise power estimation [25].

3.1.4 Entropy-based detection

Entropy is a measure of the amount of information carried in a signal [27]. Since knowledge of a signal removes all ambiguity about it, entropy is also a measure of information that is acquired by knowing a signal. This property can be used to determine the presence or absence of PU signal in a received signal by the CR.

Traditionally, a histogram-based approach is used to compute the entropy of a signal. The number of energy levels of the PU signal is equal to the number of bins of the histogram [28]. The entropy of the received signal is calculated at the CR using this method and then compared with a threshold to decide on spectrum occupancy. Entropy is expected to be low when the PU signal is present and high when only random noise is received. Zhang et al. [29] demonstrate that the entropy values of the signal received at CR vary around a specific value and are invariant against different SNR levels making it difficult to distinguish the noise and PU signal. To solve this issue, the received signal is transformed to the frequency domain using FFT, and the entropy of the signal is computed in the frequency domain. The entropy value is then compared against a threshold to determine spectrum occupancy.

Another approach to entropy-based spectrum sensing is proposed by Swetha et al. [30] where the entropy in the received signal is computed using the Kernal density estimation method. In this method, a Parzen-Rosenblatt window method is used to estimate the probability density function (pdf) of the received signal samples without any prior knowledge of the distribution. A cooperative spectrum sensing network is used to make a more informed decision about spectrum occupancy. After combining information received from all CRs, a decision on the presence of PU signal is made by comparing it with a threshold.

3.1.5 Matched filter

The optimal detection method for spectrum sensing in AWGN noise in a narrowband system is the matched filter since it maximizes the SNR. This filter is implemented by correlating a copy of the transmitted signal with the received signal at the CR. Unfortunately, the matched filter requires complete knowledge of the transmitted signal characteristics which are typically unknown to the CR [7].

3.1.6 Machine learning based spectrum sensing

Machine learning is the process of extracting useful information or knowledge from available data [31]. The primary purpose of a machine learning algorithm is to identify a mathematical formula that provides solutions to practical problems when they are provided with inputs [32]. The mathematical formula is developed by determining the output of the system to several inputs (known as training data). Using this knowledge, the algorithm then makes informed decisions on the expected output when it receives any new input.

The input to the machine learning algorithm consists of distinguishable and special attributes of the data called features. Each element of the dataset may contain several features, with every feature being used to identify a special trait or property of the data.

Depending on the type of data available, machine learning can be broadly categorized into:

1. Supervised Learning: is when the machine learning algorithm learns the relationship between inputs and outputs of a dataset from known inputs and outputs. The dataset is commonly referred to as labeled data since inputs and corresponding outputs are known beforehand. Thus, the objective of supervised machine learning is to gain a generalized idea such that given any new input, the expected output is appropriately predicted [31, 32].
2. Unsupervised Learning: this is when the machine learning algorithm autonomously collects the data and extracts useful information and special properties of the dataset without external guidance. In other words, the inputs and outputs available are without labels [33].
3. Reinforcement Learning: is a subfield of machine learning where the algorithm is used to perceive the state of the environment it is in and then execute actions based on its state. Each action brings a different 'reward'. The goal of the algorithm is to learn a policy that uses the states as inputs and determines the optimal action or output [32].

Supervised learning tools are further divided into two applications which are listed below:

- Regression: A trained machine learning regression algorithm must predict a real-valued output when provided with any input. This problem is solved by taking a collection of data – both inputs and corresponding outputs – and producing a model from this dataset which can then estimate the output for any input value [32].
- Classification: A machine learning classification algorithm is a pattern recognition problem in which each element of the available data set belongs to one of several categories or classes. The algorithm is first trained using a labeled dataset which identifies the category (or class) of each data element. This information is used to produce a model that predicts the class of any unlabeled input [32].

Unsupervised learning tools are also divided into several applications. Two of the most used applications are listed below:

- Clustering: the model developed by the unsupervised learning tool divides the unlabeled dataset into clusters (or groups) based on special properties (or features) of the dataset. Clustering is the unsupervised learning equivalent of the supervised classification algorithm.
- Dimensionality Reduction: the output of the algorithm model is a feature vector that has fewer features than the input features.

The use of machine learning algorithms in a wide range of signal processing applications has gained a lot of research interest lately. Recent advances in computer technology have resulted in enormous opportunities for machine learning algorithms to be employed in different engineering applications. In fact, machine learning and deep learning algorithms have emerged as powerful and effective tools to solve complex optimization problems. As discussed in Sect. 3, spectrum sensing is an optimization problem. Thus, it becomes an exciting candidate for machine learning applications. The objective of the CR is to detect the presence or absence of the PU signal using spectrum sensing. The output of spectrum sensing can belong to one of two 'classes':

- Class 1: Primary user is absent (H_0 in (2))
- Class 2: Primary user is present (H_1 in (2))

Thus, it is evident that the spectrum sensing problem can be considered as a machine learning classification problem. With the appropriate dataset, any classification algorithm can then be used to effectively sense the spectrum. Some commonly used machine learning algorithms for classification and clustering are discussed below:

1. Linear Classifier: A linear classifier is a commonly used model to implement a machine learning problem when the data set is linearly separable. Data belonging to multiple classes is separated through linear decision boundaries called discriminant function, therefore the name linear classifier. A linear classifier is also known as Logistic Regression in the literature.
2. Artificial Neural Networks: These are algorithms that try to mimic the functions of the brain. Neural networks are

learning machines, comprising many neurons, which are connected in a layered fashion [34]. Neural networks are used widely to solve classification problems that are linearly and nonlinearly separable.
3. K-means clustering: This unsupervised learning technique is used to group data into clusters. A fixed number of clusters are selected arbitrarily from the given data and the mean of each cluster is computed. The data points are then reassigned to the cluster with the closest mean. The process is repeated iteratively until it converges.
4. Support Vector Machines: Support Vector Machines is an advanced algorithm that relies on preprocessing of the data to represent it in a much higher dimension than the original feature space. With an appropriate nonlinear mapping, data from two classes can always be separated by a discriminant function even if it was originally inseparable [35].

One of the first papers to use the concept of spectrum sensing as a classification problem was [36–38]. Hassan et al. [36–38] used a linear and polynomial classifier to decide on the presence of the PU signal based on features extracted from the received signal at the CR. The PU signal is modulated using BPSK while a Rayleigh channel model was used. The features extracted from the received signal at the CR were energy and correlation. These extracted features are then sent to a fusion center which uses the data received from all CRs in the network as different features. The classifier was first trained using training data consisting of energy and correlation features to create a model for the system. The performance of the system was then determined using testing data.

Muzaffar et al. [39] considered OFDM as the PU signal modulation technique in a cooperative CR network. Two different features are used: energy and correlation. The CR computes the energy and correlation and transmits it to the fusion center. At the fusion center, features received from all CRs are combined and are sent to the trained classifier. The classifier then decides on the existence of the primary user. It is observed that the correlation classifier outperformed the energy classifier at low SNR conditions in a flat fading channel. In addition to energy and correlation, entropy is also used as a feature in [40] where a linear classifier classifies incoming OFDM PU signal under slow fading effects and AWGN.

Mikael [41] proposed a data fusion center for a cooperative cognitive radio network that uses energy as a feature vector. This algorithm decides on the presence or absence of the primary user transmission. In this work, four different machine learning classifiers are used: K-nearest neighbors (KNN), support vector machine (SVM), Naive Bayes (NB), and Decision Tree (DT). It was concluded that KNN and DT outperform the other classifiers.

Actual readings of primary user signals are used to sense the spectrum by Azmat et al. [42]. Instead of converting the received PU signal into a feature, the PU signal is itself used as a feature and input into the machine learning algorithms. Several algorithms are applied to the feature vector: NB, DT, SVM (and many variants of SVM), Logistic Regression (LR), and Hidden Markov Models (HMM). A limitation to the algorithms and performances discussed in this work is that it was assumed that there is no fading and signals pass through an AWGN channel only.

Thilina et al. [43] employ SVM and KNN for Cooperative Spectrum Sensing on a CR network with a single PU signal. The signal experiences path loss, shadowing, and Rayleigh fading, all of which are taken into consideration in the channel model. The feature used for classification is the received signal strength (energy). In [44], Thilina et al. computes an energy vector by compiling the energy of the received signal at all CRs in a cooperative CR network. Multiple CRs receive signals from multiple PU's and based on the distance between the PU and CR, the energy of the received signal follows a chi-squared distribution. A novel approach is used to label the received signal into classes by using the K-means clustering algorithm. Once the classes are labeled, supervised machine learning algorithms such as K-nearest neighbors (KNN), Gaussian mixture models (GMM), and SVMs are applied to the dataset to decide on the spectrum state. The type of the primary user signal is unknown for all cases. It is concluded that the support vector machines algorithm outperforms all other techniques of machine learning since it maps the feature space into higher dimensions with the help of kernel functions.

A similar approach is proposed by Arjoune and Kaabouch [45] to solve the spectrum sensing problem. First, K-means clustering is used to label a dataset by classifying the received PU signal into two classes: PU signal present or absent. Once clustered into two distinct classes, the energy of the received signals is computed as a feature and passed through several ML algorithms such as KNN, Support Vector Machines (SVM), Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF) for the purpose of classification of the signal into either of the classes. The limitation of the paper is that only the AWGN signal has been considered and the type of modulation assumed for the PU signal is not provided.

Kaiqing et al. [46] also utilize the method of labeling the classes using a clustering algorithm. Then, the data is applied to a support vector machine algorithm for actual spectrum sensing. Energy is once again used as a feature for this entire process. However, the PU signal is transmitted at multiple power levels which change the spectrum sensing from a binary classification problem to a multi-class problem. The SVM, therefore, has decision boundaries for different power levels. The channel statistics are unknown, but the authors suggest they are incorporated in the learning phase of the algorithm where the system learns the environment using K-means clustering. In addition, the noise levels and the primary user signal type are unknown.

The concept of secondary base station (SBS) is introduced by Awe and Lambotharan [47]. A system with multiple PUs and multiple CRs is proposed where the CR's (or the CRs) report to the SBS. The primary function of the CR during spectrum sensing is to sense the energy of the received signal and report it to the SBS. At the SBS, clustering is performed to label the received signals using K-means clustering. Finally, SVM, KNN, and their variants are used to decide on the spectrum state. Since there are multiple PU signals in the vicinity of the CR, the problem does not remain a simple binary classification. In fact, there are several classes. Based on the number of PUs present and the number of PUs active, a combination of PUs that are active needs to be determined to identify the classes that the data will be divided into. In this case, using K-means clustering to label the data into classes proves useful since it will be able to correctly identify the number of classes occupied by the received signals at the CR. Another advantage of using energy and clustering is that spatial diversity is captured in the data as further PUs will have lower energy signals than nearby PUs.

A cooperative CR network is considered by Yingqi et al. [48] where multiple CRs determine the energy of the received signal. The combined energy from all CRs results in a high-dimensional feature vector. The energy vectors from different CRs follow a chi-squared distribution and this knowledge is used to down covert the high dimensional feature vector into a 2-d probability feature vector. This results in smaller training duration and shorter classification times during testing. After down-converting to a 2-d feature vector, K-means clustering is used to label the data into the two classes. Then, SVM is used to determine the spectrum state. SVM is trained using the data labeled by K-means clustering.

Eigenvalues obtained from the covariance matrix of the received signal are used as features by Awe et al. [49] for a multi-antenna CR with multiple transmitting PU signals. The multiple antennas of a single CR are like having multiple CRs operating in a small geographical area. The obtained eigenvalue feature vector is passed through an SVM algorithm to identify the state of the spectrum. The system does not consider a fading channel. However, since the setup can be considered as multiple CRs operating nearby, the effects of shadowing are almost negligible.

A multi-class classification approach is adopted by Jan et al. in [50] and [51]. The class that identifies the spectrum as being vacant (H_0 in (2) is quantized into four different levels based on the received signal energy using thresholding. Based on the decided class by the SVM algorithm, the transmission power of the CR is varied to avoid interference. In total, any received signal at the CR can be classified into five different classes. A novel approach to feature extraction is proposed by extracting three distinct features from the received signal: the average of the received signal is calculated and indexed to a power of 10 and then multiplied by 10, the average of the squared signal is computed, the square root of the cube root of the mean of the signal is computed. These three features are input to the SVM to decide on spectrum occupancy. By adjusting the transmission power of CR, the risk of interference for the case when the PU is present but was miss-detected to be absent is greatly reduced.

In [52], Shah and Koo used a different approach to apply machine learning to the spectrum sensing problem. The sensing time slot is first divided into multiple slots to reduce the effects of fading. Then, the KNN algorithm is used to sense the spectrum after extracting energy (as a feature) from the received signal. The energy vector is quantized into four levels to determine the strength of the received PU signal if any at all. The two upper levels of energy are identified as belonging to one class (PU signal present) and the remaining two levels belong to the other class (PU signal absent). Spatial diversity is introduced by having cooperative spectrum sensing and a total of 8 classes need to be classified by the algorithm based on energy levels as well as local and global decisions that occur due to cooperation between CRs.

A variant of machine learning called Extreme Learning Machine (ELM) is proposed as the solution to the spectrum sensing problem by Ma et al. [53] for a CR network with multiple PUs. ELM is a tuning-free three-step machine learning algorithms with extremely fast learning speed. Each PU is depicted by a state with regard to spectrum occupancy. The CR computes the energy of the received signal over a Rayleigh channel and sends to the FC for a decision on whether the spectrum is vacant for CR transmission. The Energy feature vector is computed from samples collected by each CR and sent to FC which makes a final decision on spectrum occupancy.

3.2 Wideband spectrum sensing

Conventional CRs are expected to restrict themselves to specific bands of the spectrum and therefore require sensing in a particular frequency band only. However, with the introduction of modern communications technologies and the resulting increase in spectrum occupancy and high data rates, CRs must also be able to scan a wide band of frequencies to find an available frequency band for transmission. This leads to the concept of wideband spectrum sensing [54]. This section explains the different types of Wideband Spectrum Sensing Techniques.

3.2.1 Nyquist sampling

If the same conventional methods that are applied to narrowband systems are utilized for wideband spectrum sensing, it would require CRs to perform standard analog to digital conversions at Nyquist Rate. Due to the wide range of frequencies, this would eventually result in an unaffordable high sampling rate or severe implementation complexity [54]. Despite these drawbacks, several Nyquist-rate-based spectrum sensing techniques have been proposed which are discussed in the sections below:

Wavelet based

If the received signal at the CR occupies multiple frequency bands, whose frequencies and power are unknown, wavelet transform can be applied to the received signal. Wavelet transform acts as an edge detector and aids in identifying the edges of the occupied frequency bands by locating the local maxima in the wavelet transform modulus [55]. Once a frequency band is found to be vacant and its location is determined, CR can start transmitting at the frequency band. To improve latency, the channel can be divided into multiple bands and then sensed simultaneously [10].

Multiple narrowbands

Another approach is to split the wide band of frequencies into several narrow bands. Then, using the narrow band techniques discussed in the previous section, spectrum sensing is performed on each narrow band [10]. However, this approach is flawed due to the high sensing time required which is not compliant with the demands of modern communications.

Filter bank

An alternative to the multiple narrowband method is the use of filter banks. Using this method, the wideband signal is passed through multiple prototype filters [10]. Each of these filters has a different central frequency and it modulates the received signal to a baseband frequency [54]. As a result, for each filter, the corresponding portion of the wideband is down-converted and effectively passed through a low-pass filter. The output of the filter can be passed through an energy detector (or any other narrowband detection technique) to determine the state of PU signal in that frequency range. With this method, the wideband signal can be analyzed at much lower baseband sampling rates. However, since the filter bank operates in parallel, it increases the complexity of implementation.

3.2.2 Sub-nyquist sampling

As discussed above, scanning the entire wideband for PU signal presence results in very high sampling rates, and dividing the wideband into smaller narrowbands requires very high sampling time, a sub-Nyquist spectrum sensing approach can be used [54]. This approach allows the CR to detect any PU signals occupying the wideband spectrum at lower sampling rates than the Nyquist sampling rates and, consequently, decide on any spectral transmission opportunities for the CR. This provides the CR ability to scan a wideband spectrum at a lower sampling rate without a significant increase in sensing time.

Sub-Nyquist sampling for wideband signals can be divided into two main types which are discussed in the following sections.

Compressive sensing

Compressive sampling is a technique through which a signal can be efficiently recovered using relatively fewer samples than required by conventional sampling which follows the Nyquist criterion [54, 56]. The PU signal transmissions are typically sparsely distributed on the wideband range of frequencies since the spectrum is scarcely occupied. This allows for compressive sensing to recover the received signals at sampling rates lower than the required Nyquist rates [10, 54]. Taking advantage of the sparsity of signals, the idea behind compressive sampling is to recover the signal through a small set of linear measurements [57]. A sparse signal is defined as a signal with very few non-zero elements. A signal with N samples is k-sparse if it has only k non-zero elements and $(N-k)$ zero elements and $N \gg k$ [58].

Compressive sensing involves representing a signal using few measurements or samples. If a signal $x = [x_0 \; x_1 \; \ldots \; x_(N-1)]$, of length N, is not sparse, a projection of this on a basis or dictionary can make it sparse. The new sparse signal s is given by:

$$s = \Psi x. \tag{4}$$

This implies that any signal can be converted to a sparse signal by projecting it to a suitable basis [10].

Several algorithms have been proposed to solve this linear reconstruction problem. Arjoune and Kaabouch [10] discuss three of the commonly used techniques namely convex and relaxation, greedy and Bayesian. Optimization algorithms such as gradient descent are used to solve the optimization problem in the convex and relaxation method [59]. In the greedy approach, the solution is built iteratively to reach the minimum value and reduce detection time [60]. Finally, the optimal solution is found by using Bayesian models to define the probability distributions of the signal [61]. Once the reconstruction is complete, energy detection or other spectrum sensing algorithms are discussed in Sect. 3.1. can be applied to decide on the existence of a PU signal.

El-Khamy et al. [62] use a wavelet transform-based approach to compressive sensing by using wavelet transforms to create the basis functions defined in (4). A cooperative CRN is proposed by Zhang et al. [63] which employs a compressive sensing-based blind user selection technique to select the cooperating CRs. Additionally, each CR also uses compressive sensing to determine the minimum sensing time required to detect the spectrum.

Khalfi et al. [64] propose a machine learning-based compressive sensing algorithm. The proposed algorithm uses compressive sensing to reduce the size of the wideband signal and then extracts feature such as PU signals activity statistics, CR's neighbors, previous spectrum occupancy information, and current spectrum measurement. Finally, instead of applying a classification algorithm to determine spectrum occupancy, a regression algorithm such as linear regression (LR) is used to predict when the spectrum will be occupied in the future.

Multi-coset sampling

Multi-coset sampling is another Sub-Nyquist sampling approach in which only some samples are selected from a standardized grid by using a sampling rate f_s higher than the Nyquist rate. This grid is divided into blocks of j consecutive samples. Only i samples are considered in each block such that $i < j$. All other samples are discarded. In effect, this sampling technique is implemented by having i sampling channels. Each channel has a different time offset [54]. The main advantage of multi-coset sampling is that the sampling rate is lower than the Nyquist rate by a factor of j. However, obtaining a unique solution for the wideband spectrum occupancy from only a few measurements is a challenge [54].

Utilizing the fact that spectrum sensing only requires the location of the occupied frequency bands and not a complete reconstruction of the signal, a non-uniform multi-coset sampling approach is proposed by Yang et al. [65]. A two-step iterative detection scheme is proposed which utilizes correlation and eigen values since they are non-zero only when the channel is occupied.

3.3 5G communications and spectrum sensing

The fifth-generation standard of wireless communications technology, more commonly known as 5G is the planned successor of the widely used 4G LTE standard. The 5G system has been tested in some countries of the world as early as 2019 and a full deployment worldwide is expected soon.

The number of users of wireless cellular networks has increased exponentially in the last few years. This has had a direct impact in the data rate and bandwidth requirements for communication. In fact, video and music streaming platforms have gained a lot of popularity recently and the demand for faster cellular data has never been higher.

5G communication networks will provide a high-speed communication platform to users worldwide. 5G is expected to operate at very high frequencies and may range from 3 GHz to 100 GHz [66, 67]. The actual frequency bands utilized by the protocol will depend on the licenses issued in each country. Due to the very high frequencies, 5G signals will occupy large bandwidth and provide an average data transmission rate of 1 Gbits/s [67]. 5G communication systems will use the OFDM modulation technique for transmission. Each individual slot of a 5G signal will consist of 14 OFDM symbols. Several slots combine to form a subframe and 10 subframes make up one frame.

5G communication system will allow Dynamic Spectrum Access (DSA) which enables multiple users to access the spectrum and help in optimizing spectrum usage [68]. This is directly related to the concept of CRNs which provides opportunities to unlicensed users to access the licensed portion of the spectrum when it is vacant. The incorporation of DSA to the 5G protocol implies that CRNs will be an integral part of 5G networks and therefore spectrum sensing by the CRs will become even more crucial. Additionally, due to the high bandwidth of 5G systems, the CR must sense the spectrum in the range of hundreds of megahertz [69].

Even though 5G has not yet been implemented worldwide, research on spectrum sensing techniques has already caught the attention of several researchers. Zhang et al. propose a spectrum sensing architecture for 5G networks in [69]. In this work, spectrum agents are proposed which are equipped with spectrum sensing capabilities. Each CR in the network must send a request to the nearby spectrum agent to sense the spectrum. All spectrum agents send their sensing results to the Fusion Center which combines the information and decides on the occupancy of the spectrum.

The high bandwidth of 5G systems will require spectrum sensing to be performed over a large range of frequencies. In 5G, a CRN must utilize multiple channels or bands to transmit. Liu et al. [70] discuss spectrum sensing based on the generation of basis functions for modulation of the signal to be transmitted. The generated basis function will be orthogonal and will allow multiple access to the CR. This will enable the CR to access a larger number of vacant channels.

Xu et al. [71] propose a reinforcement learning-based approach to spectrum sensing in 5G networks with the aim to improve the performance of the CRN in terms of throughput, energy saving, and sensing accuracy. Reinforcement learning uses traditional spectrum sensing schemes to find an optimal policy via trials in Markov decision processes. If there is an obvious divergence of sensing results among cooperating CRs, repeat sensing is done to ensure high performance.

A 5G CRN multiband spectrum sensing approach with resource allocation using Game theory is proposed by Ejaz and Ibnkahla [72]. Spectrum sensing is carried out using compressive sensing. Once the signal is reconstructed, energy detection is used to determine spectrum occupancy. The system is then optimized to consume minimum energy during the spectrum sensing stage.

Xu et al. [73] propose a sliced spectrum sensing technique that aims to eliminate the out-of-phase feature distortions that occur due to variations in a fast-fading channel or a non-static channel. In this method, the sensing window is split into multiple slices effectively converting the non-static channel to several quasi-static channels. After this, conventional spectrum sensing techniques can be applied to detect spectrum occupancy.

Awe et al. investigate a machine learning-based spectrum sensing method in [74]. A 5G network with multiple PUs and multiple CRs is assumed and the spectrum sensing problem is defined through temporal and spatial spectrum holes. In this way, the spectrum sensing problem becomes a non-binary classification problem. The energy feature vector is generated using a beamforming algorithm. This feature vector is passed to an SVM algorithm to decide on the existence of PU signals in a particular frequency range at a specific time.

Ahmed et al. [75] proposed a deep learning-based spectrum sensing technique for a CRN in a 5G communication system. The proposed detector employs residual connections with cascaded multi-kernel convolutions to identify the PU spectrum occupancy by extracting the inherent multi-scale signal and noise features during the sensing time. This allows the CRN to learn of the presence of spectrum holes. The signal considered in this work passes through an AWGN and Rayleigh fading channel. The signal is operating on a 5G communication system, but the modulation techniques used are conventional digital techniques. The use of deep learning CNNs greatly improves the performance even at low SNR values.

A filter-based approach is proposed by Algriree et al. [76] for the detection of 5G PU signal in three cascaded stages: cosine filtering, Welch segmentation, and Hamming windowing. The detection probability is measured for different SNR values and an improvement in performance is seen with this filter-based approach. The CR is operating in a 5G system, but the signal is only corrupted by AWGN (Additive White Gaussian Noise), and no channel variations (or impairments) are considered. Dikmese et al. [77] propose another filter-based approach for CSS in a 5G system combining it with energy detection in the frequency domain. FFT is applied to the received wideband signal to generate equally spaced subband signals. The channel is modeled by AWGN and log-normal path loss impairments. The results indicate good performance even at low SNR values. Since the proposed method is for a CRN, a decision is achieved by using either the OR AND or Majority rule. Based on the results, the best results were achieved using the OR rule.

Perumal and Nagarajan [78] propose a machine learning-based compressive sampling spectrum sensing approach in a 5G CRN. A Convolutional Neural Network (CNN) is trained using cyclostationary features of the dataset which are obtained from the carrier signal structures using the time delay and cyclic frequency. These features are maintained even at low SNR values. The signal is modeled as a 5G signal corrupted by AWGN and Rayleigh fading channel. The work depicts good detection probability at SNR values above 5 dB. However, no information is provided about the performance of the proposed classifier in low SNR conditions (such as SNR < 5 dB).

Cycolstationary features of a 5G signal are also used by Nouri et al. [79] using the Gaussian Kernel Least Mean Square (KLMS) algorithm. The paper suggests that to sense a specific frequency band, the proposed algorithm uses a set of inaccurate cyclic frequencies belonging to the PU. Using this information, a detector is designed, and spectrum sensing is performed. The performance is shown for both AWGN and Fading channels at different SNR values and this detector performs very well even at very low SNR. The detection probability crosses 90% at around -15 dB which is an excellent performance.

Using the properties of eigen values of the covariance matrix of a signal, Zhao et al. [80] propose a spectrum sensing for CRN. Eigenvalues capture signal correlations and noise characteristics and parameters such as eigenvalue to arithmetic mean and eigenvalue to geometric mean are computed. Taking these parameters and combining them with the matrix theory framework, the authors determine the detection probability using the Tracy-Widom distribution of maximum eigenvalue. The signal is corrupted by AWGN and Rayleigh fading channel and the spectrum sensing algorithm produces excellent results at different SNR values. Even at low SNR values (< -10 dB), the algorithm performs reasonably well.

Koteeshwari and Malarkodi [81] propose another compressive sensing-based approach in a 5G network. The least Absolute Shrinkage and Selection Operator (LASSO) is found to be the most suitable choice for communication in compressive sensing and recovery in wideband 5G networks. A good performance is shown but there is no mention of channel impairments used in the signal model. Additionally, only positive SNR values (> 0 dB) are evaluated and show promising results. However, low SNR values are not looked at.

Sinha and Trivedi [82] have proposed a unique spectrum sensing method based on two-state discrete-time Markov chain models in a non-fading channel with additive Laplacian noise. The proposed system provides good results for different modulation techniques but does not evaluate the performance under fading channel conditions.

Zhao et al. [83] propose to construct a dual-threshold CSS framework for a 5G network. The proposed algorithm utilizes the presence of a cyclic prefix in the 5G OFDM signal which results in autocorrelation in the PU signal. The autocorrelation is performed after grouping the received signal and performing FFT on them. The proposed system uses two thresholds to determine the existence of PU signal. If the detection statistic falls between the two thresholds, the individual CR indicates spectrum sensing failure. Since the framework involves multiple CRs, a decision is made locally by each CR and sent to the FC for the final decision. The performance is evaluated for low SNR values and a good detection probability at low SNR values.

4 Discussions

In this section, we compare and analyze the different variety of spectrum sensing techniques presented in the literature. As discussed earlier, spectrum sensing techniques are broadly divided into two categories: Narrowband and Wideband spectrum sensing. Between these, narrowband spectrum sensing is more prominent in the literature.

Energy detection is, by far, the most common type of spectrum sensing method due to its simple implementation. It is deployed in different variations under AWGN and Rayleigh Fading conditions and several research works have shown that the main challenge in energy detection is the selection of the optimal threshold. On the other hand, improvement in performance is observed when known statistical properties of the PU signal are employed to sense the presence of the PU signal. These properties include correlation and cyclostationary. With these properties, the performance is vastly improved especially under fading conditions. Another property that can be used to detect the presence of a PU signal is entropy. Noise, being unknown, has a much higher entropy compared to the PU signal, and this feature is used to detect spectrum occupancy. With this method, the performance improves in an AWGN channel for different SNR levels but degrades in fading conditions.

Machine learning has emerged as another promising candidate for the spectrum sensing problem and different types of machine learning algorithms are employed under both AWGN and fading channel conditions to evaluate their performance. In most cases, energy is used as the discriminating feature between the PU signal and noise. Some of the research works employ different features than energy and show great improvement in performance. Research has been done on both the AWGN and fading channel conditions and it has been observed that SVM and Naive-Bayes outperform other algorithms in most cases.

The above-mentioned spectrum sensing techniques display great improvement in performance under both AWGN and fading conditions when a cooperative Cognitive Radio Network is deployed and a fusion center is used to make the final decision on spectrum occupancy.

In summary, all spectrum sensing methods have their pros and cons. For the most simple to implement techniques, such as energy, lack in complexity is countered by degradation in performance in low SNR levels and fading conditions. On the other hand, the more advanced techniques that perform well under severe channel conditions are computationally expensive to implement. Similarly, machine learning techniques require computational power to train and update the models. The selection of the best technique comes down to the application. If less processing power is available, energy detection becomes the best solution. However, if processing power is sufficient, machine learning-based algorithms become the better choice.

Table 2 shows a summary of the findings that have been discussed in this section.

Table 2 Summary of spectrum sensing techniques

Spectrum sensing method	Channel	Performance	Computational requirement
Energy	AWGN	Good	Low
	Fading	Poor	
Statistical	AWGN	Good	Medium
	Fading	Average	
Entropy	AWGN	Good	Medium
	Fading	Poor	
Machine Learning	AWGN	Good	High
	Fading	Good	

5 Conclusion and future work

In this review, different types of spectrum sensing algorithms for narrowband and wideband signals and their performance, advantages and constraints were exhaustively discussed. It has been established that spectrum sensing remains the most critical task of a CRN and the performance of the CRN depends on the successful detection of spectrum holes. With the introduction of 5G communications, the demand for successful spectrum sensing has never been higher. Moreover, the ability to apply machine learning algorithms to engineering problems has given rise to boundless opportunities for performance improvements and research.

Through an extensive review of the current state of the art, it can be concluded the future course of work in spectrum sensing must be focused on spectrum sensing in 5G Cognitive Radio Networks. A dearth in research on spectrum sensing for 5G signal was observed and there is significant scope in cognitive radios in 5G networks. With more countries adapting 5G communications, most devices are expected to operate in 5G environment. Future cognitive radio networks will function in 5G networks. 5G signals have multiple use cases and two different frequency ranges resulting in multitude of combinations of spectrum sensing applications.

Access to more computational power and recent advances in machine learning algorithms has made the prospect of application of machine learning algorithms in 5G Cognitive Radio networks very high. Applying different machine learning algorithms to a variety of 5G signal parameters and various different channel conditions to determine the best performing algorithms could be a possible avenue of future research.

Author Contributions MUM wrote the main manuscript text and prepared all figures with contributions from RS. All authors reviewed the manuscript.

Funding The authors did not receive any funding to conduct this research.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Khattab, A., Perkins, D., & Bayoumi, M. (2013). *Cognitive radio networks: From theory to practice*. https://doi.org/10.1007/978-1-4614-4033-8
2. Spectrum policy task force: Report of the spectrum efficiency working group. Report, Federal Communications Commission (2002)
3. Cotton, M., Vu, L., Eales, B., & Hicks, A. (2020). 3.45-3.65 ghz spectrum occupancy from long-term measurements in 2018 and 2019 at four coastal sites. Report NTIA Report 20-548, US Department of Commerce.
4. Haykin, S. (2005). Cognitive radio: Brain-empowered wireless communications. *IEEE Journal on Selected Areas in Communications, 23*(2), 201–220. https://doi.org/10.1109/jsac.2004.839380
5. Mitola, J., & Maguire, G. Q. (1999). Cognitive radio: Making software radios more personal. *IEEE Personal Communications, 6*(4), 13–18.
6. Notice of proposed rule making and order: Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies. Et docket no. 03-108 (2005).
7. Yucek, T., & Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. *IEEE Communications Surveys & Tutorials, 11*(1), 116–130. https://doi.org/10.1109/surv.2009.090109
8. Zhang, W. (2019). *Handbook of cognitive radio*. https://doi.org/10.1007/978-981-10-1394-2
9. Fette, B. (2009). *Cognitive radio technology*. Academic Press.
10. Arjoune, Y., & Kaabouch, N. (2019). A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions. *Sensors (Basel)*. https://doi.org/10.3390/s19010126
11. Hwang, C.-H., Lai, G.-L., & Chen, S.-C. (2010). Spectrum sensing in wideband OFDM cognitive radios. *IEEE Transactions on Signal Processing, 58*(2), 709–719.
12. Kay, S. (1998). Fundamentals of statistical signal processing, Volume II: Detection theory.
13. Lim, T., Liang, Y., & Zeng, Y. GLRT-based spectrum sensing for cognitive radio. In *IEEE GLOBECOM 2008—2008 IEEE global telecommunications conference* (pp. 1–5). IEEE.
14. Bokharaiee, S., Nguyen, H. H., & Shwedyk, E. Spectrum sensing for OFDM-based cognitive radio. In *2010 IEEE 72nd vehicular technology conference-fall* (pp. 1–5). IEEE.
15. Pawelczak, P., Nolan, K., Doyle, L., Oh, S. W., & Cabric, D. (2011). Cognitive radio: Ten years of experimentation and development. *IEEE Communications Magazine, 49*(3), 90–100.
16. Hossain, E., & Bhargava, V. (2007). *Cognitive Wireless Communication Networks*. Springer.
17. Shen, J., Liu, Y., Liu, S., Gao, J., Xie, G., & Chi, C. Robust energy detection based on Bayesian estimation for cognitive radios. In *IEEE global telecommunications conference GLOBECOM* (pp. 1–5).
18. Kim, K., Xin, Y., & Rangarajan, S. (2010). Energy detection based spectrum sensing for cognitive radio: An experimental study. In *2010 IEEE Global Telecommunications Conference GLOBECOM 2010* (pp. 1–5). IEEE.
19. Jinbo, W., Tao, L., & Guangxin, Y. An energy detection algorithm based on double-threshold in cognitive radio systems. In *The 1st international conference on information science and engineering (ICISE2009)* (pp. 493–496). IEEE. https://doi.org/10.1109/ICISE.2009.257
20. Gupta, M. S., & Kumar, K. (2019). Progression on spectrum sensing for cognitive radio networks: A survey, classification, challenges and future research issues. *Journal of Network and Computer Applications, 143*, 47–76. https://doi.org/10.1016/j.jnca.2019.06.005
21. Altrad, O., & Muhaidat, S. (2013). A new mathematical analysis of the probability of detection in cognitive radio over fading channels. *EURASIP Journal on Wireless Communications and Networking, 2013*(1), 1–11. https://doi.org/10.1186/1687-1499-2013-159
22. Atapattu, S., Tellambura, C., & Jiang, H. (2011). Energy detection based cooperative spectrum sensing in cognitive radio networks. *IEEE Transactions on Wireless Communications, 10*(4), 1232–1241.
23. Yu, S., Liu, J., Wang, J., & Ullah, I. (2020). Adaptive double-threshold cooperative spectrum sensing algorithm based on history energy detection. *Wireless Communications and Mobile Computing, 2020*, 1–12. https://doi.org/10.1155/2020/4794136
24. Sharma, R. K., & Wallace, J. W. (2011). Correlation-based sensing for cognitive radio networks: Bounds and experimental assessment. *IEEE Sensors Journal, 11*(3), 657–666. https://doi.org/10.1109/jsen.2010.2058097
25. Saxena, V., & Bsaha, S. J. (2013). A survey of various spectrum sensing techniques in cognitive radio networks: Non cooperative systems. *International Journal of Electronics Communication and Computer Engineering, 4*(3), 857–862.
26. Ming, J., Youming, L., & Heung-Gyoon, R. (2012). On the performance of covariance based spectrum sensing for cognitive radio. *IEEE Transactions on Signal Processing, 60*(7), 3670–3682. https://doi.org/10.1109/tsp.2012.2194708
27. Proakis, J. G., & Salehi, M. (2007). *Digital communications*. Mcgraw-Hill.
28. Nagaraj, S. V. (2009). Entropy-based spectrum sensing in cognitive radio. *Signal Processing, 89*(2), 174–180. https://doi.org/10.1016/j.sigpro.2008.07.022
29. Zhang, Y., Zhang, Q., & Wu, S. (2010). Entropy-based robust spectrum sensing in cognitive radio. *IET Communications, 4*(4), 428–436. https://doi.org/10.1049/iet-com.2009.0389

30. Swetha, N., Sastry, P. N., Rao, Y. R., & Sabat, S. L. (2016). Parzen window entropy based spectrum sensing in cognitive radio. *Computers & Electrical Engineering, 52*, 379–389. https://doi.org/10.1016/j.compeleceng.2016.02.002
31. Sugiyama, M. (2016). *Introduction to statistical machine learning*. Morgan Kaufmann.
32. Burkov, A. (2019). *The hundred-page machine learning book* (Vol. 1).
33. Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1). MIT Press.
34. Theodoridis, S. (2015). *Machine learning: A Bayesian and optimization perspective*. Academic press.
35. Duda, R., Hart, P., & Stork, D. (2001). *Pattern classification*. Wiley.
36. Hassan, Y., El-Tarhuni, M., & Assaleh, K. (2010). Knowledge based cooperative spectrum sensing using polynomial classifiers in cognitive radio networks. In *4th international conference on signal processing and communication systems*. IEEE.
37. Hassan, Y., El-Tarhuni, M., & Assaleh, K. (2010). Comparison of linear and polynomial classifiers for co-operative cognitive radio networks. In *IEEE 21st international symposium on personal indoor and mobile radio communications* (pp. 797–802). https://doi.org/10.1109/PIMRC.2010.5671981
38. Hassan, Y., El-Tarhuni, M., & Assaleh, K. (2012). Learning-based spectrum sensing for cognitive radio systems. *Journal of Computer Networks and Communications, 2012*, 1–13. https://doi.org/10.1155/2012/259824
39. Muzaffar, M. U., El-Tarhuni, M., & Assaleh, K. (2012). Learning-based spectrum sensing in OFDM cognitive radios. In *COCORA 2012: The second international conference on advances in cognitive radio* (pp. 57–62).
40. Muzaffar, M. U. (2012). *Learning based spectrum sensing in OFDM cognitive radios*. American University of Sharjah.
41. Mikaeil, A. M., Guo, B., & Wang, Z. (2014). *Machine learning to data fusion approach for cooperative spectrum sensing*. https://doi.org/10.1109/CyberC.2014.80
42. Azmat, F., Chen, Y., & Stocks, N. (2016). Analysis of spectrum occupancy using machine learning algorithms. *IEEE Transactions on Vehicular Technology, 65*(9), 6853–6860. https://doi.org/10.1109/tvt.2015.2487047
43. Thilina, K. M., Kae Won, C., Saquib, N., & Hossain, E. (2012). Pattern classification techniques for cooperative spectrum sensing in cognitive radio networks: SVM and W-KNN approaches. In *Globecom 2012—Cognitive radio and networks symposium* (pp. 1260–1265). https://doi.org/10.1109/GLOCOM.2012.6503286
44. Thilina, K. M., Kae Won, C., Saquib, N., & Hossain, E. (2013). Machine learning techniques for cooperative spectrum sensing in cognitive radio networks. *IEEE Journal on Selected Areas in Communications, 31*(11), 2209–2221. https://doi.org/10.1109/jsac.2013.131120
45. Arjoune, Y., & Kaabouch, N. (2019). On spectrum sensing, a machine learning method for cognitive radio systems. https://doi.org/10.1109/EIT.2019.8834099
46. Kaiqing, Z., Jiachen, L., & Feifei, G. (2014). Machine learning techniques for spectrum sensing when primary user has multiple transmit powers. In *IEEE ICCS* (pp. 137–141). https://doi.org/10.1109/ICCS.2014.7024781
47. Awe, O. P., & Lambotharan, S. (2015). *Cooperative spectrum sensing in cognitive radio networks using multi-class support vector machine algorithms*. https://doi.org/10.1109/ICSPCS.2015.7391780
48. Yingqi, L., Pai, Z., Donglin, W., & Fattouche, M. (2016). Machine learning techniques with probability vector for cooperative spectrum sensing in cognitive radio networks. In *IEEE wireless conference and networking conference (WCNC 2016) Track 1: PHY and fundamentals* (Vol. 2016, pp. 1–6). https://doi.org/10.1109/WCNC.2016.7564840
49. Awe, O. P., Ziming, Z., & Lambotharan, S. (2013). Eigenvalue and support vector machine techniques for spectrum sensing in cognitive radio networks. In *2013 conference on technologies and applications of artificial intelligence* (pp. 223–227). https://doi.org/10.1109/TAAI.2013.52
50. Jan, S., Vu, V.-H., & Koo, I. (2018). Throughput maximization using an SVM for multi-class hypothesis-based spectrum sensing in cognitive radio. *Applied Sciences, 8*(3), 421. https://doi.org/10.3390/app8030421
51. Jan, S. U., Vu, V. H., & Koo, I. S. (2018). Performance analysis of support vector machine-based classifier for spectrum sensing in cognitive radio networks. In *2018 international conference on cyber-enabled distributed computing and knowledge discovery* (pp. 385–3854). https://doi.org/10.1109/CyberC.2018.00075
52. Shah, H. A., & Koo, I. (2018). Reliable machine learning based spectrum sensing in cognitive radio networks. *Wireless Communications and Mobile Computing, 2018*, 1–17. https://doi.org/10.1155/2018/5906097
53. Ma, X., Ning, S., Liu, X., Kuang, H., & Hong, Y. (2018). Cooperative spectrum sensing using extreme learning machine for cognitive radio networks with multiple primary users. In *2018 IEEE 3rd advanced information technology, electronic and automation control conference (IAEAC 2018)* (pp. 536–540). https://doi.org/10.1109/IAEAC.2018.8577777
54. Hongjian, S., Nallanathan, A., Cheng-Xiang, W., & Yunfei, C. (2013). Wideband spectrum sensing for cognitive radio networks: A survey. *IEEE Wireless Communications, 20*(2), 74–81. https://doi.org/10.1109/MWC.2013.6507397
55. Zhi, T., & Giannakis, G. B. (2006). A wavelet approach to wideband spectrum sensing for cognitive radios. *IEEE*. https://doi.org/10.1109/CROWNCOM.2006.363459
56. Ali, A., & Hamouda, W. (2017). Advances on spectrum sensing for cognitive radio networks: Theory and applications. *IEEE Communications Surveys & Tutorials, 19*(2), 1277–1304. https://doi.org/10.1109/comst.2016.2631080
57. Eldar, Y. C., & Kutyniok, G. (2012). Compressed sensing: Theory and applications. Edited by Yonina C. Eldar, Gitta Kutyniok. Cambridge University Press.
58. Salahdine, F., Kaabouch, N., & El Ghazi, H. (2016). A survey on compressive sensing techniques for cognitive radio networks. *Physical Communication, 20*, 61–73. https://doi.org/10.1016/j.phycom.2016.05.002
59. Garg, R., & Khandekar, R. (2009). Gradient descent with sparsification: An iterative algorithm for sparse recovery with restricted isometry property. In *Proceedings of the 26th annual international conference on machine learning* (pp. 337–344).
60. Karahanoglu, N. B., & Erdogan, H. (2012). A orthogonal matching pursuit: Best-first search for compressed sensing signal recovery. *Digital Signal Processing, 22*(4), 555–568. https://doi.org/10.1016/j.dsp.2012.03.003
61. Shihao, J., Ya, X., & Carin, L. (2008). Bayesian compressive sensing. *IEEE Transactions on Signal Processing, 56*(6), 2346–2356. https://doi.org/10.1109/TSP.2007.914345
62. El-Khamy, S. E., Abd-el-Malek, M. B., & Kamel, S. H. (2017). A stationary wavelet transform approach to compressed spectrum sensing in cognitive radio. *International Journal of Communication Systems*. https://doi.org/10.1002/dac.3140
63. Zhang, X., Ma, Y., Gao, Y., & Zhang, W. (2018). Autonomous compressive-sensing-augmented spectrum sensing. *IEEE Transactions on Vehicular Technology, 67*(8), 6970–6980. https://doi.org/10.1109/tvt.2018.2822776
64. Khalfi, B., Zaid, A., & Hamdaoui, B. When machine learning meets compressive sampling for wideband spectrum sensing. In *2017 13th international wireless communications and mobile computing conference (IWCMC)* (pp. 1120–1125). IEEE.

65. Yang, J., Jia, M., Gu, X., & Guo, Q. (2018). Low complexity sub-nyquist wideband spectrum sensing for cognitive radio. *IEEE Access, 6*, 45166–45176. https://doi.org/10.1109/access.2018.2865099
66. Osseiran, A., Monserrat, J. F., & Marsch, P. (2016). *5G mobile and wireless communications technology*. Cambridge University Press.
67. Dahlman, E., Parkvall, S., & Skold, J. (2018). 5G NR: The next generation wireless access technology (1st edn). Fifth generation new radio. Includes bibliographical references and index.
68. Rodriguez, J. (2015). *Fundamentals of 5G mobile networks*. John Wiley & Sons.
69. Zhang, Z., Zhang, W., Zeadally, S., Wang, Y., & Liu, Y. (2015). Cognitive radio spectrum sensing framework based on multi-agent architecture for 5g networks. *IEEE Wireless Communications, 22*(6), 34–39. https://doi.org/10.1109/mwc.2015.7368822
70. Liu, X., He, D., & Jia, M. (2017). 5g-based wideband cognitive radio system design with cooperative spectrum sensing. *Physical Communication, 25*, 539–545. https://doi.org/10.1016/j.phycom.2017.09.010
71. Xu, T., Zhou, T., Tian, J., Sang, J., & Hu, H. (2020). Intelligent spectrum sensing: When reinforcement learning meets automatic repeat sensing in 5g communications. *IEEE Wireless Communications, 27*(1), 46–53. https://doi.org/10.1109/mwc.001.1900246
72. Ejaz, W., & Ibnkahla, M. (2018). Multiband spectrum sensing and resource allocation for IoT in cognitive 5g networks. *IEEE Internet of Things Journal, 5*(1), 150–163. https://doi.org/10.1109/jiot.2017.2775959
73. Xu, T., Zhang, M., Hu, H., & Chen, H.-H. (2018). Sliced spectrum sensing-a channel condition aware sensing technique for cognitive radio networks. *IEEE Transactions on Vehicular Technology, 67*(11), 10815–10829. https://doi.org/10.1109/tvt.2018.2869381
74. Awe, O. P., Deligiannis, A., & Lambotharan, S. (2018). Spatio-temporal spectrum sensing in cognitive radio networks using beamformer-aided SVM algorithms. *IEEE Access, 6*, 25377–25388. https://doi.org/10.1109/access.2018.2825603
75. Ahmed, R., Chen, Y., & Hassan, B. (2021). Deep learning-driven opportunistic spectrum access (OSA) framework for cognitive 5G and beyond 5G (B5G) networks. *Ad Hoc Networks, 123*, 102632.
76. Algriree, W., Sulaiman, N., Isa, M., Sahbudin, R. K., Hassan, S. L., Salman, E. H., & Alghrairi, M. (2022). A CR-5G network based on multi-user for various waveforms detection. *Egyptian Informatics Journal, 23*(3), 517–527.
77. Dikmese, S., Lamichhane, K., & Renfors, M. (2021). Novel filter bank-based cooperative spectrum sensing under practical challenges for beyond 5g cognitive radios. *EURASIP Journal on Wireless Communications and Networking, 2021*(1), 1–27.
78. Perumal, R., & Nagarajan, S. K. (2022). A machine learning-based compressive spectrum sensing in 5g networks using cognitive radio networks. *International Journal of Communication Systems, 35*(16), 5302.
79. Nouri, M., Behroozi, H., Mallat, N. K., & Aghdam, S. A. (2021). A wideband 5g cyclostationary spectrum sensing method by kernel least mean square algorithm for cognitive radio networks. *IEEE Transactions on Circuits and Systems II: Express Briefs, 68*(7), 2700–2704.
80. Zhao, W., Li, H., Jin, M., Liu, Y., & Yoo, S.-J. (2020). Eigenvalues-based universal spectrum sensing algorithm in cognitive radio networks. *IEEE Systems Journal, 15*(3), 3391–3402.
81. Koteeshwari, R., & Malarkodi, B. (2022). Compressive spectrum sensing for 5g cognitive radio networks-lasso approach. *Heliyon, 8*(6), e0962e09621.
82. Sinha, K., & Trivedi, Y. (2022). Spectrum sensing based on two state discrete time Markov chain in additive Laplacian noise. *Wireless Networks, 28*(6), 2393–2402.
83. Zhao, Y., Wang, C., Hu, M., Wu, H., Lin, F., & Liu, Z. (2022). A cooperative wideband spectrum sensing framework in the frequency domain for resource allocation with 5g-NR. *Measurement, 191*, 110756.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Muhammad Umair Muzaffar is a Ph.D. student at Heriot-Watt University. He is currently pursuing his doctoral research on spectrum sensing in modern cognitive radio networks. His research interests include machine learning, signal processing and communication systems. He graduated with a Master of Science in Electrical Engineering in 2012 and Bachelor of Science in Electrical Engineering in 2010 from American University of Sharjah.

Rula Sharqi is an MIT-trained assistant professor with a B.Sc. in Electronics Engineering, an MSc in Electrical Circuit Design and a Ph.D. in Construction Built Environment with a focus on image processing and automation. She is a qualified multidisciplinary engineer with 15 years of experience in university-level teaching and construction design.