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Convergence of IoT and Cognitive Radio Networks: A Survey of Applications, Techniques, and Challenges

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ABSTRACT

Cognitive Radio Networks (CRNs) have been proposed as a solution to the problem of spectrum scarcity in wireless communication systems. CRNs allow for dynamic spectrum access by secondary users, who can opportunistically use the spectrum when it is not being utilized by primary users. The integration of CRNs with the Internet of Things (IoT) has the potential to bring significant benefits to both wireless communication systems and IoT applications. Spectrum sensing is a crucial component of CRNs, as it enables the secondary users to detect the presence of primary users and opportunistically use the available spectrum. Routing is another important aspect of CRN IOT-based systems, as it enables efficient communication between the devices. Traditional routing protocols may not be suitable for CRN IOT-based systems, due to the dynamic nature of the available spectrum. In this survey paper, we explore the recent research and developments in CRN IOT-based systems, including the architecture, key technologies, and potential applications. Mainly, we will focus on the key aspects of spectrum sensing and routing in CRNs integrated with the IoT. Hence, we review the sensing and routing protocols and discuss their performance in different scenarios. We will also discuss the challenges and future research directions in this field. Overall, this survey aims to provide a comprehensive overview of the state-of-the-art in IOT-based CRNs and to highlight the potential of this technology for addressing the growing demands of wireless communication and IoT applications.

INDEX TERMS Cognitive Radio Networks, IoT, Sensing, Routing

I. I. INTRODUCTION

The integration of Cognitive Radio Networks (CRNs) [1] with the Internet of Things (IoT) [2] has the potential to bring significant benefits to both wireless communication systems and IoT applications. The rapid growth of wireless communication and IoT applications has led to increasing demand for spectrum resources. However, the traditional static spectrum allocation approach, in which the spectrum is assigned to specific users or applications, is becoming increasingly inefficient due to the limited availability of spectrum resources. CRNs have been proposed as a solution to the problem of spectrum scarcity by allowing for dynamic spectrum access by secondary users, who can opportunistically use the spectrum when it is not being utilized by primary users. In CRN-IOT systems, the IoT devices can act as secondary users and can opportunistically use the available spectrum to communicate with other devices or with the Internet. The integration of CRNs with IoT can enhance spectrum utilization efficiency and improve the quality of service (QoS) for IoT applications. Additionally, CRN-IOT systems can enable the seamless integration of wireless communication and IoT technologies, enabling the development of new and innovative applications such as smart cities, industrial internet, and smart healthcare.

Spectrum sensing and routing are two key aspects of CRN-IOT systems. Spectrum sensing is a crucial component of CRNs, as it allows the secondary users to detect the presence of primary users and opportunistically use the available spectrum. Various spectrum sensing techniques have been proposed in the literature, including energy detection, cyclo-stationary detection, and feature-based detection [3]. These techniques have been evaluated under different scenarios, such as white space detection, spectrum hole detection, and cognitive jamming detection.

Routing is another important aspect of CRN-IOT systems, as it permits efficient communication between the devices. Traditional routing protocols may not be suitable for CRN-IOT systems, due to the dynamic nature of the available spectrum. Therefore, various routing protocols have been proposed in the literature, such as multi-channel MAC, adaptive routing, and opportunistic routing. These protocols have been evaluated under different scenarios, such as dense deployment, low-power operation, and high mobility.

In this survey paper, we aim to provide a comprehensive overview of the state-of-the-art CRN-IOT systems with a focus on spectrum sensing and routing. We will review the recent research and developments in this field, including the architecture, key technologies, and potential applications of CRN-IOT systems. We also discuss the challenges and future research directions in this field. The goal of this survey is to provide a comprehensive understanding of the current state of the art in CRN-IOT systems and to highlight the potential of this technology for addressing the growing demands of wireless communication and IoT applications. Furthermore, this survey will serve as a valuable resource for researchers, engineers, and practitioners who are interested in the field of CRN-IOT systems. This survey paper aims to provide a comprehensive overview of the state-of-the-art in Cognitive Radio Networks (CRNs) integrated with the Internet of Things (IoT) with a focus on spectrum sensing and routing. The main contributions of this survey paper are:

1. A comprehensive review of recent research and developments in IOT-based CR systems, including the architecture, key technologies, and potential applications.
2. A detailed analysis of different spectrum sensing techniques and their performance in different scenarios.
3. A comprehensive examination of various routing protocols proposed for IOT-based CR systems and their performance in different scenarios.
4. A discussion of the challenges and future research directions in the field of IOT-based CR systems.
5. A valuable resource for researchers, engineers, and practitioners who are interested in the field of IOT-based CR systems.

Overall, this survey paper aims to provide a comprehensive understanding of the current state of the art in CRN-IOT systems and to highlight the potential of this technology for addressing the growing demands of wireless communication and IoT applications. It will serve as a valuable resource for researchers, engineers, and practitioners who are interested in the field of CRN-IOT systems and will help to guide future research and development in this area.

The remainder of this paper is organized as follows. In section II, we describe the importance of IoT. Section III gives more detailed descriptions of CRNs. In section IV, we describe how CR can be integrated in IoT-based systems. Section V presents various applications of IoT-based systems in CRNs. State-of-the art methods in spectrum sensing and routing are summarized in Section VI and Section VII respectively. VIII section shed a light on the challenges for IoT-based CRNs that can be addressed by researchers. Finally, section IX concludes the paper.

II. Internet of Things

IoT is a rapidly evolving field that has garnered significant attention from the scientific community in recent years. The IoT refers to a system of interconnected physical devices, vehicles, buildings, and other items that are embedded with sensors, software, and network connectivity, allowing them to collect and exchange data. The technical implementation of the IoT involves the use of various technologies and protocols, including sensors and actuators, wireless connectivity, networking protocols, cloud computing and big data analysis, and device management. At its core, the IoT is about connecting devices to the internet so they can communicate and share data with each other and with central systems. Some common examples of IoT devices include smart home systems, connected cars, wearable fitness trackers, industrial control systems, and smart city infrastructure. The data generated by these devices is used to optimize operations, improve decision-making, and provide new and improved services to users. The growth of the IoT is being driven by advances in technology, including miniaturization, improvements in wireless connectivity, and the increasing availability of cloud computing and big data analytics tools. However, the widespread adoption of the IoT also brings new challenges, such as data privacy and security concerns, the need for standardization and interoperability, and the challenge of managing and processing large amounts of data. Despite these challenges, the IoT is widely seen as a transformative technology that has the potential to revolutionize many industries and has a significant impact on society. As the number of connected devices continues to grow, the IoT will likely continue to evolve and expand in the coming years, bringing new and innovative applications and services to users around the world. It is anticipated by Statista that by the year 2025, there will be about 76 billion IoT-connected devices all over the world as illustrated in Figure 1 [4]. Therefore, with this tremendous growth in the number of connected objects, the demand for spectrum resources has also increased. In this scenario, Cognitive Radio technology presents itself as a highly promising solution for addressing the spectrum requirements of current and future IoT devices. This innovative technology provides the necessary support for efficient and flexible spectrum access, thereby ensuring that IoT devices can communicate effectively with each other and with other network components.

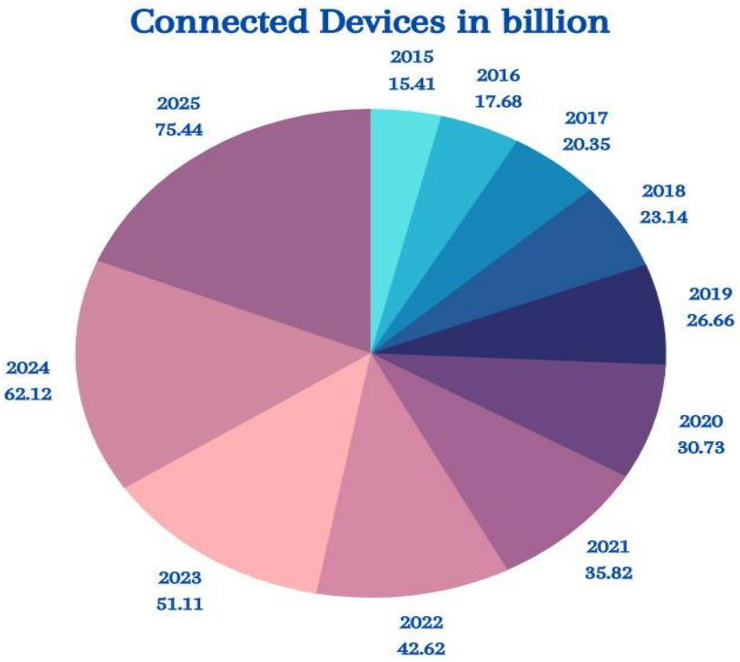

Figure 1 Number of IoT Devices (2015 – 2025)

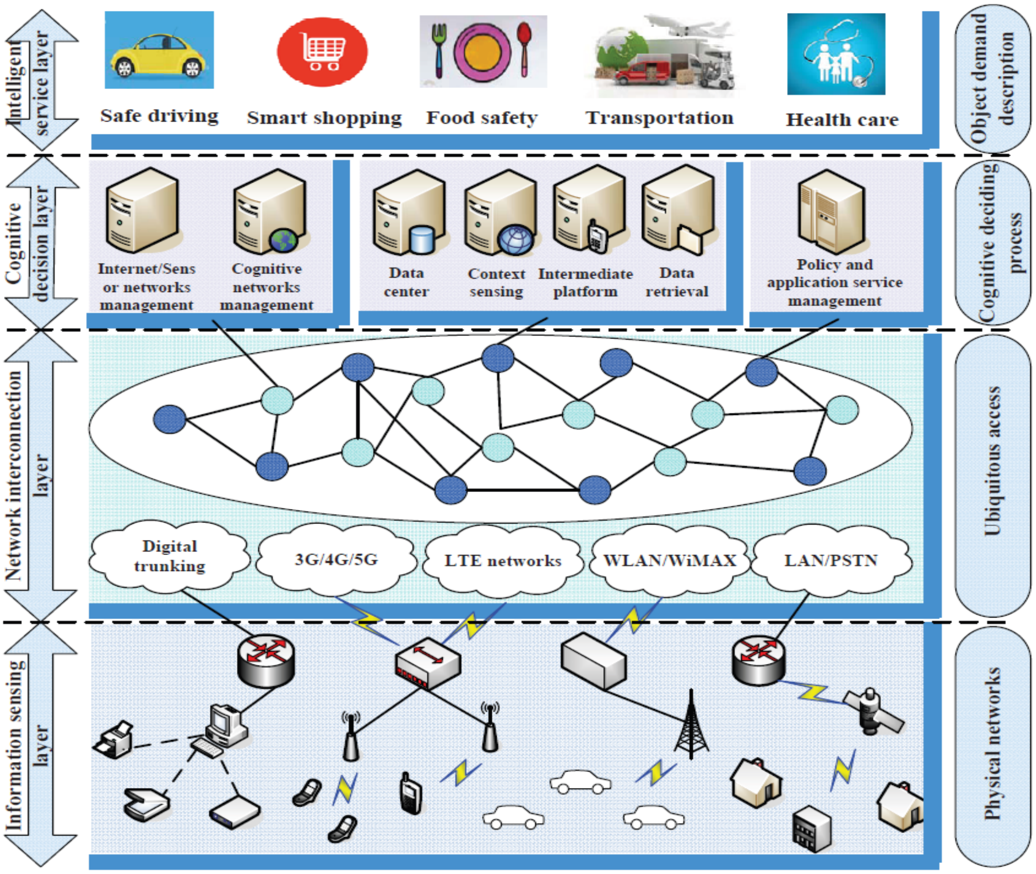

Figure 2 The Architecture of Cognitive IoT [5]

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III. Cognitive Radio

The radio frequency spectrum is a precious and limited resource that plays a crucial role in the transmission of information in the radio environment. This spectrum is used by various communication services, such as radio communication, radio broadcasting, maritime radio, and satellite communications. It is essential to allocate this resource effectively and efficiently to meet the demands of these various services.

To ensure proper management and regulation of the radio frequency spectrum, local authorities, such as governmental agencies, play a critical role in determining the appropriate frequency band to be used, the geographical extent of its use, the maximum transmission power, and more. These agencies are responsible for minimizing interference between different radio technologies to ensure the effective use of the spectrum. Effective utilization of the spectrum not only benefits communication services but also contributes to the growth and development of the communication industry. Furthermore, efficient utilization of the spectrum can result in the availability of more bandwidth for new and innovative communication services. In this context, it is imperative to explore ways to improve the utilization of the assigned spectrum and ensure that it is used effectively. This can be achieved by utilizing cutting-edge technologies and developing innovative approaches to spectrum management.

Cognitive Radio (CR) technology has gained widespread recognition as an efficient solution to tackle the aforementioned challenges in spectrum utilization. This technology enables the opportunistic use of frequency bands that are not heavily utilized by licensed users, thereby improving the overall utilization of the radio frequency spectrum.

CR is a dynamic and intelligent radio technology that can explore and utilize the available radio spectrum. Cognitive Radio is designed to operate adaptively, making decisions on which frequency bands to use based on the available "spectrum holes" or unused portions of the spectrum. One of the most important considerations for the CR is to ensure that it does not cause any harmful interference to the primary users (PUs) who have a license to use the frequency spectrum and have higher priority to access it. To ensure this, the CR must take into account the impact of its operations on the primary users and make decisions accordingly. Moreover, the CR can dynamically adjust its operating parameters based on the decisions made. This helps to optimize the use of the spectrum and ensure efficient utilization of the available resources. Unlicensed users who use CR to access the spectrum are referred to as secondary users (SUs). SUs can benefit from the technology's ability to dynamically allocate frequency resources, allowing them to access the spectrum without interfering with the primary users.

The key characteristics of CR are its cognitive capability and reconfigurability. With its cognitive capability, the CR can sense and gather information about its radio environment to make informed decisions on the best frequency channel to use. This information typically includes details such as transmission frequency, power, bandwidth, and modulation.

Furthermore, the reconfigurability feature of CR enables it to automatically adjust its operating parameters, such as transmission frequency, modulation, and power, based on the information collected without requiring any hardware changes. This feature allows CR users to dynamically adapt to their changing radio environment, optimizing their use of the available frequency spectrum. Figure 2 shows a suggested architecture for cognitive IoT [5] . It ought to ensure that Quality of Service (QoS) guarantees are provided to meet the diverse demands of Device-to-Device (D2D) users. The main functionality of this framework entails sensing the QoS requirements and network performance objectives of users from different cells. It then accurately models the network behavior and makes decisions based on cognition, feedback, and network status using self-learning mechanisms. Finally, it identifies the necessary behavior of cognitive Internet of Things (IoT) in the future, while dynamically adjusting and allocating network resources of physical networks to fulfill real-time demands of users.

IV. Unlocking the Potential of IoT with Cognitive Radio

The use of CR in IoT-based systems is motivated by several important considerations. With the exponential growth of IoT and the resulting increase in demand for wireless communication bandwidth, efficient utilization of the available spectrum has become increasingly critical. CR technology offers a solution to this challenge by enabling more efficient utilization of the available spectrum, through its ability to dynamically allocate frequency resources based on the radio environment.

Another key motivation behind the use of CR in IoT systems is the need for improved reliability and robustness in wireless communication networks. IoT systems often involve the deployment of a large number of connected devices, operating in dynamic and often challenging radio environments. These devices are typically required to operate reliably to ensure that the IoT system as a whole operates effectively. CR technology provides a solution to these challenges by enabling IoT devices to adapt to changing conditions and make informed decisions on the best frequency channels to use. This results in improved reliability and robustness in IoT communication networks.

In addition, the use of CR in IoT systems helps to address the issue of interference from unlicensed devices. The CR's ability to sense its radio environment and avoid frequency bands that are already in use helps to reduce the risk of interference with other communication systems. This is particularly important for IoT systems, which often operate in unlicensed frequency bands and are vulnerable to interference from other devices. The ability of CR to minimize the risk of interference ensures that IoT communication networks are reliable and operate effectively.

Finally, the reconfigurability feature of CR technology makes it an attractive option for IoT systems. This feature enables the devices to dynamically adapt to changing conditions without requiring any hardware changes. This makes it possible to upgrade IoT systems without the need to replace existing hardware, providing a cost-effective solution for IoT network operators. Additionally, the reconfigurability feature allows IoT systems to evolve and adapt to changing requirements, helping to ensure their long-term viability and effectiveness. These motivations, combined with the growing need for effective IoT systems, make CR an attractive option for IoT network operators and a key technology for the development of future IoT systems.

V. THE APPLICATIONS OF CR-BASED IOT

The integration of cognitive radio networks has the potential to benefit a variety of IoT applications, which are covered in this section. By promoting interoperability between various devices and systems, enabling dynamic access to unused spectrum, and enabling secure and reliable communication between IoT devices, the integration of CR technology can improve the dependability, efficiency, and security of IoT systems. IoT systems with CR capabilities have a wide range of possible uses, including smart homes, smart cities, environmental monitoring, healthcare, and many more.

A. Smart Home

Smart Home is a potential application of IoT that can benefit from CRNs. With the integration of CR technology, Smart Home devices can dynamically access unused spectrum, improving the reliability and efficiency of home automation systems. CR-enabled Smart Home devices can communicate with each other and with the central hub, enabling seamless connectivity and enabling the devices to respond to changing environmental conditions. For instance, CR-enabled thermostats can dynamically adjust the temperature of the house according to occupancy and weather conditions, improving energy efficiency and reducing energy costs.

Moreover, CR technology can enhance the security of Smart Home systems by enabling secure and robust communication between the devices. With CR-enabled security systems, homeowners can receive real-time alerts about potential security threats and respond to them promptly. Additionally, CR technology can enable the integration of multiple wireless protocols in Smart Home systems, enabling interoperability between different devices and systems. This interoperability can facilitate the seamless integration of new devices and services, allowing for the expansion of Smart Home systems over time.

Overall, CR technology has the potential to transform the way Smart Home devices operate and interact with each other, improving the efficiency, security, and functionality of these systems. However, further research and development are required to realize the full potential of CR-enabled Smart Home systems.

B. Smart City

Smart City is another potential application of IoT that can benefit from CRNs. Smart City systems rely on various IoT devices and sensors to collect and transmit data in real time, enabling cities to monitor and manage different aspects such as traffic, energy consumption, and public safety. With the integration of CR technology, Smart City systems can dynamically access unused spectrum, improving the reliability and efficiency of data transmission. CR-enabled IoT devices can communicate with each other and with the central system, enabling seamless connectivity and enabling the devices to respond to changing environmental conditions.

For instance, CR-enabled traffic sensors can collect and transmit real-time data about traffic flow, congestion, and accidents, enabling transportation authorities to optimize routes and improve traffic flow. Similarly, CR-enabled energy management systems can monitor and manage energy consumption in real time, reducing waste and improving energy efficiency. Moreover, CR technology can enhance the security of Smart City systems by enabling secure and robust communication between the devices. With CR-enabled security systems, cities can receive real-time alerts about potential security threats and respond to them promptly. Additionally, CR technology can enable the integration of multiple wireless protocols in Smart City systems, enabling interoperability between different devices and systems. This interoperability can facilitate the seamless integration of new devices and services, allowing for the expansion of Smart City systems over time.

Overall, CR technology has the potential to transform the way Smart City systems operate and interact with each other, improving the efficiency, security, and functionality of these systems. However, further research and development are required to realize the full potential of CR-enabled Smart City systems.

C. Environment

Environmental monitoring is another potential application of IoT that can benefit from CRNs. With the integration of CR technology, environmental sensors can dynamically access unused spectrums, improving the reliability and efficiency of data transmission.

CR-enabled environmental sensors can collect and transmit real-time data about various environmental factors such as air quality, water quality, temperature, and humidity. This data can be used to monitor and manage environmental conditions, identify potential environmental threats, and develop strategies to mitigate the impact of environmental factors. Moreover, CR technology can enable the integration of multiple wireless protocols in environmental monitoring systems, enabling interoperability between different devices and systems. This interoperability can facilitate the seamless integration of new sensors and services, allowing for the expansion of environmental monitoring systems over time.

CR technology can also improve the security of environmental monitoring systems by enabling secure and robust communication between devices. With CR-enabled security systems, environmental monitoring data can be transmitted securely, reducing the risk of data breaches and cyber-attacks. Overall, CR technology has the potential to transform the way environmental monitoring systems operate and interact with each other, improving the efficiency, accuracy, and reliability of these systems. However, further research and development are required to realize the full potential of CR-enabled environmental monitoring systems.

D. HealthCare

CRNs can be advantageous for IoT applications in the healthcare industry. Healthcare systems can dynamically access unused spectrum with the incorporation of CR technology, enhancing data transfer reliability and efficiency. Remote patient monitoring is made possible by CR-enabled medical equipment and sensors that can capture and transmit real-time patient data like heart rate, blood pressure, and oxygen levels. Earlier intervention and less hospitalization can result in better patient outcomes and lower healthcare expenditures. In addition, CR technology can make it possible to include a variety of wireless protocols in healthcare systems, facilitating interoperability across various tools and systems.

This interoperability can enable the easy integration of new technologies and services, enabling the growth of the healthcare industry.

Because CR technology enables safe and reliable communication between devices, it can help increase the security and privacy of healthcare systems. Healthcare data can be transmitted securely via CR-enabled security solutions, lowering the possibility of data breaches and preserving patient privacy. Healthcare providers can deliver medical treatments remotely thanks to telemedicine and remote consultations made possible by CR-enabled healthcare systems. Improved healthcare access, particularly in rural and distant locations, may result from this. Overall, CR technology has the power to change how healthcare systems function and communicate with one another, enhancing their effectiveness, accuracy, and accessibility. To fully utilize CR-enabled healthcare systems, additional study, and development are necessary.

VI. Spectrum Sensing for IoT-based CRNs

Spectrum sensing is a critical component of Cognitive Radio Networks IoT-based systems. Spectrum sensing involves the continuous monitoring of the radio environment to determine the availability and utilization of the different frequency bands. In IoT-based CRNs, spectrum sensing provides information that is crucial for the effective and efficient operation of the network. For example, the information gathered through spectrum sensing can be used to determine the best frequency band for communication, reducing the risk of interference with other devices and ensuring reliable communication.

In addition to helping to ensure reliable communication, spectrum sensing also helps to optimize the use of the available spectrum. By continuously monitoring the utilization of the different frequency bands, IoT-based CRNs can dynamically allocate frequency resources based on the current demand. This results in more efficient use of the available spectrum, which is particularly important given the limited amount of available bandwidth for wireless communication. Spectrum sensing plays a crucial role in ensuring the coexistence of IoT-based CRNs with other communication systems. By detecting the presence of primary users (PUs) in the frequency bands, the CRN can avoid causing harmful interference and ensure that the PUs have priority access to the spectrum. This helps to ensure that IoT-based CRNs can operate effectively while also protecting other communication systems.

In this section, we summarize many spectrum sensing techniques that were proposed and implemented in IoT-based CRNs.

The authors of [6] proposed a spectrum sensing method that relies on deep learning algorithms. The authors used real signals collected from a wireless network to train and test their deep-learning model. Their results showed that their proposed system improves the accuracy of spectrum sensing and can effectively detect signals in a noisy environment. In [7], a fast and robust spectrum sensing method for cognitive radio-enabled IoT devices was proposed. It used a combination of energy detection and cyclostationary feature detection to improve the accuracy and speed of spectrum sensing. The method was tested and shown to have a high probability of detection and a low probability of false alarm. Additionally, the method is robust against various forms of interference, including noise and frequency offset.

In [8], the authors proposed two-way information exchange sequential algorithms in data transmission for reliable energy-efficient dynamic spectrum sensing techniques. In [9], a spectrum sensing method for CR-IoT with additive Gaussian mixture noise/interference is proposed. It maps the observation signal matrix from the original input space to a high-dimensional feature space by a nonlinear Gaussian kernel function and then constructs a kernelized test statistic in the feature space. The authors of [10], proposed a hardware implementation of a spectrum sensing scheme for CR-based IoT applications that require large bandwidth. The proposed approach was implemented on field programmable gate arrays (FPGA) for performance evaluation. Another approach is described in [11]. The authors proposed a cognitive sensor network to handle the loophole in the spectrum intelligently via spectrum sensing. It presents a method for optimizing spectrum sensing in cognitive sensor networks using a technique called differential evolution. The authors apply this approach in a smart environment, and the goal is to improve the performance of the network in terms of sensing accuracy and energy efficiency. The authors in [12] proposed a spectral sensing method that is based on cognitive radio technology, which allows for efficient use of the radio spectrum by detecting and adapting to changes in the environment. The proposed approach in [13] aims at maximizing the decision accuracy under different noisy condition and its implementation through the Neural Network system (NNS) that tremendously enhance the desired throughput. A method for optimizing spectrum sensing and packet error rate in the IoT using a cognitive approach is shown in [14]. It involves using a joint optimization algorithm to balance the trade-offs between spectrum sensing performance and packet error rate.

A method for cooperative spectrum detection in CRNs based on sensing coverage is described in [15]. It uses sensing coverage, which is the area where the signal can be detected, to improve the accuracy of spectrum detection. It employs a cooperative approach where multiple cognitive radios work together to sense the spectrum and share information, this allows for better detection of signals and more efficient use of the available spectrum. [16] presents a method for wide-band spectrum sensing in the IoT using a dynamic compressive approach. It involves using channel energy reconstruction to improve the accuracy and efficiency of spectrum sensing. This is done by reconstructing the energy of the channel in real-time, which allows for more accurate detection of signals. Additionally, the method is designed to be dynamic, meaning it can adapt to changes in the environment and adjust the sensing parameters accordingly. Another method for cooperative spectrum sensing in cognitive radio networks using a radio environment map is proposed in [17]. It utilizes a radio environment map, which is built and updated in real-time to improve the accuracy and efficiency of spectrum sensing. This is done by using information from the radio environment map to predict the location and characteristics of signals in the network. Additionally, the method employs a cooperative approach, where multiple cognitive radios work together to sense the spectrum and share information.

A method for spectrum sensing in full-duplex-enabled cognitive IoT networks based on multiple high-order cumulants is illustrated in [18]. It utilizes multiple high-order cumulates to improve the detection of signals in the network, which is done by analyzing the statistical properties of the signals and using this information to identify the presence of signals. Additionally, the proposed method is designed for full-duplex enabled networks, which allows for simultaneous transmission and reception of signals, therefore; enhancing the spectrum utilization. The authors of [19] proposed a new RF spectrum sensing receiver system for cognitive IoT sensor networks with improved frequency channel selectivity. The proposed system utilizes a receiver architecture that improves the selectivity of the system, allowing for more accurate detection of signals within a specific frequency channel. It also incorporates a cognitive approach that allows it to adapt to the changing characteristics of the network and optimize its performance accordingly. The improved frequency channel selectivity and cognitive capabilities make the system suitable for IoT sensor networks where spectrum sensing plays an important role in communication. An energy-efficient cooperative spectrum sensing scheme for cognitive IoT networks based on spatial correlation is proposed in [20]. It is a cooperative approach where multiple IoT devices work together to sense the spectrum and share information. By using the spatial correlation of the signals, the scheme reduces the number of devices required to sense the spectrum, thereby reducing energy consumption. Additionally, the scheme is designed to be adaptive, i.e., it can adjust to the changing characteristics of the network and optimize its performance accordingly. The authors of [21] proposed a multiband spectrum sensing and resource allocation in cognitive 5G networks for IoT. It formulated an optimization problem to determine a minimum number of channels to be sensed by each IoT node in a multiband approach to minimize the energy consumption for spectrum sensing while satisfying probabilities of detection and false alarm requirements. A greedy algorithm for wideband spectrum sensing in cognitive radio networks is proposed in [22]. The algorithm is based on a greedy approach, where the primary user's signal is repeatedly detected and subtracted from the received signal until it is completely removed. It can effectively deal with additive white Gaussian noise and fading channel conditions. A method for wideband spectrum sharing in cognitive IoT networks using distributed compressive sensing is shown in [23]. The method utilizes compressive sensing to efficiently and accurately estimate the power spectrum of the signal to identify the occupied frequency bands. An approach to cooperative spectrum sensing for cognitive radio sensor networks is presented in [24]. By allowing several sensor nodes to work together to identify available frequency bands, the method is intended to enhance the dynamic spectrum access of these networks. It increases the precision and dependability of the spectrum sensing process by combining the sensing results from numerous nodes using a distributed consensus technique. The method also adjusts the number of participating nodes and the sensing parameters in response to changes in the network environment. The authors of [25] propose an energy-efficient spectrum access design for cognitive radio wireless sensor networks. The design aims to improve the network's energy efficiency by lowering the amount of energy consumed during the spectrum sensing process. This is accomplished by employing a clustering algorithm that divides the sensor nodes into groups, with each group performing spectrum sensing cooperatively. The proposed method also employs an adaptive sensing schedule that adjusts the sensing interval based on the network's activity level. In [26], the authors presented an approach for cooperative spectrum sensing in energy-constrained cognitive radio networks. The method employs a channel status learning technique, which allows sensor nodes to improve their ability to detect available frequency bands by learning from neighboring nodes' sensing results. The proposed method combines the sensing results of multiple nodes using a distributed consensus algorithm, which improves the accuracy and reliability of the spectrum sensing process. Furthermore, the method adapts to changes in the network environment by adjusting the number of participating nodes and sensing parameters. The authors in [27] proposes a spectrum sensing scheme for cognitive wireless sensor networks that is low on energy. To reduce the energy consumption of sensor nodes during the spectrum sensing process, the proposed scheme employs a combination of clustering and censoring. Clustering is the process of grouping sensor nodes to perform spectrum sensing cooperatively, whereas censoring is the process of reducing the number of nodes that participate in the sensing process. The proposed method also makes use of an adaptive sensing schedule, which adjusts the sensing interval based on the network's activity level. The authors in [28] propose a solution for deploying cognitive radio sensor networks in IoT applications, with an emphasis on "green cooperative communication". This refers to the use of energy-efficient communication techniques to reduce sensor node power consumption. The paper describes how cognitive radio is used to dynamically adjust the transmission power and communication parameters of sensor nodes to reduce energy consumption while maintaining a high level of communication reliability. To maximize throughput while preserving energy efficiency, the authors of [29] proposed a method for using cognitive radio technology in IoT networks that are powered by energy harvesting. Cooperative sensing, which enables numerous devices to sense and exploit the available radio frequency spectrum, is used in the proposed method. It aims to maximize network throughput while minimizing energy consumption. The authors of [30] proposed a suggested approach for utilizing Non-Orthogonal Multiple Access (NOMA) technique in cognitive radio technology in 5G-enabled IoT networks. Using various power levels and/or codes, NOMA enables many users to share the same frequency band and time slot, which can increase spectral efficiency. To maximize the use of the available spectrum while reducing interference from other users, the study offers an algorithm for cognitive spectrum access that incorporates NOMA. A mechanism for reliable cooperative sensing in cognitive Internet of Things (IoT) networks is presented in [31]. The technique referred known as the ON/OFF reporting system, makes use of both active and passive sensing to enhance the precision and dependability of sensor data. In contrast to the passive component, which includes monitoring the environment for changes and only providing data when a change is found, the active sensing component involves sensor nodes actively reporting data. To balance the trade-off between energy consumption and data accuracy, the mechanism additionally contains a technique for managing the reporting frequency of sensor nodes. The authors in [32] present a modulated wideband converter-based sub-Nyquist spectrum sensing method for Cognitive Radio Sensor Networks (CRSN). The suggested approach decreases the quantity of data that the sensor must gather and process, increasing energy economy and simplifying the sensing process while maintaining high performance. The authors in [33] proposes a method for cooperative spectrum sensing in IoT networks, intending to improve spectrum sensing accuracy. A model is used to estimate errors in Power Spectral Density (PSD), which is a critical component of spectrum sensing. The method can improve spectrum sensing accuracy by modeling these errors and adjusting the PSD estimates. The method described in [34] makes use of decision fusion and massive multiple-input multiple-output (MIMO) technology to increase the precision of spectrum sensing in wideband systems. To increase the precision of spectrum sensing, the proposed method employs a high number of antennas at the sensor nodes to collect data, which is subsequently processed and integrated via decision fusion. Another approach for choosing the best set of channels to sense in cognitive radio networks is presented in [35] to enhance the network's functionality. To identify the ideal collection of channels, the suggested method considers a variety of variables, including the number of channels, the level of interference, and the sensing time. The use of deep learning in IoT networks powered by cognitive radio is discussed in [36] for potential security threats. The authors specifically focus on the application of adversarial deep learning techniques to target the spectrum sensing process. The authors demonstrated how these methods can be used to trick cognitive radio systems into believing that a particular frequency band is open when it actually is not, which could lead to interference. The authors offered several remedies to reduce these risks, including the use of strong deep learning models and the implementation of security measures to recognize and stop threats. The solution described in [37] uses relay-assisted spectrum sensing for secure short-packet transmission in cognitive IoT networks. The suggested technique encrypts the transmitted data while using a relay node to help find and identify available radio frequency bands for communication. Relay nodes are used to increase the effectiveness and dependability of communication in cognitive IoT networks, particularly when a direct connection between devices is challenging because of distance or obstructions. The authors of [38] presented a method for deep spectrum sensing in cognitive radio networks, which is the process of detecting and identifying available radio frequency bands for communication. The authors used a deep learning model based on autocorrelation, which is a technique that measures the similarity of a signal to itself at different time lags. In [39], a spectrum sensing using Eigenvalue-Moment-Ratio (EMR) for IoT devices is proposed. EMR is a signal processing technique that can be used to detect the presence of a signal in a given frequency band. EMR-based spectrum sensing can achieve high detection probability and low false alarm rate, making it a suitable technique for IoT devices. The authors in [40] proposed a model for a sensing strategy that takes into account the real-time nature of video communication and the need for

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high data rate and low latency. The proposed model includes a dynamic sensing mechanism that can adjust the sensing parameters based on the video traffic and the network conditions. The proposed algorithm in [41] is based on digital energy detection, which is a technique that uses the energy of the received signal to determine the presence of a primary signal (a signal that has priority over other signals) in a given frequency band.

The algorithm is designed to have a low computational complexity and a high detection probability, making it suitable for implementation in cognitive radio devices with limited resources. Table I shown below summarizes and compares most of the different spectrum sensing methods explained above. The different approaches are compared based on the sensing model (i.e., centralized or distributed), the metrics used for performance evaluation, comparison with other schemes, and the simulation tool used.

TABLE I
COMPARISON OF DIFFERENT SENSING APPROACHES IN IOT-BASED CRNS

REF	YEAR	PROPOSED IDEA	CENTRALIZED/ DISTRIBUTED	PERFORMANCE METRICS	COMPARED WITH OTHER SCHEMES	SIMULATION AND SIMULATOR
[6]	2021	Deep learning-based spectrum sensing	Distributed	False alarm probability, detection probability, classification accuracy	Yes	MATLAB
[7]	2021	A combination of energy detection and cyclo-stationary feature detection	Distributed	False alarm probability, detection probability, classification accuracy	Yes	MATLAB and real testbed
[8]	2019	A combination of energy detection and cyclo-stationary feature detection	Centralized	False alarm probability, SNR, Packet Loss Rate,	Yes	NS2
[9]	2020	Address the problem of multiple antenna spectrum sensing for CR-IoT in the presence of Gaussian mixture noise.	Distributed	False alarm probability, detection probability	Yes	NS2
[10]	2017	Efficient implementation of VDF-based low complexity spectrum sensing scheme and provide hardware implementation architectures for the VDFs on field-programmable gate array (FPGA) platforms.	Distributed	Normalized Frequency, Magnitude.	Yes	MATLAB
[12]	2017	Spectral detection method for characterizing the noise floor within the ISM band employing a cyclo-stationary technique.	Distributed	Detection Accuracy Missed Detection Rate, Sensing Time, Computational Complexity, and Spectral Efficiency.	Yes	MATLAB
[13]	2016	maximize the decision accuracy under different noisy conditions and its implementation through the Neural Network system (NNS)	Centralized	Frequency, Maximum amplitude	Yes	MATLAB
[14]	2018	Jointly optimize the spectrum sensing time and the packet error rate to maximize the effective throughput.	Centralized	Sensing Time, Computational Complexity, Packet Error Rate (PER)	No	NS2
[15]	2019	Derive the spectrum sensing coverage of the SN that guarantees the performance of spectrum sensing schemes. Demonstrate the feasibility of the proposed schemes by conducting real-environment experiments.	Distributed	Sensing Accuracy, Detection Probability, False Alarm Rate, Spectral Efficiency, and Energy Efficiency.	Yes	MATLAB
[16]	2018	Dynamic compressive wide-band spectrum sensing method based on channel energy reconstruction.	Centralized	Sensing Accuracy, Detection Probability, False Alarm Rate, Spectral Efficiency, Throughput, Latency, Energy Efficiency.	Yes	MATLAB
[18]	2021	Multiple high-order cumulants-based spectrum sensing (MCS) methods and multi-antenna-assisted multiple high-order cumulants-based spectrum sensing (MMCS) methods.	Distributed	False-alarm probability, detection probability, sample number, SNR, Sensing antennas, SIS factor	Yes	NS2
[19]	2016	Channel-selective RF receiver system with improved channel selectivity.	Distributed	Sensitivity, Accuracy, Channel Selectivity, Channel Selectivity.	No	NS2

[20]	2020	Energy-efficient cooperative spectrum sensing scheme based on spatial correlation for CioT.	Distributed	The number of nodes, Probability of missed detection, Energy consumption, Energy efficiency, SNR, Global error probability, rounds, and Detection probability.	Yes	NS2
[21]	2018	Multiband cooperative spectrum sensing (CSS) and resource allocation framework for IoT in cognitive 5G networks.	Distributed	Energy consumed, versus the number of channels, targeted global probability of detection, Energy consumed, number of IoT nodes, Delay, throughput, and Reliability.	Yes	NS2
[22]	2018	A greedy algorithm for spectrum recovery that combines the generality of OMP and the knowledge of sparsity structure from BOMP.	Centralized	Absolute Error, SNR	Yes	NS2
[23]	2018	Blind joint sub-Nyquist sensing scheme by utilizing the surrounding IoT devices to jointly sample the spectrum based on the multi-coset sampling theory.	Distributed	Frequency, Power, SNR, Detection Probability, number of coset samplers,	Yes	NS2
[25]	2019	Energy efficient Spectrum Access (EESA) model for multi-channel mobile cognitive radio wireless sensor network.	Centralized	Mobility speed, Throughput, Number of wireless sensor devices, Energy consumed.	Yes	C# Programming language, Dot Net framework 4.5.
[26]	2019	HMM-based Cooperative Spectrum Sensing (CSS) method.	Distributed	Energy consumption, Spectrum, transition probability, Throughout-energy rate.	Yes	MATLAB
[27]	2017	energy-saving spectrum sensing scheme with the combination of clustering and censoring in CWSNs.	Distributed	Energy consumption, number of CNs, transmission time, transmission distance, Optimal local censoring rate, intra-cluster censoring rate, number of CMs	Yes	MATLAB
[28]	2020	Energy-efficient cooperative technique for Cognitive Radio Sensor Networks (CRSNs) for IoT applications. Identify active nodes based on a smart computing technique.	Distributed	Probability of detection, SNR, response time, Time lag, Autocorrelation, Simulations, Average energy consumption, Likelihood, No. of nodes.	Yes	real-time
[29]	2021	Throughput optimization in energy harvesting-based cognitive IoT, under cooperative spectrum sensing mode.	Distributed	Transmission Power, Time Splitting, Throughput, PU Idle Probability, SU Transmission Power.	Yes	MATLAB
[30]	2021	Two interference cancellation (SIC) schemes guarantee the decoding performance of IoT and PU.	Centralized	Transmission rate, decoding-PU-first scheme, decoding-PU-last scheme	No	MATLAB
[31]	2017	Reducing reporting overhead and its impact on imperfect report channels.	Distributed	False alarm, detection probability.	Yes	MATLAB
[32]	2018	Blind multiband signal reconstruction method (statistics MMV iterative algorithm) to achieve sub-Nyquist spectrum sensing.	Distributed	Sampling channels, SNR, empirical recovery rate, frequency, magnitude, Probability.	Yes	NS2
[33]	2021	Improve the accuracy of spectrum sensing in the context of IoT by accounting for modeling errors in the estimation of power spectral density.	Distributed	Distribution, PEIE, MSE, SNR, detection probability, false alarm.	Yes	NS2

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[34]	2020	Enhance the accuracy and reliability of spectrum sensing in cognitive radio networks by using a MIMO system to combine the sensing information from multiple SUs	Centralized	Detection probability, False alarm probability, Probability of missed detection, Probability of correct classification, Bit error rate (BER)	Yes	Monte Carlo
[36]	2022	A method for attacking the spectrum sensing process in cognitive radio-enabled IoT networks using adversarial deep learning	Centralized	Probability of false alarm, SNR, Accuracy, eps, frequency, methods, time, amplitude.	Yes	public dataset RADIOML 2016.10b
[37]	2021	Relay-assisted secure short-packet communications in cognitive IoT with spectrum sensing.	Distributed	Throughput, block length.	No	MATLAB
[38]	2022	A convolutional neural network-based deep learning model called deep spectrum sensing (DSS) receives an autocorrelation curve as input.	Distributed	Detection probability, SNR, false alarm.	Yes	MATLAB
[39]	2019	eigenvalue moment ratio (EMR) figuring is defined for range recognizing from the random matrix theory (RMT)	Centralized	Frequency, SNR, probability of detection, T value.	No	MATLAB
[40]	2020	a novel sensing strategy that helps to find out the additional transmission opportunity that increases the overall throughput of CRN	Distributed	Probability of detection, probability of false alarm, throughput, energy detection.	Yes	MATLAB
[41]	2020	improve the sensing performance of (CRNs) by developing a digital energy sensing algorithm for detecting primary signals in CRNs.	Distributed	Probability of detection, Probability of false alarm, Receiver operating characteristic, Detection delay, Missed detection rate, False alarm rate.	No	MATLAB

VII. Routing for IoT-based CRNs

Routing is a critical component in any network and can be particularly challenging in wireless networks, especially when striving for higher data rates and lower latency. As cognitive radio allows Secondary Users (SUs) to dynamically access frequency channels controlled by Primary Users (PUs), Routing becomes a vital issue in CRNs that must be addressed. Researchers have developed different routing protocols and algorithms to route data in CRNs. In this section, we will summarize the most recent routing solutions developed for IoT-based CRNs.

The authors in [42] looks into the problem of routing in a multi-hop configuration for SUs with a known destination while PUs are present. To change how SUs choose to route themselves, the routing problem was conceptualized as a stochastic learning process of non-cooperative games. In 6G-IoT networks, it is a distributed, non-cooperative reinforcement learning-based method for dynamic routing that can reduce user and channel interference between rival SUs. In [43], the authors presented a routing and channel assignment technique that, without requiring additional resources, solves proactive jamming assaults in CR-based IoT networks. The protocol tries to increase the network's overall packet delivery ratio while accounting for the actions of the main users, multi-channel fading, and jamming behavior. A cognitive routing framework for reliable communication in IoT networks for Industry 5.0 is proposed in [44]. The proposed mechanism takes into consideration factors such as reliability, energy efficiency, and communication delay. The authors in [45] are discussing the integration of wireless information and power transfer for IoT applications in overlay cognitive radio networks. The proposed mechanism presents a technique for simultaneously transmitting information and power over a shared wireless channel in an efficient manner. The technique is based on the use of overlay cognitive radio networks, which enable the efficient use of available spectrum resources. It also proposes a power allocation algorithm that takes into account the energy consumption and data rate requirements of IoT devices. [46] is discussing the provisioning of Quality of Service (QoS) for heterogeneous services in cognitive radio-enabled Internet of Things (IoT) networks. It presents a technique for ensuring that different types of IoT services receive the appropriate level of QoS. The technique is based on the use of cognitive radio technology, which allows for the efficient use of available spectrum resources. It proposes a QoS provisioning algorithm that takes into account the different requirements of different IoT services and allocates resources accordingly.

a routing scheme that uses reinforcement learning to improve the performance of cognitive radio ad hoc networks is proposed in [47]. It proposes a scheme that dynamically adapts the routing strategy based on the current network conditions to improve network throughput and packet delivery ratio. Reinforcement learning is a type of machine learning that involves learning from experience. In this case, the devices in the network learn from their experiences with different routing strategies and use this information to make better decisions about how to route packets. The authors of [48] proposed a routing protocol that utilizes a cluster-based approach, where nodes in the network are organized into clusters with a cluster head. The cluster head is responsible for managing the communication within the cluster and making routing decisions. The protocol also includes a mechanism for selecting the cluster head, which is based on the nodes' remaining energy and the number of transmissions. a reinforcement learning-based routing approach for cognitive radio-enabled IoT Communications is proposed in [49]. The proposed approach aims to improve the efficiency of routing in cognitive radio networks by using a reinforcement learning algorithm to adapt the routing decisions based on the network's current state. The algorithm is trained using a Q-learning approach, which is a popular method for solving problems in reinforcement learning.

A new routing approach for cognitive radio-enabled IoT networks that takes into account the quality and availability of the spectrum is proposed in[50]. The proposed approach aims to improve the efficiency of routing by selecting the best route based on the quality and availability of the spectrum at different frequencies. It proposes a new metric called the "spectrum availability index" (SAI) that is used to evaluate the quality and availability of the spectrum. The SAI is based on the signal-to-noise ratio (SNR) and the number of available channels. The authors in [51] propose a multi-layer hyper-graph routing algorithm, which is a type of routing algorithm that takes into account multiple layers of information to make routing decisions. Additionally, it is jamming-aware, meaning that it takes into account the presence of jamming signals, which can interfere with the normal operation of the network. By considering both the multiple layers of information and the presence of jamming, this method aims to improve the overall performance and throughput of the network. The authors of [52] proposed a resource allocation method for Narrowband Cognitive Radio-Internet of Things (IoT) systems using Deep Reinforcement Learning (DRL). It uses DRL for the resource allocation problem in Cognitive radio-IoT systems. RL is a machine learning technique that allows an agent to learn how to make decisions in an environment by interacting with it and receiving feedback in the form of rewards. The authors modeled the resource allocation problem as a Markov Decision Process (MDP) and applied DRL to solve it. In[53], the authors proposed a new routing protocol called RIoT (Routing for the Internet of Things) that addresses the specific characteristics of IoT networks. The proposed protocol uses a combination of distance-vector routing and energy-efficient techniques to improve the performance of the network.

Table II shown below summarizes and compares most of the different routing methods explained above. The different approaches are compared based on the routing model (i.e., centralized or distributed), the routing metric, the metrics used for performance evaluation, the use of control channel to share the routing table with other nodes, comparison with other schemes, and the simulation tool used.

TABLE II
COMPARISON OF DIFFERENT ROUTING APPROACHES IN IOT-BASED CRNS

REF	**YEAR**	**PROPOSED IDEA**	**ROUTING METRIC**	**CENTRALIZED/DISTRIBUTED**	**USE OF A CONTROL CHANNEL**	**EVALUATED METRICS**	**COMPARED WITH OTHER SCHEMES**	**SIMULATION AND SIMULATOR**
[42]	2022	Non-cooperative reinforcement learning technique to formalize the routing strategy for the CR-enabled 6G-IoT network.	Channel transmission rate	Distributed non-cooperative	Yes	Packet loss rate, end-to-end delay	YES, with AODV and OSA	NS-2
[43]	2019	A security-aware routing algorithm that deals with proactive jamming attacks which target IoT-based multi-hop CRNs.	Number of hops, number of available channels, average availability time, average jamming interval	Distributed cooperative	Yes	Packet delivery ratio,	YES, with MaxPoS and Minimum Hop (MH)	MATLAB

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[44]	2022	A cognitive routing framework for reliable communication in IoT for Industry 5.0. The framework aims to address the challenges in communication reliability in IoT and enable Industry 5.0 applications such as smart factories and industrial automation.	Link quality, congestion level, and energy efficiency	Distributed	Yes	Packet delivery ratio, end-to-end delay, energy consumption, and network lifetime.	YES, with SPF and DUAL	MATLAB
[45]	2020	A wireless information and power transfer scheme for IoT applications in overlay cognitive radio networks. It aims to improve the energy efficiency of IoT devices by enabling them to harvest energy from radio frequency signals while also facilitating reliable communication.	Radio frequency signals	Distributed	No	Harvested energy, transmission rate, and bit error rate.	NO	MATLAB
[46]	2018	Quality of service provisioning for heterogeneous services in cognitive radio-enabled Internet of Things	SUs Arrival rate and priority	Distributed	Yes	Packet loss rate, end-to-end delay, SUs blocking probability and throughput.	YES, with non priority schemes.	MATLAB
[47]	2014	A reinforcement learning-based routing scheme for cognitive radio ad hoc networks	Channel availability and channel quality	Distributed	No	Packet delivery ratio, end-to-end delay, throughput, and network lifetime	YES, with shortest path (SP) and PU aware shortest path (PASP)	NS-2.35.
[48]	2016	A routing protocol for cognitive radio ad hoc networks (CRAHNs) based on clustering model.	Hop count	Distributed and cooperative	Yes	Routing delay, Number of Requests	YES, with AODV	NS2
[49]	2022	RL-IoT: Reinforcement Learning-Based Routing Approach for Cognitive Radio-Enabled IoT Communications.	Channel availability and channel quality	Distributed	No	Throughput, end-to-end delay, and packet delivery ratio.	YES, AODV-IoT, SpEED-IoT and ELD-CRN	NS3
[50]	2018	Quality and availability of spectrum-based routing for cognitive radio-enabled IoT networks.	Channel availability and channel quality	Distributed and cooperative	Yes	Quality of service (QoS) and spectrum utilization.	YES, with static deployment, static deployment with local and global spectrum information	MATLAB
[51]	2022	A multi-layer hyper-graph routing with jamming awareness for improved throughput in full-duplex cognitive radio networks	Channel availability and channel quality	Distributed	No	Throughput	YES, with ARA, ASA, and ASRA	MATLAB

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[52]	2022	Deep reinforcement learning-based resource allocation for satellite Internet of Things with diverse quality of service (QoS) guarantee	Channel availability and channel quality	Distributed	Yes	Packet delivery ratio, average throughput, and average delay	-----	MATLAB
[53]	2020	RIoT: A routing protocol for the Internet of Things	Channel availability and channel quality	Distributed	No	Packet delivery ratio, end-to-end delay, network lifetime	YES, with RPL and AODV	NS3

VIII. Challenges for IoT-based CRNs

More study and development are required in areas including hardware design, standardization, spectrum optimization, privacy protection, and heterogeneous network fusion for cognitive radio technology to be effectively utilized in the Internet of Things. This section will give a general overview of the outstanding problems and possible research challenges associated with cognitive IoT.

A. Standardization

The continuous and extensive development of cognitive IoT networks depends on standardization, which also provides a crucial foundation for security preservation, application expansion, dynamic spectrum access, and the merging of heterogeneous networks. A lot of standardization work is currently being done in the fields of IoT and cognitive radio by both academics and the industry. Full consideration should be given regarding how to effectively combine related studies from working groups and technical committees to develop cognitive IoT.

The current IoT structure and protocol might be enhanced or improved to enable and standardize the functionality of dynamic spectrum access for IoT nodes, which would speed up the standardization of cognitive IoT.

B. Spectrum Efficiency

Incorporating cognitive radio technologies into the Internet of Things is primarily intended to enhance spectrum efficiency through dynamic spectrum access and spectrum sharing. However, effective spectrum sharing without significant overhead and energy consumption in distributed IoT networks need more research. Additionally, for IoT to be capable of adapting to changing conditions, the integration of IoT with other network technologies such as caching networks, fog computing, and satellite networks needs the improvement of present dynamic spectrum-sharing approaches. These topics have not yet been completely investigated.

C. Security and Privacy

The integration of network heterogeneity and dynamic spectrum access for IoT nodes results in a complex security problem that cannot be resolved using traditional security measures. This issue is compounded by the increasing application of IoT in various fields and the incorporation of cognitive functionalities in IoT nodes, which enables them to sense and detect spectrum holes and network elements. These developments have led to the emergence of new security and privacy challenges that need to be addressed.

Moreover, the adoption of dynamic spectrum access in IoT nodes results in more interactions within the IoT network, which increases the likelihood of potential security threats. As a result, traditional security modes cannot be solely relied upon to mitigate these risks.

To address these challenges, there is a need for a comprehensive understanding of the IoT network's security and privacy requirements. This understanding should include a detailed examination of the different security and privacy issues that may arise due to the integration of dynamic spectrum access and cognitive functionalities in IoT nodes. Further, it is essential to explore new security measures that can effectively address these concerns while minimizing overhead and energy consumption.

IX. CONCLUSION

This paper surveyed the current research on IoT-based cognitive radio networks (CRNs) and explored the potential applications and challenges of this technology. The integration of CR technology with IoT systems has the potential to revolutionize the way we interact with our environment, enabling more efficient, secure, and sustainable IoT systems.

The potential applications of CR-enabled IoT systems are diverse and include smart homes, smart cities, environmental monitoring, healthcare, and many others. However, realizing the full potential of CR-enabled IoT systems requires extensive research and development efforts in areas such as hardware design, standardization, spectrum optimization, and privacy protection.

Despite the challenges, significant progress has been made in the development of CR-enabled IoT systems, and many promising applications of this technology have been identified. The integration of CR technology with IoT systems is expected to enable more efficient, reliable, and secure communication between IoT devices, enabling the seamless integration of new devices and services, and improving the interoperability and expandability of IoT systems.

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