Hindawi
Applied Computational Intelligence and Soft Computing
Volume 2022, Article ID 6988847, 14 pages
https://doi.org/10.1155/2022/6988847

Research Article

Cognitive Wireless Networks Based Spectrum Sensing Strategies: A Comparative Analysis

Anandakumar Haldorai,[1] **Jeevanandham Sivaraj**,[2] **Munivenkatappa Nagabushanam**,[3] **and Michaelraj Kingston Roberts**[4]

[1]*Department of CSE, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India*
[2]*Department of IT, KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India*
[3]*Department of ECE, Ramaiah Institute of Technology, Bangalore, Karnataka, India*
[4]*Department of ECE, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India*

Correspondence should be addressed to Anandakumar Haldorai; anandakumar.h@sece.ac.in

Received 26 July 2022; Revised 15 October 2022; Accepted 19 October 2022; Published 30 October 2022

Academic Editor: Dimitrios A. Karras

Because of numerous dormant application fields, wireless sensor networks (WSNs) have emerged as an important and novel area in radio and mobile computing research. These applications range from enclosed system configurations in the home and office to alfresco enlistment in an opponent's landmass in a strategic flashpoint. Cognitive radio networks (CRNs) can be created by integrating radio link capabilities with network layer operations utilizing cognitive radios. The goal of CRN design is to optimize the general system operations to meet customer requirements at any location worldwide by much more efficiently addressing CRNs instead of simply connecting spectrum utilization. When compared to conventional radio networks, CRNs are more versatile and susceptible to wireless connections. Recent advancements in wireless communication have resulted in increasing spectrum scarcity. As a modern innovation, cognitive radio aims to tackle this challenge by proactively utilizing the spectrum. Because cognitive radio (CR) technology gives assailants additional possibilities than a normal wireless network, privacy in a CRN becomes a difficult challenge. We concentrate on examining the surveillance system at a societal level, in which both defense and monitoring are critical components in assuring the channel's privacy. The current state of investigation into spectrum sensing and potential risks in cognitive radios is reviewed in this study.

1. Introduction

WSNs have caught the imagination of academic researchers during the last generation due to their immense variety of possible applications. A WSN is made up of thousands or millions of small sensors, processors, and communication devices that are used to analyze a real situation. They are anticipated to play a crucial part in an extensive choice of activities, including essential surveillance systems, bushfire tracking, and facility security measures. Communication and networking, two of the most basic human needs, are necessary for developing social bonds and communicating a range of feelings and wants, and they are vital to civilization. In technology, digitalization [1] and network administration [2] serve as technological assistance to social interaction. Researchers are rethinking the consequences of classic architectural models and strategies for communications and networking in the wake of contemporary increases in usage of high quality of service (QoS) pervasive electronic technology.

Effective spectrum usage has become a major concern with the continued growth for spectrum in wireless connectivity. Cognitive radio (CR) has emerged as the main system to meet this critical need. A CR is a communication platform that is alert and responsive and adjusts its core factors to ensure effective and stable transmission while maximizing resource utilization [3]. Among the numerous types of wireless technology providing Internet connection as well as other operations, incorporating multiple wireless networks and using one of them effectively, based on the communication contexts and varied technical specifications, is a remarkably successful notion. Also, this leads to the establishment of cognitive radio via software-defined radio (SDR). Basically, the main objective of this concept was to increase spectrum usage. The desire for spectrum for future wireless applications is growing, and there is a spectrum shortage for these applications. Cognitive radio technology appears to be a plausible option for wireless network frequency shortages [4, 5]. It defines consumers of 2 types in wireless networks: approved consumers and abandoned consumers, allowing for optimal use of limited available spectrum [6]. Unlicensed users can use a band that is not provisionally utilized by approved users in CRN. When a licensed user claims to be using the spectrum, the unlicensed user should return it and look for another spectrum. Because the spectrum in cognitive radio networks is employed periodically, conventional strategies cannot meet the specific network demands. In order to control the changing frequency band and assure quality of service, a collection of methods must be developed (QoS).

Cognitive radio (CR) [7, 8] is a crucial platform that helps adaptive resource systems to use bandwidth better effectively in an advantageous manner [6, 9, 10] and provides a groundbreaking viewpoint in the building of technique which provides communication networks [11–13]. Secondary users (SUs), or unapproved customers, in CRN are envisaged to be capable of sensing and analyze their surroundings, gaining knowledge from environmental factors, and connecting directly to the licensed bands to accomplish extremely accurate correspondence without interfering with primary users (PUs) or licensed users. The key purposes of CR technology in CRNs are as follows:

(1) Spectrum is able to sense or determine the spectrum band and detect the existence of PUs
(2) Spectral efficiency or choosing the appropriate available frequency spectrum sensing to meet users' communication requirements
(3) Spectrum sharing or coordinating access to this broadcaster with other customers
(4) Spectrum analysis or vacating the broadcaster when a PU is discovered

Because individuals in CRNs are sentient and have the potential to study, understand, and react to change their productivity, graph theory and game theory are two well-developed methods that support detailed investigation into connectivity and usage patterns [14].

The paper is organized in such a way that Section 2 reveals the fundamentals of CRN; Section 3 provides the spectrum sensing functionalities; and Section 3 gives the key security challenges and methodologies to tackle. Finally, we conclude in Section 4.

2. Fundamental Features of the CRN

2.1. Evolution of Software-Defined Radio. Modifying radio devices quickly and affordably has become crucial for businesses because of the explosive growth in the means and methods by which users need to converse—data correspondence, voice services, virtual assistants, telecast notifications, coordination and control messaging, emergency response connectivity, and so on. Recently, software-defined radio (SDR) has been widely preferred by various telecom operators, device manufacturers, and end consumers due to its power efficiency, versatility, and cost-effectiveness. Software-defined radio, often known as software radio or SDR, is categorized in a variety of terms. The SDR Conference has attempted to develop a description of SDR that offers uniformity and a clear overview of the technique and its accompanying advantages. This description was developed in partnership with the Institute of Electrical and Electronic Engineers (IEEE) P1900.1 group. Software-defined radio is simply radio in which most or all of the physical layer functionalities are determined by software. Any model that remotely collects and transmits signals in the radio frequency (RF) region of the electromagnetic spectrum is referred to as a radio. Radios can be found in a wide variety of modern products, including smart phones, workstations, car door openings, transportation, and televisions.

An SDR is a radio communication system that processes and converts digital signals using software-based components that are programmable. These radio devices, as opposed to conventional radio communication systems, are very adaptable and versatile. This is a cutting-edge technology that connects our ever-expanding digital environment.

A typical SDR system has an analog front-end and a digital back-end, as seen in Figure 1. The transmit (Tx) and receive (Rx) operations of a radio communication system are handled by the analog front-end. The highest bandwidth SDR platforms, which are often found close to DC-18 GHz, are built to function over a wide frequency range.

2.1.1. Related Technologies of SDR. For several additional reconfigurable radio devices that are frequently discussed in the advanced wireless sector, SDR can serve as a crucial enabling technology. Although none of these radio types must use SDR to be implemented, SDR technologies can provide them with the flexibility they need to realize their full potential, which has the potential to save costs and improve system efficiencies:

Adaptive Radio. Adaptive radio is a sort of radio in which communication devices are equipped with a way to track their own performance and alter their operating conditions to enhance it. Higher levels of adaptability are made possible using SDR innovations in a reactive radio system, leading to improved communications connection efficiency and durability.

Cognitive Radio. The term "cognitive radio" refers to radio in which communication systems are conscious of their inner representation and surroundings, including location and RF spectrum usage at that location. By comparing these data to predetermined targets, they can decide on their radio

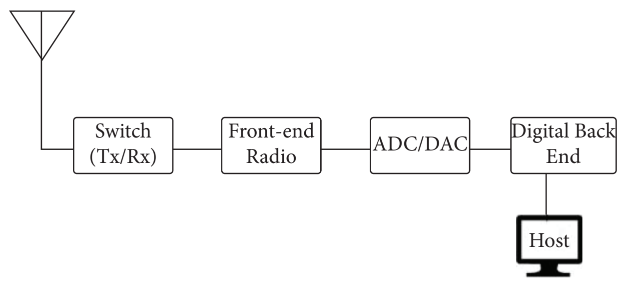

Figure 1: Basic block diagram of SDR.

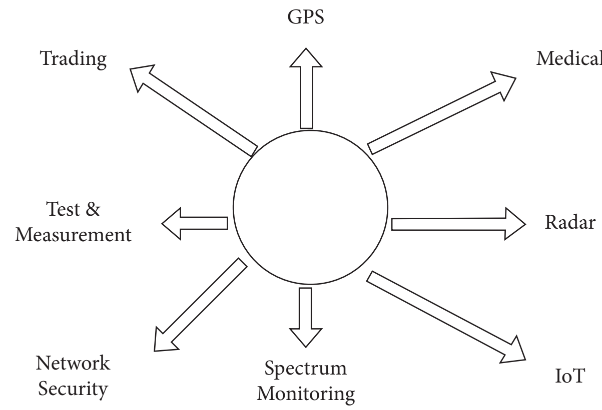

Figure 2: SDR applications.

operating behavior. Many go on to characterize radio technology as using capabilities like software-defined radio, adaptive radio, and others to autonomously modify its behavior or operations to achieve desired goals. By utilizing these components, end users will be able to utilize the available wireless connections and frequency bands to their fullest potential using a standard set of radio equipment.

Intelligent Radio. Cognitive radio with machine learning capabilities is known as intelligent radio. This enables the cognitive radio to better meet the needs of the end user by improving the way it adjusts to changes in performance and surroundings. These radio technologies such as adaptive radio, cognitive radio, and intelligent radio do not always refer to a single piece of hardware but may instead include elements dispersed throughout an entire network[15–17].

Figure 2 depicts the vital role that SDR plays in various markets.

2.2. Cognitive Radio. The electromagnetic spectrum is required for wireless communication devices to deliver data. The administration of a region or a province has given its approval for the usage of the spectrum. Nevertheless, there is fierce rivalry for the limited amount of acceptable spectrum that is accessible given the number of wireless network carriers already operating. As a result, the government auctions the spectrum to numerous Internet providers. Each auction winner receives complete access to a certain spectrum band and is referred to as the primary user (PU). The PUs now possess the legal authority over the portion of the spectrum that was given to them. The CR is a smart device that communicates to detect the full-spectrum to identify the unoccupied streams and unscrupulously use these unoccupied channels of communication as and when necessary. Utilizing these idle channels strategically can improve the use of the priceless spectrum. The SUs may be allowed by CR to use the licensed streams of the PUs on a contractual or as-needed basis. The capacity of nodes to change any of their transmission or reception properties to adapt to a constantly changing world can serve as the foundation for effective wireless interactions between people.

Firstly, CR is a radio frequency transceiver created to quickly exploit the unoccupied radio spectrum without disturbing other authorized users' transmissions by cognitively detecting whether a specific radio spectrum section is in use. A transponder can cognitively determine which methods of communication are already in use but which others are not even in cognitive radio (CR), a type of radio connectivity. The transponder then immediately switches to bidirectional communication, eliminating busy signals. These features aid in the radio frequency (RF) spectrum's best possible utilization. It lessens its possible meaning overall. Additionally, it boosts bandwidth utilization and enhances consumers' quality of service (QoS) by eliminating congested channels. The wireless RF spectrum is a finite resource that is often distributed via licensing. The Federal Communications Commission (FCC) and the National Telecommunications and Information Administration are jointly in charge of it in the United States (NTIA). The NTIA manages the frequency for government (such as the military and FBI) usage, while the FCC handles the same for nonfederal (commercial) uses. The licensed spectrum is not always exploited to its full potential. Because of this, some bands are overused (such as the GSM cellular networks) while others are comparatively underutilized (e. g., military). The amount of data that can be delivered to customers is constrained by the spectrum's inefficiency, which also decreases the level of service. This finite resource is quickly turning scarce due to the increase of connected devices in use. Utilizing cognitive radio effectively allows for the fair, optimal, and intelligent sharing of this resource. Table 1 depicts the radio frequency bands that CR optimizes for efficient communication.

A cognitive radio network (CRN) consists of two key systems: a core system and a subsidiary system. The core radio base station and model conceptualize up the main system, which is the owner of the licensed band. The core network and the secondary network split the available bandwidth. Users and the cognitive radio ground station make up the system. The following three features set cognitive radio apart from conventional radio.

2.2.1. Cognitive. CR is aware of its physical and operational surroundings.

2.2.2. Reconfiguration. Using this cognitive understanding, CR may choose to modify its parameters dynamically and independently.

Table 1: Radio frequency bands.

RF band	Frequency
Very low frequency (VLF)	9 kHz to 30 kHz
Low frequency (LF)	30 kHz to 300 kHz
Medium frequency (MF)	300 kHz to 3 MHz
High frequency (HF)	3 MHz to 30 MHz
Very high frequency (VHF)	30 MHz to 300 MHz
Ultra-high frequency (UHF)	300 MHz to 3 GHz
Super-high frequency (SHF)	3 GHz to 30 GHz
Extremely high frequency (EHF)	30 GHz to 300 GHz

2.2.3. Learning. CR can take what it has learned and try new setups in other circumstances.

The basic goal of CR is to maximize the restricted band's usage by empowering SUs to gain exercise of the right to the radio spectrum that PUs control. CR is a situational smart radio developed on a software-defined radio framework that is independent of human customization by understanding and adapting to the transmission medium. CR is a link-level technique that necessitates accurate spectrum sensor information, dynamic spectrum access, and possibly customizable radio compatibility, among other things. As a result, as illustrated in Figure 3, SUs could modify their propagation to fit into the spectral gap. Cognitive ability and extensibility are the two fundamental properties of CR. Cognitive ability of CR is the process of capturing or perceive knowledge out of its radio signal; refinement of CR is the capability to proactively adapt operational conditions for the transponder without modifying the hardware device. As a result, spectrum consciousness is provided via cognitive capability, while refinement allows the radio to be vigorously programmed in response to the wireless signal.

A basic CRN model is shown in Figure 4, which is filled with PUs, SUs, relay nodes, and base stations. In CRNs, Figure 4 depicts one impulsive connection window. In practice, there are two forms of (CRN) in use: clustered and scattered. The clustered network is a framework-based system in which auxiliary base stations oversee the SUs, which are interconnected by a wired backbone. The SUs interact with one another on an ad hoc basis in a distributed system. Two SUs in direct transmission range can share relevant information, but SUs in oblique transmission range must share information through numerous steps. In a distributed system, spectrum sensing is frequently done jointly.

A CRN can detect accessible networks and communication systems in its immediate vicinity, relying on spectrum sensing to maximize spectrum consumption. CNRs are forms of heterogeneous networks that are made up of multiple types of communication devices and services. Instead of focusing on link transmission rate, the goal of CRN architecture design is to improve overall network utilization as depicted in Figure 5. In fact, network usage from the customer's viewpoint implies that they will just meet their requirements, whenever and everywhere, by connecting CRNS without interfering with other systems. CRNs can be used in centralized-based networks, disseminated, ad hoc, and mesh topologies to support both authorized and unregistered applications.

In the framework model depicted in Figure 6, amobile station can only connect to a base station or access point via a single hop. MS in the same base station or transmission access point's variability interconnecting with each other via the BS/AP.Mainstay/essential networks serve as a conduit for communication between cells. The ad hoc architecture has no infrastructure facilities. If an MS identifies that additional MSs are around and can be connected via communicating standards/protocols, they can find the correlation and form an ad hoc system, which can be seen in Figure 7. The Mesh design, as depicted in Figure 8, is a composite wireless mesh system that combines infrastructural and ad hoc design by permitting wireless connections among BSs/APs.

2.3. Facets of Cognitive Radio

2.3.1. Spectrum Sensing. To locate users who have the proper authorization to use a certain band, CR devices monitor the spectrum in their immediate vicinity. Additionally, they search for "white spaces" or "spectrum gaps," which are underused regions of the RF spectrum. These holes can be used without a license and are dynamically formed and erased. Spectrum sensing can be helpful or unhelpful. While each cognitive radio (CR) device functions independently in a noncooperative manner, the cooperative method allows CR devices to share spectrum information. The requirements for spectrum sensing are depicted in Figure 9.

2.3.2. Spectrum Database. The FCC has a database where TV stations update their RF spectrum usage for the upcoming week. Cognitive radio devices do not need to rely on complicated, time-consuming, and expensive spectrum sensing techniques because they can search this database for information about available spectrum. This method's disadvantage is that the database finds it challenging to update dynamic spectrum activity in real time. Therefore, CR devices might pass up chances to access untapped spectrum. A combined strategy is helpful to handle the expanding number of devices that use the RF band. It guarantees that devices may promptly and precisely identify unutilized spectrum, thereby enhancing QoS.

2.4. Novel Architecture of Cognitive Radio. In a cognitive radio, there are two main segments: a cognition section that decides depending on multiple signals and a versatile SDR unit whose operating software offers a variety of potential operation conditions. A distinct channel estimation component is frequently added to the original design process of a cognitive radio to monitor the broadcast environment to identify the existence of other facilities or clients. It is crucial to remember that these modules may have elements dispersed over a whole network rather than defining a single piece of equipment. Because of this, cognitive radio is frequently referred to as a cognitive network or a cognitive radio system. The block diagram in Figure 10 shows how the cognition component is further split into two pieces. Based

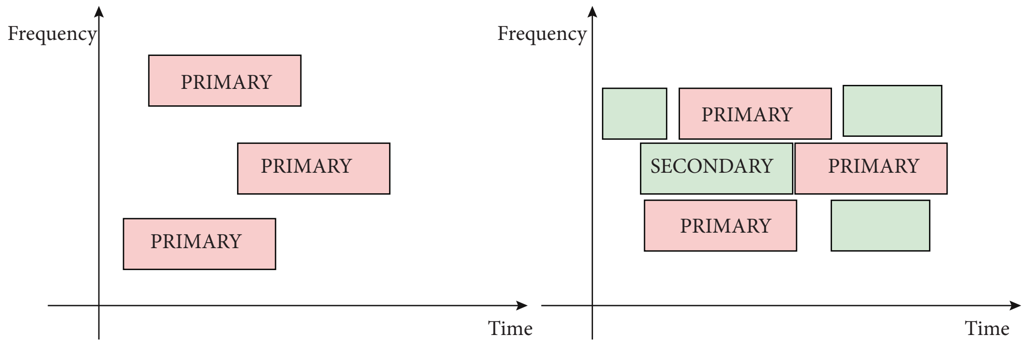

FIGURE 3: Illustration of cognition.

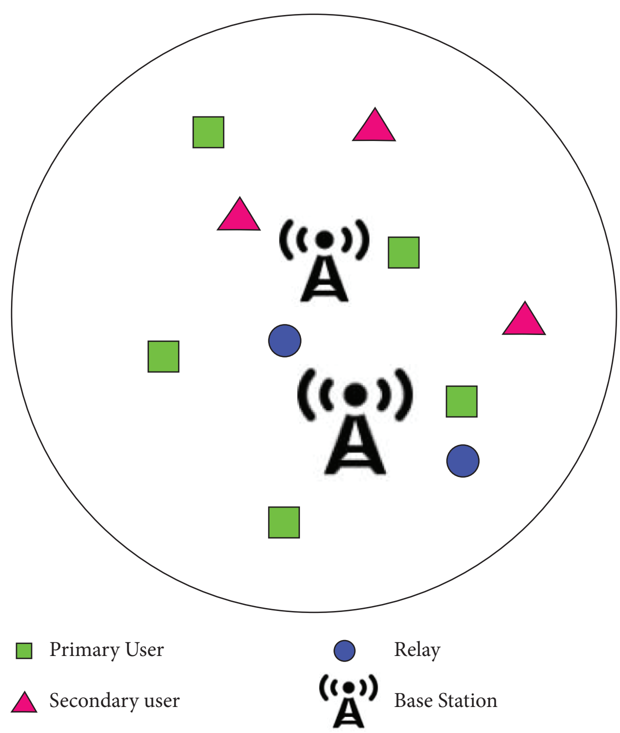

FIGURE 4: Cognitive radio model.

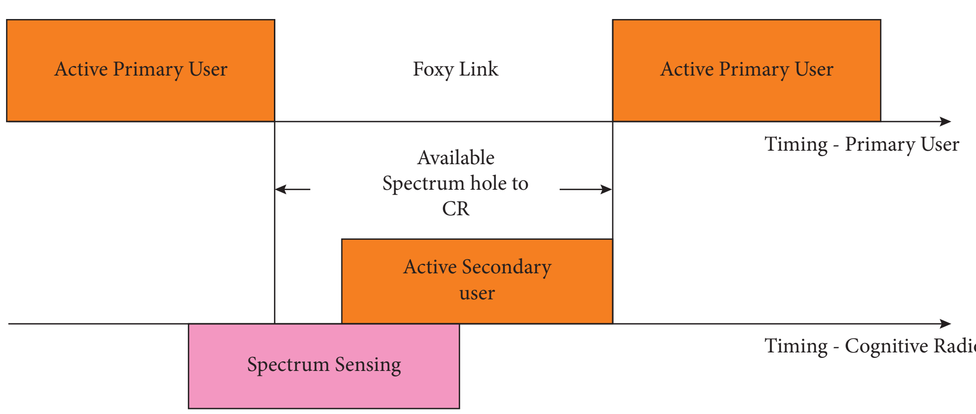

FIGURE 5: Impulsive connection in CRN.

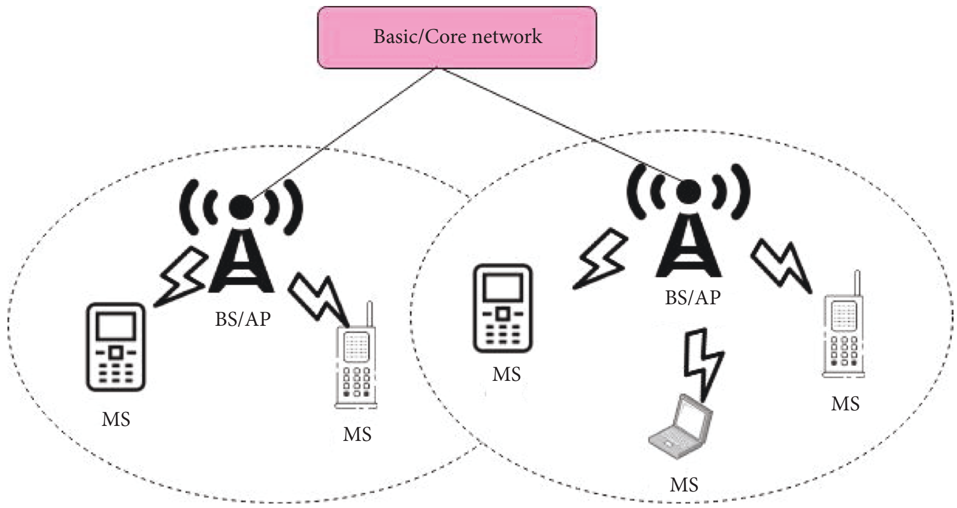

Figure 6: Infrastructure model.

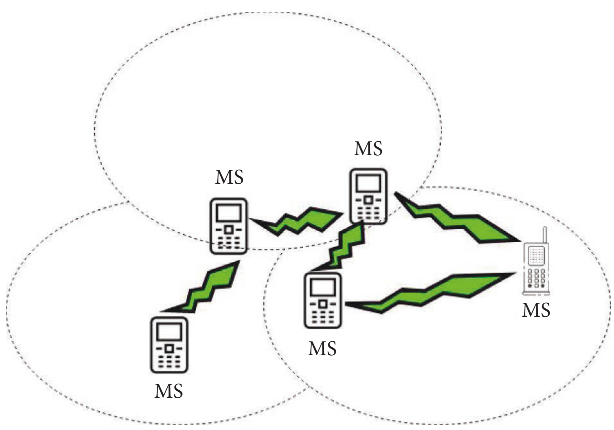

Figure 7: Ad hoc model.

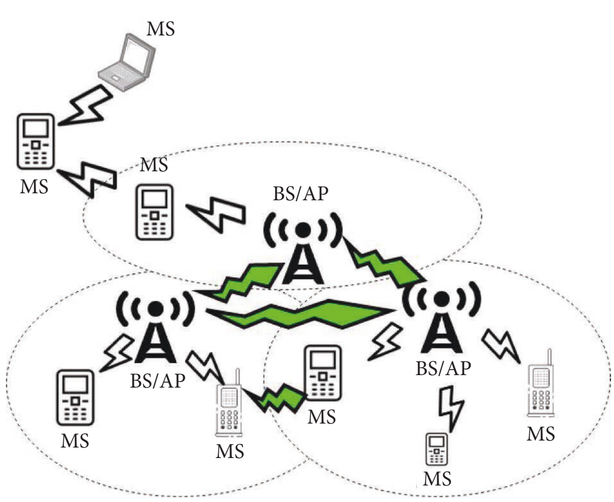

Figure 8: Mesh model.

on the parameters obtained describing the radio's present internal state and operational context, the first component, called the "cognitive engine," seeks to identify a solution or optimize a stated goal. The "policy engine" is the next enabler, and it is used to assure that the "cognitive engine's" response complies with legal requirements and other externally imposed policies.

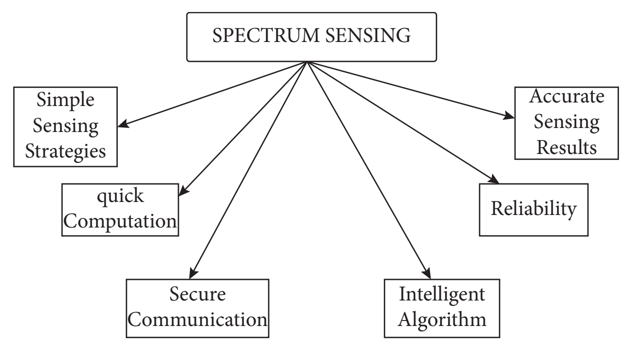

Figure 9: Requirements for spectrum sensing.

3. Spectrum Sensing Strategies and Challenges

As previously stated, the licensed spectrum is currently underutilized. As a result, there are possible spectrum gaps in the licensed spectrum that can be effectively used for conversation by secondary/unlicensed networks or users. Cognitive users must undertake spectrum sensing to assess the existence of spectrum gaps.

A smart device like CR may be able to simulate its location- and time-varying surroundings to choose the optimum carrier frequencies, mechanisms, and connections for interaction. The basic cognitive cycle is shown in Figure 11.

A cognition cycle is one that engages with the outside world. Stimuli are sent to the cognition cycle for a response as interruptions reach the wireless medium. This spectrum sensing constantly scans the environment, then directs, makes plans, chooses, and acts. In these stages, machine learning is utilized. Cognitive radio offers rest and wakefulness that help machine learning since the compilation of

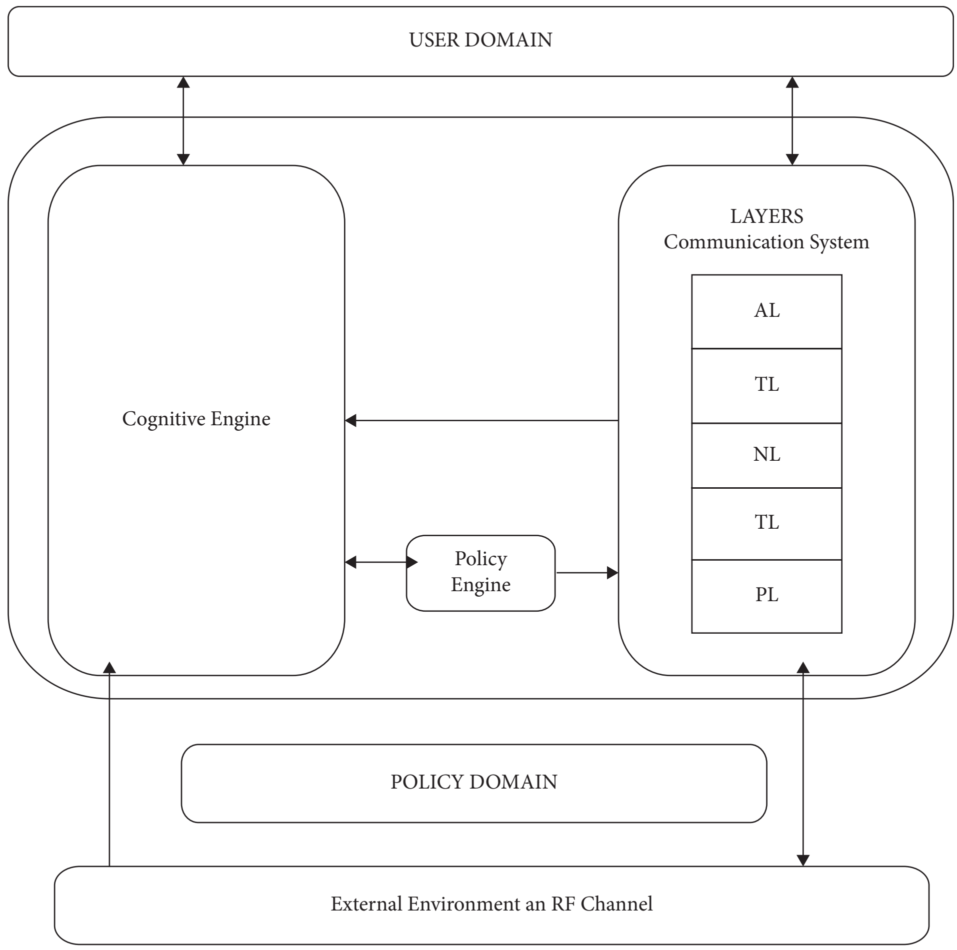

Figure 10: CR architectural framework.

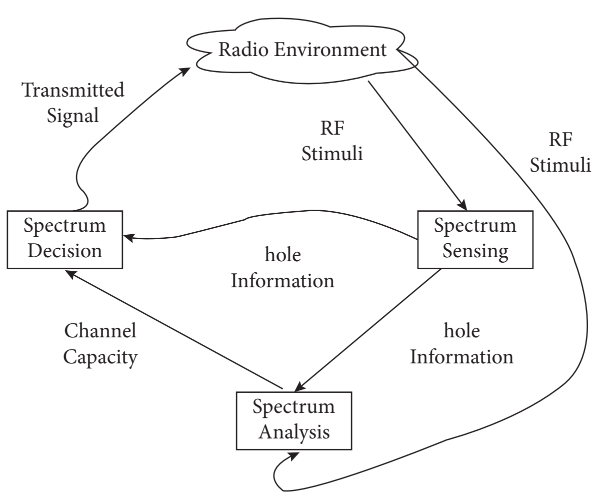

Figure 11: Basic cognition cycle.

information via machine language might be computationally complex. The radio will not be used during the rest periods, which is a reasonably long amount of time, but it still has enough electrical power for processing. The radio employs machine learning techniques while users are sleeping to meet their demands.

A new primary cognitive cycle begins during the wake period whenever a new stimulus is received on any of its sensors. The cognitive radio analyses the incoming information streams to gauge its surroundings. Additionally, listening to radio programs like the weather channel and stock ticker tapes is included. To determine the user's communications context, it additionally reads location, temperature, and light level sensors during the observation phase. The priority attached to the stimulus is used by the cognitive radio to orient on to it. An "Immediate" path could be promptly triggered by a power outage. When a network has an irrecoverable signal loss, resources may need to be redistributed, such as from input analysis to alternative RF channel searches. The path marked "Urgent" is how to do this. However, a plan would typically be generated to respond to an incoming network message. Plan creation is a part of planning. The candidate plans are chosen in the "Decide" step. The radio may provide the user the option to be informed of an incoming message or to postpone it until a later time. Acting uses an impact or component to start the chosen procedures. Judgments and perceptions influence learning. These actions are depicted in Figure 12.

(i) Observe: the ability of CR to detect the surroundings gives it full-awareness of that environment.

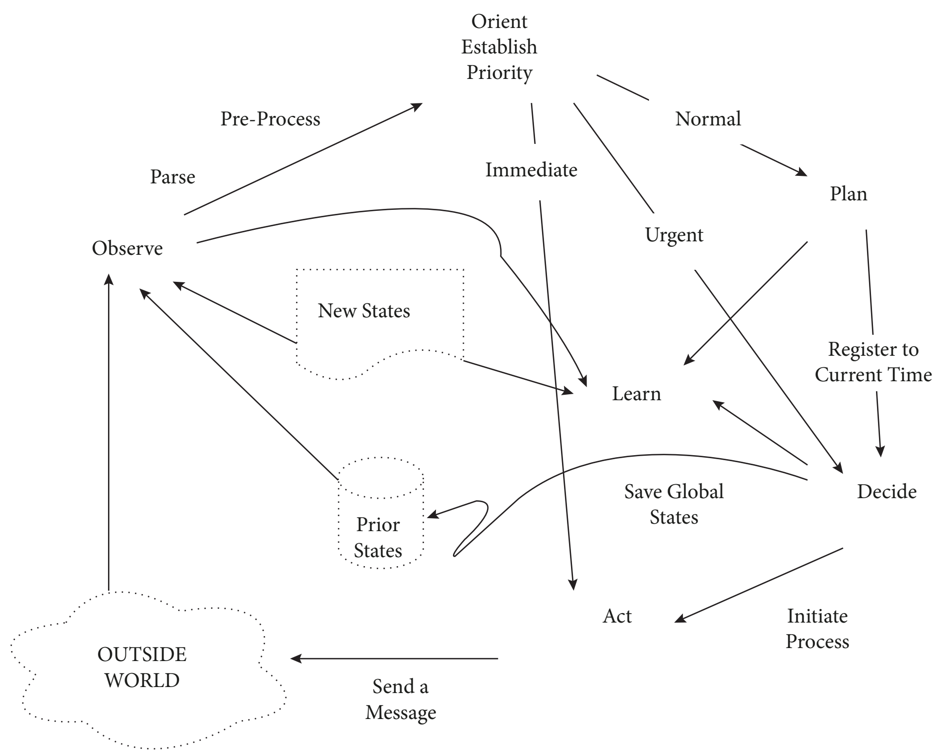

Figure 12: Actions of cognitive cycle.

(ii) Orient: the significance of the data gathered is evaluated.

(iii) Plan: CR analyses all its possibilities for efficiency improvement based on the evidence gathered.

(iv) Decide: the finest option is chosen from the ones that are offered.

(v) Act: for capacity improvements, CR follows the optimum plan of action. CR then updates the distortion pattern to incorporate the adjustments.

(vi) Learn: the CR uses learning strategies to use all its prior perceptions and judgments to inform its present and potential judgments.

In Figure 13, we depict the taxonomy of conventional and under-research strategies to sense spectrum using CRN. Spectrum sensing gathers data about spectrum usage in various aspects, including location, time, frequencies, coding, and direction [18]. Spectrum sensing is the duty of detecting and being conscious of factors connected to radio channel properties, as well as instantaneous assessment of signal categories inhabiting the band, frequency hopping, shape, signal power, and so forth. Various strategies for effective spectrum sensing have been presented. Energy detection (ED), matched filter detection (MFD), cyclo-stationary-based detection (CSD), and cooperative/collaborative spectrum sensing (CSS) are the most popular.

Energy detection uses white Gaussian noise with a very precise power spectral density measurement [19]. This hypothesis provides a high likelihood of detection including for relatively brief transmissions. It is proved that identification of these impulses by a multichannel radiometer might be significantly more challenging in practice than suggested by the conventional result by explicitly considering the influence of imprecise information on the disturbance conversion efficiency [20]. Despite the minimal complexity of ED, it faces a number of difficulties, including the assortment of an appropriate limit for sensing PUs, the helplessness to distinguish among PUs and clatter, deprived recital in the case of blow out band indicators, and deprived recital below short SNR [21]. Figure 14 depicts the workings of the energy detection model.

Figure 14 calculates the energy of the samples as the squared magnitude of the FFT averaged over the number of samples N. This is given by

$$T_{\mathrm{ED}} = \frac{1}{N} \sum_{n=1}^{N} (Y[n])^2, \tag{1}$$

where N denotes the total number of received samples and $Y[n]$ denotes the nth received sample. To determine the sensing choice, the computation's output is then measured against a specified limit. The prime consumer is deemed available if the energy is above the limit; alternatively, the prime customer is deemed absent.

Unlike matched filtering, cyclo-stationary analysis is a noncoherent strategy since it does not require intensity or phase synchronization as depicted in Figure 15. As a result, for signals with uncertain carrier wave and symbol synchronization, CSD is a very appealing approach that may be recognized via cyclo-stationary study and used as a special code. The computational cost and detection speed can be easily modified in the current electromagnetic environment. When compared to older radiation detectors, the computational study's findings produce satisfying results.

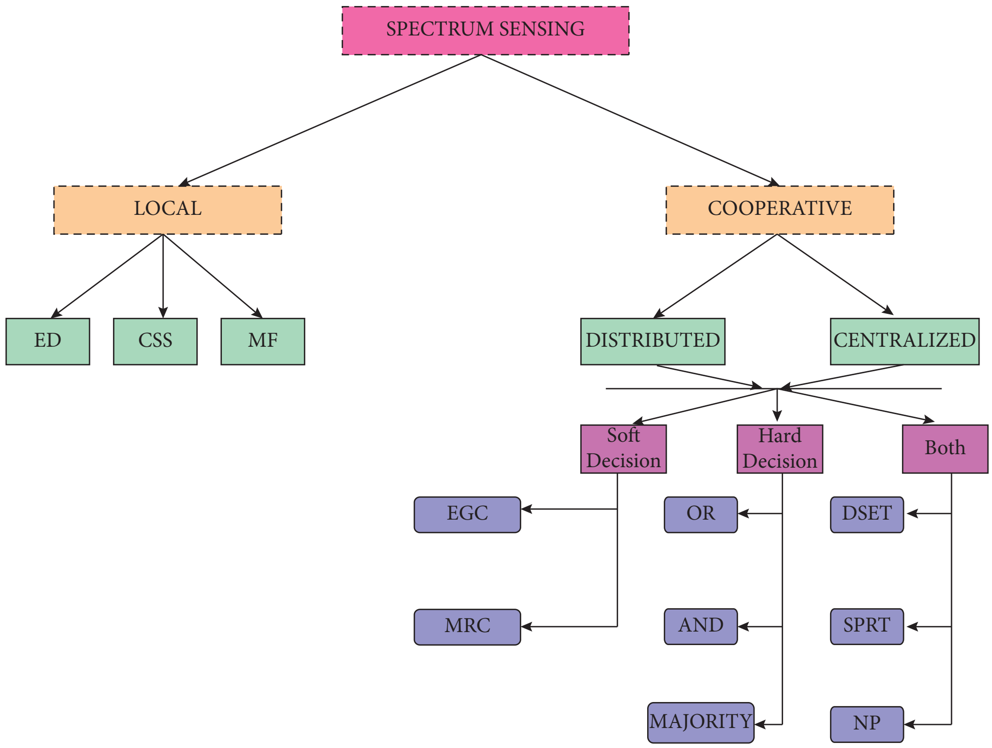

Figure 13: A taxonomy of spectrum sensing strategies.

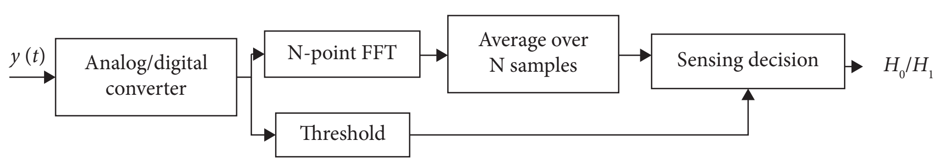

Figure 14: Block diagram of the energy detection model.

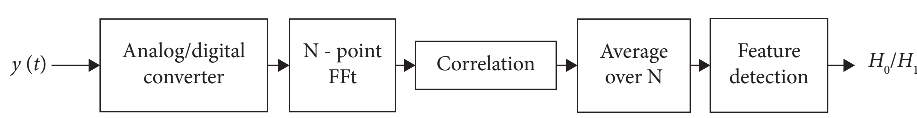

Figure 15: Block diagram of the cyclo-stationary analysis model.

The notion of this technique is depicted in Figure 15, where the fast Fourier transform of the incoming analog signal is computed by the N-point FFT block after the analog-to-digital converter block digitizes it. These FFT values are then aggregated over N elements and associated with one another. To determine the sensing conclusion, pattern filtering is done on the aggregate of the results.

If the signal's means and autocorrelation are regular, the incoming signal $y(t)$ is said to be cyclo-stationary. This can be quantitatively stated as follows:

$$\begin{aligned} m_y(t) &= A[y(t)] = m_y(t + T_0), \\ C_y(t, \omega) &= C_y\left(t + T_{0,\omega}\right), \end{aligned} \tag{2}$$

where T_0 stands for the signal's period, A for the anticipation operator, C_y for the signal's autocorrelation function, and ω for the time skew.

CRs can use collaborative detecting to counteract the issues related to fading, occlusions, and loudness ambiguity, as well as to solve the concealed principal errors and bugs. This results in enhanced discovery execution results, lower compassion requirements, and shorter sensing times, on the acceptance of increased collaboration overhead. As a result, achieving an optimal trade-off between cooperative and cooperation overhead is a difficulty in cooperative sensing. Because the location of PU in CR is unknown, local sensing may reduce sensing performance. Obliging sensing based on views gathered through space communication from distinct CR groups at different locations can be used to generate integrated cooperative conclusions that transcend the inadequacies of individual CR node insights. Because cooperative sensing exploits geographical diversity, it is exceedingly improbable that all CR manipulators will experience fading, masking, or clatter ambiguity at the same moment. As a result, individual observations on the condition of the band from diverse CR manipulators can be pooled to reach a consensus on the inclusion or exclusion of PU.

The abovementioned narrowband sensing methods are contrasted in Table 2. The first technique, energy detection, is straightforward and simple to use because it does not require any prior knowledge of the signal's characteristics. One of its drawbacks is that it cannot tell the difference between the signal and noise. Additionally, it performs poorly in terms of detection at low SNR levels and is more subject to noise uncertainty. The performance of this sensing technique can be improved by dynamic threshold selection and increasing the sample size, albeit at the expense of longer sensing times.

3.1. Wideband Spectrum Sensing Approaches. The goal of wideband spectrum sensing techniques is to detect a frequency band that is wider than the channel's coherence band. For instance, wideband spectrum sensing techniques should be used to take advantage of spectral opportunities throughout the whole ultra-high frequency (UHF) TV range (between 300 MHz and 3 GHz). It is important to note that narrowband sensing techniques cannot be used to accomplish wideband spectrum sensing since they can only identify the broad spectrum as a whole and not the specific spectral possibilities that exist within it.

There are two basic types of solutions for the wideband detection challenge, depending on the sample frequency.

Quan et al. proposed a novel method to sense the spectrum in the wideband spectrum. Multiband joint detection is a unique wideband spectrum sensing approach that concurrently recognizes the principal signals throughout many frequency bands rather than just one channel at a time [38]. The "spectrum sensing challenge" is explicitly defined as a set of optimization problems that aim to increase the consolidated serendipitous throughput of a CR while keeping disturbance to the primary users under predefined restrictions. Under real-world circumstances, it is possible to identify the most effective approaches for multiband joint detection by making use of the hidden convexity in problems that appear to be nonconvex. It is also considered that due to channel ageing or masking, individual CRs might not be capable of consistently discerning feeble core impulses. The effectiveness of the suggested spectrum sensing methods has been tested numerically.

The signal spectrum over a broad frequency range is divided into fundamental subbands, which are distinguished from one another by their regional variations in frequency. The wavelet transform is used to discover and assess the local spectral asymmetric shape, which conveys substantial information on the frequency ranges and energy spectral distributions of the subbands. The wavelet transform is a potent statistical tool for investigating discontinuities and boundaries. Along these lines, a few wideband spectrum sensing methods are created based on the multiscale wavelet derivatives and local maxima of the wavelet transform modulus. To find and detect the unused spectrum in the signal spectrum, the suggested sensing approaches offer an efficient radio sensing architecture [39].

Any CR network's main responsibility is to proactively scan the radio spectrum and correctly identify any frequency band segments that could be utilized for the communication link(s). Consequently, a spectrum analyzer is required for each CR node in the network. In this study, we suggest filter banks as a tool for CR systems' spectrum sensing. Different filter bank options are presented, and their effectiveness is assessed theoretically and using numerical examples. Additionally, the Thomson's multitaper (MT) technique, which has recently been acknowledged as the optimum option for spectrum sensing in CR systems, is examined with the suggested spectrum analyzer [40].

Any CR network's main responsibility is to proactively scan the radio spectrum and correctly identify any frequency band segments that could be utilized for the communication link (s). Consequently, a spectrum analyzer is required for each CR node in the network. In this study, we suggest filter banks as a tool for CR systems' spectrum sensing. Different filter bank options are presented, and their effectiveness is assessed theoretically and using numerical examples. Additionally, the Thomson's multitaper (MT) technique, which has recently been acknowledged as the optimum option for spectrum sensing in CR systems, is examined with the suggested spectrum analyzer [41].

Wideband detection is first realized by assuming that the necessary spectrum may be sampled at the normal Nyquist rate [42]. Some methods in this situation assume that the issue can be split up into numerous narrowband detection issues. Others just use edge detection to attempt to differentiate between the occupied segments and the empty ones. When practical concerns are considered, the high computational complexity of the solutions, the high computational complexity of the required ultra-high sample rates, and the high computational complexity of the required sensing time present a common issue. Table 3 lists the algorithm, its classification, its brief description and limitations, and the relevant recent references.

3.2. Research Challenges in Spectrum Sensing. Spectrum sensing systems must have a high likelihood of detection and a low probability of false alarm to reduce the effects of harmful interference [42]. However, there are several drawbacks to current narrowband sensing methods. For instance, weak signals that are below thermal noise cannot be detected with energy detection [50]. Furthermore, sophisticated methods like autocorrelation and cyclo-stationary features demand a significant amount of processing power, which is undesirable in portable devices [51]. However, they are far more complicated than cyclo-stationary detection. More complex techniques, such as those based on Eigenvalues and sample covariance matrices, have been studied in TVWS and can obtain a good probability of detection [52]. These methods must undergo more complexity reduction research to be implemented on real-time hardware. High sample rates, high-resolution A/D converters, and fast signal processors are necessary for wideband

Table 2: Performance comparison of narrow band spectrum sensing models.

Sensing strategy	Approach	Merits	Demerits
Energy detector [19–23]	Sensing	Does not really necessitate understanding of the principal system and is incoherent	Noise- and uncertainty-prone
Matched filter [24–26]	Sensing	Less time needed to achieve high processing gain	Computational complexity depends on the primary network
Feature detection [27–32]	Sensing	Fast sensing as compared to energy detection	Higher accuracy requires a longer length of known sequences that results in lower efficiency of the spectrum
Receiver statistics [33–35]	Monitor	Monitoring during reception	Sensitive to receiver impairments
Energy ratio [36, 37]	Monitor	Insensitive to receiver impalements	May require long monitoring cycle

Table 3: Performance comparison of wide band spectrum sensing models.

Sensing strategy	Approach	Merits	Demerits
FFT detector [38]	Nyquist WB	Noncoherent	Require high sampling rate
Wavelet detector [39, 43]	Nyquist WB	Edge detector	High computational complexity
Filter-bank detector [40]	Nyquist WB	High performance	High computational complexity
Compressive sensing [41, 44–49]	Subnyquist WB	Low sampling rate	Dynamic behaviors for sparsity level

spectrum sensing [53]. It is difficult to create wideband spectrum sensing systems that meet these characteristics while still being simple and inexpensive to compute [54]. Wideband spectrum sensing has achieved significant advancements previously, yet there are still many problems in this field [55–63].

Estimating the wideband signal's sparseness degree is crucial since it serves as background information for choosing the right number of observations [64]. However, in a rapidly evolving distributed environment, it is challenging to continue learning this prior knowledge [65]. The intricacy of cumulative wideband detecting, or sensing time, may also rise with the addition of additional procedures to assess the sparsity of this wideband signal. Compressive wideband sensing with an uncertain level of sparsity will be required by future cognitive radio systems. Therefore, creating blind subNyquist wideband sensing methods that do not require knowledge of the wideband signal's sparsity to execute spectrum reconstruction will be a difficult task.

Choosing the number of measures is difficult as well. This figure is based on the wideband signal's fluctuating sparsity level. Some researchers reported using a set sparsity level while adjusting the number of measurements. The wideband signal's sparsity level varies with time in practice, making it challenging to predict. Therefore, wideband sensing methods that intelligently choose the right number of observations without knowing the sparsity level beforehand are required [66].

How to manage noise uncertainty presents another difficulty. A static threshold that is dependent on the noise level is used by most compressive wideband spectrum sensing techniques. These sensing methods are inaccurate because the noise is unknown. Techniques to deal with uncertainty have been suggested in a few research articles, including some that employ probabilistic models. The performance of the classifier of the sensing systems must then be improved through assessment of the noise [67].

Another problem is that shadowing, fading, and noise uncertainty constantly make it difficult to discern a principal user signal. Cooperative spectrum sensing has been suggested as a potential remedy to lessen these effects by increasing the detection rate by making use of geographical variety. The cooperating nodes use subNyquist or Nyquist-based methods to carry out narrowband sensing. Most of the research to date has concentrated on the centralized cooperative model, in which the sensing nodes utilize either hard decision or soft combining techniques to communicate their sensing results to the fusion centre via a common control channel [68–72]. Overall, spectroscopic and energy efficiency should be the sole goals while addressing the safety issue. Investigators have neglected two factors: quality and energy effectiveness.

3.2.1. Summary. The following list includes the main obstacles/problems that researchers encounter when creating CSS approaches for CRN that could affect the system's performance.

Channel Uncertainty. Due to multipath channel fading or occlusions, received signal intensity is unpredictable in wireless communication networks, and the receiver may incorrectly interpret the existence of PUs as a result.

Co-Operation Overhead. Any additional sensing duration, latency, power, and performance loss are referred to as overhead. Variations across CR users are observed while preserving these criteria for collaboration, which may lead to a reduction in the ability to detect accessible spectrum.

Decision Fusion. The sensing choice in CSS can be either hard (0/1) or soft. When there are few CR users, soft decisions work well, and when there are many cooperating users in the same region, hard decisions work just as well as soft ones. However, implementing soft judgments in large networks becomes a difficult task because it adds a lot of complexity to the fusion rules while combining a lot of data.

Interference Temperature Measurement. A CR user is naturally aware of its transmit power level and, with the aid of a positioning system, its exact location, but is not aware of PUs. As a result, its transmission may seriously interfere with a nearby receiver using the same frequency.

Mobility. Performance in terms of sensing could be significantly impacted by mobility in CRN. The ideal sensing and transmission time of a stationary CRN model might not be well suited for a mobile CRN model due to the movement nature of PU or SU or both. On the other hand, collaboration between SUs is difficult because of mobility.

4. Conclusion

In general, networks that are wireless and WSN face totally new forms of security vulnerabilities because of the cognitive radio paradigm. It makes developing efficient security models and mechanisms extremely difficult. Wireless security in cognitive radio networks, on the other hand, has obtained less attention, even though security is anticipated to be critical to the technology's long-term commercial success. Various spectrum sensing approaches are discussed, including energy discovery, cyclo-stationary-based discovery, and obliging band sensing, as well as their benefits and drawbacks. Furthermore, attacks in the CRNs are classified, and major aids to combating these security issues are studied. The study has covered several existing security techniques to fight against these dangers and attacks in addition to identifying numerous threats. A complete taxonomy of the assaults is also offered, as well as their associated security measures. Some significant research difficulties in CR networks are recognized and briefly reviewed, particularly from the standpoint of security and privacy. These issues must be solved by the research community soon if CWSN implementation in essential and sensitive real-world applications is to be made possible.

By 2020, there are predicted to be billions of wireless devices connected to the Internet, making it likely that getting access to the radio spectrum would be quite difficult. One of the most pressing problems that still needs to be solved is this one. Spectrum access issues could potentially be resolved with cognitive radio technology. In this work, we examined cognitive radio technology's most recent developments and difficulties, particularly in wideband spectrum sensing research. We divided the sensing methods into two primary groups: narrowband spectrum sensing and wideband spectrum sensing. Then, the scope for open directions is considered after presenting techniques from each area. This survey also addresses how cognitive radio technology might be implemented into the next networks to address issues with radio spectrum access. Finally, we go over a few unexplored avenues for study into attacks on secure spectrum sensing and transmission.

Data Availability

No underlying data was collected or produced in this study.

Conflicts of Interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or nonfinancial interest in the subject matter or materials discussed in this manuscript.

Acknowledgments

The authors would like to thank the Indian Space Research Organization (ISRO) through RACS scheme project ISRO BASKET 2021/RACS_029 for funding this research work.

References

[1] R. G. Gallager, *Principles of Digital Communications*, Cambridge University Press, Cambridge, UK, 2008.
[2] A. S. Tanenbaum and D. J. Wetherall, *Computer Networks*, Prentice-Hall, Hoboken, NJ, USA, 2011.
[3] J. Mitola, *Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio*, Doctoral Dissertation, Royal Institute of Technology, Stockholm, Sweden, 2000.
[4] A. Haldorai and A. Ramu, "Security and channel noise management in cognitive radio networks," *Computers & Electrical Engineering*, vol. 87, Article ID 106784, 2020.
[5] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, pp. 201–220, 2005.
[6] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohantly, "Next generation/dynamic spectrum access/cognitive eadio wireless network: a survey," *Elsevier Computer Networks*, vol. 50, pp. 2127–2159, 2006.
[7] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Pers. Commun*, vol. 6, no. 4, pp. 13–18, 1999.
[8] A. Haldorai, A. Ramu, and S. Murugan, "Social aware cognitive radio networks: effectiveness of social networks as a strategic tool for organizational business management," in *Social Network Analytics for Contemporary Business Organizations*, pp. 188–202, IGI Global, Hershey, PA,USA, 2018.
[9] Q. Zhao and B. Sadler, "A survey of dynamic spectrum access," *IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 79–89, 2007.
[10] E. Hossain, D. Niyato, and Z. Han, *Dynamic Spectrum Access and Management in Cognitive Radio Networks*, Cambridge University Press, Cambridge, UK, 2009.
[11] Q. H. Mahmoud, C. N. Mathur, and K. P. Subbalakshmi, *Cognitive Networks: Towards Self-Aware Networks*, John Wiley & Sons, New York, NJ, USA, 2007.
[12] N. Devroye, M. Vu, and V. Tarokh, "Cognitive radio networks," *IEEE Signal Processing Magazine*, vol. 25, no. 6, pp. 12–23, 2008.
[13] K. J. R. Liu and B. Wang, *Cognitive Radio Networking and Security: A Game Theoretical View*, Cambridge University Press, Cambridge, UK, 2011.
[14] D. Easley and J. Kleinberg, *Networks, Crowds, and Markets: Reasoning about a Highly Connected World*, Cambridge University Press, Cambridge, UK, 2010.

[15] W. Lu, Y. Gong, X. Liu, J. Wu, and H. Peng, "Collaborative energy and information transfer in green wireless sensor networks for smart cities," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 4, pp. 1585–1593, 2018.
[16] W. Lu, P. Si, G. Huang et al., "SWIPT cooperative spectrum sharing for 6G-enabled cognitive IoT network," *IEEE Internet of Things Journal*, vol. 8, no. 20, pp. 15070–15115, 2021.
[17] W. Lu, Y. Mo, Y. Feng et al., *Secure Transmission for Multi-UAV-Assisted Mobile Edge Computing Based on Reinforcement Learning*, IEEE Transactions on Network Science and Engineering, Manhattan, NY, USA, 2022.
[18] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 116–130, 2009.
[19] A. Margoosian, J. Abouei, and K. N. Plataniotis, "An accurate kernelized energy detection in Gaussian and non-Gaussian/impulsive noises," *IEEE Transactions on Signal Processing*, vol. 63, no. 21, pp. 5621–5636, 2015.
[20] A. Nafkha and B. Aziz, "Closed-form approximation for the performance of finite sample-based energy detection using correlated receiving antennas," *IEEE Wireless Communications Letters*, vol. 3, no. 6, pp. 577–580, 2014.
[21] I. Sobron, P. S. R. Diniz, W. A. Martins, and M. Velez, "Energy detection technique for adaptive spectrum sensing," *IEEE Transactions on Communications*, vol. 63, no. 3, pp. 617–627, 2015.
[22] C. Liu, M. Li, and M.-L. Jin, "Blind energy-based detection for spatial spectrum sensing," *IEEE Wireless Communications Letters*, vol. 4, no. 1, pp. 98–101, 2015.
[23] A. A. Alkheir and H. T. Mouftah, "An improved energy detector using outdated channel state information," *IEEE Communications Letters*, vol. 19, no. 7, pp. 1237–1240, 2015.
[24] A. Fernandez Eduardo and R. Gonzalez Caballero, "Experimental evaluation of performance for spectrum sensing: matched filter vs. energy detector," in *Proceedings of the IEEE Colombian Conference on Communications and Computing*, Popayan, Colombia, 2015.
[25] L. Ma, Y. Li, and A. Demir, "Matched filtering assisted energy detection for sensing weak primary user signals," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 3149–3152, Kyoto, Japan, 2012.
[26] X. Zhang, R. Chai, and F. Gao, "Matched filter based spectrum sensing and power level detection for cognitive radio network," in *Proceedings of the IEEE Global Conference on Signal and Information Processing*, pp. 1267–1270, Atlanta, GA, USA, 2014.
[27] A. Nasser, A. Mansour, K. Yao, H. Charara, and M. Chaitou, "Efficient spectrum sensing approaches based on waveform detection," in *Proceedings of the International Conference on E-Technologies and Networks for Development*, pp. 13–17, Beirut, Lebanon, 2014.
[28] E. Axell and E. G. Larsson, "Optimal and sub-optimal spectrum sensing of OFDM signals in known and unknown noise variance," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 2, pp. 290–304, 2011.
[29] S. Chaudhari, V. Koivunen, and H. Poor, "Autocorrelation-based decentralized sequential detection of OFDM signals in cognitive radios," *IEEE Transactions on Signal Processing*, vol. 57, no. 7, pp. 2690–2700, 2009.
[30] Y. Zhu, J. Liu, Z. Feng, and P. Zhang, "Sensing performance of efficient cyclostationary detector with multiple antennas in multipath fading and lognormal shadowing environments," *Journal of Communications and Networks*, vol. 16, no. 2, pp. 162–171, 2014.
[31] G. Huang and J. K. Tugnait, "On cyclostationarity based spectrum sensing under uncertain Gaussian noise," *IEEE Transactions on Signal Processing*, vol. 61, no. 8, pp. 2042–2054, 2013.
[32] E. Rebeiz, P. Urriza, and D. Cabric, "Optimizing wideband cyclostationary spectrum sensing under receiver impairments," *IEEE Transactions on Signal Processing*, vol. 61, no. 15, pp. 3931–3943, 2013.
[33] S. W. Boyd, J. M. Frye, M. B. Pursley, and T. C. Royster IV, "Spectrum monitoring during reception in dynamic spectrum access cognitive radio networks," *IEEE Transactions on Communications*, vol. 60, no. 2, pp. 547–558, 2012.
[34] S. W. Boyd, M. B. Pursley, T. C. Royster, and H. B. Russell, "A soft-decision scaling metric employing receiver statistics for directsequence spread-spectrum packet radio networks," in *Proceedings of the IEEE Military Communications Conference*, San Diego, CA, USA, 2008.
[35] M. Orooji, E. Soltanmohammadi, and M. Naraghi-Pour, "Improving detection delay in cognitive radios using secondary-user receiver statistics," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 9, pp. 4041–4055, 2015.
[36] A. Ali and W. Hamouda, "Spectrum monitoring using energy ratio algorithm for OFDM-based cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 4, pp. 2257–2268, 2015.
[37] A. Ali and W. Hamouda, "A novel spectrum monitoring algorithm for OFDM-based cognitive radio networks," in *Proceedings of the IEEE Global Communications Conference*, San Diego, CA, USA, 2015.
[38] Z. Quan, S. Cui, A. Sayed, and H. Poor, "Optimal multiband joint detection for spectrum sensing in cognitive radio networks," *IEEE Transactions on Signal Processing*, vol. 57, no. 3, pp. 1128–1140, 2009.
[39] Z. Tian and G. Giannakis, "A wavelet approach to wideband spectrum sensing for cognitive radios," in *Proceedings of the IEEE International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Mykonos, Greece, 2006.
[40] B. Farhang-Boroujeny, "Filter bank spectrum sensing for cognitive radios," *IEEE Transactions on Signal Processing*, vol. 56, no. 5, pp. 1801–1811, 2008.
[41] Z. Tian and G. Giannakis, "Compressed sensing for wideband cognitive radios," *IEEE International Conference on Acoustics, Speech and Signal Processing*, vol. 4, pp. IV1357–IV1360, 2007.
[42] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: a survey," *IEEE Wireless Communications*, vol. 20, no. 2, pp. 74–81, 2013.
[43] S. El-Khamy, M. El-Mahallawy, and E. Youssef, "Improve wideband spectrum sensing techniques using wavelet-based edge detection for cognitive radio," in *Proceedings of the IEEE International Conference on Computing, Networking and Communications*, San Diego, CA, 2013.
[44] E. Candes, J. Romberg, and T. Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information," *IEEE Transactions on Information Theory*, vol. 52, no. 2, pp. 489–509, 2006.
[45] C. Luo and J. Mcclellan, "Discrete random sampling theory," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, Vancouver, BC, Canada, 2013.

[46] C. Luo, *Non-uniform Sampling: Algorithms and Architectures*, Georgia Institute of TechÂnologyAtlanta, Georgia, USA, 2012.

[47] I. Daubechies, "Time-frequency localization operators: a geometric phase space approach," *IEEE Transactions on Information Theory*, vol. 34, no. 4, pp. 605–612, 1988.

[48] M. A. Davenport and M. B. Wakin, "Analysis of orthogonal matching pursuit using the restricted isometry property," *IEEE Transactions on Information Theory*, vol. 56, no. 9, pp. 4395–4401, 2010.

[49] J. A. Tropp and A. C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," *IEEE Transactions on Information Theory*, vol. 53, no. 12, pp. 4655–4666, 2007.

[50] A. Bujunuru and T. Srinivasulu, "A Survey on Spectrum Sensing Techniques and Energy Harvesting," in *Proceedings of the 2018 International Conference On Recent Innovations In Electrical, Electronics & Communication Engineering (ICRIEECE)*, Bhubaneswar, India, 2018.

[51] K. Leena and S. G. Hiremath, "Enhanced spectrum sensing techniques in cognitive radio based internet of things," *Journal of Physics: Conference Series*, vol. 1921, no. 1, Article ID 012035, 2021.

[52] A. Ali and W. Hamouda, "Advances on spectrum sensing for cognitive radio networks: theory and applications," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 1277–1304, 2017.

[53] R. A. Gafoor, R. Kuriakose, M. Sibila, C. K. Lakshmi, S. Reshmi, and A. S. Kumar, "A Survey on Traditional and Advanced Spectrum Sensing Techniques in Cognitive Radio Networks," in *Proceedings of the 2018 International Conference On Control, Power, Communication And Computing Technologies (ICCPCCT)*, Kannur, India, 2018.

[54] J. N. Javed, M. Khalil, and A. Shabbir, "A Survey on Cognitive Radio Spectrum Sensing: Classifications and Performance Comparison," in *Proceedings of the 2019 International Conference on Innovative Computing (ICIC)*, Lahore, Pakistan, 2019.

[55] M. Yang, Y. Li, X. Liu, and W. Tang, "Cyclostationary feature detection-based spectrum sensing algorithm under complicated electromagnetic environment in cognitive radio networks," *China Communications*, vol. 12, no. 9, pp. 35–44, 2015.

[56] E. Arias-Castro and Y. C. Eldar, "Noise folding in compressed sensing," *IEEE Signal Processing Letters*, vol. 18, no. 8, pp. 478–481, 2011.

[57] D. Cohen and Y. C. Eldar, "Sub-NyquistCyclostationary detection for cognitive radio," *IEEE Transactions on Signal Processing*, vol. 65, no. 11, pp. 3004–3019, 2017.

[58] Q. Zhao, Z. Wu, and X. Li, "Energy efficiency of compressed spectrum sensing in wideband cognitive radio networks," *Journal on Wireless Communications and Networking*, vol. 2016, pp. 1–15, 2016.

[59] M. A. Davenport, J. N. Laska, J. R. Treichler, and R. G. Baraniuk, "The pros and cons of compressive sensing for wideband signal acquisition: noise folding versus dynamic range," *IEEE Transactions on Signal Processing*, vol. 60, no. 9, pp. 4628–4642, 2012.

[60] Y. Kim, W. Guo, B. V. Gowreesunker, N. Sun, and A. H. Tewfik, "Multi-channel sparse data conversion with a single analog-to-digital converter," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 2, no. 3, pp. 470–481, 2012.

[61] L. Huang, Q. Deng, X. Qiao, D. Gu, W. Wang, and H. Yang, "SDR implementation of cognitive radio: sensing and disjoint spectrum access," in *Proceedings of the International Conference on Communications and Networking*, Xian, China, 2009.

[62] Y. Gao and Z. Qin, "Implementation of compressive sensing with real-time signals over TV white space spectrum in cognitive radio," in *Proceedings of the IEEE 84th Vehicular Technology Conference*, Montreal, QC, Canada, 2016.

[63] F. Salahdine, N. Kaabouch, and H. El Ghazi, "A survey on techniques for dealing with uncertainty in cognitive radio networks," in *Proceedings of the Annual Computing and Communication Workshop and Conference*, Las Vegas, NV, USA, 2017.

[64] S. Benazzouza, M. Ridouani, F. Salahdine, and A. Hayar, "A survey on compressive spectrum sensing for cognitive radio networks," in *Proceedings of the IEEE International Smart Cities Conference (ISC2)*, Casablanca, Morocco, 2019.

[65] K. S. Nandini and S. A. Hariprasad, "A Survey of Spectrum Sensing Mechanisms in Wireless Cognitive Radio Networks," in *Proceedings of the 2017 14th IEEE India Council International Conference (INDICON)*, Roorkee, India, 2017.

[66] V. Ramani and S. K. Sharma, "Cognitive radios: a survey on spectrum sensing, security and spectrum handoff," *China Communications*, vol. 14, no. 11, pp. 185–208, 2017.

[67] M. Mehdawi, N. Riley, M. Ammar, A. Fanan, and M. Zolfaghari, "Spectrum occupancy measurements and lessons learned in the context of cognitive radio," in *Proceedings of the 2015 23rd Telecommunications Forum Telfor (TELFOR). IEEE*, Belgrade, Serbia, 2015.

[68] M. Sharma, P. Chauhan, and N. Sarma, "A brief review of cooperative spectrum sensing: issues and challenges," in *Proceedings of the 2016 International Conference on Accessibility to Digital World (ICADW)*, Guwahati, India, 2016.

[69] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: a survey," *Physical Communication*, vol. 4, no. 1, pp. 40–62, 2011.

[70] S. M. Mishra, A. Sahai, and R. Brodersen, "Cooperative sensing among cognitive radios," in *Proceedings of the IEEE International Conference on Communications (ICC)*, pp. 1–6, Istanbul, Turkey, 2006.

[71] J. Ma, G. Zhao, and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 7, pp. 4502–4507, 2016.

[72] H. Guo, W. Jiang, and W. Luo, "Linear soft combination for cooperative spectrum sensing in cognitive radio networks," *IEEE Communications Letters*, vol. 21, no. 7, pp. 1573–1576, 2017.