Probabilistic Spectrum Sensing Based on Feature Detection for 6G Cognitive Radio: A Survey

ANTONI IVANOV, (Member, IEEE), KRASIMIR TONCHEV, (Member, IEEE), VLADIMIR POULKOV, (Senior Member, IEEE), AND AGATA MANOLOVA, (Member, IEEE)

Faculty of Telecommunications, Technical University of Sofia, 1000 Sofia, Bulgaria

Corresponding author: Antoni Ivanov (astivanov@tu-sofia.bg)

This work was supported by the European Regional Development Fund through the Operational Program “Science and Education for Smart Growth” under Contract UNITe BG05M2OP001-1.001-0004-C01/28.02.2018 (2018–2023).

ABSTRACT With the advent of Sixth Generation (6G) telecommunication systems already envisioned, increased effort is made to further develop current communication technologies, so they can be incorporated together with the novel ones, to deliver uninterrupted and satisfactory service for any application in every location on the ground, underwater, in the air, or in space. One such technology is Cognitive Radio (CR) which has received much attention due to its potential for increase of utilization, especially in the bands below 6 GHz. The main enabler for CR is spectrum sensing because it provides the opportunity for dynamic assessment of the radio environment to identify unused channels. This functionality has been the object of many research works for that very reason. In spite of this, the provision of accurate and fast spectrum characterization in time, frequency and space has proven to be a non-trivial task. This paper presents a detailed review of probabilistic spectrum sensing methods classified by the feature they extract from the received signal samples, to provide accurate detection of the primary user (PU) signal. The main design characteristics (such as probability of detection, robustness to noise and fading, signal/noise model assumptions, and computational complexity), strengths and weaknesses for each type are also summarized. Based on current concepts for 6G networks and applications, a framework for human-centric cognition-based wireless access is presented, which specifies the role of spectrum sensing-based CR in future networks.

INDEX TERMS 6G, cognitive radio, feature detection, human-centric wireless access, Internet of Things, probabilistic spectrum sensing, wireless communications.

I. INTRODUCTION

For over two decades, the application of CR and software-defined radio (SDR) based devices has been established as a significant and ever-expanding field in wireless communications. Throughout this time, the benefits of extending current networks and introducing new ones by applying the concepts of transmission parameters adaptation, dynamic spectrum access (DSA) and coordinated spectrum sharing, have been continuously highlighted [1]–[3]. Looking to the upcoming integrated space and terrestrial networks (ISTN, as conceptualized in [4]) for 6G, CR has been envisioned to mature into the 6G Mitola radio, and be an important factor for facilitating the coexistence of a wide range of wireless communication systems via ”self-regulating societies of mobile radios” [5].

The most prominent gains from the introduction of CR in contemporary and future networks, have been recognized as:

- Increased spectrum utilization has been established that the static spectrum assignment of most current and legacy networks is quite inefficient because a significant portion of the expensive frequency resource is not used at all times in many regions covered by a wireless system. Multiple recent measurement campaigns of variable length and in different countries have shown that spectrum under-utilization is a prevalent phenomenon [6]–[8]. They revealed that the average duty cycle in the sub-GHz spectrum, ranges between 10 and 40% (with the exception of the 900 MHz cellular frequencies where in some regions, it is much higher). It was evaluated to be even lower in the higher frequencies below 6 GHz,

1 Quantifies the amount of time, on average, during which a signal is detected on a specific frequency band for the measurement period.
with under 30% (the most heavily occupied being the 2.4 GHz license-free and the cellular bands). The measured duty cycle depends substantially on the bandwidth size resulting in higher estimations for narrower band. Thus, the traditional wireless communication bands are significantly under-utilized. In a particular geographical area, a specific band can be unused for a limited amount of time and this would constitute a spectrum hole [9]. Thus, new services and applications can be introduced via the utilization of that spectrum if its availability is properly identified by a CR-enabled device (also referred to as secondary user, SU).

- Facilitated coexistence between unlicensed and licensed networks or different non-licensed ones. Taking advantage of the spectrum holes occurring in the currently deployed networks can advance the roll-out of new wireless standards. As legacy networks are usually slow to be phased out, their spectrum usage can be optimized if it is opportunistically shared with state-of-the-art systems. On another hand, un-utilized spectrum in non-licensed industrial, scientific and medical (ISM) bands can be appropriated by other network types (such as cellular). An example being the cognitive Long Term Evolution (LTE) systems operating in the Wireless Fidelity (Wi-Fi) 5 GHz band which have been studied in greater detail [10]. In addition a cognitive SU can opportunistically determine which network will provide the most favorable quality of service (QoS) and switch to it [2].

- Increased economic gain. Providing higher utilization of the same chunk of spectrum via CR can benefit an operator economically, even if the prices for SU access is low. It has been shown that spectrum sharing of a cellular band can be justified, provided reasonable authentication and transmission restrictions are implemented in the cognitive devices [11]. In addition, satisfactory financial gain can be achieved with only a few simultaneous secondary subscribers on particular band. Thus, the possibility for substantial interference to the primary uses (PUs) decreases.

In order to provide these advantages, a cognitive device has to implement means for both intelligent analysis of the radio environment in multiple domains (such as time, frequency, space) and the hardware adaptability which allows it to reconfigure its transmission parameters [1]. The former area has been pivotal in CR research due to the many problems related to signal processing in complex wireless channels and variety of bandwidths. Both the environment characterization and the multiple access in a CR network need to be dynamically adapted in order to provide maximum utilization of the unused spectrum. In addition, spectrum holes are not only altered dynamically in time and frequency but also distributed non-homogeneously in space/height/geographical location. This is due to the usually rapid movement of PUs and effects such as multipath propagation, shadowing, fading and the substantial signal attenuation in indoor environments. Furthermore, in modern communications, the analysis of spectrum utilization in three-dimensions (3D) has become more prevalent due to the introduction of unmanned aerial vehicle-based base stations and high-density Internet of Things (IoT) deployments [12]. The concept of 3D spectrum holes is illustrated in Fig. 1. At a given time, a particular chunk of the frequency band may be occupied (in colors illustrating their utilization by different primary links) at a specific space/location (or as shown in Fig. 1, each plane), while it can be available (white) at a different one. On each plane, the utilized bandwidth is separate and it is used for a different period of time. An SU (depending on the region/plane it is located in) is required to accurately detect the available chunk of spectrum and if it has to send a message, to utilize the resource. There are four modes for CR implementation - overlay, underlay, interweave and hybrid (between the latter two) [13], [14]. In the overlay approach, there is a kind of symbiosis between the primary and cognitive users - the SUs alleviate a portion of the PUs’ communications while using the incumbent spectrum for their own transmissions. They still are required to assure protection of the PUs against significant interference. In a similar manner, the underlay technique allows a simultaneous usage of the spectrum by both incumbent and non-licensed users. However, they do not collaborate and for that reason the SUs are under much more stringent requirement - their transmissions must be below the PUs’ interference threshold [15]. The interweave approach has been assumed in a large portion of the current research.
because its agility allows the CR system to provide the aforementioned benefits to a much greater extent. By utilizing this technique, the SUs can increase the incumbent spectrum utilization, communicate autonomously from the primary network, and achieve greater throughput without impeding the PUs’ communications. Thus, it requires rigorous analysis and characterization of the spectrum, in order to determine whether it is available for secondary transmission or not. The hybrid technique combines the underlay and interweave approaches to enhance the spectrum utilization even greater. In contrast to standard interweave CR, if the SU detects a PU signal, it can continue to use that spectrum with lower transmission power. In general, spectrum sensing methods can be implemented in any of these paradigms but the interweave and hybrid CR networks are usually assumed in many works because fast and precise detection is most relevant to them. The classic cognitive cycle presented by Haykin [16] has set the general framework of CR devices’ operation. It illustrates the way in which the intelligent wireless system reconfigures its parameters based on interactions with the environment. The cognitive cycle’s main features are 1) Radio environment analysis (detecting the presence of a signal and identifying its type/source); 2) Channel quality estimation (among the channels available for secondary transmissions, those with highest quality are to be determined and chosen); 3) Dynamic spectrum management (control and distribute the power and frequency resources among the cognitive users so as to limit their mutual interference as well as degradation of PU’s communications). A variant of Haykin’s scheme is illustrated in Fig. 2. Its elements can be briefly described as follows [1], [2], [16]:
- Spectrum sensing. In the sense of implementing DSA, this term refers to the function of measuring the intensity of the environment’s radio frequency (RF) stimuli. In other words, this operation performs analysis based on measurements of a certain portion of the frequency spectrum to determine whether it is occupied by a PU signal or not. Thus, it is the most vital function for Radio Environment Analysis. It should be noted that sensing as a CR function has to be differentiated than the tasks of object recognition and localization as well as channel occupancy prediction in modern communication systems [17], [18]. Regardless, spectrum sensing can be applied as a basis for some of these problems and so there is a potential for them to be somewhat related to each other in implementing higher level functionalities within an intelligent device or system. Probabilistic spectrum sensing methods (i.e. such that gather statistical information from the measured signal, analyze it, and extract a certain feature which characterizes the presence of the PU signal) are surveyed in this paper. Only non-cooperative, i.e. local, spectrum sensing is considered - these methods are observed from the point of view of an individual node, and they do not need to cooperate with other devices in the network to perform their functions, but can independently assess the spectrum occupancy. Cooperative algorithms can be based on the reviewed methods to enhance their accuracy.
- Signal identification. If a signal is detected, it can be beneficial that it’s type and/or source are identified. Thus, the CR device can determine whether the detected signal originates from an incumbent transmitter or is interference from the PU’s point of view. In the latter case, the spectrum is considered vacant and can be potentially utilized by the SU. Depending on the signal detector’s model, this function can be implemented within the spectrum sensing method.
- Spectrum prediction. Such methods aim to predict the frequency resource availability based on specific a priori information, usually in addition or as a substitute to spectrum sensing.
- Spectrum decision. This functionality determines which of the channels, determined to be vacant from PU transmissions, will achieve highest signal-to-noise-plus-interference ratio (SINR). This, together with the channels’ width will substantially define the achievable capacity for the current SU link.
- Channel estimation. Similar to spectrum decision and can supplement it. This function’s goal is to determine the channel gain, and thus, its viability for satisfactory QoS.
- Resource distribution. Within the CR network, the available channels are allocated for the necessary links via an appropriate multiple access/spectrum sharing scheme. In addition, each SU has to adapt its transmission power so as to not impede either other secondary links, or the primary ones.
- Spectrum mobility (handover). The SU needs to detect and relocate to other portions of the spectrum as soon as the PU returns to any of the previously available channels. This operation also needs to be performed with very little discernible degradation from the user’s point of view.

It should be noted that the Radio Environment Analysis aspect of the cognition cycle can be implemented entirely through the spectrum sensing function depending on the particular application. Furthermore, it is possible that it can be substituted by any of the other two, or that they are implemented through spectrum sensing. Thus, it has a vital importance for the design of CR devices and network architectures.

This survey focuses on variants of spectrum sensing which rely on precise PU signal detection and do not necessarily require location database for primary transmitters or a map of the spectrum usage in a particular area (which are also accepted means for characterizing the radio environment [19], [20] but outside of this work’s scope). Furthermore, only probabilistic methods (based on statistically-derived models of the noise and the PU signal) are considered. Thus, detection methods with machine learning-based channel occupancy estimation are outside of the scope of this work.
Most surveys in the field of spectrum sensing (some prominent ones are reviewed in Section II), do not consider in detail the similarities and differences in the mathematical formulations of the detectors within their relevant categories. Thus, to fill the existing gaps, this survey presents a detailed taxonomy of not just the various types of sensing methods but also the features which each of them aims to extract from the input so as to identify the presence of a PU signal in different wireless channels. In addition, for each category of approaches, their adaptability in terms of a priori information requirements is outlined. Furthermore, the performance indicators are identified and their efficiency is quantitatively compared. Finally, a perspective on the applications of CR-enabled devices in the upcoming 6G communications is given, with a focus on the role spectrum sensing will provide in them. The contributions provided are summarized as follows:

- The development of probabilistic-based local spectrum sensing methods in relation to their performance is surveyed. They are categorized according to the features they extract from the received signal and their analytical characteristics in terms of robustness to channel impairments and requirements of a priori information, are reviewed and compared. The main design characteristics (such as probability of detection, robustness to noise and fading, signal/noise model assumptions, and computational complexity) for each spectrum sensing type, as well as directions for future developments, are also conveniently summarized.

- The applicability of CR to emerging technologies in 6G wireless communications is discussed together with the role which spectrum sensing will play in deploying these communication technologies. Based on current concepts for global 6G communications, incorporating any device and all physical environments, a human-centric cognition-based wireless access (HC²WA) framework is proposed. It describes the operation of spectrum sensing-enabled CRs within the scope of a 6G network, including the necessary functionalities for spectrum utilization assessment and mutual coexistence between primary and secondary networks.

Lists of acronyms and notations their respective definitions are presented in Table 1, Table 2, Table 3, and Table 4.

Throughout this article, it is common that vector and matrix representations of the relevant variables are denoted via small and capital letters in **boldface**, respectively. In addition, complex conjugate is denoted as $^*$.

The rest of this paper is organized in the following manner. Similar survey papers in the field are briefly examined in Section II, to outline the motivation for producing this work. Common metrics for assessing the performance of local spectrum sensing are described in Section III. Section IV surveys the probabilistic local spectrum sensing methods according to the features they use for detection of the PU signal. Their classification is presented in Fig. 3. Then, Section V reviews upcoming wireless systems in the context of 6G telecommunications, and explores the influence of spectrum sensing on their operations. In addition, relevant challenges in future research are described. Finally, Section VI concludes this survey.

## II. MOTIVATION

Hereby, a review of several surveys in the field of probabilistic-based spectrum sensing, is presented to both describe their relevance, and to outline the areas in which this paper expands the discussion. The authors in [21] review algorithms which, based on the standard sensing techniques, determine the overall decision on spectrum occupancy in the span of a CR network. Main attention is given on neural network, genetic, particle swarm optimization and other similar algorithms. The survey [22] presents a limited taxonomy of local spectrum sensing methods according to the characteristic features each of them uses to identify the PU signal. Overall research challenges and the applicability of autonomous CR networks in ultra-dense deployments, are discussed. A discussion on the most prominent sensing methods, and their main implementational characteristics is given in [23]. For each category, a general algorithm for its practical implementation is outlined. In addition, the performance benefits of combining two detector types in a specific logical sequence are presented. Several areas of further research for spectrum sensing enhancements to make cognitive devices more agile, are described. A similar survey in [3] includes both narrow and wideband sensing methods categorization together with a concise review of the respective implementation challenges. In addition, possible applications of cognitive devices in wireless monitoring and tracking, are summarized. Diverse algorithms for narrow and wideband sensing, with particular focus on the latter, are reviewed in [24]. The discussion includes but is not limited to machine learning-based approaches. Some CR potential applications within the television broadcast white spaces (TVWS), as well as, relevant research challenges are outlined. An extensive, though somewhat restricted to earlier advances in the field, survey of narrow and wideband sensing methods is presented in [25]. General implementational aspects of both local and cooperative sensing are also outlined. Finally, a review of the current CR-based standards is given together with a brief perspective on the challenges in integrating cognitive communications.
in IoT networks. A notable tutorial of compressed sensing for wideband spectrum occupancy characterization for CR is presented in [26]. The survey’s scope is extended beyond spectrum sensing to include approaches for localization and monitoring, as well as relevant hardware implementations. Finally, the authors provide a literature discussion and conceptualization of a radio environment map construction. Another notable survey [14] explores spectrum sensing and other CR capabilities (such as multiple access, power control, beamforming etc.) with consideration to various practical transmitter/receiver/channel imperfections. Special attention is given to the analytical solutions for spectrum sensing in various channel impairments. In addition, the authors give recommendations for the realization and integration of practical CR systems. A more general survey of both Nyquist and compressed wideband spectrum sensing is provided in [27]. It also outlines open questions as to the implementation of such approaches. The authors in [28] present a prominent survey of the general types of spectrum sensing approaches including narrow and wideband methods together with their standard limitations in terms of the a priori information (such as the PU signal’s parameters or noise fluctuations) required for efficient detection. Particular focus is given to approaches for energy efficiency enhancements of cooperative detectors. A noteworthy survey of these is provided in [29]. It is focused on the elements which the cooperative sensing methods are comprised of, such as detection, decision fusion, overhead exchange and others. The factors contributing to the overhead’s size and intensity (for example, sensing time, channel impairments, synchronization, etc.) are considered as well as their influence on delay and power consumption. Another very influential (although somewhat limited from the present standpoint) survey of narrowband and cooperative spectrum sensing, is presented in [30]. It includes the general problems for local sensing and how they are solved via the cooperation of multiple CR nodes. A short discussion on spectrum prediction, as well as some CR-based wireless standards, is provided. A brief summary of these survey papers, including their focus, advantages and limitations, is given in Table 5.

### III. PERFORMANCE METRICS FOR SPECTRUM SENSING

The most prominent performance indicators for spectrum sensing methods are the probability of detection and the probability of false alarm. They characterize the two fundamental properties of each signal detector depending on the measurement parameters (such as the number of samples) and the conditions of channel impairments (noise power, for example). These two metrics express the fundamental states between which, a signal detector must differentiate - the frequency band \( W \) is free from the PU signal \( s \) (the null hypothesis \( H_0 \)), or it is occupied \(^1\) (the alternate hypothesis \( H_1 \)). The relationship between these conditions is expressed through the binary detection problem (for a single batch of \( N = T_s F_s \) measurement samples):

\[
H_0 : y(n) = w(n), \quad n = 0, 1, \ldots, N - 1, \\
H_1 : y(n) = w(n) + h(n)s(n).
\]

In other words, the received signal \( y \) must only consist of noise \( w \) samples for \( H_0 \) to be true.\(^3\) The channel gain, sensing time and sampling frequency are denoted by \( h \), \( T_s \) and \( F_s \), respectively. The probability of detection \( P_D \) is defined as the likelihood that the PU’s presence can be detected

\(^1\)It is possible for additional hypotheses to be added in the detection task’s formulation. For example, the spectrum sensing method may be required to discriminate between several different pre-defined levels of PU transmission power, such as in [31].

\(^3\)Interfering signals from the PU’s point of view are usually not referred to as noise but if such are present in the band, it will still be available to SU transmissions.
A. Ivanov et al.: Probabilistic Spectrum Sensing Based on Feature Detection for 6G CR: Survey

TABLE 1. Table of acronyms and their definitions.

| Acronym | Definition |
|---------|------------|
| 3D      | Three dimensions |
| 5G      | Fifth generation wireless communications |
| 6G      | Sixth generation wireless communications |
| ACF     | Autocorrelation function |
| AD      | Anderson-Darling |
| AGM     | Arithmetic-to-geometric mean |
| AP      | Access point |
| AR      | Augmented reality |
| AUC     | Area under the curve |
| AWGN    | Additive white Gaussian noise |
| BALRT   | Buffer-added likelihood ratio test |
| BS      | Base station |
| BW      | Bandwidth |
| CAF     | Cyclic autocorrelation function |
| CAV     | Covariance absolute value |
| CD      | Cyclostationary detector |
| CDIF    | Cumulative distribution function |
| CDR     | Constant detection rate |
| CEUD    | Cognitive end-user device |
| CFO     | Carrier frequency offset |
| CLT     | Central limit theorem |
| CP      | Cyclic prefix |
| CR      | Cognitive radio |
| CRLB    | Cramer-Rao lower bound |
| CSD     | Cumulation of the spectral correlation density |
| CSCG    | Circularly-symmetric complex Gaussian |
| DC      | Direct current |
| DSA     | Dynamic spectrum access |
| EBD     | Eigenvector-based detector |
| EC      | Estimator-Correlator |
| ED      | Energy detector |
| EH      | Energy harvesting |
| ER      | Effective rate |
| EUD     | End-user device |
| FAM     | Fast Fourier Transform accumulation method |
| FFO     | Fractional center frequency offset |
| FPT     | Fast Fourier Transform |
| FLOM    | Fractional lower order moment |
| FS      | Fractional sampling |
| GLRT    | Generalized likelihood ratio test |
| GOF     | Goodness-of-Fit |
| GSM     | Global system for mobile communications |
| HAP     | High altitude platform |
| HC      | Human-centric |
| HC²WA   | Human-centric cognition-based wireless access |
| HSA     | Hybrid spectrum access |
| IMA     | Improved multi-antenna |
| IMF     | Intrinsic mode function |
| IoT     | Internet of Things |
| ISM     | Industrial, scientific and medical |
| ISTN    | Integrated space and terrestrial network |
| LIS     | Large intelligent surfaces |
| LNA     | Low-noise amplifier |
| LRT     | Likelihood ratio test |
| LTE     | Long Term Evolution |
| MA      | Multi-antenna |
| MAP     | Maximum a posteriori probability |
| MC      | Multi-cycle |
| MDL     | Minimum descriptive length |
| ME      | Maximum eigenvalue |
| MET     | Maximum eigenvalue to the trace |
| MFD     | Matched filter-based detector |
| MG      | Mixture Gaussian |
| MGF     | Movement-generation function |
| MIMO    | Multiple-input multiple-output |
| MLE     | Maximum likelihood estimate |
| MME     | Maximum-to-minimum eigenvalue |
| MSC     | Magnitude squared coherence |

TABLE 2. Table of acronyms and their definitions (continued).

| Acronym | Definition |
|---------|------------|
| N-P     | Neyman-Pearson |
| NOLRT   | Near-optimal likelihood ratio test |
| OFDM    | Orthogonal frequency division multiplexing |
| PAM     | Pulse-amplitude modulated |
| PAS     | Pool of available spectrum |
| PDF     | Probability density function |
| PU      | primary user |
| QoS     | Quality of service |
| RF      | Radio frequency |
| ROC     | Receiver operating characteristic |
| SAC     | Spectrum access control |
| SC      | Single-cycle |
| SCD     | Spectral correlation density |
| SCD-SC  | Single cycle detector with sliding correlation |
| SCF     | Spectral coherence function |
| SCN     | Standard condition number |
| SDR     | Software-defined radio |
| SDRA    | Spectrum Decision and Resource Allocation |
| SNIR    | Signal-to-noise-plus-interference ratio |
| SNR     | Signal-to-noise ratio |
| SNSO    | Spectrum Sharing and Network Self-Organization |
| SUG     | Spectrum utilization gain |
| SVD     | Singular value decomposition |
| TS      | Test statistic |
| TVWS    | Television broadcast white spaces |
| UAV     | Unmanned aerial vehicles |
| UE      | User equipment |
| VR      | Virtual reality |
| VROMP   | Vector regularized orthogonal matching pursuit |
| Wi-Fi   | Wireless Fidelity |

from $N$ quantized samples $y = [y_0, y_1, \ldots y_{N-1}]$ (of the received signal $y$), acquired via a measurement sweep of the spectrum, provided that a true positive condition is indeed factual ($P_D = p(H_1|H_1)$). Correspondingly, the probability of false alarm $P_{FA}$ describes the false positive likelihood ($P_{FA} = p(H_1|H_0)$). These two metrics are contradictory because as the received signal’s level decreases, it becomes harder to discriminate between the null ($H_0$) and the alternative ($H_1$) hypotheses. In order to derive analytical expressions for $P_D$ and $P_{FA}$, a likelihood ratio $L_G$ is used and it can be generally defined via the Neyman-Pearson (N-P) likelihood test [32]. It expresses the relationship between the probability density function (PDF) of $y$ under $H_1$ (i.e. $p(y|H_1)$), $p(y|H_0)$, and the threshold value $\xi$ which evaluates the degree of their separation. The detection method’s goal is to extract a particular feature $\varpi$ from the received signal samples $y$ so that the threshold may be rigid enough in low signal-to-noise ratio (SNR) levels when the difference between $p(y|H_1)$ and $p(y|H_0)$ is very small. When the signal samples $y$ are acquired via measurements, the detector’s test statistic (TS) $T(\varpi)$ is formed by extracting the relevant feature, and is compared to the decision threshold. If it is equal to $\xi$ or higher, then the PU signal is determined to be present. Otherwise, the sensing method establishes the null hypothesis as truthful.

$$T(\varpi) \begin{cases} H_1 & \text{if } T(\varpi) \geq \xi \\ H_0 & \text{otherwise} \end{cases}$$
TABLE 3. Table of notations and their definitions.

| Notation | Definition |
|----------|------------|
| $\mathcal{A}$ | Average AUC |
| $\bar{\mathcal{A}}$ | Average AUC |
| $\alpha$ | Path loss exponent |
| $\alpha_c$ | Cyclic frequency |
| $\Delta \alpha_c$ | Cyclic frequency offset |
| $CN(\cdot, \cdot)$ | circularly-symmetric complex Gaussian distribution |
| $C_{\alpha_c}^y$ | Spectral correlation density of $y$ for $\alpha_c$ |
| $\Gamma(\cdot)$ | Gamma function |
| $\gamma$ | SNR |
| $\gamma_C$ | Critical SNR |
| $\gamma_G$ | Generalized SNR |
| $\gamma_{wall}$ | Value of SNR wall |
| $\gamma_i$ | Instantaneous SNR |
| $\gamma_i^{\max}$ | Average SNR |
| $D_D$ | Deflection coefficient |
| $D_{th}$ | Deflection coefficient threshold |
| $E$ | Mathematical expectation |
| $E_b$ | Energy per bit |
| $\bar{E}$ | Average signal energy |
| $\epsilon_0$ | CAF of noise-only samples for $H_0$ |
| $\epsilon_1$ | CAF of noise-only samples for $H_1$ |
| $\epsilon(S)$ | Truncating error of the PDF of SNR |
| $F_0$ | Sampling frequency |
| $F_{0,y}(\cdot)$ | CDF of $y$ under $H_0$ |
| $F_P(\cdot)$ | PDF of the Student’s $t$-distribution |
| $F_{c,o}$ | Carrier frequency offset |
| $F_c$ | Exact center frequency |
| $f_P$ | PDF of SNR |
| $f_h(y)$ | Histogram estimate of the PDF of $y$ |
| $G_{\alpha_c}^y(\cdot)$ | Cumulation function of the SCD |
| $\mathcal{H}$ | Channel coefficients matrix |
| $H_0$ | Null hypothesis |
| $H_1$ | Alternative hypothesis |
| $h$ | Fading channel coefficient |
| $\Theta_c$ | Matrix of correlation coefficients |
| $\theta_d$ | Delay exponent |
| $I_n(\cdot)$ | Imaginary part |
| $I_n(\cdot)$ | Modified Bessel function of the first kind and order $n$ |
| $\mathbf{I}$ | Identity matrix |
| $K$ | Number of interferers |
| $\lambda$ | Eigenvale of the covariance matrix of $y$ |
| $L_1$ | Smoothing factor |
| $L_2$ | Generalized LRT |
| $L_3$ | Length of channel coefficients vector |
| $L_4$ | Oversampling factor |
| $\mu_s$ | Mean of the PU signal |
| $M$ | Length of a frame |
| $M_{\alpha_c}$ | Average dispersion of the SNR |
| $\mu_n$ | Nakagami fading coefficient |
| $N$ | Number of samples |
| $N_{\alpha_c}$ | Minimum number of samples |
| $N_{\alpha_c}$ | Number of OFDM samples |
| $N_0$ | Number of noise-only samples |
| $N_0$ | Noise energy |
| $N_T$ | Number of transmit antennas |
| $N_R$ | Number of receiving antennas |
| $N(\cdot)$ | Gaussian distribution |
| $N_d$ | Number of samples of the CP |
| $N_c$ | Number of samples of the OFDM symbol |
| $N_{c,o}$ | Number of samples of the OFDM symbol |
| $N_T$ | Number of lags |
| $N_F$ | Number of frames |

TABLE 4. Table of notations and their definitions (continued).

| Notation | Definition |
|----------|------------|
| $N_{PS}$ | Number of PS samples |
| $\Xi$ | CDF of the Student’s $t$-distribution |
| $\xi$ | Decision threshold |
| $P_D$ | Probability of detection |
| $\bar{P}_D$ | Average probability of detection |
| $P_{MD}$ | Probability of miss-detection |
| $P_{MD}$ | Desired probability of miss-detection |
| $\bar{P}_{MD}$ | Average probability of miss-detection |
| $P_{FA}$ | Probability of false alarm |
| $P_{FA}$ | Desired probability of false alarm |
| $P_s$ | PU signal power |
| $P_E$ | Probability of error |
| $P_{0}$ | A priori probability for the PU signal’s absence |
| $P_{1}$ | A priori probability for the PU signal’s presence |
| $P_{0,c,n}$ | PU signal’s power at $n$-th CF |
| $P_{0,n}$ | Probability of correct decision |
| $P_{dis}$ | Probability of discrimination |
| $\mathcal{P}$ | Matrix of the oblique linear predictors |
| $\tau$ | PU signal’s feature |
| $Q(\cdot)$ | Gaussian Q-function |
| $Q_k(\cdot, \cdot)$ | Gaussian Q-function |
| $\rho$ | Noise uncertainty coefficient |
| $\rho_c$ | Correlation coefficient |
| $\gamma$ | Eigenvalue of the channel coefficients matrix |
| $R(y)$ | Real part |
| $R_{ac}$ | Autocorrelation function of $y$ |
| $R_y$ | Covariance matrix of $y$ |
| $R_s$ | Covariance matrix of $s$ |
| $R_w$ | Covariance matrix of $w$ |
| $R_{ac}^y$ | Cyclic autocorrelation function of $y$ |
| $R_{ac}$ | Maximum distance of PU’s coverage |
| $R_{ac}$ | Cross-correlation covariance of $y$ |
| $R_{s,c,n}$ | PU signal’s CAP at $n$-th CF |
| $R_{ef}$ | Effective rate |
| $r$ | Distance between PU and SU |
| $\Sigma_2$ | Asymptotic covariance matrix of $y$ |
| $\sigma_v$ | Variance of the PU signal |
| $\sigma_n$ | Variance of the noise |
| $S$ | Number of computational terms |
| $s$ | PU signal |
| $s_{r,c}$ | Pilot signal |
| $\tau$ | Lag parameter |
| $\tau_m$ | Maximum lag |
| $\sigma_{syn}$ | Number of synchronization symbols |
| $\Sigma$ | Test statistic |
| $T_{op}$ | Operational period |
| $T_s$ | Sensing time |
| $T_{tr}$ | Transmission period |
| $T_L$ | Average TS from the last $L$ instances |
| $T_{0}$ | Period of the signal |
| $T_{d}$ | Period of the CP |
| $T_c$ | Period of the OFDM symbol |
| $\Phi$ | Composite measurement matrix |
| $\phi_p$ | Phase of the PU signal |
| $w$ | Noise |
| $\omega_{ac}$ | Scanning frequency |
| $\omega(f)$ | Finite Fourier representation of $y$ |
| $Y_{ps}$ | Past samples matrix |
| $Y_{fs}$ | Future samples matrix |
| $Y_{c}$ | Compressed signal matrix |
| $y$ | Received signal |

Inaccurate setting of $\xi$ can lead to either false alarm (determining the PU signal as present when it is not) or miss-detection (resolving that the spectrum is unoccupied when in fact, the opposite is true). Then, $P_D$ and $P_{FA}$ can be derived from the N-P test as functions of $\xi$ if it is predetermined. Otherwise, as is the case for most spectrum sensing
TABLE 5. Comparison of relevant surveys on spectrum sensing methods and their applications.

| Survey | Main focus | Notable advantages | Limitations |
|--------|------------|--------------------|-------------|
| Bappen et al. (2020) [21] | Soft computing techniques for cooperative spectrum sensing enhancement | Novel research directions for upcoming communications | Limited discussion of feature extraction in general sensing methods, and of wideband sensing |
| Ivanov (2019) [22] | Sensing methods categorization | Applications of CRs in UDNs | Limited analysis of the mathematical formulations of local sensing methods |
| Gupta et al. (2019) [3] | Narrow and wideband sensing methods categorization | Modern applications of CRs in different industries | Limited discussion of cooperative sensing methods |
| Awin et al. (2018) [23] | General sensing methods categorization | Implementation tutorial for each detector type; discussion of two-stage spectrum sensing approaches | Limited discussion of cooperative and of wideband sensing methods |
| Arjoune et al. (2019) [24] | Narrowband (Machine Learning-based) and wideband sensing methods categorization | Detailed tutorial on wideband sensing and comparisons | Limited discussion of cooperative sensing methods |
| Ali et al. (2016) [25] | Narrow and wideband sensing methods categorization | Detailed comparisons between the methods in each category; review of the CR standards | Limited discussion of narrowband, Nyquist wideband and cooperative sensing methods |
| Sharma et al. (2016) [26] | Compressed wideband sensing and monitoring methods categorization | Application of compressed sensing for localization, monitoring and radio environment map construction; hardware implementations of compressed sensing; cooperative compressed sensing approaches | |
| Sharma et al. (2015) [14] | Categorization of narrowband sensing methods and the influence of realistic imperfections | Analysis of channel impairments and current CR-based solutions | Limited discussion of wideband and cooperative sensing methods; limited analysis of the mathematical formulations of the sensing methods |
| Sun et al. (2013) [27] | Wideband sensing methods categorization | Implementational challenges for wideband spectrum sensing | Limited analysis of the mathematical formulations of the sensing methods |
| Axell et al. (2012) [28] | General narrow and wideband sensing methods categorization | Energy efficiency in cooperative spectrum sensing methods; general problems in the implementation of narrowband sensing | Limited discussion of cooperative and wideband sensing methods |
| Akyildiz et al. (2011) [29] | General cooperative sensing methods categorization | Implementation aspects of cooperative spectrum sensing methods; overhead reduction and energy efficiency | Limited discussion of narrow and wideband sensing methods and detectors’ implementation challenges |
| Yüce et al. (2009) [30] | General narrowband and cooperative sensing methods categorization | Main aspects of cooperative sensing; review of the CR standards | Limited discussion of cooperative and wideband sensing methods; limited analysis of the mathematical formulations of the sensing methods |

methods, the detector design procedure usually begins by fixing either the probability of detection or that of false alarm. Very often this is the $P_{\text{FA}}$ (by the choosing of which the method is termed constant false-alarm rate or CFAR) which is used to determine the value of $\xi$. Then, the $P_D$ is used as a detection accuracy characteristic for the relevant environmental parameters (such as a range of SNR levels).\(^4\)

The Bayesian approach offers an alternative framework for threshold derivation. It relies on the assuming the availability of information for the PU’s traffic pattern which is described via the a priori probability for the PU signal’s absence $p(H_0) = p(H_0)$ (or its presence $p(H_1) = 1 - p(H_0)$, respectively). In contrast to the alternative approach, however, it does not require the fixation of either $P_D$ or $P_{\text{FA}}$ to derive the other. Thus, it provides a threshold which satisfies both $P_{\text{des}}^\text{FA}$ and $P_{\text{des}}^\text{MD}$. The decision threshold can also be defined as a solution of the Bayesian cost optimization problem which minimizes the total error probability $P_E = P_{\text{FA}} + P_{\text{MD}}$ (where $P_{\text{MD}} = p(H_0|H_1) = 1 - P_D$) such that both of these probabilities are below predefined desired values ($P_{\text{des}}^\text{FA}$ and $P_{\text{des}}^\text{MD}$). Another way of expressing the spectrum sensing performance is by the relationship $P_D = f(P_{\text{FA}})$ for a fixed $\xi = f(\gamma, N)$, $\gamma = \frac{\sigma_s^2}{\sigma_w^2}$ denoting the SNR level which is the ratio of the PU signal’s variance $\sigma_s^2$ and that of the noise $\sigma_w^2$. The two metrics generally used to illustrate this dependency are the receiver operating characteristic (ROC) and the area under the curve (AUC). The latter emphasizes the effectiveness of threshold setting by measuring the probability for a correct decision which is illustrated by the area under the ROC curve [33]. It serves to illustrate the difference in performance when parameters such as $\gamma$ and $N$ vary (the corresponding ROC curves may not be easily discriminated). The AUC (denoted as $A$) is given in [34]. The complimentary ROC and AUC are analogous in principle but they are based on the relationship $P_{\text{MD}} = f(P_{\text{FA}})$. A more in-depth look at these metrics can be found in [33].

IV. ADVANCES IN FEATURE-BASED PROBABILISTIC LOCAL SPECTRUM SENSING

This section surveys a broad range of sensing methods for which the emphasis is on accurate detection of the PU signal for an individual CR device. They are categorized according to the feature they extract from the acquired measurement samples in order to determine whether the spectrum band

---

\(^4\)The opposite, i.e. setting the $P_D$ as a parameter in the constant detection rate (CDR) approach is also viable.
is occupied or not. Relevant implementation challenges, sub-categories and their characteristics are summarized for each detector type. For a great majority of these methods, bandwidth is not a consideration but it is assumed that it is narrow enough for processing to be performed in a reasonable time. It should be noted that a CR device (often assumed as being half-duplex) operates on two principal modes spectrum sensing and transmission (when the spectrum is available). Each of these two operations is performed on a separate time slot. Together, they form the operational period $T_{op} = T_s + T_t$ ($T_s$ and $T_t$ being the lengths of the sensing and transmission slots, respectively).

### A. ENERGY-BASED DETECTION SPECTRUM SENSING

Energy detection (ED), referred to as radiometer method in earlier literature, has remained the most prominent spectrum sensing method in CR research, even to the present day. These methods offer significant benefits in terms of their implementation simplicity and speed, in comparison to other types of spectrum sensing. The ED’s TS is comprised of the average energy of the received signal samples $y$ (the sum of their squared magnitudes, i.e. they comprise the features $\sigma_{ED}^2$ used for PU detection).

$$\Sigma_{ED}(\sigma) = \frac{1}{N} \sigma_{ED}^2 = \frac{1}{N} \sum_{n=0}^{N-1} |y(n)|^2.$$  \hspace{1cm} (3)

The dynamics of CR operations require both fast and accurate detection which can, in most cases, only be achieved to a degree as processing time increases significantly in attempting to detect the PU signal in low SNR ($\ll 0$ dB). Urkowitz’s classic formulation [35] in the field of radio signal detection assumes the availability of a substantial number of samples ($N > 125$, usually in the range of a few thousand or more) to describe the TS as a Chi-squared distribution by the application of the central limit theorem (CLT). This model has been established as the foundation for most current ED-based spectrum sensing approaches. However, this model leads to exponential increase in $N$ as the SNR declines [33]. The presence of non-Gaussian noise and fading additionally confounds this requirement.

An important consideration in ED-based spectrum sensing design, is the noise uncertainty which is a determining factor for detection performance even in an additive white Gaussian noise (AWGN) channel [36]. The reason for that being the substantial variation in noise level with time, which may lead to a TS value in the absence of a PU, which is comparable to the alternative case. Additionally, in low SNR, this effect can lead to a miss-detection. Most approaches which aim to solve this problem, propose a threshold setting that accounts for these dynamics in the wireless channel.

To keep the computational complexity low, many modern methods (such as [37]–[41]) derive the TS and decision threshold using a non-standard distribution. In this way, viable detection in particular assumptions can be achieved with much fewer ($< 100$) samples. A structured summary of the reviewed spectrum sensing methods of this type, as well as their performance, is presented in Table 7 and Table 8. Similar outlines are also done for the other detector types. The robustness of each method is denoted as "Low", “Moderate” or “High” depending on the SNR level $\gamma$ at which the standard detection metrics ($P_D = 0.9$ and $P_{FA} = 0.1$) are achieved. The relationship between these notations is illustrated in Table 6.

#### 1) GENERALIZED ENERGY DETECTION FOR COMPUTATIONAL OPTIMIZATION

The ED development for achieving accurate detection in AWGN ($w(n) \sim N(0, \sigma_0^2)$) with lower computational complexity and thus, faster processing is hereby reviewed. These methods range from the general CLT-based Gaussian approximation for the TS’s distribution, to newer derivations which provide suitable precision for much fewer samples. Gaussian distribution with zero mean for the PU signal is generally assumed, $s(n) \sim N(0, \sigma_0^2)$.

The traditional ED model (Chi-squared distribution of the TS) yields the exact formulation of the $P_{FA}$ and $P_D$ in AWGN (given in [33]) via the upper incomplete Gamma function (defined as $\Gamma(a) = \int_0^\infty x^{a-1} \exp(-x) \, dx$) of $N$, $\gamma$ and $\xi$. Using the CLT, these expressions can be approximated via the Gaussian Q-function $Q(x) = \frac{1}{2} \int_0^\infty \exp \left( \frac{-u^2}{2} \right) \, du$ [33]. Based on them, a single decision threshold can be found, according to either the CFAR or CDR approaches [33]. By the same means, the value of $N$ as function of $\gamma$ for certain desired $P_{FA}$ and $P_D$ can be obtained. According to the IEEE 802.22 standard [20], detection methods should aim for $P_{FA} \leq 0.1$ and $P_D \geq 0.9$ at $\gamma = -20$ dB, which introduces a significant computational challenge (large minimum number of samples $N_{min}$) [33], even when assuming a precise estimation of Gaussian noise’s level. In the case of Gaussian PU signal with unknown variance, the $P_D$ for ED has been derived as $P_D = Q_{\overline{N}} (\sqrt{\gamma}, \sqrt{2\overline{N} \xi})$, where

$$Q_k(a, b) = \int_b^\infty x \left( \frac{x}{a} \right)^{k-1} \exp \left( -\frac{x^2 + a^2}{2} \right) I_{k-1}(ax) \, dx \hspace{1cm} (4)$$

is the Marcum’s Q-function of $k$-th order, and $I_n$ - the modified Bessel function of the first kind and order $n$. [42]. A convenient practical implementation of this function can be found in [43]. The exact formulation for $P_{FA}$ is applied.

The aspect of threshold setting depending on whether its value is set for each separate sample (local thresholding), or averaged over $N$ samples (global thresholding) as is the case in most ED methods, is studied in [44]. It has been found that for a variety of real measured signals in TV and radio broadcast channels, the latter approach is better for capturing the occurrences of peaks. In addition, local thresholding

### TABLE 6. Performance metrics notations.

| Notation | Corresponding SNR level |
|----------|-------------------------|
| Low      | $\gamma \geq 0$ dB      |
| Moderate | $\gamma \in [-15; 0]$ dB|
| High     | $\gamma < -15$ dB       |

---

3 Generally referred to in earlier literature as a time-bandwidth product.
shows much lower detection performance, with a relatively high $P_{FA}$. The exact thresholds are determined empirically for each signal type.

In attempting to improve the traditional ED’s performance, the authors in [45] propose modifying the TS as follows. At each detection instance $i$, the TS is obtained by the average $\bar{x}_{ED}$ of the last $L$ instances’ values for $x_{ED}$ as computed by (3). The $P_{FA}$ and $P_{D}$, apart from $N$, $\gamma$, $\sigma_w^2$, and $\xi$, depend on the number of previous instances $L$ and those $L'$ at which the PU has been detected ($L' \leq L$). It has been shown that this method yields greater performance than the traditional ED because it considers the TS dynamics due to the varying received signal level and imperfect threshold setting. It has been found that, increasing $L$ does not significantly affect the execution time. The authors in [46] derive an optimal threshold $\xi_{opt}$ for the detection task. A version of the traditional ED with an SNR-adaptive thresholding for multiple-input multiple-output (MIMO) systems is derived in [47]. The TS is estimated with the use of Slepian tapers of varying length. $P_E$ of less than 0.2 is achieved at $\gamma = -20$ dB for $P_0 > 0.5$. When it comes to estimating the noise variance, measurement instances of different length from the general sensing periods, can be utilized [42]. For their duration, the $H_0$ hypothesis is assumed again by applying (3) for $N_w$ samples. $P_D = 0.9$ at $\gamma < -20$ dB for $P_{FA} = 0.1$ is acquired at $N_w = N = 10^5$.

This study has, in addition, found that $N_w$ has to be within the order of magnitude of $N$, or higher for a range of minimum SNR values $\gamma_{min}$ to retain the desired detection performance in low SNR. A similar principle is utilized in [48] by acquiring information about the PU signal empirically via the intrinsic mode function (IMF). Thus, a demixing matrix is determined in order to separate the signal components from the noise. For this purpose, the autocorrelation function (ACF) $R_{\gamma}(\tau) \triangleq E[y(t)y^*(t + \tau)]$ of the received samples is used, where $E[\cdot]$ is the mathematical expectation, $\tau \neq 0$ is a time (respectively, sample) delay or lag parameter, and $y^*$ denotes the complex conjugate of $y$. To decrease the computational complexity, a cube-of-Gaussian approximation of the TS for very few number of samples, is proposed in [41]. Just as the standard expression for the minimal value of $N$, this approximation depends on the desired $P_D$ and $P_{FA}$ for a particular SNR level. In high levels ($\gamma > 10$ dB), the PU signal can be detected with a $P_{FA} = 0.01$ utilizing as few as 3 samples. An alternative approach [37] for complexity alleviation utilizes the generalized $p$-norm ED\(^6\) and several different approximations for the TS under $N \ll 100$. All of them depend on $N$, $\gamma$, $P_{FA}$ and $P > 0$. The results show satisfying detection performance at $\gamma = -5$ dB for $N = 50$ and $p = 1.5$. Patnaik and Pearson approximations yield the least estimation errors for $P_D$ in $\gamma < -5$ dB. Even for $p$ ranging between 1 and 10, obtaining a $P_D$ of 0.9, requires for $N$ to be in the order of thousands. By utilizing a Fisher approximation to the exact expressions for ED, the authors in [38] derive closed-form solutions for $\xi$, $P_{FA}$ and $P_D$.

In an attempt to increase the ED’s efficiency in low SNR, [49] proposed an adaptive threshold which is a function of the traditional CFAR-based value for $\xi$, as well as $\gamma$ at each measurement instance.

Due to the many applications of orthogonal frequency division multiplexing (OFDM) and spread spectrum signals in modern wireless standards, appropriate attention has been given to spectrum sensing for PU signals of these types [50]–[52]. A detector for unknown variances of the signal and noise (both being Gaussian), as well as an optimal one if they are known, is developed in [50]. The authors propose a efficient generalized likelihood ratio test (GLRT) based estimator which uses the autocorrelation statistic $R_{CP}$ of the OFDM cyclic prefix (CP). In this way, a Neyman-Pearson TS can be formulated without knowledge of $\sigma_w^2$ and $\sigma_s^2$ from the $t_{syn}$ synchronization symbols. A simplified version of the same detector can be utilized if they are known. By applying limited number of samples, the computational complexity of these generalized models is balanced. A constant-energy detector for spread spectrum signals is proposed in [51]. It estimates the PU signal energy separately from that of the noise by dividing the batch of $N$ measured samples into $N'$ smaller portions and evaluating their means and variances. Based on them, analytical expressions for $\xi$ and $P_D$ are derived. Via the MDT metric, it is found that higher gain in terms of speed is achieved by increasing $N'$. A Cramer-Rao lower bound (CRLB) on the discrimination of signal and noise for OFDM signals using ED, is developed in [52]. The known signal structure (CP and useful data) is used for estimating both $\sigma_s^2$ and $\sigma_w^2$.

2) COMBATING THE SNR WALL IN ENERGY DETECTION

A major challenge for practical ED-based spectrum sensing is the presence of noise uncertainty defined by Tandra and Sahai [36] as an interval (or set) of values within which, the noise variance $\sigma_w^2$ is assumed to fluctuate. Thus, even if it is estimated within regular periods, its value may vary significantly which, as has been shown in multiple studies [36], [42], [53]–[58], can dramatically influence the detector’s performance. Noise uncertainty (denoted as $\rho_{dB}$ in dB or $\rho$ in absolute unit) even within 1 dB compared to the expected noise level/variance, can lead to overlapping between the signal and noise PDFs, thus, rendering them inseparable for certain SNRs under 0 dB. In addition, as illustrated in [58], due to noise variance uncertainty, it is possible for $\sigma_w^2$ to exceed $\sigma_s^2$ which would result in a miss-detection. The influence of noise uncertainty is analytically expressed as $\rho \in [\rho^0_{min} \sigma_w^2, \rho \sigma_s^2]$, $\rho = 10^{\rho_{dB}/10}$. $\rho_{dB}$

In traditional ED, has been established that increasing $N$ and $N_w$ results in better detection as the SNR declines. The critical significance of noise uncertainty is that for a certain $p$-norm ED and $\rho$, there exist an SNR level at which, $P_D$ converges to a value which cannot be exceeded even by thousand-fold increase of $N$. This effect is termed an SNR wall, determined in [53] as $\gamma_{wall} = (\rho^2 - 1) / \rho$. A prominent

\(^6\)In the traditional model $p = 2$. 
solution is periodical noise estimation [42], [57], even though it also has certain limitations because a balance is to be found between an appropriate a priori spectrum availability probability \( P_0 \) and the detector’s efficiency for a certain \( \gamma_{\text{wall}} \) level [53]. The study in [42] discovered the bounds in terms of SNR for the noise estimation. These bounds are dependent on the upper and lower noise variances caused by the uncertainty. Considering a two-step ED (noise is first estimated under assumed \( H_0 \)), for a sufficiently high \( N_h \) (in the order of \( 2^{20} \)) it is shown that noise uncertainty can be avoided even for \( \gamma < -20 \) dB. However, a substantial number (over \( 10^5 \)) of samples for \( \mathcal{E}_{\text{ED}} \) are necessary. These conditions hold only in AWGN channels. If fading is considered, at \( N = 2 \times 10^6 \) detection can only be retained for \( \rho_{\text{dB}} < 0.02 \) dB [56].

Another approach is to assign arbitrary weights to the desired \( P_D \) and \( P_{FA} \) in order to set an SNR-dependent lower \( \xi_l \) and higher \( \xi_h \) thresholds which describe the confusion region between the PDFs of \( H_0 \) and \( H_1 \) [54]. These two thresholds if \( \mathcal{E}_{\text{ED}}(\sigma) \) falls within that region while \( \sigma_w^2 \) is constant. By accounting for the PU transmission patterns and assigning weights to the desired \( P_D \) and \( P_{FA} \), an optimal threshold is derived in [58]. It adapts on the basis of \( \gamma \) and \( \rho \), reaching the threshold. In addition, the AUC is 0.82.

Similarly to noise variance, PU signal fluctuations (termed as primary signal variability) are considered in [55]. It is expressed via a modified Gaussian (Rayleigh) distribution and the average probability of detection is derived. Real-world signals of different wireless standards are used as data. In the absence of noise uncertainty, the signal variability is shown to have an influence on the \( P_D \) within 3 dB depending on the fluctuations’ intensity. It is described via the correlation between the signal samples - the lower it is, the better the detection performance. Noise uncertainty is shown to negatively affect the \( P_D \) to even greater extend when signal variability is present, leading to the necessity of increasing \( N \) in the range of thousands in \( \gamma < 0 \) dB as well as the occurrence of SNR wall.

3) ENERGY DETECTION IN NON-GAUSSIAN AND FADING CHANNELS

An important area of research for ED-based spectrum sensing, is considering the impairments introduced by particular wireless channels (various noise and fading models) in combination to the classic AWGN. Hereby, EDs with non-Gaussian approximation of the TS as well as their most important characteristics, are reviewed.

Approximations of \( P_D \) based on the moment-generation function (MGF) and Gamma PDF are derived in [59] for both single and multiple antenna CR receivers in the cases of Nakagami-\( m \), Rayleigh (\( m = 1 \)) and Rician fading. Simulations have shown that the computational complexity (in terms of number of iterations \( N_f \) to achieve a certain \( P_{FA} \) convergence) of these approximations is not significantly influenced by the application of multi-antenna reception.

It does, however, significantly improve the detection performance as the number of reception branches increases. The authors in [57] describe the distributions of non-Gaussian noise models through their respective kernel functions to derive the detector’s TS. By U-statistics theory, the TS \( \mathcal{E}_{\text{ED}} \) and threshold \( \xi \) are derived for Gaussian, generalized Gaussian and Laplacian kernels which are evaluated for Gaussian and Laplacian noises. In addition a fractional lower order moment (FLOM) ED is considered for \( \alpha \)-stable noise for which \( \alpha < 2 \). In this case, a generalized SNR is defined as \( \gamma_G = \frac{E[|\mathbf{x}|^a]}{M_{\alpha'}} \), where \( M_{\alpha'} \) is the average dispersion. The FLOM ED is implemented by a p-norm detector for \( p < 2 \).

The proposed approach includes a periodic measurement of noise-only samples to determine the mean and variance of the TS, and the threshold. In these channels, antenna diversity alleviates the influence of noise uncertainty which is otherwise, very harmful to the detector’s performance. Impulsive \( \alpha \)-stable noise leads to substantial degradation as \( \alpha \) declines. The \( P_D \) is improved in the case of multi-antenna reception and \( P_{FA} = 1.6 \). A Bayesian framework for derivation of \( P_D \) and \( P_{FA} \) under the CLT in [61] yielding:

\[
P_{FA} = Q \left( \xi, \sqrt{N} \right), \quad \xi = \xi(\pi_0, N, \gamma, \{ p_b \}),
\]

\[
P_{MD} = 1 - P_D = \int_0^{\infty} Q \left( -\sqrt{N} (\xi - h\gamma) \right) f_{\mathbf{h}}(h^2)dh^2,
\]

\[
P_E = \pi_0 P_{FA} + (1 - \pi_0)P_{MD}.
\]

where \( \{ p_b \} \) describes the set of parameters which characterize the fading distribution denoted by \( f_{\mathbf{h}}(h) \). Based on this approach, approximations for the decision threshold in log-normal shadowing, Nakagami-\( m \), Weibul and Suzuki fading models, are proposed. The generalized Gamma (Stacy or \( \alpha-\mu \)) fading in [62]. The PDF of this distribution is expressed as:

\[
f(x; a, d, n) = \left( \frac{x}{a} \right)^{d-1} \exp \left( \frac{x^d}{a} \right),
\]

\[
\Gamma \left( \frac{x}{a} \right).
\]

By setting appropriate values of the parameters \( a, d, \) and \( n \), the distribution densities of the previously explored fading models, can be obtained. Using the Bayesian approach, the \( P_E \) is developed as a function of the number of samples, the a priori probability of \( H_0 \), the instantaneous SNR \( \tilde{\gamma} \) and the optimal decision threshold:

\[
P_E = f \left( N, \pi_0, \tilde{\gamma}, \xi_{opt}, \alpha, \mu \right),
\]

\[
\tilde{\gamma} = E[|\mathbf{x}|^a]^{1/\alpha} \frac{E_b}{N_0}, \quad \mu = \frac{d}{n}, \quad \alpha = 2n,
\]

\[
\xi_{opt} = f \left( N, \pi_0, \tilde{\gamma}, \alpha, \mu \right),
\]

where \( \alpha > 0 \) is an arbitrary parameter, \( r \) is the distance between the PU and SU, \( E_b \) is the energy per bit and \( N_0 \) is the noise spectral density. As the fading parameters decrease, the detection performance is improved.

It determines the extend of variation in the distribution around its location parameter. The dispersion is similar, in principle, to the variance which is infinite for symmetric \( \alpha \)-stable distributions [60].
Generalized non-linear and composite (including shadowing and multipath effects caused by the absence of line-of-sight, LOS propagation) fading channels are considered in [39]. They are modeled via $\alpha$-$\kappa$-$\mu$ and $\alpha$-$\eta$-$\mu$ distributions. The expression for the average probability of detection $P_D$ is derived by using Mixture Gaussian (MG) distribution $f^M_\gamma(y) = \sum_{\eta=0}^{\infty} a_\eta y^{\eta-1} e^{-\zeta_\eta y}$, where $\bar{\alpha}$, $\beta_{\eta-1}$ and $\zeta_\eta$ illustrate the fading and shadowing effects. Simulations have shown that effective detection is possible in high values of the fading parameters ($\alpha$, $\kappa$, $\mu$ and $\eta$) for $P_{FA} = 0.01$, $\gamma = -5$ dB and $N = 20$. The influence of random interference together with Gamma-distributed shadowing and Nakagami-$m$ fading on $p$-norm ED is characterized in [40]. In this work, $P_D$ is derived as a function of the shadowing standard deviation, inverse shadowing severity, shadowed area mean power, the Nakagami fading severity index, noise power and the sum of the transmitted powers $P_n$ of $K$ interferers (distributed via a Poisson point process), faded according to their distances $r_n^{-\alpha}$, $\alpha$ being the path loss exponent. Analogically, the received power of the PU $\sigma_n^2 = P_n r_0^{-\alpha}$. Further generalization of the wireless channel through composite $\alpha$-$\eta$-$\kappa$-$\mu$ fading, is considered in [34], where $\mu$, $\kappa$ and $\eta$ describe different relationships between the received signal’s multipath components. To reduce the computational complexity of the following expressions, the authors, in addition, derive the truncating error of the PDF $\varepsilon(S)$, which determines the number of terms $S$ under which the PDF of $\gamma$ is to be computed for a specific approximation accuracy. The proposed ED is assessed via the average probability of detection $P_D$, the average AUC $\bar{A}$ and the effective rate (ER) $R_E$, the latter of which is defined as:

$$R_E = -\frac{1}{A} \log_2 \left( \int_0^\infty (1 + \gamma)^{-A} f_\gamma(\gamma) d\gamma \right), \quad A \equiv \frac{\theta_d N}{\ln(2)},$$

(8)

where $\theta_d \in [0; 1]$ is the delay exponent, $\ln(\cdot)$ denoting the natural logarithm. The $\alpha$-$\kappa$-$\mu$ fading model leads to a significant degradation in detection performance, $P_D$ and $P_{FA}$ of 0.9 and 0.1, respectively, being achieved for $\gamma \geq 20$ dB, with difference in the fading parameters’ intensities, causing very little changes. The AUC, however, reaches 0.1 for $\gamma \geq 14$ dB. Increasing the delay exponent, in contrast, is shown to negatively affect the performance to a much greater degree. The effective rate increases together with $P_D$, reaching up to 6 bits/s/Hz. A generalized formulation of the average miss-detection probability $P_{MD}^{Gen}$ is expressed as a function of the standard expression for $P_D$ in AWGN [33] and a mixture of gamma distributions describing the channel gain $h$ [63]:

$$P_{MD}^{Gen} = (1 - P_D^{AWGN}) f_\gamma(x) \approx \frac{1}{2} \sum_{n=0}^{N} a_n \mathcal{I} \left( \beta_n - 1, \zeta_n, \sqrt{N} \frac{2}{2N\alpha_n^2} \right),$$

(9)

where $a_n$, $\beta_n$ and $\zeta_n$ are the particular fading and shadowing distribution parameters, $\text{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty \exp(-t^2) dt$ being the complimentary error function and $N_\mathcal{I}$ is the number of terms in the equation (depends on the fading model [63]). Based on that expression, closed-form approximations for the $P_{MD}^{Gen}$ in Nakagami-$m$ and Rayleigh fading are developed in [56]:

$$P_{MD}^{Rayleigh} \approx \frac{1}{2} \left[ \text{erfc}(b) - e^{a^2} 2^a b \text{erfc}(c + b) \right],$$

$$P_{MD}^{Nakagami} \approx \frac{1}{2G(m)} \left( \frac{m}{\bar{\gamma}} \right)^m \times \mathcal{I} \left( m - 1, \frac{m}{\bar{\gamma}}, \sqrt{\frac{N}{2}} \frac{N\sigma_n^2 - \xi}{\sqrt{2N\alpha_n^2}} \right),$$

(10)

where $a = (\sqrt{2\gamma N})^{-1}$, $b = \frac{N\sigma_n^2 - \xi}{\sqrt{2N\alpha_n^2}}$, $\bar{\gamma}$ is the average SNR. Furthermore, via the Bayesian framework, the error avoidance thresholds $\xi_E$ for AWGN, Rayleigh and Nakagami-$m$ channels, are derived as functions of the thresholds which guarantee $P_{FA}(\xi) \leq P_{des}^{FA}$ (i.e. $\xi_{FA}$), and $P_{MD}(\xi) \leq P_{MD}^{des}$ (i.e. $\xi_{MD}$, respectively), for particular values of $\sigma_n^2$, $\gamma$ and $N$. A variant of the same rule for determining $\xi_E$ is proposed in [64]. The critical SNR (denoted by $\gamma_C$), which is defined as the maximum SNR level for which $\xi_E$ can be achieved. It is defined as a function of $P_{des}^{MD}$, $P_{des}^{MD}$, and $N$. Depending on $N$, the $\xi_E$ can be established. Furthermore, the authors in [65] show that for this method, the Nakagami-$m$ ($m = 2$) fading leads to a smaller degradation to $P_D$ than the Rayleigh model. Cooperative spectrum sensing, though, alleviates this influence even at $\gamma = -20$ dB.

When the receiver’s RF imperfections are considered, they have been found as very significant for the detection performance. Impairments such as phase noise, quadrature-phase imbalance, non-linear operation of the low-noise amplifier (LNA) are modeled using the Gamma distribution in [66]. Their influence leads to a significant degradation of the ROC curve such that efficient detection is shown for SNR not lower than 10 dB ($N = 5$), with the most substantial factor being the LNA non-linearity.

4) SPATIAL ENERGY DETECTION-BASED SPECTRUM SENSING IN 3D SPACE

The development of unmanned aerial vehicles (UAVs) based base stations (BSs) or access points (APs) has spurred recent research related to their extension with cognitive capabilities like spectrum sensing [67], [68]. There is a variety of UAV types, with different speed altitude and frequency bands (many of which, in the sub-6 GHz range) which creates an ample opportunity for DSA communications. Their speed and freedom of movement allow for much more agile spectrum utilization. Due to these properties, however, they require fast and accurate spectrum sensing. It has been recognized that, due to the UAVs’ ability to move in 3D space and thus quickly find more spectrum opportunities, that it is more important that the spectrum sensing guarantees a certain $P_D$
than a $P_{FA}$. Thus, the developed detector models use the CDR approach. The authors in [67] propose an ED with a noise estimator which minimizes the error $\delta \sigma_w$ between the actual and estimated noise variance within the span of $K_g$ frequency bands. A simulation of an UAV performing spectrum sensing in the global system for mobile communications (GSM) bands, is performed. The proposed algorithm is able to detect the PU’s presence at height over 350 m above the ground.

Another ED variant presented in [68] considers the spectrum utilization opportunity in both time and space, depending on the distance to the PU. This work assumes that the PU is only required to be protected from SU transmissions within a particular range $R_p$ which is the maximal distance of the PU’s coverage. If an SU is outside of that area, the spectrum will be considered vacant even if the PU signal is detected. Thus, a new variant of TS distribution (Gaussian, under the CLT) is described:

$$
\mathbb{E}_{ED}(\mathbf{\sigma}) \sim \begin{cases} 
N(\mu_0, \sigma_0^2), & H_0 \\
N(\mu_1(r), \sigma_1^2(r)), & H_1,
\end{cases}
$$

where $\mu_0 = \sigma_0^2 = 2\sigma_w^2/N$, $\mu_1(r) = (1 + \gamma)\mu_0$ and $\sigma_1^2(r) = (1 + 2\gamma)\sigma_0^2$, $r$ being the distance between the UAV SU and the PU. Thus, the probabilities of detection and of false alarm are defined as:

$$
P^3D_{FA} = \begin{cases} 
P(\frac{X - \mu_0}{\sigma_0^2}), & r \leq R_p, \\
(1 - P_1)P(\frac{X - \mu_0}{\sigma_0^2}) + P_1P(\frac{X - \mu_1(r)}{\sigma_1^2(r)}), & r \geq R_p,
\end{cases}
$$

$$
P^3D_{D} = P\left(\frac{X - \mu_1(r)}{\sigma_1^2(r)}\right), \quad r \leq R_p,
$$

where $P_1$ is the a priori probability for the PU signal’s presence in the band. Simulations have shown that for the local spectrum sensing case, this detector can achieve the desired efficiency only when the UAV is within the PU’s coverage area (i.e. $r \leq R_p$).

5) LESSONS LEARNED

The ED has retained its relevance in CR research due to the continual efforts to facilitate its implementation in two main directions - 1) Complexity mitigation for low-energy devices and 2) Accurate detection in realistic channels. Implementation in real-world prototypes requires fast processing which can in the ED’s case be provided by decreasing the number of samples used for the TS computation. Reliable detection can be achieved for SNR as low as $-15$ dB [46] with $N$ being over 60 times smaller than the necessary for CLT approximation [33]. Substantial relaxation of $N$ is possible even for some complex fading channels (such as Rayleigh/Nakagami-$\tilde{2}(a-\kappa, \mu a, a-\mu)$) in $\gamma < 0$ dB [39], [65]. Even when non-Gaussian noise and fading are not considered, the presence of noise variance uncertainty has been proven to be a significant factor in determining the ED’s performance, and even more so when the analysis includes such channel models. It is, nonetheless, possible to achieve viable spectrum sensing for as few as 200 samples for limited noise uncertainty in SNR $= -10$ dB [58]. However, reaching the standard $P^3D_{FA} = 0.9$ and $P^3D_{D} = 0.1$ at $\gamma = -20$ dB may not be yet possible using the current advancements which leads to two natural research directions:

- More flexible approximations which are relaxed by utilizing a priori information about the environment (such as expected PU transmission patterns as well as known features of the PU signals detected normally at a specific location and on a particular band) and spectrum sensing history (integrating results from previous detection iterations into the TS [45], [69], [70]).
- Determining the appropriate noise and fading parameters via detailed measurement campaigns in order to choose the most realistic TS distribution for a particular type (such as UDN, UAV-based etc.) of network. Such information will additionally reduce the complexity of novel ED-based spectrum sensing methods.

B. CYCLOSTATIONARY-BASED DETECTION

The presentation of modern communication signals as cyclostationary (in a wide sense) has been an important field in signal processing even before the advent of CR networks [71], [72]. This property is established by their inherent periodicity of the ACF $R_{\tau}$ for some period $T_0 \neq 0$ (usually accepted as equal to the sampling period or $\frac{1}{f_0}$), generally expressed as $R_{\tau}(\tau) = R_{\tau}(t + \tau) = R_{\tau}(t + T_0, t + T_0 + \tau)$, where $R_{\tau}(t, t + \tau) \overset{d}{=} E[y(t)v^*(t + \tau)]$ (the second order moment). Due to this characteristic, through Fourier expansion, the cyclic autocorrelation and spectral correlation density functions, respectively, can be derived as:

$$
R^\alpha_{\nu}(\tau) = \frac{1}{T_0} \int_{-T_0/2}^{T_0/2} y(t)v^*(t + \tau)e^{-i2\pi f\alpha} dt,
$$

$$
S^\alpha_{\nu}(f) \overset{d}{=} \int_{-\infty}^{\infty} R^\alpha_{\nu}(\tau)e^{-i2\pi f\tau} d\tau, \quad \alpha_c = \frac{n}{T_0}, n \in \mathbb{Z}.
$$

These relationships quantify the magnitude of the cyclostationary properties of the received signal $y(t)$. In other words, they show the autocorrelation magnitudes for a particular set of frequencies $\{\alpha_c : R^\alpha_{\nu} \neq 0\}$ (called cyclic frequencies or CFs) and values of the lag parameter $\tau$. The cyclic autocorrelation function (CAF) is zero for all other frequencies, outside of that set, while its magnitude varies depending on $\tau$ for all CFs. Furthermore, the spectral correlation density (SCD) shows the degree to which two components of $y(t)$ at $f - \frac{\alpha_c}{2}$ and $f + \frac{\alpha_c}{2}$, are correlated within the interval $\Delta\tau$. Thus, the SCD is also commonly expressed in this manner:

$$
S^\nu_{\nu}(-\nu) = \lim_{\Delta\tau \to 0} \lim_{T_0 \to \infty} \frac{1}{T_0\Delta\tau} \int_{-\Delta\tau/2}^{\Delta\tau/2} Y(t, f + \frac{\alpha_c}{2})Y^*(t, f - \frac{\alpha_c}{2}) dt,
$$

$$
Y(t, f) \overset{d}{=} \int_{T_0/2}^{T_0/2} y(u)e^{-i2\pi fu} du.
$$

117006
### Table 7. Table of feature distinctions and characteristics of energy detection-based spectrum sensing.

| Reference | TS/Feature used for detection | Method for metrics derivation | Robustness depending on noise | Robustness depending on fading | Assumption for PU signal’s distribution | Assumption for noise/fading parameters | Evaluation Metrics | Notes |
|-----------|-------------------------------|------------------------------|-------------------------------|-------------------------------|-----------------------------------------|----------------------------------------|-------------------|-------|
| [45]      | $\pi_{ED}, \pi_{ED}^L$      | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, T_s, \text{ROC}$ | Detection at $\gamma \geq -4 \text{ dB for } N = 1000$; $L'$ is unknown in real deployments |
| [69]      | $\pi_{ED}, \pi_{ED}^L$      | N-P                          | Low                           | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \gamma_{\text{min}}$ | Detection at $\gamma = -6 \text{ dB for } N_{\text{sym}} = 50$; Empirical threshold setting; sub-optimal detection in unknown $\sigma_w$ and $\sigma_s$ |
| [70]      | $\pi_{ED}, \pi_{ED}^L$      | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \gamma_{\text{min}}$ | Detection at $\gamma > 0 \text{ dB for } N << 100$ |
| [42]      | $\pi_{ED}$                   | Bayesian                      | High                          | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}$ | Detection at $\gamma = -5 \text{ dB for } N << 100$ |
| [50]      | $\pi_{ED}$                   | Bayesian                      | Low                           | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \gamma_{\text{min}}$ | Detection at $\gamma = -5 \text{ dB for } N << 100$ |
| [49]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, \text{Threshold value}$ | Detection at $\gamma \geq -5 \text{ dB for } N = 100$; SNR-adaptive threshold |
| [47]      | $\pi_{ED}$                   | N-P                          | High                          | N/A                           | Gaussian                                | Gaussian                               | $P_D, \text{Threshold value}$ | Detection at $\gamma > -20 \text{ dB}; SNR-adaptive threshold for MIMO CRs |
| [46]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \gamma_{\text{min}}$ | Detection at $\gamma \geq -15 \text{ dB for } N = 100$; SNR-adaptive optimal threshold |
| [52]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \gamma_{\text{min}}$ | Detection of OFDM under CRLB at $\gamma \geq -9 \text{ dB for } N < 2000$ |
| [48]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, \text{ROC}$ | Detection at $\gamma = -6 \text{ dB}; Empirical threshold setting and estimation of the signal’s $R_S$ |
| [51]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, MDT$ | Detection for spread spectrum signals at $\gamma = -8 \text{ dB for } N = 5 \times 10^4$ |
| [38]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}, \text{ROC}$ | Optimal threshold adapting to $\rho$ and $\gamma$ for $N = 200$; requires information on PU transmission patterns |
| [54]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, P_{FA}$ | Detection at $\gamma = -10 \text{ dB}; SNR-adaptive threshold |
| [55]      | $\pi_{ED}$                   | N-P                          | Moderate                      | N/A                           | Gaussian                                | Gaussian                               | $P_D, N_{\text{min}}$ | Signal and noise uncertainty consideration; real-world signals as input |
| [59]      | $\pi_{ED}$                   | Gamma PDF, MGF               | Low                            | Gaussian                      | Modified Gaussian/ Rayleigh/ Nakagami-m/ Rician | ROC, $N_I$ | $P_D, N_{\text{min}}$ | Detector with diversity reception, reaching $P_D \geq 0.9$ for $\gamma \geq 10 \text{ dB}$ |
| [61]      | $\pi_{ED}$                   | Bayesian                      | Moderate                      | Gaussian                      | Lognormal/ Nakagami-m/ Weibull/ Suzuki | ROC, $N_I$ | $P_D, N_{\text{min}}$ | Detection at $\gamma > -13 \text{ dB}; optimal thresholds for $N > 10^4$ |
| [62]      | $\pi_{ED}$                   | Bayesian                      | Low                            | Gaussian                      | $\alpha\eta_{\mu}$ | $\alpha_{\mu}$ | $P_D, N_{\text{min}}$ | Detection at $\gamma \geq 1 \text{ dB}; optimal threshold for $N < 200$ |
| [34]      | $\pi_{ED}$                   | N-P                          | Low                            | Gaussian                      | $\alpha_{\eta_{\mu}}$ | $\alpha_{\gamma_{\mu}}$ | $P_D, P_{FA}$ | Effective detection for $\gamma > 20 \text{ dB}$ |
| [56]      | $\pi_{ED}$                   | MG, Bayesian                  | Low                            | Gaussian                      | Nakagami-m/ Rayleigh | $P_D, P_{FA}, \text{ROC}$ | Detection at $\gamma \geq -20 \text{ dB for } N = 2 \times 10^6$; optimal thresholds for fading but high complexity in $\gamma << 0 \text{ dB}$ |
Table 8. Table of feature distinctions and characteristics of energy detection-based spectrum sensing (continued).

| Reference | TS/Feature used for detection | Method for metrics derivation | Robustness depending on noise | Robustness depending on fading | Assumption for PU signal's distribution | Assumption for noise/fading parameters | Evaluation Metrics | Notes |
|-----------|-------------------------------|-------------------------------|------------------------------|-------------------------------|----------------------------------------|---------------------------------------|------------------|-------|
| [64]     | \(\pi^{ED}_c\)               | MG, Bayesian                  | High                         | N/A                           | Gaussian                               | Gaussian                             | \(P_D, P_{PA}\) | Throughput, Threshold, Effcient detection at \(\gamma = -17\) dB for \(N = 15 \times 10^3\) |
| [57]     | \(\pi^{ED}_c\)               | N-P                           | N/A                          | Moderate                      | Gaussian                               | Gaussian/constant, ROCC              | \(P_D, P_R\) | Detection at \(\gamma_C = -2\) dB for \(N \geq 400\) in non-Gaussian noise |
| [40]     | \(\pi^{ED}_c\)               | N-P                           | Low                          | Low                           | Gaussian                               | Gamma/\(\text{Nakagami-m}\)         | ROCC | Effective p-norm ED at SNR > 0 dB and \(N \leq 20\) |
| [66]     | \(\pi^{ED}_c\)               | N-P                           | Low                          | Gaussian                      | Gamma                                  | ROCC | Detection at \(\gamma \geq 10\) dB for \(N = 5\), substantial degradation of ROCC due to RF impairments |
| [39]     | \(\pi^{ED}_c\)               | N-P                           | N/A                          | Moderate                      | Gaussian                               | \(\alpha-\kappa-\mu-\alpha-\eta-\mu\) | \(P_D\) | Detection for \(N \geq 30\) at \(\gamma = -5\) dB |
| [67]     | \(\pi^{ED}_c\)               | N-P                           | Moderate                     | N/A                           | Gaussian                               | \(P_{PA}, P_D\)                     | Detection in vertical movement at \(N = 8192\) and \(\gamma = -13\) dB; estimation of \(\sigma_n^2\) |

where \(Y(t, f)\) is the finite Fourier representation of \(y(t)\). In other words, the SCD identifies the CFs because it will be equal to zero for all others.

Provided that the types of PU signals are known to the CR device, the cyclostationary parameters \(\alpha_c\) and \(\tau\) are available in the literature [71], [72]. Thus, a cyclostationary detector (CD) based spectrum sensing method can distinguish the signal’s presence in low SNR. That is due to the lack of cyclostationarity in noise, and the fact that it is retained in the signal even for \(\gamma < 0\) dB. In other words, the autocorrelation’s magnitude when the signal is present, will still be significantly higher than in its absence (in the ideal case \(R_y(t, t + \tau) = 0\) for the null hypothesis but this is usually not the case in reality). It is the presence of cyclostationarity (by \(\alpha_c\) and \(\tau\)), that the CD needs to establish when the spectrum is occupied by the PU. Thus, they are the detection features \(\Xi^{CD}(\alpha_c, \tau)\) for this type of spectrum sensing. The three main ways in which the TS is defined in the relevant literature are through \(R_y(t, t + \tau), \bar{R}_y^c(\tau)\) or \(S_y^c(\tau)\).

### 1) AUTOCORRELATION-BASED DETECTION

Herein, a review of spectrum sensing methods which utilize the ACF as a TS. The authors in [73] propose an OFDM-specific CD for which the autocorrelation properties of the CP are utilized. Under the CLT, expressions for \(P_D = f(\sigma_s^2, \alpha_w^2, \xi, T_c, \tau)\) and \(P_{PA} = f(\sigma_s^2, \alpha_w^2, \xi)\) are derived using the ACF, where \(\tau = T_d\) or the OFDM symbol period and \(T_c\) is the CP. Another autocorrelation detector for OFDM signals, presented in [74], considers the center (or carrier) frequency offset (CFO) denoted as \(F_{c,o}\) expressed by the corresponding number of samples \(N_{F_{c,o}} \in \{0, \ldots, N_c + N_d\}\) (where \(N_c\) and \(N_d\) are the number of samples representing \(T_c\) and \(T_d\), respectively). The ACF \(R_y(\tau)\) for this method is computed as:

\[
R_y(n, \tau) = \frac{1}{N_{sym}} \sum_{l=0}^{N_{sym}-1} r_y(n + l(N_c + \tau)),
\]

where \(r_y(n) = y(n)y(n + \tau), n = 0, \ldots, N_c + \tau - 1,\) and \(N_{sym} = \lfloor \frac{N_c + \tau}{N} \rfloor\) is the number of OFDM symbols. To consider the CFO, the set \(S_{F_{c,o}}\) of \(N_c\) consecutive samples for which \(R_y(\tau)\) has a non-zero mean is defined (\(S_{F_{c,o}} = \{N_{F_{c,o}} + 1, \ldots, N_{F_{c,o}} + N_c - 1\} \mod (N_c + \tau)\)). Thus, the TS of the CFO resilient CD is defined as a function of \(R_y(n, \tau)\) of the samples in the set \(S_{F_{c,o}}\). A variant of this TS is employed in [75], and it is further developed by the inclusion of both fractional center frequency offset (FFO) and direct current (DC) offset compensation. This method is further expanded in [76] where the authors consider, besides CFO, Doppler shift and sample synchronization offset, the influence of a LOS doubly-selective channel. The proposed detector estimates the correlation between the samples within an OFDM symbol. It has been found that change in the channel between LOS and NLOS conditions does not cause significant variation in the detector’s efficiency. An autocorrelation-based detection method which utilizes the signal’s statistical covariance matrix \(\bar{R}_y = \mathbb{E}\{y(n)y^T(n)\}\) (a version of \(\bar{y}(n) = [y(n), y(n-1), \ldots, y(n-L_s + 1)]^T\) smoothed by a factor of \(L_s\), is assumed), where \(T\) denotes the vector’s transpose, is employed in [77]. The goal being to decrease the computational complexity resulting from the ED’s need of substantial \(N\) for high detection performance. The covariance absolute value (CVA) TS \(\Xi^{CVA}\) is defined as:

\[
\Xi^{CVA} = \frac{1}{L_s} \sum_{n=1}^{L_s} \sum_{m=1}^{L_s} |r_{nm}|
\]

\[
\Xi^{CVA} = \frac{1}{L_s} \sum_{n=1}^{L_s} |r_{nm}|
\]
where $r_{nm}$ is the element of $R$, at the $n$-th row and $m$-th column. If there is no PU signal $T^{C_{AW}} = 1$, while the alternative hypothesis is established when $T^{C_{AW}} > 1$. To quantify the detector’s performance in an non-ideal environment, expressions for the threshold, $P_D$ and the required $N$, are derived as functions of $T_1$, $T_2$, $\sigma^2_r$, and $\sigma^2_w$, where $T_1 = \frac{1}{T} \sum_{n=1}^{T} |r_{nm}|$, and $T_2 = \frac{1}{T} \sum_{n=1}^{T} |r_{nm}|$. Simulations performed for both wireless microphone and recorded digital TV signals, show that introducing Doppler shift leads to a significant degradation in detection which can somewhat be alleviated via diversity reception. An autocorrelation estimator-based CD is proposed in [78]. It considers the $F_{c,o}$ by introducing the scanning frequency $\omega_{sc}$ which covers the whole captured bandwidth to locate the exact center frequency $F_c$. The $T^{C_{sc}}(\omega_{sc}, r)$ is derived as:

$$T^{C}(\omega_{sc}, r) = \frac{1}{N_{c}} \sum_{n=1}^{N_{c}} g(\tau, \omega_{sc}),$$

$$\hat{c}_r(\omega_{sc}) = \hat{n}(\tau, \omega_{sc}) = \frac{1}{N_{c}} \sum_{n=1}^{N_{c}} n(n) y_s^*(n), \quad \tau \geq 0$$

$$r \tau = \left\{ \begin{array}{ll}
\frac{1}{N-r}, & \tau \geq 0 \\
\sum_{n=0}^{N-r-1} y_s^*(n), & \tau < 0
\end{array} \right.,$$

where $N_{c}$ is the highest considered value of the lag (a set of $N_{c}$ lags being considered $\tau \in \{1, \ldots, N_{c}\}$), while $g(\tau, \omega_{sc})$ is a set of weights which characterize the correlation’s intensity. Provided that there is an a priori known information about the PU signal, these weights can be optimized to increase the detector’s performance. Expressions for $P_{FA} = f(R_{y}, \hat{c}_r(\omega_{sc}), \xi, N)$ and $P_{D} = f(R_{y}, \hat{c}_r(\omega_{sc}), \xi, N, \gamma)$ are derived for AWGN and Rayleigh channels. The performance can be retained at a significantly lower value of $N_{c}$, if diversity reception is employed, even in the case of Rayleigh fading, which otherwise degrades the $P_D$ by several dB.

2) CYCLIC AUTOCORRELATION-BASED DETECTION

In this subsection, a review of notable methods with utilize the CAF as a TS, is presented. CAF and SCF-based CDS can be implemented as single-cycle (SC) or multi-cycle (MC) detectors, i.e. determining the presence of the PU signal by evaluating the TS for only one, or multiple CFS, respectively. The TS for SC and MC detectors (when they utilize the CAF, for the SC case, the expressions are analogous) are defined as $T^{C_{SC}}(\tau, \alpha_{c}) = R_{y}^{c}(\tau)$ and $T^{C_{MC}}(\tau, \alpha_{c}) = N_{c} \sum_{n=1}^{N_{c}} R_{y}^{c}(\tau, \alpha_{c})$, where the SCF accumulates the CAF for all CFS a part of the set $\{\alpha_{c,n}\}^{N_{c}}_{n=1}$ [79], [80]. A relevant metric for CDs (especially in the MC case), is the deflection coefficient. It measures how well the detector separates null from alternate hypotheses depending on the SNR, and is defined as [79]:

$$D_{C}(\gamma) = \frac{|E[\gamma(y_{n})H_{1}] - E[\gamma(y_{n})H_{0}]]}{\sqrt{E[\gamma(y_{n})H_{0}]}}.$$  

A well-established approach [81] estimates a vector of the CAF values for each $\tau$ within the set $\{\tau_{n}\}^{N_{F}}_{n=1}$, as well as a covariance matrix constructed via the SCF for a particular $\alpha_{c}$, to derive a chi-squared distribution-based CFAR detector. If the TS is higher than the threshold for a certain frequency $\alpha_{c}$, it is established as a CF. The TS in [81] is derived to be $T^{C_{DP}}(\tau, \alpha_{c}) = N_{c} \sum_{n=1}^{N_{c}} T^{C_{SC}}(\tau, \alpha_{c})$, with:

$$c_{y} = \left[ \begin{array}{c}
\|R_{y}^{sc}(\tau_{1}), \ldots, \|R_{y}^{sc}(\tau_{N_{c}}) \| \\
\| R_{y}^{sc}(\tau_{1}), \ldots, \| R_{y}^{sc}(\tau_{N_{c}}) \|
\end{array} \right]$$

$$\Sigma_{y} = \left[ \begin{array}{cc}
\frac{E[S_{y}(\tau_{1}, \alpha_{c}) + S_{y}(\tau_{N_{c}}, \alpha_{c})]}{2} & \frac{E[S_{y}(\tau_{1}, \alpha_{c}) - S_{y}(\tau_{N_{c}}, \alpha_{c})]}{2} \\
\frac{E[S_{y}(\tau_{1}, \alpha_{c}) - S_{y}(\tau_{N_{c}}, \alpha_{c})]}{2} & \frac{E[S_{y}(\tau_{1}, \alpha_{c}) + S_{y}(\tau_{N_{c}}, \alpha_{c})]}{2}
\end{array} \right]$$

where $S_{y}(\tau_{1}, \alpha_{c})$ corresponds to the SCF in (14) for the $\alpha_{c}$ argument being zero while $f = -\alpha_{c}$, and

$$S_{y}(\tau_{1}, \alpha_{c}) = \lim_{T_{1} \rightarrow \infty} \lim_{\Delta_{T} \rightarrow \infty} \frac{1}{T_{1}} \int_{-\Delta_{T}/2}^{\Delta_{T}/2} Y(t, 2\alpha_{c} + \frac{\alpha_{c}}{2}) Y(t, 2\alpha_{c} - \frac{\alpha_{c}}{2}) dt.$$  

The detector is formulated in both time and frequency domains, and for higher order autocorrelations. Simulations are performed for amplitude and frequency modulated signals, for which the CFS are identified. The authors in [82] evaluate the same method for simulated GSM/DECT/ CDMA/OFDM signals in AWGN and urban channels (as defined in [83], [84]). For a sufficient $N$, $P_{D}$ of 90% (for $P_{FA} = 5\%$) is achieved at $\gamma = 3$ dB in non-pure AWGN channel. For the OFDM signal, the same performance is achieved at $\gamma \geq 0$ dB. A distributed MC detector is proposed in [80] and evaluated for AWGN and Rayleigh fading. It is built via multiple SC detectors (each sensing at different CF) which combine their results. The $P_{D}$ and $D_{C}$ of the proposed SC detector for the $\alpha_{c,n}$, CF, are derived as $P_{SC} = Q_{1}(\phi_{1, \kappa_{1}}, \sqrt{\phi_{1, \kappa_{1}}})$ and $D_{C}^{SC} \approx N_{c} \frac{\mu_{s}}{\sqrt{2} \sigma_{w}^{4}}$, $\phi_{1} = \frac{P_{D}}{P_{FA}}$, and $\kappa_{1} = (2\mu_{s} + \sigma_{w}^{4})$ with $\mu_{s} = \frac{1}{N_{c}} \sum_{n=1}^{N_{c}} |\hat{s}(n)|^{2}$ being the PU signal’s mean, and $P_{D,C,n}$ - the power at the $\alpha_{c,n}$ CF. The deflection coefficient for a Rayleigh channel is derived as $D_{C}^{SC,Rayleigh} = h D_{C}^{SC}$. To further quantify the detector’s efficiency, the outage probability is defined as the likelihood that the deflection coefficient will be lower than a certain threshold $D_{th}$. This metric is derived as $P(D_{C}^{SC,Rayleigh} < D_{th}) = 1 - \exp \left(-\frac{D_{th}}{h D_{C}^{SC,Rayleigh}} \right)$.
frames, each of length $M$ (so that $M \times N_F \leq N$), thus forming the following TS ($\tau$ is assumed to be zero):

$$
\Sigma_{CD}(\tau, \alpha_c) = \frac{1}{N} \sum_{k=1}^{N_F} \sum_{n=1}^{M} y_k(n) y_k^*(n)e^{-j2\pi \alpha_c n/F_s},
$$

(21)

where $k$ is the frame index. The proposed method aims to determine the optimal values of $N_F$ and $M$ such that the influence of $\Delta \alpha_c$ may be minimized. Thus, an average decay function $F_{(N_F, M)}$ is derived ($\Delta \alpha_c$ is defined as uniformly distributed in the interval $[0, \Delta \alpha_c]$). By maximizing this function, the optimum pair of $(N_F, M)$ is obtained. Real-time data is generated and recorded via SDR at $\gamma = 20$ dB so that the influence of $\Delta \alpha_c$ can be evaluated individually. The estimation of $\alpha_c$ varies non-linearly with the increase of $N$ (which would be necessary in $\gamma$ declines) and of $\Delta \alpha_c$. A very good stability is achieved through the proposed optimization method for $\Delta \alpha_c$ of 0.1%. The authors in [86] aim to decrease the computational complexity of previous algorithms (most of which require the covariance matrix) and achieve reliable detection in non-white (colored) noise. For a single-antenna SU the TS is derived as a function of the CAF for all time lags. Variants of this TS are also derived for OFDM and GMSK signals, and for the receiver diversity case. Significance complexity relaxation is achieved. For OFDM signals in colored Gaussian noise, $P_D$ reaches 90% at $\gamma = -10$ dB for $N = 2 \times 10^4$ and $P_{FA} = 1\%$ when 2 CFs and 2 lags are considered. Rayleigh fading reduces that performance to about $-4$ dB and the improvement due to multi-antenna reception is not very significant. A four-fold increase in $N$ yields $P_D$ of 0.9 at $\gamma = -13$ dB. The same performance for GMSK signals is reached for $N = 540$. Further complexity reduction is pursued in [87] which studies a SC detector for OFDM signals in AWGN and Rayleigh fading. The same TS as in [85] with $\tau = N_{sym}$ and $\alpha_c = nF_s$, $n = 0, 1, 2, \ldots$, this detector is termed as single cycle with sliding correlation (SCD-SC). The $P_{FA}$ and $P_D$ (for Rayleigh fading) are derived as:

$$
P_{FA} = \exp\left(-\frac{\xi N_F M}{2\sigma_{\alpha_c}^2}\right)
$$

$$
P_{D, Rayleigh}^{SC} = \int_0^\infty Q_1\left(\frac{\Phi_1}{\kappa_1}, \frac{\sqrt{\xi}}{\kappa_1}\right)e^{-h^2}dh^2.
$$

The $P_{D, Rayleigh}^{SC}$ for the AWGN channel is the same as that in [80]. In addition, this detector is evaluated through its average deflection coefficient $\hat{D}_{C, Rayleigh}^{SC} = [N_F M K_{R, M}(N_{sym})]/\sigma_{\alpha_c}^2$. It is equal to the exact expression of the $D_{C}^{SC}$ for AWGN because the fading gain $h$ approximates a Gamma function for $N \gg 1$. A deflection coefficient of 10 is achieved for $\gamma = -8$ dB for the proposed detector. In addition, significant computational relaxation is gained. $P_D$ of 0.9 and $P_{FA}$ of 0.1 are reached at $\gamma = -6$ dB for $N = 140$ in a Rayleigh channel with noise uncertainty of 1 dB. A robust detector in unknown noise distribution, is derived in [88]. The PU signal $s$ and noise $w$ are assumed to be statistically independent with zero mean and their TS for a pair of $(\tau, \alpha_c)$ under the two hypotheses are generalized as:

$$
H_0 : \quad \Sigma_{CD}(\tau, \alpha_c) = \varphi_0(\tau, \alpha_c)
$$

$$
H_1 : \quad \Sigma_{CD}(\tau, \alpha_c) = R_{\alpha_c}(\tau) + \varphi_1(\tau, \alpha_c),
$$

(22)

where $\varphi_0(\tau, \alpha_c)$ and $\varphi_1(\tau, \alpha_c)$ are the error terms which describe the noise’s CAF (it is non-zero for realistic environments) in $H_0$ and $H_1$, the $R_{\alpha_c}(\tau)$ being the estimated PU signal’s CAF. Assuming the received signal $y$ can be expanded as a sum of its cyclic cross-cumulant functions and $N \gg 1$, the TS in [88] is estimated via the random vector $Z_y$:

$$
Z_y | H_1 \sim N(\mu_i, \Sigma_i, \Sigma_i(s)), \quad i = 0, 1
$$

$$
\mu_0 = 0, \quad \mu_1 = \left\{ \sqrt{N} R_{\alpha_c} (\tau); n = 1, \ldots, N_t \right\}
$$

$$
\Sigma_i(n_1, n_2) = \lim_{N \to \infty} \text{cov} \left\{ \hat{y}_i(n_1), \hat{y}_i(n_2, \alpha_c, n_2) \right\}
$$

$$
\Sigma_i^{(c)}(n_1, n_2) = \lim_{N \to \infty} \text{cov} \left\{ \hat{y}_1(n_1), \hat{y}_1(n_2, \alpha_c, n_2), \hat{y}_1^{(s)}(n_2, \alpha_c, n_2) \right\},
$$

(24)

where $\Sigma_i(n_1, n_2)$ and $\Sigma_i^{(c)}(n_1, n_2)$ describe the entries of the asymptotic covariance matrix $\Sigma_i$ and of the asymptotic conjugate covariance matrix $\Sigma_i^{(s)}$, respectively, and $\mu_i$, $i = 0, 1$ being the mean vectors. These components form the basis for the so termed augmented random vector $\xi_y \triangleq \left[ Z_y^T, Z_y^{H} \right]^T$ (the superscript $H$ denoting the Hermitian transpose) which is used together with its augmented covariance matrix $\Gamma_\xi$ to form the TS $\Sigma_{CD}(\xi) = \hat{\Gamma}_\xi \Gamma_\xi^{-1} \xi$. The proposed detector reaches $P_D$ of 0.9 for $P_{FA} = 0.001$ and $N = 4096$ when used to evaluate a pulse-amplitude modulated (PAM) signal without a priori assumptions for the PU signal or noise. A gain of about 1 dB is achieved if preliminary measurements for threshold estimation, are performed. The experiment is performed for a single pair of $(\tau = 0, \alpha_c = F_s/8)$.

3) SPECTRAL CORRELATION-BASED DETECTION

These detectors form their TS by using a version of the SCD. A common formulation is the spectral coherence function (SCF) [89]:

$$
C_{f}^{(s)}(f) = \frac{S_{f}^{(s)}(f)}{\sqrt{S_{f}^{(s)}(f + \frac{\nu}{2}) S_{f}^{(s)}(f - \frac{\nu}{2})}}.
$$

(25)

which is a normalized measure equal to 0 (in the ideal case) when the PU signal is not present for all $\alpha_c \neq 0$. It is utilized as $|C_{f}^{(s)}(f)|$ in [89] referred to as a magnitude squared coherence (MSC). To estimate the SCD, the authors in [89] utilize a finite discrete approximation called Fast Fourier Transform (FFT) accumulation method (FAM). Using this approach, expressions for $P_{FA}$ and $P_D$ similar to (22) are derived. In a like manner to the method in [85], the MSC-based TS is divided into $N_F$ frames (each of length}$
where $PU$ signal’s power $P_s$ is assumed to be known. The MSC detector achieves $P_D = 0.9$ at $\gamma = -21$ dB for $P_{FA} = 0.01, N = 8192$ and noise uncertainty of $0.5$ dB, $\alpha_c = 2F_c$. The SCD detector has similar but slightly lower performance. When evaluated using recorded digital TV signals, the MSC detector retains its robustness and achieves sensing time $T_s$ of around 19 ms. Furthermore, a high-precision SCD formulation for cyclostationarity estimation of OFDM signals is derived in [90]. The method utilizes the CAFs of the signal after processing via pulse shaping filter and Inverse FFT. In this way, the CFS of OFDM symbols and CPs can be identified on the SCD. In addition, the authors in [91] illustrate how for realistic PSK signals (including channel impairments such as Doppler shift), the SCF can determine the center frequency and bit rate. The CF for which the highest magnitude of the SCF is achieved, shows the estimated frequency’s value. A detection method which does not require the explicit knowledge of $\tau$ is proposed in [92]. It uses the autocorrelation’s convolution (denoted by the $\otimes$ operator), processed via FFT, to derive the cumulation of the SCD (CSCD). Examples are illustrated, which show the method’s efficiency in identifying the unknown CFS. The same approach is employed in [93] to provide spectrum sensing-based energy harvesting (EH) which enables the SU to utilize the identified PU signal as a battery charge. Specific expressions for $G_y(\alpha_c)$ in the cases of several modern wireless communication signals (such as MSK/PSK/QAM) are derived. They are illustrated to be fitting for CF estimation. Similarly to [89], the CAFs are accumulated in $N_F$ frames of length $M$. In AWGN channel, the CSCD detector achieves $P_D > 0.9$ for $P_{FA} = 0.1$ and $N = 10^3$ at $\gamma = -25$ dB and its performance does not degrade very significantly in Rayleigh fading. The difference in detection efficiency is not substantial between different signal types. In $\gamma < -20$ dB, $N$ needs to be significantly increased for efficient EH.

4) LESSONS LEARNED
Apart from the previously explored ED, the CD-based spectrum sensing methods, have been the most prominent in current CR research due to the greater robustness of their TS formulation. Works in this field have diverged into two areas - rigid detection in low SNR, and lower number of computations for the TS. The former direction has yielded notable advancements in detecting the PU signal via TS based on the ACF, CAF or SCD, even in the presence of noise uncertainty and fading [77], [78], [89], [93]. On the other hand, if the pairs $(\alpha_c, \tau)$ for which the received signal is tested, are known, lowest complexity is usually achieved by ACF approaches because, in order to compute CAF and SCD, more Fourier transformations are necessary. It is seen that CAF-based detectors provide a good trade-off between computational complexity (due to additional summations for computing the SCD or testing for multiple lags or CFs) and robustness in $\text{SNR} \ll 0$ dB. Greatest performance is obtained via SCD-based detectors due to their ability for rigid identification of CFs, even if they are unknown. Generally, the CDs can achieve the standard detection performance requirements with $N$ being in the order of a few thousand, which is much less than that required for most EDs. In addition, they can be utilized to not just detect but classify the PU signal’s type, thus enabling the SU to determine whether the spectrum is unused from a PU’s point of view, even when interfering signals are present. In this way, the SU can increase the spectrum utilization, use the detected signals to charge its battery, or perform canceling on these signals for the purposes of electronic warfare.

C. EIGENVALUE-BASED DETECTION
These spectrum sensing methods utilize the likelihood ratio test (LRT), usually via the N-P framework to derive their TS, as well as expressions for $P_D$ and $P_{FA}$. Their main strength is in providing rigid detection unimpaired by uncertainty in noise and signal variance estimation. In addition, they can be easily expanded to account for multiple antennas in both the transmitting and receiving ends, which naturally grants greater efficiency and flexibility. Provided that the SU has $N_{RX}$ antennas, the received signal $y$ can be expressed as $Y = [y[0], \ldots, y[N−1]]$, and each vector $y[n]$ is a column of $Y$ with $N_{RX}$ elements (most derivations are done assuming the transmitter has $N_{TX} < N_{RX}$ antennas). Both the PU signal $s$ and noise $w$ are commonly assumed to be circularly-symmetric complex Gaussian (CSCG) variables: $w \sim \mathcal{CN}(O, \sigma_w^2)$ and $s \sim \mathcal{CN}(O, R_s)$. $R_s = E[s[n]s^H[n]]$ being the PU signal’s covariance matrix. The distribution parameters $\sigma_w^2$ and $R_s$ are fundamental for solving the task of detection, so the approach for TS derivation depends on whether they are assumed to be known or not. The feature which this type of spectrum sensing methods aim to extract from the received signal, is a function of particular eigenvalues $\sigma(\lambda)$ obtained from the decomposition of $R_s$ (dimensions $N \times N_{RX}$) - the received signal’s covariance matrix, commonly computed as:

$$R_y = \frac{1}{N} \sum_{n=0}^{N-1} y[n]y^H[n] = U_y\Lambda_yU_y^H,$$  (27)

where $U_y$ and $U_y^H$ are unitary matrices, while $\Lambda_y$ is a diagonal matrix filled with the respective eigenvalues along its main diagonal. The distinction between $H_0$ and $H_1$ is made by evaluating the eigenvalues of $R_y$ - the smallest $N - N_{RX}$ will approximate $\sigma_w^2$ (it is assumed that, for example, the receiving end is equipped with less antennas than the transmitter, or that the signal $y$ is smoothed by a factor of $L_s < N$) due to the rank of $R_y$ being smaller than $N$. 
TABLE 9. Table of feature distinctions and characteristics of cyclostationary detection-based spectrum sensing.

| Reference | TS/Feature used for detection | Robustness depending on noise | Robustness depending on fading | Assumption for PU signal’s distribution | Assumption for noise/fading parameters | Evaluation Metrics | Notes |
|-----------|-------------------------------|-------------------------------|-------------------------------|----------------------------------------|---------------------------------------|-------------------|------|
| [73]      | $R_y(\tau)$                   | Moderate                       | N/A                           | Gaussian                               | Gaussian                             | $P_D$, ROC        | Detection for OFDM at $\gamma \geq -14$ dB and $N = 6.5 \times 10^4$ |
| [74]      | $R_y(\tau)$                   | Moderate                       | N/A                           | Gaussian                               | Gaussian                             | $P_D$, ROC        | Detection for OFDM with CFO at $\gamma \geq -15$ dB and $N_{sym} = 1024$ |
| [75]      | $R_y(\tau)$                   | Moderate                       | N/A                           | Gaussian                               | Gaussian                             | $P_D$, ROC        | Detection for OFDM with FFO and DC offset at $\gamma \geq -7$ dB and $N = 10762$ |
| [76]      | $R_y(\tau)$                   | Moderate                       | N/A                           | Gaussian                               | joint                                 | ROC               | Detection for OFDM over fast changing channels at $\gamma \geq -12$ dB and $N_{sym} = 15$ |
| [77]      | $R_y(\omega_x, \tau)$        | High                           | N/A                           | Gaussian                               | Rayleigh                              | $P_D$, ROC        | Detection at $\gamma = -20$ dB and $N = 5 \times 10^4$ |
| [78]      | $R_y(\omega_x, \tau)$        | High                           | Moderate                      | Gaussian                               | Rayleigh                              | $P_D$, ROC        | Detection at $\gamma = -20$ dB and $N = 6 \times 10^5$ |
| [81]      | $\sigma(\tau, \omega)$       | Moderate                       | N/A                           | Gaussian                               | Rayleigh                              | $P_D$, ROC        | Detection at $\gamma = -4$ dB and $N = 2048$ |
| [80]      | $\sigma(\tau, \omega)$       | Moderate                       | N/A                           | Gaussian                               | Rayleigh                              | ROC, $D_C$       | MC detection at $\gamma = -10$ dB |
| [85]      | $\sigma(\tau, \omega)$       | Moderate                       | colored Gaussian              | Rayleigh                              | $P_D$, Number of multiplications      | ROC, $D_C$       | Compensation of CF offset for $\Delta_{\alpha_c} = 0.1\%$ |
| [86]      | $\sigma(\tau, \omega)$       | Moderate                       | colored Gaussian              | Rayleigh                              | $P_D$, Number of multiplications      | ROC, $D_C$       | Detection for OFDM at $\gamma \geq -10$ dB and $N = 2 \times 10^4$ |
| [87]      | $\sigma(\tau, \omega)$       | Moderate                       | colored Gaussian              | Rayleigh                              | $P_D$, Number of multiplications      | ROC, $D_C$       | Detection for OFDM at $\gamma \geq -6$ dB and $N = 140$ |
| [88]      | $\zeta$                       | Moderate                       | Unknown                       | Unknown                               | $P_D$                                 | $P_D$             | Detection for unknown noise at $\gamma \geq -9$ dB and $N = 4096$ |
| [89]      | $\alpha_c$                    | High                           | High                          | Gaussian                               | Rayleigh                              | $P_D$             | Detection for known $P_s$ at $\gamma \geq -27.5$ dB and $N = 8192$ |
| [90]      | $G_y(\alpha_c)$               | High                           | High                          | Gaussian                               | Rayleigh                              | $P_D$             | Detection for unknown CFs at $\gamma = -15$ dB |
| [91]      | $G_y(\omega_x, \alpha_c)$    | High                           | N/A                           | Gaussian                               | Rayleigh                              | ROC, Power harvested | Detection for unknown CFs at $\gamma \geq -25$ dB |

Provided that both $R_y$ and $\sigma_w^2$ are known, then the Estimator-Correlator (EC) method with the following TS, can be applied - $\Xi_{EC} = y^H R_y (R_y + 2\sigma_w^2 I)^{-1} y$, where $I$ is the identity matrix. Some fundamental eigenvalue-based detectors (EBDs) are proposed in [94], [95], which derive the TS as a GLRT based on maximum likelihood estimates (MLEs) of the unknown parameters for each of the both the null and alternative hypotheses under Gaussian assumption for both the noise and the PU signal. The TS expressions for MIMO systems, in three cases (either $\sigma_w^2$ or $R_y$ being known, and both unknown) are derived in [94]. If $\sigma_w^2$ is known, the optimization problem of finding the smallest eigenvalues yields the following TS:

$$\Xi_{\sigma_w^2} = \frac{N}{2} \left( \sum_{m \leq m'} \ln \left( \frac{\lambda_m}{2\sigma_w^2} \right) - \sum_{m \leq m'} \ln \left( \frac{\lambda_m}{2\sigma_w^2} - 1 \right) \right), \quad (28)$$

where $m'$ is the greatest $m$ such that $\lambda_m > 2\sigma_w^2$, assuming that the eigenvalues are ordered thus $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{N_{RX}} \geq \lambda_{N_{RX}}$, being the smallest. If the received signal covariance matrix $R_y$ is available but the $\sigma_w^2$ is not, then the expression for TS becomes:

$$\Xi_{R_y} = \ln \left( \prod_{m \leq N_y} \frac{\lambda_m}{\lambda_{N_{RX}}} \right)^{1/N_y} - \frac{1}{N_S} \sum_{m \leq N_y} \lambda_m, \quad (29)$$

$N_y = 1$, this expression is simplified to the TS of the maximum-to-minimum eigenvalue (MME) detector - $\Xi_{MME} = \lambda_1/\lambda_{N_y}$. This ratio is also referred to as standard condition number (SCN) of a matrix because it describes the conditioning (or rank-deficiency) of a matrix [96], i.e. the extend to which the eigenvalues differ from one another (in the case of $H_0$, all of them will be nearly equal). When considering a multi-antenna (MA) receiver [97], a variant of this TS is derived (under Gaussian-distributed PU signal and noise) in a similar way - $\Xi_{MA} = \lambda_1 \left( \sum_{n=0}^{N_{RX}} \lambda_n \right)$. To derive the detector’s TS, in the case when neither are known, the PDFs of the received signal under $H_0$ and $H_1$, are generalized to only depend on $R_y$, $\sigma_w^2$, $N$ and $N_{RX}$. Using similar derivation, the produced TS forms the ratio of the arithmetic-to-geometric mean (AGM) of the eigenvalues vector $\lambda$:

$$\Xi_{AGM} = \frac{1}{N_{RX}} \left( \prod_{m \leq N_{RX}} \lambda_m \right)^{1/N_{RX}} \sum_{m} \lambda_m. \quad (30)$$

The big advantage of this detector is that, it does not require any a priori knowledge of the PU signal or noise, apart from the Gaussian assumption. Simulations in [94] show that all of the three detectors achieve $P_D$ of 0.9 around $\gamma = -18$ dB for $P_{FA} = 0.1$, $N_{RX} = 4$, $N_{TX} = 1$ and $N = 10^4$. Slightly better performance for $\Xi_{R_y}$ is noted. These detectors are also largely unaffected by noise uncertainty. Increasing $N_{RX}$ and $N_{RX}$ being equal to rank($R_y$). Considering the case in which, $N_y = 1$, this expression is simplified to the TS of the maximum-to-minimum eigenvalue (MME) detector - $\Xi_{MME} = \lambda_1/\lambda_{N_y}$. This ratio is also referred to as standard condition number (SCN) of a matrix because it describes the conditioning (or rank-deficiency) of a matrix [96], i.e. the extend to which the eigenvalues differ from one another (in the case of $H_0$, all of them will be nearly equal). When considering a multi-antenna (MA) receiver [97], a variant of this TS is derived (under Gaussian-distributed PU signal and noise) in a similar way - $\Xi_{MA} = \lambda_1 \left( \sum_{n=0}^{N_{RX}} \lambda_n \right)$.
$N_{RX}$ leads to a performance rise of about 3 dB. Two kinds of EBDs, namely the MME and energy to minimal eigenvalue (termed as EME, the TS is a ratio of the average signal energy $E_{\gamma} = \frac{1}{N} \sum_{n=0}^{N-1} y(n)$ and the smallest eigenvalue) algorithms are compared, and their expressions for $P_{FA}$ and $P_D$ derived via random matrix theory, in [95]. The received signal is smoothed by a factor of $L_s \leq \frac{N_{RX}}{N_{TX}}$ (to decrease the computational complexity). For a fixed $P_{FA}$, the threshold and $P_D$ of the MME detector are derived as functions of the following parameters:

$$
\xi_{\text{MME}} = f \left[ N, N_{RX}, L_s, F^{-1}(1 - P_{FA}) \right],
$$

$$
P_D^{\text{MME}} = f \left( \xi_{\text{MME}}, \xi_{\text{Ls}}, \xi_1, \sigma_w^2 \right),
$$

(31)

where $F_1(\cdot)$ denotes a Tracy-Widom distribution of order 1 [98] (can be obtained via modern libraries and tables, such as those found in [95]), and $\xi_1 \geq \xi_2 \geq \cdots \geq \xi_{L_{RX}}$ are the eigenvalues of the channel matrix $H$ with dimensions of $N_{RX} \times (N + N_{TX} L_s)$. Similarly, these parameters for the EME are presented as the following functions:

$$
\xi_{\text{EME}} = f \left[ N, N_{RX}, L_s, Q^{-1}(P_{FA}) \right],
$$

$$
P_D^{\text{EME}} = f \left( \xi_{\text{EME}}, \xi_{\text{Ls}}, \xi_1, \sigma_w^2, \text{Tr} \left( H W H \right) \right),
$$

(32)

where Tr(·) denotes the trace of the matrix. The main advantage of these two detectors is the independence from the noise variance (and the uncertainty in estimating it) in setting the decision thresholds. Simulation results show that the MME detector is more efficient, reaching $P_D$ and $P_{FA}$ of 0.9 and 0.1, respectively, at $\gamma = -18$ dB for $N = 10^5$, $N_{TX} = 2$, $N_{RX} = 4$ and $L_s = 8$ (which has been shown to be the optimum smoothing factor in these experimental settings). The EME has worse performance of about 2 dB. However, as $\gamma$ declines further, the detection for both of these algorithms degrades significantly. For a recorded wireless microphone signal ($BW = 200$ kHz), the MME detector reaches $P_D > 0.9$ and $P_{FA} < 0.1$ at $\gamma = -19$ dB for $N = 5 \times 10^4$ and $L_s = 10$, while the alternative does the same at $\gamma \approx -16$ dB. The detectors are also evaluated for digital TV signals ($BW = 10.762$ MHz), showing nearly the same performance for $N = 10^5$ and $L = 8$. EBD in the more realistic condition of correlated noise samples, is developed in [99]. The SU performs fractional sampling (FS) on the received signal, i.e. the $F_s$ is increased beyond the symbol rate so that $N_{FS}$ samples are produced from each original sample. Instead of FS, the same effect can be achieved by utilizing smoothing, diversity reception or cooperative spectrum sensing. The correlated noise matrix $\hat{U}_w$, with dimensions of $N_{SF} \times N$ is expressed as $\hat{U}_w = \Theta^1/2 U_w$, where $\Theta^1$ ($N_{SF} \times N_{SF}$) is the correlation matrix which contains the coefficients of correlation between the Gaussian noise samples contained in $U_w$ ($N_{SF} \times N$), and $\Theta^1/2$ denotes the square root of $\Theta$. The noise samples correlation’s influence on the EBD is described via the asymptotic eigenvalue probability distribution function (aepdf) of the noise covariance matrix (expressed as $R_w = \Theta^1/2 U_w U_w^T \Theta^1/2$):

$$
\lambda_{r_w}(\lambda) = (1 + \beta_r)^+ \delta(\lambda) + \frac{\sqrt{(\lambda - \bar{a})^+ (\bar{b} - \lambda)^+}}{2 \pi \lambda (1 + \lambda \mu_c)^2},
$$

(33)

where $\bar{a} = 1 + \beta_r + 2 \mu_c \beta_r - 2 \sqrt{\beta_r \sqrt{(1 + \mu_c)(1 + \mu_c \beta_r)}}$, $\bar{b} = 1 + \beta_r + 2 \mu_c \beta_r + 2 \sqrt{\beta_r \sqrt{(1 + \mu_c)(1 + \mu_c \beta_r)}}$, $(1 - \beta_r^2) \delta(\lambda)$ describes the cardinality of zero eigenvalues in the case of $N_{FS} > N$, $\beta_r = N/N_{FS}$ being the ratio index, $\mu_c = \rho^2_c / (1 - \rho^2_c)$, $\rho_c$ is the correlation coefficient which is a function of $N$ and $N_{FS}$, and $\bar{a}$ and $\bar{b}$ correspond to the minimum and maximum eigenvalues. Their ratio is taken as threshold against which the SCN is compared, such that $H_0$ is established if $\text{SCN} \leq \bar{b}/\bar{a}$. The empirically computed probability of correct decision $P_{cd} = (P_D + (1 - P_{FA})/2$ is used as a metric in this study. Using it, an SNR estimation method is also devised. The proposed modification of the MME detector reaches $P_{cd} = 0.9$ at $\gamma = -6$ dB for $N = 60$, $N_{FS} = 360$ ($N_{FS} = 6N$ is found to be optimal) and $\rho_c = 0.5$, which is very closely resembles the performance in uncorrelated noise. It, however, quickly deteriorates for $\rho_c < 0.5$. The same work is expanded in [100] by including channel correlation and evaluation of the EME detector. It is shown to perform worse than the MME, reaching $P_D$ of 0.9 at $\gamma = -1$ dB for the same conditions.

The influence of non-Gaussian (more particularly, sub-Gaussian) distributed noise on the EBD, is explored in [101]. The maximal eigenvalue (ME) $\lambda_1$ is regarded as a TS, and an upper bound for the detector’s performance, dependent on $N_{RX}$, $N$ and $\gamma$, is derived. This detector achieves $P_D = 0.9$ and $P_{FA} = 0.1$ at $\gamma = -15$ dB for $N_{RX} = 4$ and $N = 10^3$ which is well below the upper bound that reaches the same performance for 10 times larger $N$. The LogDet approach for deriving the TS and detection threshold for Gaussian, and colored (the samples of $w$ are correlated with each other) noise, is applied in [102]. The received signal is divided into $N_F$ frames which consist of $L_s$ (smoothing factor) consecutive samples, the covariance matrix $R_{y,k}$ being calculated for each of them (the k-th frame, in this expression):

$$
R_{y,k} = \frac{1}{N_F} \sum_{i=(k-1)N_F+1}^{(k+1)N_F} y_i y_i^T.
$$

(34)

The following LogDet (natural logarithm of the determinant) TSs are proposed to improve the detector’s ability to discriminate between $H_0$ and $H_1$, the presence of noise uncertainty and non-Gaussian noise:

$$
\Sigma_{LD_1} = \logdet \left( \frac{1}{N_F} \sum_{k=1}^{N_F} R_{y,k} \right) = \frac{1}{N_F} \sum_{i=1}^{L_s} \text{ln}(\lambda_i),
$$

$$
\Sigma_{LD_2} = \left\{ \begin{array}{ll}
\Sigma_w^c & \text{if } \Sigma_{LD_1} \leq \Sigma_{LD_1}^c \\
\frac{\Sigma_{LD_1}}{\ln(\Sigma_w^c)} & \text{otherwise}
\end{array} \right.,
$$

(35)
where \( \log\det(\cdot) \) denotes the natural logarithm of the determinant, \( \tilde{\gamma}_{LD_2}^w \) and \( \tilde{\gamma}_{LD_1}^w \) being the TSs in the white and colored noise cases, respectively. Using the \( N \) assumption (thus, utilizing the Tracy-Widom distribution), expressions for the CFAR-based decision threshold are derived for these two TSs as functions of \( P_{FA} \), \( N \), \( L_s \), \( \sigma_R^2 \) and \( \rho_c \). Experiments are performed on recorded TV signals, with SNR and colored noise being added during simulations. Both of the proposed detectors yield high performance, achieving \( P_D \) of 0.9 at \( \gamma \leq -20 \) for \( P_{FA} = 5\% \) and \( N = 10^5 \) (\( N_F = 10^4 \), \( L_s = 10 \)). EBDs in the case of correlated PU signal samples (which is a realistic assumption considering multiple PU sources with similar modulation schemes) is explored in [103]. This study considers a MA SU with \( N_{RX} \) antennas and \( N_{PU} \) PU sources, and correlated received PU signal samples between the receiver’s antennas, such that their covariance matrix \( \mathbf{R}_s \), at the i-th row and u-th column (corresponding to the i-th and u-th antennas) is expressed as \( \mathbf{R}_{si,lu} = \sigma_i \sigma_u \rho_{iu} \), \( \rho_{iu} = \mathbb{E}[s_is_u^*] / (\sigma_i \sigma_u) \), where \( s_i \) and \( s_u \) represent the PU signal samples at the i-th and u-th antenna, while \( \sigma_i \) and \( \sigma_u \) are their standard deviations. It is assumed that for each antenna, the received signal variances are ordered as follows: \( \sigma_1^2 \geq \sigma_2^2 \geq \ldots \geq \sigma_{N_R}^2 \), similarly to the ordinary assumption for the eigenvalues of \( \mathbf{R}_s \). The input samples are first divided into \( N_F \) frames with \( M = N - N_F + 1 \) samples in each, and a partial TS is computed for each frame. Afterwards, a Goodness-of-Fit (GoF) based overall TS is computed. Two variants of the partial TS for the i-th frame are proposed: 

\[
\tilde{\gamma}_{ME}(l) = \frac{\lambda_{\text{max}}(\mathbf{R}_s^l)}{\sigma^2_w}, \\
\tilde{\gamma}_{MET}(l) = \frac{\lambda_{\text{max}}(\mathbf{R}_s^l)}{\text{Tr}(\mathbf{R}_s^l) / N_{PU}}, 
\]

(36)

where \( \tilde{\gamma}_{ME}(l) \) and \( \tilde{\gamma}_{MET}(l) \) denote the partial TSs for the ME and maximum eigenvalue to the trace (MET), respectively. The overall TS is derived as a function of the following parameters - \( \tilde{\gamma}_{GoF} = f(N_F, M, \tilde{\gamma}(l), N_{PU}) \), where \( \tilde{\gamma}(l) \) denotes either \( \tilde{\gamma}_{ME}(l) \) and \( \tilde{\gamma}_{MET}(l) \), depending on which partial TS is applied. From the expressions, for the CFAR-based decision threshold \( \xi \) and \( P_D \) in the ME and MET detectors, are derived as functions of \( N_F \), \( M \), \( \lambda_{\text{max}}(\mathbf{R}_s) \) and \( \gamma \). For the case of uncorrelated PU signals, the ME variant achieves \( P_D \) of 0.9 at \( \gamma = -7 \) dB for \( P_{FA} = 0.1 \), \( N_{RX} = 4 \), \( N = 100 \) and \( N_F = 11 \), while the alternative has 3 dB lower performance. Both algorithms yield a 3 dB additional gain for PU signals with correlation coefficient of 0.5, for the same simulation parameters. They are also very resilient to noise uncertainty. Simulations also show that increasing \( N \) in the order of thousands is much more efficient to increase the detectors’ robustness, than adding more antennas.

1) LESSONS LEARNED

EBDs show great potential for spectrum sensing in realistic environments because of their resilience to noise uncertainty and correlated noise/PU signal samples. There are, however, two major disadvantages in their development: 1) Increased implementational difficulty due to the complex matrix operations necessary for threshold derivation; and 2) Considerable computational complexity which may render them impractical in some applications (especially when the traffic changes very quickly, and fast signal processing is required). These challenges can be partly alleviated through multiple antennas, processing a small number of samples, each, or by combining TSs for smaller, individual frames of the input signal. As seen from the reviewed notable works, however, the applications of such algorithms in terminals with less that 4 antennas, may be unwarranted considering that less computational intensive ED or CD algorithms yield comparable performance. For the case of MIMO and massive-MIMO user equipment (UE), the EBDs are very potent. In addition, they are nearly-independent from uncertainty in the noise variance estimation and yield higher performance (\( P_D > 0.9 \) and \( P_{FA} < 0.1 \) for \( \gamma < -20 \) dB [94], [102]) compared to most alternatives.

D. MATCHED FILTER-BASED DETECTION

If the SU supports coherent reception, i.e. it has knowledge of the PU signal structure (such as preamble, code despooling combination, pilot/reference signals etc.) denoted here as \( s_r \), then a matched filter-based detector (MFD) can be applied. This a priori information is correlated to the input signal, yielding a peak in the TS \( \tilde{\gamma}_{MFD}(s_r) \) if there is a match with the PU signal [105]: 

\[
\tilde{\gamma}_{MFD}(s_r) = \frac{1}{N} \sum_{n=0}^{N-1} y(n)s_r^*(n). 
\]

(37)

Then, this information \( s_r \) is the defining feature which the MFD aims to extract from the received signal \( y \), so as to discriminate accurately \( H_0 \) from \( H_1 \). Naturally, this method will provide optimal detection in uncorrelated AWGN, and lower computational cost even compared to the ED, because the number of samples increases much slower - \( N \sim \frac{1}{\gamma} \) [106]. The threshold and \( P_D \) in [105] are derived as \( \tilde{\gamma}_{MFD} = \sqrt{E[s_r^2]}Q^{-1}(P_{FA}) \) and \( P_{MFD}^D = Q((Q^{-1}(P_{FA}) - \sqrt{\gamma})) \), respectively. This detector’s deflection coefficient is, however, equal to the SNR, which makes it inefficient in \( \gamma < 0 \) dB. Nevertheless, by empirical threshold determination, such as in [107], \( P_D \) of 0.9 is achieved at \( \gamma < -20 \) dB and \( N = 10^5 \). Additionally, utilizing an array of multiple receiving antennas in the SU, the MFD’s performance can be improved due to the MA gain which shows that the SNR increases with a factor of \( 10 \log(N_{RX}) \) even for \( N \) in the order \( 10^2 \) [108] (here \( \log(\cdot) \) denotes a logarithm on base 10). Simulations have shown that having a larger \( N_{RX} \) yields higher performance gains than increasing \( N \), and in doing so, the computational time does not change dramatically. An assumption for the reference signal’s variance \( \sigma^2_r = K_r \sigma^2_s \), \( K_r > 0 \) and length \( N_t \) is made for the filtering task.
solved in [109]. The filter’s output $y_f(n)$ is defined as:

$$y_f(n) = \frac{1}{N_o} \sum_{i=0}^{N_o-1} y(n + i \times N), \quad n = 0, 1, \ldots, N - 1,$$

(38)

where $N_o$ is the filter’s observation length (it defines the overall length $N_f = N_o \times N$). To obtain the TS, the absolute value $a_y$ of $y_f(n)$ is used, $a_y(n) = \text{abs} \{y_f(n)\}, \quad n = 0, 1, \ldots, N - 1$. The TS is defined as a ratio between the maximum and mean values of $a_y$: $M_{\text{MFD}} = \max \{a_y\} / \mathbb{E}\{a_y\}$. By assuming sufficiently large $N_f$, the CFAR-based threshold $P_{\text{fa}}$ and $P_D$ are derived as functions of $N$ and $\gamma$. Simulations using a recorded TV signal with $F_s = 30.24$ MHz, $N = 4200$, $N_f = 420$, $K_s = 2$ and $N_o = 3$, are performed. $P_D$ of 90% is reached at $\gamma = -20$ dB and $P_{\text{fa}} = 1%$. The method retains its performance even in noise uncertainty of 2 dB.

The MFD is extended to discriminate between the (a priori known) PU’s power levels in [110]. A multi-hypothesis detection problem is defined where the spectrum sensing method estimates the probability of a correctly-determined hypothesis $H_i$, corresponding to the $i$-th power level $P_{s,i}$, $i \in \{0, 1, \ldots, N_P\}$, where it’s assumed that $P_{s,0} \leq P_{s,1} \leq \cdots \leq P_{s,N_P}$ and $P_{s,0} = 0$ (i.e. the absence of a PU). The a priori probability $p(H_i)$ for each power level is known. The likelihood ratio to differentiate between the $i$-th and $j$-th power level is formulated via the maximum a posteriori probability (MAP) approach:

$$L_{ij}(y) = \frac{p(H_j)p(y|H_i)}{p(H_i)p(y|H_j)}.$$

(39)

The decision threshold for differentiation between each two levels ($i$ and $j$ in this case) is defined as:

$$\xi_{ij} = \frac{\sigma_{\text{w}}^2}{\sigma_{\text{w}}^2} \ln \left[ \frac{p(H_j)}{p(H_i)} \right] - (P_{s,j}h - P_{s,i}h) \sqrt{P_{s,j}h - P_{s,i}h}. \quad (40)$$

Based on GLT, the $P_D$ (for a particular power level) and the probability of discrimination $P_{\text{dis}}$ (between all levels) are derived as:

$$P_{\text{dis}} = \frac{1}{N_P} \sum_{i=0}^{N_P} \left[ Q(\zeta_{i,i+1}^+) - Q(\zeta_{i,i+1}^-) \right],$$

(41)

$\zeta_{i,i+1}^\pm = \frac{\xi_{i,i+1}^\pm - 2\sqrt{P_{s,i}h}}{\sqrt{2\sigma_{\text{w}}^2}}.$

The proposed solution achieves $P_D$ of 0.9 at $\gamma = -15$ dB for $N = 100$, whereas the $P_{\text{dis}}$ reaches that efficiency at $\gamma = -5$ dB. It does, however, require a much larger $N$ to reach a probability of error (incorrect discrimination between two consecutive levels) of under 10%. In case the received signal’s phase $\phi_p$ is unknown, this parameter can be found via a MLE [111]:

$$\hat{\phi}_p = \min_{\phi_p} \left\{ |y|^2 - 2 \Re \left[ \sqrt{P_{s,i}h} e^{i\phi_p} y H_s \right] \right\} + P_{s,i}h|y|^2. \quad (42)$$

This approach, however, cannot compensate the performance degradation resulting from the unknown phase.

### Table 10. Table of feature distinctions and characteristics of eigenvalue detection-based spectrum sensing.

| Reference | TS/Feature used for detection | Robustness depending on noise | Robustness depending on fading | Assumption for PU signal's distribution | Assumption for noise/fading parameters | Evaluation Metrics | Notes |
|-----------|-------------------------------|-------------------------------|-------------------------------|----------------------------------------|----------------------------------------|------------------|-------|
| [94]      | $\varpi(\lambda)$             | High                          | N/A                           | Gaussian                               | Gaussian                               | $P_D$            | Detection for unknown $R_s$ and $\sigma_w^2$ at $\gamma \geq -21$ dB and $N = 10^4$ |
| [95]      | $\varpi(\lambda)$             | High                          | N/A                           | Gaussian                               | Gaussian                               | $P_D$, $P_{FA}$, ROC | Detection (independent from $\sigma_w^2$) at $\gamma \geq -19$ dB and $N = 5 \times 10^4$ |
| [99]      | $\varpi(\lambda)$             | Moderate                      | N/A                           | Gaussian (correlated)                  | Rayleigh                               | $P_{cd}$, $P_D$, $P_{FA}$ | MME detection for correlated noise at $\gamma \geq -6$ dB and $N_{FS} = 6N = 360$ |
| [100]     | $\varpi(\lambda)$             | Moderate                      | N/A                           | Gaussian (correlated)                  | Rayleigh                               | $P_{cd}$         | ME detection for correlated noise at $\gamma \geq -1$ dB and $N = 10^3$ |
| [101]     | $\varpi(\lambda_{\text{max}})$ | Moderate                      | N/A                           | Sub-Gaussian                           | Sub-Gaussian                           | $P_{PA}$, $P_D$ | ME detection for sub-Gaussian noise at $\gamma \geq -15$ dB and $N = 10^3$ |
| [102]     | $\varpi(\lambda)$             | High                          | N/A                           | Gaussian                               | Gaussian                               | $P_D$            | Detection for colored noise at $\gamma \geq -28$ dB and $N = 10^3$ |
| [97]      | $\varpi(\lambda)$             | Moderate                      | Gaussian/Correlated           | Gaussian                               | Gaussian                               | $P_D$            | MA Detection at $\gamma \geq -15$ dB and $N = 2000$ and $N_{RX} = 4$ |
| [104]     | $\varpi(\lambda)$             | N/A                           | Moderate                      | Gaussian                               | Rayleigh                               | $P_D$            | IMA Detection at $\gamma \geq -3$ dB and $N = 2$ and $N_{RX} \geq 100$ |
| [103]     | $\varpi(\lambda_{\text{max}})$ | Moderate                      | N/A                           | Gaussian                               | Gaussian/Correlated                    | $P_D$            | GoF-based Detection at $\gamma \geq -10$ dB and $N = 100$ and $N_{RX} = 4$ |
Simulations in [111] show that the $P_D$ and $P_{dis}$ of 90% (in the same conditions) are achieved at $\gamma = -10$ dB and $\gamma > -5$ dB, respectively. This method is extended for SU equipped with an MA receiver in [112]. LRT-based MFDs, which utilize the OFDM signal structure for the cases when time synchronization is either available or not, are proposed in [113]. A pilot sequence $s_{r,o}(n) = s_{d}(n) + s_{o}(n)$ is defined where $s_{o}(n)$ appears in every OFDM symbol and $s_{d}(n)$ - only once every $\kappa_s$ symbols. Provided that the SU is synchronized in time to the PU, a near-optimal LRT (NOLRT) detector is derived where

$$\hat{s}_{r,o}(n) = \frac{1}{[N_{sym}/\kappa_v]} \sum_{l=0}^{N_{sym}-1} y(n-lN). \quad (43)$$

Thus, the buffer-aided LRT (BALRT) detector is derived with the following threshold and $P_D$ (presented here only as functions of their dependent parameters for brevity) respectively,

$$\hat{s}_{BALRT} = f \left( N, \sigma_n^2, N_{sym}, \kappa_v, P_{FA} \right)$$

and

$$P_{D}^{BALRT} = f \left( N, \sigma_n^2, N_{sym}, \kappa_v, \hat{s}_{BALRT}, P_{r} \right).$$

Considering AWGN and $N_{sym} = 200$, the NOLRT detector achieves $P_D$ of 90% at $\gamma = -21$ dB, while the BALRT does at $\gamma = -16$ dB. In the case of multipath fading channels, however, only the latter method (via pilot signal estimation) can provide reliable detection, reaching $P_D$ of 90% at $\gamma \geq -14$ dB for $P_{FA} = 1\%$ and $N_{sym} = 800$. Via noise variance estimation, the detector experiences only small performance degradation for $\rho_{dB}$ of up to 1 dB which is a significant advantage.

1) LESSONS LEARNED

As the summary in this subsection shows, the development of matched filter based spectrum sensing methods is limited in scope and variety. The primary reason is that detection methods for CR usually aim for efficiency in conditions of little a priori knowledge of the PU signal. It is also unrealistic in many practical deployments, to assume that the reference/pilot signals are known, or their estimation may be computationally intensive. In addition, modern spectrum sensing methods are required to detect the PU in complex non-Gaussian as well as fading channels, which may degrade their performance advantage in comparison to the other detector types. Definite strengths of the MFDs are:

1) Their resilience to noise variance uncertainty [109], [113];
2) Efficiency in very low SNR achieved through much smaller $N_{RX}$ and $N$ in the MA receiver case [112], [112];
3) Discrimination between the PU’s transmission power levels (this necessitates the availability of a priori known probability for each level, which may not be trivial to obtain realistically) [110]–[112]. The prominence of OFDM-based communication systems makes training MFDs to recognize reference symbols of this kind, to become an important design consideration for spectrum sensing. If there are no other PU signal types in the region of a CR’s operation, it will be beneficial to utilize this class of spectrum sensing to achieve agility and low computational complexity [113]. Additionally, MFDs can be coupled with supervised learning-based modulation classification to achieve not just the detection of the PU signal, but also its source and modulation type. In this way, interferers from the PU’s point of view (i.e. such that use different modulation) can be identified, and the spectrum may be utilized by the SU because actual PU signal and interference will be differentiated.

E. BLIND DETECTION

The algorithms summarized hereby focus on generalizing (or expanding the applicability of) spectrum sensing so that a single detector can identify various signal types, irrespective of the wireless channel’s characteristics. They are termed “blind” in this survey, in the sense that they require very little or none a priori information about the PU signal/noise distributions and their parameters (such as variance, cyclostationarity, etc.).

Thus, such methods are much more resilient to uncertainty in estimating the variances of both noise and PU signal. They, however, often utilize complex matrix operations to derive their TSs. Due to the variety of approaches used for their derivation, there is no single characteristic feature which all of the blind detectors reviewed here, extract from the received signal. Thus, it will be noted for each individual method.

An eminent approach to blind spectrum sensing is introduced in [115]. Efficient detection in low SNR ($\ll 0$ dB) is achieved through linear prediction and QR decomposition of the received signal in the case of MA SUs, without the need for assuming the distribution of the PU signal or of fading. The input samples are oversampled with a factor of $L_0$, and each sample is summed over a channel vector $h$ with length $L_h$, to obtain the received data vectors $y_{N_{sym}}(n)$ which form the matrix $Y_{N_{sym}}(n)$ of dimensions $N_{sym}L_0 \times N_1$:

$$y(n) = \sum_{l=0}^{L_h} h_l s(n-l) + w(n),$$

$$y_{N_{sym}}(n) = \left[ y(n), y(n-1), \ldots, y(n-N_{sym}+1) \right],$$

$$Y_{N_{sym}}(n) = \left[ y_{N_{sym}}(n), y_{N_{sym}}(n-1), \ldots, y_{N_{sym}}(n-N_1+1) \right], \quad (44)$$

where $w(n)$, $n \in \{n, n-1, \ldots, n-N_1+1\}$, is the noise samples vector, $N_1$ represents the maximum time instance at $\ldots$
which the signal is sampled before the oversampling filters, and \(N_{sym}\) is the number of oversampled symbols. As part of the spectrum sensing process, the authors employ backward linear predictor, the coefficient of which are stored in the \(L_0 \times (N_{sym} - 1) L_0\) matrix \(P_{N_{sym} - 1}\). By taking the first \(N_{sym} - 1\) rows of \(Y_{N_{sym}}(n)\), the matrix \(\tilde{Y}_{N_{sym}}^H(n)\) is formed, on which the QR decomposition is applied to obtain the unitary \(Q\) matrix of dimensions \(N_1 \times N_1\). This operation allows for discrimination of \(H_0\) and \(H_1\) because the first \(r_c\) columns \([q_1, q_2, \ldots, q_{r_c}]\) of \(Q\) represent the signal space of \(\tilde{Y}_{N_{sym}}^H(n)\), while the rest \(N_1 - r_c\) are in the null space of \(\tilde{Y}_{N_{sym}}^H(n)\) (these spaces form two sub-matrices which are orthogonal to each other). The TS \(S_{QR}(Y)\) (\(Y\) being the feature extracted by this detector) is defined as:

\[
S_{QR}(Y) = \frac{||S_1||_F}{||S_2||_F},
\]

\[
S_1 = \left[ y(n - N_{sym} + 1), y(n - N_{sym}), \ldots, y(n - N_1 - N_{sym} + 2) \right] [q_1, q_2, \ldots, q_{r_c}],
\]

\[
S_2 = \left[ -P_{N_{sym} - 1} | I_{L_0} \right] Y_{N_{sym}}(n) [q_1, q_2, \ldots, q_{r_c}],
\]

(45)

where \(I_{L_0}\) is an \(L_0 \times L_0\) identity matrix, and ||.||_F is the Frobenius norm. This detector decides on the null hypothesis if \(||S_1||_F\) and \(||S_2||_F\) are equal or close, and the alternative, if their ratio is \(\geq 2\) (as shown empirically by the authors for \(P_{FA} < 0.15\)). The proposed method is also potent for detecting multiple PUs. Simulations show that for \(N_{sym} = 5000\) the detector achieves over 90% of \(P_D\) at \(\gamma = -10\) dB for different channels and signals (simulated and recorded). It is not significantly affected by noise uncertainty even when it is severe (\(\rho_{dB} = 2\) dB) and the presence of more than 1 PUs. Even higher performance can be obtained by further empirical threshold determination. The same spectrum sensing method is applied in [116] but for MA receiver with compressed sampling. The received signal at each antenna (the \(i\)-th is considered in the following equations) is expressed as \(\tilde{y}_i = \Phi_i^T y_i\), \(i = 1, 2, \ldots, N_{RX}\), where the vectors \(\tilde{y}_i\) comprise the compressed signal matrix \(\tilde{Y}\) (which is also the feature extracted by this detector), and \(\Phi_i\) is an \(N \times D_1\) compressed measurement matrix, \(D_1 \ll N\). It is determined through the vector regularized orthogonal matching pursuit (VROMP) via the index set \(\lambda_{t,i}^\prime\), expressed as:

\[
\lambda_{t,i}^\prime = \max_{j=1,2,\ldots,D_1} \left| < \tilde{x}_{t-1}^{\prime} \Phi_j > \right|,
\]

\[
\tilde{x}_{t}^\prime = \tilde{\Phi}_t \tilde{M}_t^\prime \tilde{z}_{t,i}^\prime = \tilde{\Phi}_t \tilde{M}_t^\prime \tilde{z}_{t,i}^\prime - \Phi_t \tilde{z}_{t,i},
\]

(46)

where \(\tilde{\Phi}_t\) is the \(j\)-th column of \(\Phi_t\), \(\lambda_{t,i}^\prime\) expresses the correlation of \(\tilde{\Phi}_t\) with \(\tilde{x}_{t-1}^\prime\). Simulations show that, compressing (up to 50%) the measurement samples within the \(N_{sym}\) symbols does not lead to significant degradation in the detection performance, still achieving \(P_D > 0.9\) at \(\gamma = -10\) dB.

Another approach to blind spectrum sensing is proposed in [117], which holds for a small number of samples (thus, providing computational improvement). The input signal \(y\) is segmented into \(N_F = N/M\) frames, \(M\) being an integer greater than 1, and the mean \(\bar{Y}_j\) and variance \(\varsigma_j\), \(j = 1, 2, \ldots, N_F\) of each frame are computed. Then for each frame, the variable \(x_j\) is determined as:

\[
x_j = \frac{\bar{Y}_j}{\varsigma_j / \sqrt{M}}
\]

(47)

which is the feature extracted by this detector, and has a Student’s \(t\)-distribution with \(M - 1\) degrees of freedom. It is assumed that \(x_1 \leq x_2 \leq \cdots \leq x_{N_F}\). The Anderson-Darling

TABLE 11. Table of feature distinctions and characteristics of matched filter detection-based spectrum sensing.

| Reference | TS/Feature used for detection | Robustness depending on noise | Robustness depending on fading | Assumption for signal’s distribution | Assumption for noise/fading parameters | Evaluation Metrics | Notes |
|-----------|------------------------------|------------------------------|------------------------------|-----------------------------------|----------------------------------------|-------------------|------|
| [107]     | \(s_r\)                      | High                         | N/A                          | Gaussian                          | Gaussian                               | \(P_D\)           | Detection at \(\gamma \geq -25\) dB and \(N = 10^5\) for empirical threshold determination |
| [109]     | \(s_r\)                      | High                         | N/A                          | Gaussian                          | Gaussian                               | \(P_D\)           | Detection at \(\gamma \geq -21\) dB in \(\rho_{dB} = 2\) dB for \(N \approx 4000\) |
| [108]     | \(s_r\)                      | Moderate                     | N/A                          | Gaussian                          | Gaussian                               | \(P_D, ROC\)      | Detection at \(\gamma \geq -18\) dB for \(N = 100\) and \(N_{RX} = 4\) |
| [110]     | \(s_r\)                      | Moderate                     | N/A                          | Gaussian                          | Gaussian                               | \(P_D, P_{d_{ls}}\) | Detection at \(\gamma \geq -15\) dB for \(N = 100\); PU power level discrimination at \(\gamma \geq -5\) dB |
| [111]     | \(s_r\)                      | Moderate                     | N/A                          | Gaussian                          | Gaussian                               | \(P_D, P_{d_{ls}}\) | Detection at \(\gamma \geq -10\) dB for \(N_{RX} = 10\) and \(N = 150\); PU power level discrimination at \(\gamma \geq -12\) dB |
| [112]     | \(s_r\)                      | Moderate                     | N/A                          | Gaussian                          | Gaussian                               | \(P_D\)           | Detection at \(\gamma \geq -12\) dB in \(\rho_{dB} = 1\) dB for \(N_{sym} = 800\) |

9 Also referred to as compressed sensing.
that the received signal samples in the vector spectrum sensing method is developed in [118]. Assuming and unknown noise variance. A Cramer-von Mises TS-based versatility. Simulations show that the proposed blind detector are independent of $\sigma_n^2$ which gives the method additional versatility. Simulations show that the proposed blind detector achieves $P_D$ of 90% at $\gamma = 11$ dB for $P_{FA} = 5\%$, $N = 32$ and $M = 4$, which is only slightly higher than the result for $M = 2$. This performance is yielded for a Rayleigh channel and unknown noise variance. A Cramer-von Mises TS-based spectrum sensing method is developed in [118]. Assuming that the received signal samples in the vector $y$ (which is the feature extracted by this detector), are arranged in an increasing order (i.e. $y_1 \leq y_2 \leq \ldots \leq y_n$), the TS $\Sigma_{CM}(y)$ is expressed as:

$$\Sigma_{CM}(y) = \frac{1}{12N} + \sum_{n=0}^{N} \left( \frac{2n-1}{N} - F_0(y_n) \right)^2,$$

(49)

where $F_0(y_n)$ is the CDF of $y$ under $H_0$. To estimate the noise, this method first computes the TS for pure noise samples (again, sorted in an increasing order) vector with length of $N_1$. The threshold is estimated empirically. Through simulations, it is shown that for $N_1 = 10^3$, $N = 30$ and $P_{FA} = 0.1$, this method achieves $P_D$ of 0.9 at $\gamma = -6$ dB.

The work in [119] provides the "blindness" property of the proposed spectrum sensing method by developing a noise variance estimation approach. A combination of EBD (which estimates $\sigma_n^2$ and senses in lower SNR via the MME method) and ED (which determines the spectrum availability in higher SNR using the EBD’s estimate of the $\sigma_w^2$), both of them assuming a Gaussian distribution under the CLT, is devised. The proposed method aims to estimate the minimum descriptive length (MDL) $\hat{l}_{MDL}$ of the samples (out of all $N$) which contain the PU signal as corrupted by noise (thus, $\hat{l}_{MDL}$ is the feature which this detector extracts from the received signal). This is done by dividing the eigenvalues of the covariance matrix $R_y$ into groups, to discriminate between the eigenvalues, which correspond to the PU signal-and-noise samples in $Y$ (the received signal is smoothed with a factor of $L_y$), from those corresponding to the noise-only ones. Using the proposed strategy, the sensing speed is improved about 3 times (for $P_{FA} = 0.1$), and the estimation errors is low, even for $\gamma = -20$ dB. For $L_y = 20$, $N = 5000$ and $P_{FA} = 0.1$, a $P_D$ of 0.9 is achieved at $\gamma = -12$ dB using recorded TV broadcasting and wireless microphone signals. In the case of these signals occupying just 50% of the measured spectrum, the detection performance is improved by several dB. To overcome this limitation, the blind spectrum sensing method presented in [115] is modified to provide much more resilience in detecting the PU signal, regardless of how much bandwidth (of the measured spectrum) it occupies [120]. The linear prediction utilized in [115] is extended via an oblique projection of the received signal matrix $Y_{sym}$ to extract the past samples matrix $Y_{past}$, predict the future samples matrix $Y_{fut}$, and assess their temporal correlation via QR decomposition (producing the matrices $Q_1$, $Q_2$, $Q_1^T$ and $Q_2^T$). Through this operation, $H_0$ can be differentiated from $H_1$ in low SNR, without the knowledge of even the bandwidth occupied by the PU signal. Thus, the TS components from (45) are expressed as [120]:

$$S_1 = \overline{Y}_{sym}(n) \left[ Q_1 Q_1^T \right],$$

$$S_2 = \overline{PY}_{sym}(n) \left[ Q_2 Q_2^T \right],$$

(50)

where $\overline{P}$ contains the oblique linear predictor’s coefficients. Simulations show considerable improvement over similar methods, where for the case of PU signal occupying the whole of the spectrum, $P_D = 0.9$ and $P_{FA} = 0.1$ are obtained at $\gamma = -12$ dB for $N_{sym} = 5000$. For the case of low occupation (17.5% of the spectrum), this detector yields $P_D$ of 0.9 at $\gamma = -15$ dB, irrespective of the channel.

1) LESSONS LEARNED

The methods reviewed in this subsection achieve moderate detection performance in low SNR with little to no a priori knowledge of the PU signal, wireless channel characteristics or the background noise (it should be noted, that just as in most other classes of spectrum sensing, it is assumed to have Gaussian distribution, but its variance $\sigma_w^2$ is not required to be known). They achieve this via complex matrix operations that limit their relevance in applications which require very fast determination of spectrum occupancy [115], [120]. Some methods, nonetheless, require a very small number of samples ($N$) or utilize compressed sampling, thus providing a notable computational complexity relaxation [116], [118]. Thus, a suitable trade-off between detection speed (defined by the signal processing operations complexity and/or $N$) and applicability (whether the particular application suggests any a priori data such as the type of PU signals which the detector is required to recognize).

V. SPECTRUM SENSING-BASED COGNITIVE RADIO FOR 6G WIRELESS COMMUNICATIONS

It has been recognized that upcoming and future communication technologies for beyond 5G will include diverse kinds of use cases and end-user devices (EUDs) to accommodate for novel applications which cover a much broader range of human enterprises, and are characterized by a variety of throughput and latency requirements [4], [121]–[123].
They are anticipated to substantially influence people’s recreational activities, technological development, industry, transportation, health-care, disaster prevention and response, information exchange, remote control for decades to come [121], [122]. This is made possible through human-centric (HC) interaction with a variety of sensors, communication terminals and other intelligent devices, which operate both as fixed (such as fixed BSs, APs, terminals, etc.) and mobile (handheld UEs, wearable IoT devices, UAVs, mobile APs, and others). They are envisioned to be deployed in any environment (terrestrial/underwater/air/space) to deliver the necessary services to any location which humans may find themselves in. This section reviews recent concepts for 6G communications and relevant applications, identifies the technologies which will benefit from the integration of CR in these networks, and describes the role of spectrum sensing in achieving this. Furthermore, design considerations for 6G transceivers with cognitive expansions (Fig. 5), and the resulting HC^2-WA is conceptualized (Fig. 6). Fig. 4 takes the established all-encompassing concept for future networks [4], [121] and puts emphasis on integrating cognitive links between various types of SUs (handheld and wearable devices, drones, satellites, etc.) for optimal utilization of different portions of the spectrum. The graphic shows a variety of terrestrial, underwater and aerial communication devices, including UAVs, handheld, augmented reality (AR) or virtual reality (VR) headsets, robots, drones, high altitude platforms (HAPs), underwater and terrestrial vehicles, eHealth and IoT appliances, waterborne vessels, some of which are PUs (shown in red in Fig. 4), while others (shown in green) are non-incumbent SUs. All users connect via available infrastructure depending on the wireless access type (incumbent or secondary), i.e. BS/APs/satellites provide service to their relevant users (primary or secondary) as shown in Fig. 4. Some descriptive connections between some of the nodes are also illustrated. The SU’s purpose is to identify under-utilized spectrum and employ it for HC communications (such as the established CR implementations utilizing wireless microphone and Wi-Fi [124]) in the following directions/applications in the context of modern visions for 6G:

- Multiple radio access technology (multi-RAT) terminals;
- Overhead/uplink exchange of PUs’ communications can be offloaded onto small-cells via DSA;
- Wi-Fi and Radar coexistence [125];
- Service provision to remote/rural locations through satellites/UAVs, disaster response and scientific exploration [126];
- Joint satellite-terrestrial CR-based spectrum sharing through combined access (the user is connected to both terrestrial and satellite networks via a multi-RAT terminal) [127];
- UAV-based environmental sensors and information gathering [128];
- Inter-operator spectrum sharing through interweave and underlay CR operation for small-cells in the millimeter-wave (mmWave) channels [129];
- Large intelligent surfaces (LIS) for CR. They can realign the SU signals to point them in the direction of their intended SU receiver, while preserving the PU’s interference threshold and maximum SU transmission power [130];

Thus, CR can facilitate the implementation and inter-connectivity of all three layers (ground, air and space) of the ISTN (as conceptualized in [4]), which generalizes the CR-integrated future network illustrated in Fig. 4. As suggested in [131], CR-enabled coexistence and/or combination of radars and IoT/UAV devices can be applied in multiple everyday applications, home automation and security, drone-based environment sensing, as well as smart vehicles.
The deployment of both non-incumbent, as well as the primary devices provide more complete utilization for the sub-6 GHz and mmWave spectrum which will facilitate the collaboration between UAVs/satellites and other networks [132]. Introducing cognition in all of these applications will require resilient spectrum sensing algorithms to assess the frequency resource availability for devices with various movement speed (on the ground, or in the air), height (in the air or space), depth (under water), bandwidth, PU interference sensitivity, and sensing speed requirements. Subsequently, it should be noted, that many (if not all) of these terrestrial, air, underwater and space networks that incorporate secondary CR nodes, may require the introduction of protected (exclusion) regions in which, only the PUs are allowed to operate so their services are better maintained. Whether such precautions are employed in a particular location (in 3D space) for a specific set of frequency bands, or not, it is necessary for spectrum sensing to be reliable and fast so as to accurately capture the resource utilization opportunity (in height, frequency and time) when it is present.

Thus, the transceiver design aspects (Fig. 5) already described for the 6G vision in works such as [121] should be further expanded. Fig. 5 illustrates these design considerations ("Multi-antenna", "Multi-power", "Multi-RAT"), including Multi-spectrum access ("Multi-SA") which describes the implementation of CR for intelligent wireless access provided by the coexistence of densely-deployed incumbent and non-incumbent users. As has been recognized in [121], the versatile 6G transceiver should consider the application of multiple antennas which is enabled by the higher carriers in mmWave and terahertz (THz) spectrum("Multi-antenna") , the usage of multiple transmission power levels depending on the intensity and characteristics of the user traffic("Multi-power"), as well as to support of multiple RATs ("Multi-RAT"). The "Multi-SA" aspect emphasizes the consideration of how the device accesses the spectrum which it utilizes, i.e. whether it is an incumbent user of that spectrum, applies DSA for opportunistic utilization, or a combination of them - hybrid spectrum access (HSA), in the case of overlay or hybrid CR deployments.

Based on the aforementioned concepts and design aspects, the framework of operation for spectrum sensing-enabled CRs within the scope of a 6G network is illustrated through the proposed HC\textsuperscript{2}WA concept (shown in Fig. 6). A human (or an operator-controlled machine) requests service/providers physical stimulus to a Cognitive EUD (CEUD)\textsuperscript{10} which is a SU of the spectrum, and has two general sets of functionalities. First, it includes the procedures which fulfill the EUD’s purpose based on its application, and the interface it uses to interact with the user/environment so as to process service requests/physical stimuli, and generate the relevant responses or supply the desired information. Based on the application requirements, the EUD requests resources from the Spectrum Access Control (SAC) Units, which are responsible for providing access for SUs (or both PUs and SUs) and can be implemented within BSs/stationary or mobile APs/more complex EUDs etc. The SAC Units can only be responsible for the SU network, if it is autonomous from the primary. Additionally, some of the SAC Unit’s functions can be provided by the EUD, or vice versa. On the other hand, the EUD employs CR operation principles, chief of which is spectrum sensing. The SAC Unit determines the best spectrum and bandwidth for the required application through the Spectrum Decision and Resource Allocation (SDRA) function (which may also be implemented in the EUD), and acquires communication channel(s) from the pool of available spectrum (PAS). The PAS contains a spectrum database or a list of available channels determined via spectrum sensing by the EUD itself or its serving SAC unit. The PAS may also be comprised of a combination of these two. Then, information exchange is performed on channels, selected from the PAS, and allocated for the SUs by the SDRA function. Thus, the communication exchange affects the wireless environment (all incumbent and secondary devices which are close enough so as to participate in, or be influenced by this communication link, are included) - multiple access is to be efficiently provided to the CR devices, and PU communications are to be protected. These procedures are performed by the Spectrum Sharing and Network Self-Organization (SNSO) function which may be responsible for only SUs, or both PUs and SUs. In the later case (underlay/overlay/hybrid CR mode), then the spectrum utilization gain (SUG) information (it reports the throughput gains from utilizing the spectrum via CR, as well as other parameters, relevant to the SUs’ communications) may be used to facilitate the self-configuration of both PUs and SUs. Otherwise, the SNSO will use this information for the continuous optimization of the CR network, so that it remains autonomous from that of the PUs. Thus, the wireless environment is constantly altered by both the primary and cognitive links, and the interaction with humans, due to quick movement in 3D space and the dynamic variations in traffic requirements. As a consequence, the PAS is updated to reflect the environment’s variations. This framework is also compatible with the novel paradigm of symbiotic communications which takes the concept of cognition-based wireless access to the next level by allowing different (both PU and SU) networks to interact and learn from each other via multi-agent deep Q-learning [123], [133].

To achieve this functionality from the design of the individual device, to that of multiple access protocols for intelligent symbiosis between networks, spectrum sensing plays an important role. Thus, several remarks (with relevant challenges outlined) regarding its implementation in the context of 6G, are hereby summarized:

\begin{itemize}
  \item Applying spectrum sensing - as of now, it is uncertain whether spectrum sensing methodologies will be unified in future networks. ED is the most prominent method, especially for 3D spectrum assessment [67], [68], [128], ...
\end{itemize}

\textsuperscript{10}It is hereby considered to be a communication device or intelligent appliance, the user/machine interacts with, regardless of its size, type or the application it provides.
and with the latest developments, it can achieve fair performance even for $\text{SNR} \ll 0 \text{ dB}$ without significant computational complexity. EBD and blind detectors, despite their increased complexity, are also promising for achieving accurate detection in low SNR, with a greater degree of autonomy. In addition, their weaknesses can be mutually negated through an appropriate logic for combining them. Thus, the spectrum sensing agility will be increased, considering the stringent latency requirements in 6G ($\leq 0.1 \text{ ms}$).

**Relevant challenge:** Determining the suitable balance between accuracy in low SNR and speed, depending on the specific application scenario, is highly recommended for CEUDs. As has been explored in the literature [134]–[136], the spectrum sensing accuracy is tied to the signal measurement duration and the PU’s traffic patterns. These need to be taken into account in the design of CEUDs for increased adaptability to the radio environment. Some terminals (such as high-throughput CEUDs) will require more expensive hardware, such as multiple antennas or faster processing chips for their communications, in the case of which, the implementation of resilient EBDs will be the most feasible approach to signal detection. The more capable hardware will allow for complexity relaxation of the computational operations involved. Alternatively, in application-specific communications based on less complex transceivers (such as IoT devices), the same result may be achieved by assuming a priori data about the PU signal in order to increase the performance of energy and cyclostationary spectrum sensing methods. Then, the research focus may be directed towards obtaining greater resilience to noise uncertainty, while retaining low computational complexity (i.e. small number of samples for agile processing).

- Characterization of spectrum in 3D - most of the spectrum sensing methods reviewed in this survey are designed to operate only in two dimensions (i.e. the frequency and time domains), and within a terrestrial network. Thus, they may not yield accurate results for operation in underwater, drone or satellite-based communications where the height/depth varies dynamically.

**Relevant challenge:** The need for volumetric spectrum sensing has been appropriately recognized [137]. Even within a small volume in an indoor location, the dynamics of spectrum usage are substantial, as shown through the measurements conducted in [138]. Thus, future signal detection methods need to implement schemes for spectrum occupancy characterization which incorporate measurements over a range of frequencies, a period of time (dependent on the application and computational limitations of the CEUD), and a volume of space (determined by the movement capabilities of the CEUD). The spectrum sensing function in itself may characterize spectrum occupancy in the frequency domain, while the results it yields for the relevant time intervals as well as locations in space, are to be combined in the Spectrum Database of the framework for HC²WA (Fig. 6). Then, volumetric (spatial) spectrum utilization heatmaps can be obtained for the purposes of RF analytics, and of spectrum occupancy prediction. Such schemes can employ machine learning to increase the efficiency and accuracy of the spectrum sensing function. The challenges, then, will concern the design of a computationally-efficient learning algorithm for the spectrum occupancy prediction scheme.
Viability of probabilistic spectrum sensing for PU signal detection - in spite of the progress in machine learning methods for radio signal analysis, it is questionable whether they will be able to reach the accuracy achieved by recent probabilistic algorithms. Recognition performance degradation in SNR < 0 dB is still a major disadvantage in this field as evidenced by the results of recent works [139]–[143]. Thus, it may be beneficial to combine probabilistic methods for spectrum sensing, with novel machine learning algorithms for resource allocation and inter-network spectrum sharing to achieve HC²WA. On the other hand, spectrum assessment can be optimized by incorporating probabilistic signal detection and machine learning-based recognition of the signal’s type.

**Relevant challenge:** Combining these two approaches in an appropriate manner in order to deliver fast operation in multi-purpose devices with limited computational and energy resources. In applications that utilize only a fixed range of frequencies and modulation types (such as legacy cellular standards), the computationally-efficient MFDs have promising potential for this challenge. Such CEUDs can detect the PU signal’s presence quickly and reliably, while information about its source (such as the identity of a particular device, its location, whether it is interfering from the PU’s point of view, etc.) can be determined through machine learning-based signal recognition.

Continual intelligent spectrum utilization assessment - it is, currently, a costly (in terms of time, effort and resources) endeavor, to gather enough data in order to characterize the utilization of a particular set of frequencies. Through agile noise estimation and spectrum sensing, future networks will be able to monitor the spectrum in 3D and provide continuous feedback on the degree of its utilization, as well as reorganize themselves in order to fill in any spectrum holes as they appear.

**Relevant challenge:** Providing efficient wireless channel allocation for the delivery of this feedback as information overhead, as well as efficient processing and storage of the volume-intensive quantized wideband spectrum measurements [144]. The volumetric analysis and prediction of the spectrum occupancy, makes this challenge all the more demanding.

Diversified wireless access - in 6G, the utilized frequency channels are not unified but specific applications use different bands, which will still entail the employment of spectrum sensing methods, especially in the sub-6 GHz and mmWave bands (it is currently debatable if DSA will be viable for THz spectrum, and how its principles could be applied) [145]. Thus, CR has a potential to facilitate the implementation of multi-RAT applications in the THz and lower frequency ranges by allowing the more complete utilization of the latter.

**Relevant challenge:** Efficient design of the digital signal processor and RF front-end, which allows for accurate assessment of the wideband spectrum. It will also have to account for the limitations defined by the application scenario of the CEUD. Thus, the design of the CR functions of the CEUD will need to be considered in conjunction with that of the application-specific functionalities.

**VI. CONCLUSION**

This paper provides an in-depth survey of the main types of probabilistic local spectrum sensing methods, according to the features they extract to determine the spectrum occupancy. Development of these methods with regard to relevant topics (such as detection in non-Gaussian channels etc.) for particular types of spectrum sensing is also addressed. A special emphasis is given to the analytical developments, and overall summary of strengths, weakness, and future progress, is given for each type. Finally, the role of spectrum sensing in future networks is conceptualized on the basis of applications and technologies already envisioned for 6G. Thus, this survey
provides a basis for future development in the following aspects:

- Novel DSA algorithms.
- Implementation of spectrum sensing in real-time SDRs, and application-specific terminals.
- Incorporation of DSA algorithms and modulation classification for more agile spectrum occupancy assessment.
- Incorporation of radio signal detection in algorithms for spectrum sharing between incumbent and secondary wireless systems.

REFERENCES

[1] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, “Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey,” IEEE Commun. Mag., vol. 50, pp. 2127–2139, Sep. 2006.

[2] C. I. Badoi, N. Prasad, V. Croitoru, and P. Ramjee, “Cognitive radio,” Wireless Pers. Commun., vol. 17, no. 1, pp. 525–539, Jun. 2000.

[3] M. S. Gupta and K. Kumar, “Feature extraction in local spectrum sensing for next generation cognitive radios—A review,” J. Mobile Multimedia, vol. 15, no. 1, pp. 111–140, Feb. 2020.

[4] F. Awin, J. Abdel-Raeem, and K. Tepe, “Blind spectrum sensing approaches for interweaved cognitive radio system: A tutorial and short course,” IEEE Commun. Surveys Tuts., vol. 21, no. 1, pp. 238–259, 1st Quart., 2019.

[5] V. Arjouve and N. Kaabouch, “A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions,” Sensors, vol. 19, no. 1, p. 126, Jan. 2019.

[6] A. Ali and W. Hamouda, “Advances on spectrum sensing for cognitive radio networks: Theory and applications,” IEEE Commun. Surveys Tuts., vol. 19, no. 2, pp. 1277–1304, 2nd Quart., 2016.

[7] S. K. Sharma, E. Lagunas, S. Chatzinotas, and B. Ottersten, “Application of compressive sensing in cognitive radio communications: A survey,” IEEE Commun. Surveys Tuts., vol. 18, no. 3, pp. 1838–1860, 3rd Quart., 2016.

[8] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, “Wideband spectrum sensing for cognitive radio networks: A survey,” IEEE Wireless Commun., vol. 20, no. 2, pp. 74–81, Apr. 2013.

[9] E. Axell, G. Leus, and H. V. Poor, “Spectrum sensing for cognitive radio: State-of-the-art and recent advances,” IEEE Signal Process. Mag., vol. 29, no. 3, pp. 101–116, May 2012.

[10] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, “Cooperative spectrum sensing in cognitive radio networks: A survey,” Phys. Commun., vol. 4, no. 1, pp. 40–62, Mar. 2011.

[11] T. Yucek and H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” IEEE Commun. Surveys Tuts., vol. 11, no. 1, pp. 116–130, 1st Quart. 2009.

[12] D. Wang, N. Zhang, Z. Li, F. Gao, and X. Shen, “Leveraging high order cumulants for spectrum sensing and power recognition in cognitive radio networks,” IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 1298–1310, Feb. 2018.

[13] S. M. Kay, “Asymptotically optimal detection in incompletely characterized non-Gaussian noise,” IEEE Trans. Acoust., Speech Signal Process., vol. 37, no. 5, pp. 627–633, May 1989.

[14] S. Atapattu, C. Tellambura, and H. Jiang, Energy Detection for Spectrum Sensing in Cognitive Radio, 1st ed. New York, NY, USA: Springer, 2014.

[15] H. Al-Hmood and H. S. Al-Rawashdeh, “On the effective rate and energy detection based spectrum sensing over a −η −κ −μ fading channels,” IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 9112–9116, Aug. 2020.

[16] H. Urkowitz, “Energy detection of unknown deterministic signals,” IEEE Trans. Acoust., Speech Signal Process., vol. 15, no. 5, pp. 523–531, Apr. 1967.

[17] R. Tandra and A. Sahai, “Fundamental limits on detection in low SNR under noise uncertainty,” in Proc. IEEE IWCMC, vol. 1, Jun. 2005, pp. 464–469.

[18] V. R. Sharma Banjade, C. Tellambura, and H. Jiang, “Approximations for performance of energy detector and p-norm detector,” IEEE Commun. Lett., vol. 19, no. 10, pp. 1678–1681, Oct. 2015.

[19] F. G. M. Elias and E. M. G. Fernández, “An analysis of energy detector based on improved approximations of the chi-square distributions,” EURASIP J. Wireless Commun. Netw., vol. 2021, no. 1, pp. 1–18, Dec. 2021.

[20] H. Huang, “Performance evaluation of energy detector over generalized non-linear and shadowed composite fading channels using a mixture gamma distribution,” 2017, arXiv:1707.07849. [Online]. Available: http://arxiv.org/abs/1707.07849.

[21] W. Caldwell, “IEEE 802.22: The first cognitive radio wireless regional area network standard,” IEEE Commun. Mag., vol. 47, no. 1, pp. 130–138, Jan. 2009.

[22] D. Wang, N. Zhang, Z. Li, F. Gao, and X. Shen, “Leveraging high order cumulants for spectrum sensing and power recognition in cognitive radio networks,” IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 1298–1310, Feb. 2018.

[23] S. M. Kay, “Asymptotically optimal detection in incompletely characterized non-Gaussian noise,” IEEE Trans. Acoust., Speech Signal Process., vol. 37, no. 5, pp. 627–633, May 1989.

[24] S. Atapattu, C. Tellambura, and H. Jiang, Energy Detection for Spectrum Sensing in Cognitive Radio, 1st ed. New York, NY, USA: Springer, 2014.

[25] H. Al-Hmood and H. S. Al-Rawashdeh, “On the effective rate and energy detection based spectrum sensing over a −η −κ −μ fading channels,” IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 9112–9116, Aug. 2020.

[26] H. Urkowitz, “Energy detection of unknown deterministic signals,” IEEE Trans. Acoust., Speech Signal Process., vol. 15, no. 5, pp. 523–531, Apr. 1967.

[27] R. Tandra and A. Sahai, “Fundamental limits on detection in low SNR under noise uncertainty,” in Proc. IEEE IWCMC, vol. 1, Jun. 2005, pp. 464–469.
A. Mariani, A. Giorgetti, and M. Chiari, “Effects of noise power estimation for energy detection in cognitive radio applications,” IEEE Trans. Commun., vol. 59, no. 12, pp. 3410–3420, Dec. 2011.

W. McGee, “Another recursive method of computing the Q function (Corresp.),” IEEE Trans. Inf. Theory, vol. IT-16, no. 4, pp. 500–501, Jul. 1970.

A. J. Onumanyi, A. M. Abus-Mahfouz, and G. P. Hancke, “A comparative analysis of local and global adaptive threshold estimation techniques for energy detection in cognitive radio,” Phys. Commun., vol. 29, pp. 1–11, Aug. 2018.

M. Lopez-Benitez and F. Casadevall, “Improved energy detection spectrum sensing for cognitive radio,” IET Commun., vol. 6, no. 8, pp. 785–796, May 2012.

H. Huang, J. Zhu, and J. Mu, “A novel sensing strategy based on energy detector for spectrum sensing,” Appl. Sci., vol. 9, no. 21, p. 4634, Oct. 2019.

A. O. A. Salam, R. E. Sherriff, S. R. Al-Araji, K. Mezher, and Q. Nasir, “Adaptive threshold and optimal frame duration for multi-taper spectrum sensing in cognitive radio,” IET Exp., vol. 5, no. 1, pp. 31–36, Mar. 2019.

H. Liu and T. Fujii, “Single-channel blind identification based advanced energy detection for cognitive radio,” in Proc. 8th Int. Conf. Ubiquitous Future Netw. (ICUFN), Jul. 2016, pp. 532–536.

R. K. Dubey and G. Verma, “Improved spectrum sensing for cognitive radio based on adaptive threshold,” in Proc. 2nd Int. Conf. Adv. Comput. Commun. Eng., May 2015, pp. 253–256.

E. Axell and E. G. Larsson, “Optimal and sub-optimal sensing of OFDM signals in known and unknown noise variance,” IEEE J. Sel. Areas Commun., vol. 29, no. 2, pp. 290–304, Feb. 2011.

F. Benedetto and G. Giunta, “A novel PU sensing algorithm for constant energy signals,” IEEE Trans. Veh. Technol., vol. 67, no. 1, pp. 827–831, Jan. 2018.

W.-L. Chin, “On the noise uncertainty for the energy detection of OFDM signals,” IEEE Trans. Veh. Technol., vol. 68, no. 8, pp. 7593–7602, Aug. 2019.

R. Tandra and A. Sahai, “SNR walls for signal detection,” IEEE J. Sel. Topics Signal Process., vol. 2, no. 1, pp. 4–17, Feb. 2008.

J. Xie and J. Chen, “An adaptive double-threshold spectrum sensing algorithm under noise uncertainty,” in Proc. IEEE 12th Int. Conf. Comput. Commun. Technol., Oct. 2012, pp. 824–827.

M. Lopez-Benitez and F. Casadevall, “Signal uncertainty in spectrum sensing for cognitive radio,” IEEE Trans. Commun., vol. 61, no. 4, pp. 1231–1241, Apr. 2013.

S. Atapattu, C. Tellambura, H. Jiang, and N. Rajatheva, “Unified analysis of low-SNR energy detection and threshold selection,” IEEE Trans. Veh. Technol., vol. 64, no. 11, pp. 5006–5019, Nov. 2015.

A. Margosian, I. Abooei, and K. N. Plataniotis, “An accurate kernelized energy detection in Gaussian and non-Gaussian/impulsive noises,” IEEE Trans. Signal Process., vol. 63, no. 21, pp. 5621–5636, Nov. 2015.

S. M. Hassan, A. Eltholth, and A. H. Ammar, “Double threshold weighted energy detection for asynchronous PU activities in the presence of noise uncertainty,” IEEE Access, vol. 8, pp. 177682–177692, 2020.

S. P. Herath, N. Rajatheva, and C. Tellambura, “Energy detection of unknown signals in fading and diversity reception,” IEEE Trans. Commun., vol. 59, no. 9, pp. 2443–2453, Sep. 2011.

V. G. Chavali, “Signal detection and modulation classification in non-Gaussian noise environments,” Ph.D. dissertation, Virginia Tech, Blacksburg, VA, USA, 2012.

S. Gurugopinath, “Near-optimal detection thresholds for Bayesian spectrum sensing under fading,” in Proc. Int. Conf. Signal Process. Commun. (COMP), Jul. 2014, pp. 1–6.

S. Gurugopinath, “Energy-based Bayesian spectrum sensing over $\alpha–\mu$ stacy / generalized gamma fading channels,” in Proc. 8th Int. Conf. Commun. Syst. Netw. (COMSNETS), Jan. 2016, pp. 1–6.

S. Atapattu, C. Tellambura, and H. Jiang, “A mixture gamma distribution to model the SNR of wireless channels,” IEEE Trans. Wireless Commun., vol. 10, no. 12, pp. 4193–4203, Dec. 2011.

A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: An energy detection approach,” Wireless Netw., vol. 25, no. 7, pp. 3917–3931, Oct. 2019.

A. Kumar, P. Thakur, S. Pandit, and G. Singh, “Threshold selection and cooperation in fading environment of cognitive radio network: Consequences on spectrum sensing and throughput,” AEU Int. J. Electron. Commun., vol. 117, Apr. 2020, Art. no. 153101.
[136] R. Kishore, S. Gurugopinath, S. Muhaidat, P. C. Sofotasios, O. A. Dobre, and N. Al-Dhahir, “Sensing-throughput tradeoff for superior selective reporting-based spectrum sensing in energy harvesting HCRNs,” IEEE Trans. Cognit. Commun. Netw., vol. 5, no. 2, pp. 330–341, Jun. 2019.

[137] W. Saad, M. Bennis, and M. Chen, “A vision of 6G wireless systems: Applications, trends, technologies, and open research problems,” IEEE Netw., vol. 34, no. 3, pp. 134–142, May/Jun. 2020.

[138] A. Ivanov, V. Stoynov, K. Angelov, R. Stefanov, D. Atamyan, K. Tonchev, and V. Poulkov, “Interference mapping in 3d for high-density indoor IoT deployments,” in Wireless Sensor Networks-Design, Deployment and Applications. London, U.K.: IntechOpen, 2020.

[139] Z. Shi, W. Gao, S. Zhang, J. Liu, and N. Kato, “Machine learning-enabled cooperative spectrum sensing for non-orthogonal multiple access,” IEEE Trans. Wireless Commun., vol. 19, no. 9, pp. 5692–5702, Sep. 2020.

[140] W. Wu, Z. Li, S. Ma, and J. Shi, “Performance improvement for machine learning-based cooperative spectrum sensing by feature vector selection,” IET Commun., vol. 14, no. 7, pp. 1081–1089, Apr. 2020.

[141] D. Zhang, W. Ding, C. Liu, H. Wang, and B. Zhang, “Modulated auto-correlation convolution networks for automatic modulation classification based on small sample set,” IEEE Access, vol. 8, pp. 27097–27105, 2020.

[142] K. Liao, Y. Zhao, J. Gu, Y. Zhang, and Y. Zhong, “Sequential convolutional recurrent neural networks for fast automatic modulation classification,” IEEE Access, vol. 9, pp. 27182–27188, 2021.

[143] Y. Liu, Y. Liu, and C. Yang, “Modulation recognition with graph convolutional network,” IEEE Wireless Commun. Lett., vol. 9, no. 5, pp. 624–627, May 2020.

[144] T. Cüöklev, V. Poulkov, D. Bennett, and K. Tonchev, “Enabling RF data analytics services and applications via cloudification,” IEEE Aerosp. Electron. Syst. Mag., vol. 33, nos. 5–6, pp. 44–55, May 2018.

[145] C. Chaccour, M. N. Soorki, W. Saad, M. Bennis, P. Popovski, and M. Debbah, “Seven defining features of terahertz (THz) wireless systems: A fellowship of communication and sensing,” 2021, arXiv:2102.07668. [Online]. Available: http://arxiv.org/abs/2102.07668

ANTONI IVANOV (Member, IEEE) received the master’s degree in innovative communication technologies and entrepreneurship from the Technical University of Sofia (TUS), Bulgaria, and Aalborg University, Denmark, and the Ph.D. degree in communication networks and systems from TUS, in 2020. He is currently a Postdoctoral Researcher with the “Teleinfrastructure Lab,” Faculty of Telecommunications, TUS. His research interests include cognitive radio networks, adaptive algorithms for dynamic spectrum access, deep learning-based solutions for cognitive radio applications, volumetric spectrum occupancy assessment, and graph signal processing for resource allocation in current and future wireless networks.

KRAISIMIR TONCHEV (Member, IEEE) is currently a Senior Researcher leading the research activities at the “Teleinfrastructure Lab,” Faculty of Telecommunications, Technical University of Sofia, Sofia, Bulgaria. He has also implemented many commercial projects, including photogrammetry, object detection and tracking using thermal vision, dynamic system modeling, and image processing for embedded systems. His research interests include model-based machine learning, Bayesian data analysis and modeling, and neural networks with applications in computer vision and data analysis.

VLADIMIR POULKOV (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees from the Technical University of Sofia (TUS), Sofia, Bulgaria. He has more than 30 years of teaching, research, and industrial experience in the field of telecommunications. He has been the Dean of the Faculty of the Telecommunications, TUS, and the Vice Chairman of the General Assembly of the European Telecommunications Standardization Institute (ETSI). He is currently a professor. He is also the Head of the “Teleinfrastructure” Research and Development Laboratory at TUS and the Chairman of Cluster for Digital Transformation and Innovation, Bulgaria. He has successfully managed numerous industrial, engineering, research and development, and educational projects. He has authored many scientific publications and is tutoring the B.Sc., M.Sc., and Ph.D. courses in the field of information transmission theory and wireless access networks. He is a fellow of the European Alliance for Innovation.

AGATA MANOLOVA (Member, IEEE) received the Ph.D. degree from the Université de Grenoble, France. She is currently an Associate Professor with the Faculty of Telecommunications, Technical University of Sofia (TUS), Sofia, Bulgaria, and the Head of the Research Laboratory “Electronic Systems for Visual Information.” Her domains of interest are machine learning, pattern recognition, computer vision, image and video processing, biometrics, and augmented and virtual reality. She is also a Laureate of the Fulbright Scholarship.

* * *