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RESEARCH ARTICLE

Efficient Spectrum Allocation for the Cognitive Radio-Based Internet of Things

GAZI ZAHIRUL ISLAM [1,2], **(Member, IEEE),**
AND S. M. A. MOTAKABBER [1], **(Senior Member, IEEE)**
[1]Department of Electrical and Computer Engineering, International Islamic University Malaysia, Kuala Lumpur 53100, Malaysia
[2]Department of Computer Science and Engineering, Southeast University, Dhaka 1208, Bangladesh

Corresponding author: Gazi Zahirul Islam (gazi.islam@seu.edu.bd)

ABSTRACT The scarcity of the spectrum is one of the key impediments to the growth of Internet of Things (IoT) applications and services. Cognitive Radio-based IoT (CR-IoT) is an advanced IoT framework in which IoT integrates cognitive radio (CR) technology for dynamic spectrum sensing to mitigate spectrum scarcity and enhance wireless communication. CR-IoT is useful in diverse applications and sectors, such as healthcare, industrial IoT, smart cities, smart agriculture, military, and defense. CR-IoT can use an IEEE 802.22-compliant Wireless Regional Area Network (WRAN) for backhaul and wide-area connectivity. In this paper, we propose an IEEE 802.22-compliant scheme called Efficient Spectrum Allocation (ESA) for CR-IoT networks. This study includes three novel algorithms for ESA to distribute channels efficiently to primary and secondary users. The system model, spectrum accessibility along with priority, and channel access mechanisms for primary and secondary users are mathematically and graphically illustrated. The complexity and performance of the algorithms are evaluated using mathematical modeling and simulations. Simulation results show that the ESA significantly improves the overall performance parameters of CR-IoT in terms of throughput (3.5%–21%), spectrum utilization (7.5%–31%), collision reduction (up to 32%), and successful packet transmission (up to 21%) over the state-of-the-art.

INDEX TERMS Internet of Things, wireless regional area network, cognitive radio, efficient spectrum allocation, licensed and unlicensed spectrum, primary and secondary users.

I. INTRODUCTION

Currently, the Internet of Things (IoT) is widespread in every sphere of human life. We are surrounded by IoT devices everywhere, whether in the office, at home, or in any other place. Most essential commodities (e.g., mobile phones, watches, air conditioners, refrigerators, and televisions) are now turning into IoT devices. IoT makes our lives more comfortable, enjoyable, and productive. IoT not only contributes to our personal lives; its widespread use is observed in industries, agriculture, healthcare, the environment, sports, entertainment, business, etc. [1], [2]. Still, the IoT is penetrating different sectors and areas to improve existing services and communication. The IoT helps in our daily activities, offices, and businesses by enabling automation, control, and comfort. A primary obstacle to the expansion of IoT is the scarcity of available radio spectrum [3], [4], [5], [6]. As billions of IoT devices continue to connect to wireless networks, the demand for the available radio spectrum has increased rapidly. Traditional static spectrum allocation cannot keep up with this growth, leading to congestion, reduced performance, and limited support for large-scale IoT deployments. This problem becomes even more critical in mission-critical applications such as medical monitoring or emergency response systems, where communication failure is unacceptable. This challenge motivates advanced solutions, such as cognitive radio, to ensure reliable communication and efficient use of available frequencies [4], [5], [6], [7].

Cognitive radio (CR) is a wireless communication technology that aims to optimize the utilization of the available radio frequency spectrum. A wireless network that uses cognitive radio is known as a Cognitive Radio Network (CRN) [5].

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The combination of IoT and cognitive radio offers significant benefits in terms of spectrum utilization, network efficiency, and overall reliability of IoT systems. Cognitive Radio-based IoT, also known as CR-IoT [7], is an advanced IoT framework in which the IoT integrates CR technology for dynamic spectrum sensing to enhance wireless communication. CR-IoT improves the network efficiency, reliability, latency, scalability, and diversity. This technology is especially required in congested areas where radio spectrum scarcity prevails. This technology efficiently uses unused or under-utilized spectrum (e.g., TV white spaces) to mitigate resource scarcity [8], [9]. CR-IoT with the proposed Efficient Spectrum Allocation (ESA) scheme is highly valuable in environments where reliable, real-time communication, and efficient spectrum use are essential. Key use cases include healthcare systems that transmit sensitive patient data; industrial IoT environments requiring low-latency machine-to-machine communication; and smart city infrastructure supporting intelligent transportation, surveillance, and public safety networks. It is also well-suited for smart agriculture, where wide-area sensor networks monitor crops and livestock, as well as military and defense systems [10] that demand secure and resilient communication in dynamic environments. Additionally, the model supports both high-priority critical applications, such as autonomous vehicles, smart grids, emergency services, and everyday consumer use cases, such as web browsing and general data transfer, by ensuring fair and prioritized spectrum allocation.

CR can use both licensed and unlicensed spectra [9], [11] depending on spectrum availability, application, and regulations. A licensed spectrum is a radio frequency that has already been allocated for different purposes. This allocation is performed by national or international authorities (e.g., ITU, FCC, and ETSI). A spectrum beyond the licensed spectrum is known as the unlicensed spectrum. Primary users are those who have prerogative access to the licensed spectrum. CR users (e.g., IoT devices) are secondary users who can access the licensed spectrum in the absence of primary users. According to the regulations, secondary users must leave the network (i.e., release licensed channels) as soon as the primary user enters the network. However, CR users can access an unlicensed spectrum at any time without interference from the primary devices.

CR-IoT can use a Wireless Regional Area Network (WRAN) [5], [12] for backhaul and wide-area connectivity. IEEE 802.22 proposes WRAN, which is a wireless communication standard developed for long-range broadband access in rural and underserved regions leveraging TV white space (TVWS). This standard operates in the TVWS spectrum, which is an unused or underutilized spectrum range of 54 MHz to 862 MHz (VHF and UHF bands) allocated for television broadcasting. Its long-range capabilities and CR technology make it a promising solution for rural broadband internet access. The IEEE 802.22 WRAN is suitable for several applications, such as public safety networks (emergency communications), smart grid communications (utility monitoring in distant regions), and agricultural and environmental monitoring. The standard is designed mainly for low-population regions to provide broadband, where the wired infrastructure is impractical or costly. This technology includes authentication, encryption, and secure communications. It also supports quality of service (QoS) for different applications (e.g., VoIP and video streaming).

The main purpose of WRAN is to provide broadband Internet in rural and distant places using CR and Dynamic Spectrum Access (DSA) [9], [13] technology. DSA and CR allow IoT to use the available TVWS channels efficiently. WRAN can serve up to 100 km, making it ideal for regional coverage. The channel bandwidth is 6, 7, or 8 MHz, depending on the regulatory region, and the technology can provide up to 22 Mbps per channel using 64-QAM (Quadrature Amplitude Modulation). It uses geolocation and spectrum databases, along with spectrum sensing, to avoid interference with licensed users (i.e., primary users). The orthogonal frequency division multiple access (OFDMA) modulation [14] technique is primarily used for downstream and upstream communication. Non-line-of-sight (NLOS) communication is also possible owing to favorable propagation in the TVWS band. Typically, in this network, a Base Station (BS) serves multiple Consumer Premise Equipment (CPE) devices. The network can employ database-assisted sensing to check a geolocation database (e.g., FCC TVWS database) to determine the available channels. Spectrum sensing is used to detect primary users (e.g., TV stations and wireless microphones) to avoid interference with cognitive radio users [15].

In this study, we have thoroughly reviewed several promising papers on CR-IoT in Section II-B. We have identified several research gaps in the literature review, which are summarized below.

A. EXPLOITING UNLICENSED SPECTRUM

The throughput of CR-IoT is limited by primary users because IoT devices must release the licensed spectrum as soon as a primary device wants to communicate in the network. In this regard, accessing the unlicensed spectrum using IoT devices can mitigate the demand for a large spectrum of CR-IoT. Most existing studies do not adopt an unlicensed spectrum and suffer from spectrum scarcity. However, utilizing the unlicensed spectrum requires careful model design because it is subject to interference, spectrum congestion, unpredictable QoS, sensing overhead, etc. [16], [17]. Nevertheless, an efficient wireless model can overcome these issues and significantly improve the overall throughput of the IoT.

B. USER HETEROGENEITY AND PRIORITY

A wide range of IoT users, applications, and use cases are increasing daily, leading to a rapid expansion of connected devices. Different users and applications require different service types, priorities, and QoS levels. Initially, CR-IoT researchers have not focused on issues that degrade the quality of services. With the expansion of IoT, especially the arrival of social IoT, the importance of heterogeneity and priority of IoT customers has been emphasized.

C. RECEIVER ACCESSIBILITY

As discussed earlier, almost no researchers have addressed this issue in their model design and analysis. Consequently, the actual performance of the scheme is not the same as that expected in the simulation and analysis. Khan et al. focus on receiver accessibility in their scheme 'ES', providing a realistic performance analysis for certain performance parameters. Unfortunately, the scheme does not evaluate several parameters in the simulation, such as the throughput and collision probability.

D. RELIABILITY

Reliability is a major concern for critical IoT systems that require transmission of sensitive and real-time data. The transmission of packets to the receiver may not be successful if the reliability of CR-IoT is not achieved at a certain threshold [7]. Again, the retransmission of packets incurs a delay and increases latency, which severely degrades performance of the critical IoT. Several studies, such as [18] and [19], have addressed this issue by compromising the system throughput.

The main goal of this study is to design an efficient scheme for a CR-IoT network to mitigate the demand for a large spectrum as well as to provide improved services to existing IoT infrastructure. This paper presents an innovative scheme called Efficient Spectrum Allocation (ESA), that complies with the IEEE 802.22 standard. The remainder of this paper is organized as follows. Section II outlines current IoT communication technologies, discusses existing studies on CR-IoT, and presents the contributions of this study. The details of the ESA protocol, along with the corresponding algorithms, are presented in Section III (i.e., System Model and Implementation). Section IV presents the mathematical modeling, complexity of the algorithms, and performance analysis of the proposed scheme. Section V evaluates the protocol using rigorous simulations. Finally, Section VI concludes the paper and provides directions for future research.

II. LITERATURE REVIEW AND CONTRIBUTIONS

IoT involves billions of devices (e.g., sensors, wearables, and smart appliances) worldwide that communicate wirelessly. The enormous growth of the IoT is unstoppable, and it is expanding at an explosive rate. There are several reasons for this acute growth, such as the increasing number of users, growing number of use cases, and emerging spectrum-hungry applications. The tremendous growth of IoT has emerged as a massive Internet of Things (m-IoT) to meet its growing needs [20], [21], [22]. The proliferation of the IoT faces several critical problems, such as spectrum scarcity and performance efficiency. The challenges of IoT span across different domains (e.g., technical, security, regulatory, and scalability). Spectrum scarcity and performance efficiency are two concerns that involve the technical, regulatory, and scalability domains.

A. IoT COMMUNICATION TECHNOLOGIES

Within the cellular communication domain, IoT connectivity is commonly referred to as machine-to-machine (M2M) communication, whereas within the 3rd Generation Partnership Project (3GPP) standardization framework, it is formally termed machine-type communications (MTC). 3GPP Cellular MTC encompasses a set of specifications designed to enable cellular networks to support IoT devices and M2M interactions effectively. These standards allow cellular systems to satisfy the distinctive requirements of IoT applications, including ultra-low power consumption, low data rates, extended coverage, and the ability to accommodate a massive number of devices simultaneously. The 3GPP Cellular MTC ecosystem comprises key technologies such as Narrowband IoT (NB-IoT), LTE-M, EC-GSM-IoT, 5G massive machine-type communications (mMTC), and 5G Reduced Capability (RedCap) [10], [23], [24]. TABLE 1 compares the reliability, efficiency, cost-effectiveness, and other performance characteristics of NB-IoT, LTE-M, and RedCap.

B. EXISTING WORKS

IoT researchers have been working on CR technology, resulting in efficient ways of leveraging it. The CR technology employs the DSA technique to mitigate spectrum scarcity and improve the overall performance of IoT networks. Researchers employ a variety of techniques to exploit cognitive radio. A group of CR-IoT studies [25], [26], [27], [28], [29], [30] focuses on channel availability and ranking to improve network efficiency. Wireless channels are primarily characterized by capacity, bandwidth, and signal-to-interference-and-noise ratio (SINR). The idle channels are evaluated and ranked based on their quality and availability. Then, idle channels are distributed to the appropriate users to meet the desired Quality of Service (QoS).

The researchers in [25] and [26] rank the idle channels based on their predicted states. However, they do not consider user heterogeneity to ensure service quality. They select channels based on their holding times. The researchers in [27] and [28] also consider the holding time along with the channel availability. However, they do not focus on the quality of the channel for ranking. They also overlook the effects of channel failures. In [29] and [30], channel quality and availability are considered to rank the channels efficiently. Several QoS parameters are considered for selecting suitable channels for data transmission. However, the impact of channel failure is not considered, leading to an inefficient performance analysis. Again, QoS is not concurrently evaluated for different parameters. In summary, articles [25], [26], [27], [28], [29], [30] do not consider heterogeneity and priority among users. Moreover, some performance issues, such as imperfect spectrum sensing and channel failure, have not been studied.

Abbas et al. [5] propose a scheme called Flexible Multiparameter-Based Channel Prediction and Ranking (FMCPR), which addresses most of the limitations mentioned in [25], [26], [27], [28], [29], and [30]. The scheme employs

TABLE 1. Comparison of NB-IoT, LTE-M, and RedCap.

Feature	NB-IoT	LTE-M	RedCap
Full Name	Narrowband Internet of Things	Long-Term Evolution for Machines	Reduced Capability
3GPP Release	Release 13 (2016) and enhanced in 14+	Release 13 (2016) and enhanced in 14+	Release 17 (2022) (5G-Advanced)
Generation	4G-LTE	4G-LTE	5G-NR
Key Purpose	Low power, low-cost, and massive scale	Balanced performance for wider IoT applications.	Bridging the gap between LPWAN and high-end 5G.
Data Rate	~20–250 Kbps	~200 Kbps – 1 Mbps	~150 Mbps (downlink), ~50 Mbps (uplink)
Latency	High (1.5s - 10s)	Moderate (~50ms - 100ms)	Low (5ms - 10ms)
Mobility	Limited (stationary/low mobility)	Full mobility support	Full mobility support, up to 500 km/h
Power Consumption	Extremely Low (Battery life: 10+ years)	Very Low (Battery life: 5-10 years)	Moderate (3–7 years, depends on usage)
Voice Support	No (data only)	Yes (VoLTE)	Yes (VoNR, VoLTE)
Bandwidth	200 kHz (single resource block)	1.4 MHz	5–20 MHz
Spectrum Deployment	In-band, Guard-band, or Standalone.	In-band within existing LTE spectrum.	Integrated within 5G NR carriers.
Module Cost	Lowest	Low	Medium
Reliability	Lowest reliability due to its narrow bandwidth	Higher reliability with broader coverage and mobility support	Most reliable among the three due to enhanced LTE/5G capabilities and reduced latency
Typical Use Cases	• Smart metering (water, gas) • Smart agriculture (soil sensors) • Environmental monitoring • Asset tracking (infrequent updates)	• Wearables (e.g., smartwatches, fitness trackers) • Fleet management and asset tracking (mobile) • Smart city (lighting, parking) • Healthcare monitors • Vending machines	• Industrial Wireless Sensors (with video) • Smart Grid (advanced metering, monitoring) • Video Surveillance • Wearables (advanced AR/VR glasses)

multiple parameters (capacity, availability, and SINR) of a channel simultaneously to analyze its suitability for the channel assignment and ranking. FMCPR considers channel failure and multitier user heterogeneity and priority, thereby ensuring the quality of service. The scheme also studies imperfect spectrum sensing, which reduces collisions and improves throughput. FMCPR also introduces a method called the Random Scheme (RS), which is WRAN-compliant. As the name implies, the RS randomly selects channels and does not consider any parameters for channel selection. As a standard random selection scheme, the RS is preferred for performance comparison and analysis with other schemes.

Several studies have focused on channel-reservation strategies for CR-based IoT [31]. In [32] and [33], the authors employ static spectrum reservation schemes efficiently, thereby improving the capacity of the network and the blocking probability (BP) of the users. However, these studies ignore fairness and spectrum-reservation tradeoffs. Moreover, receiver accessibility is not considered prior to the data transmission. If the receiver is not accessible, sending data to the receiver would be futile, requiring packet retransmission. The authors in [34] and [35] employ a dynamic reservation scheme that addresses call completion probabilities, BP, and channel utilization, along with other parameters. Nevertheless, these schemes ignore receiver accessibility, fairness, and reservation trade-offs. Several authors have focused on priority-based reservation methods to improve the QoS of the CRN. The authors of [36] propose a resource reservation scheme for multiple users. The scheme remarkably improves the throughput, BP, and channel utilization. However, in this scheme, high-priority users degrade the performance of low-priority users because they have abundant access to the channels. In [37], a static scheme focusing on the throughput is proposed. In this scheme, a control channel is allocated solely to serve secondary users. The researchers in [38] propose another priority-based scheme to improve the spectrum utilization, capacity, and blocking probability of devices. This study employs channel aggregation methods to enhance the performance of low-priority users.

Nowadays, a new paradigm of IoT known as ‘Social IoT’ has emerged that integrates social networking principles with the Internet of Things. Social IoT enables smart devices to autonomously establish social relationships, share data, and collaborate to provide intelligent services [39], [40]. Thus, the social IoT is a prominent use of IoT that requires massive smart devices to communicate extensively, such as friends. It also requires a substantial amount of bandwidth and rigid service quality. To meet the demands of the social IoT, several researchers [41], [42], [43] have emphasized utilizing CR-IoT more efficiently. Specifically, researchers aim to address several challenges associated with modern wireless networks that must be supported in the CR-based social IoT. Social IoT analyzes data from connected devices, user interactions, and environmental sensors to provide personalized, adaptive, and context-aware services to users. This implies that social IoT requires a focus on the multi-priority and heterogeneity of users. It also requires more bandwidth and spectral efficiency than traditional IoT to ensure the quality of service.

The social IoT discussed above focuses primarily on user heterogeneity, utilization of the network spectrum, and diverse QoS parameters. In particular, these studies focus on the user capacity, handoff probability, blocking probability, and spectrum efficiency. Nevertheless, these studies have ignored receiver accessibility, which is an important criterion that determines the overall performance of wireless networks. In this regard, Khan et al. [22] propose a scheme dubbed 'ES' (i.e., Extended Scheme) that focuses on receiver accessibility in addition to some other novel features. ES presents a mathematical model for analyzing the performance using a continuous-time Markov Chain (CTMC). The scheme presents a dynamic spectrum reservation (DSR) algorithm for primary users to significantly improve spectrum utilization.

Many IoT systems, such as healthcare, autonomous driving, smart grids, and military applications, involve communicating critical information [18], [44], where ensuring reliability and successful packet transmission (SPT) are crucial. Several CR-IoT studies [18], [19], [45] have focused on the reliability and SPT to improve the performance of sensitive real-time IoT systems. Lu et al. [18] have devised a metric known as the message invalidation ratio (MIR) to measure successful packet transmission where transmission occurs over channels with a high MIR. The authors propose a scheme called Jamming Attack Detection based on Estimation (JADE) to improve jamming detection in cyber-physical systems and implement the scheme in a wireless network for power substations in a smart grid. Reference [19] presents a metric for evaluating path quality in a wireless sensor network. The path with the highest rank is selected because it provides the highest SPT rate. Reference [45] presents a mathematical model that highlights packet transmission and retransmission. The scheme computes the probability of the SPT during the retransmission process. Finally, a decision is made regarding whether to continue or terminate the retransmission based on the computed value.

The authors in [46] develop a machine learning model to enhance the signal-to-interference-plus-noise (SINR) ratio and probability of SPT in an IoT network. This scheme leverages reinforcement learning to develop an optimal communication policy, thereby enabling IoT devices to leave heavily congested areas. Khadr et al. propose a channel assignment algorithm [47] to enhance network performance without adding extra network resources or power. The authors present the Packet Segmentation Simultaneous Transmission (PSST) algorithm, which is verified using the open large-scale Future Internet-of-Things (FIT) IoT-LAB testbed [48]. The scheme reduces packet transmission time and outperforms many channel assignment algorithms. Halloush et al. [7] address the reliability dimension by leveraging the multi-channel diversity. The authors devise a Highly Reliable Transmission (HRT) scheme to combat packet failures by sending multiple copies of a packet over multiple channels. The scheme shows a remarkable performance gain over the existing CR-IoT algorithms. The HRT adopts a Binary Linear Program (BLP) [49], [50] for channel assignment to maximize link reliability. The scheme also formulates several mathematical expressions using a continuous-time Markov Chain (CTMC) [51], [52]. TABLE 2 summarizes and compares the selected articles discussed in Section II.

C. CONTRIBUTIONS OF THE STUDY

In this paper, we propose a novel scheme for CR-IoT called Efficient Resource Allocation (ESA). The details of the ERA are presented in Section III. The ESA addresses the above problems and research gaps, and significantly improves the performance of CR-based IoT in terms of throughput, spectrum utilization, reliability, and collision reduction. In particular, the proposed scheme contributes to the following areas.

- The ESA maintains the provision of using the unlicensed spectrum along with the licensed spectrum for secondary users to maximize the throughput of CR-IoT. In this regard, three novel algorithms have been developed and deployed efficiently to handle relevant difficulties and comply with the CR and WRAN standards. The algorithms are written using pseudocode, which is easily convertible to computer programming code.
- The scheme considers different types of users and services for an efficient spectrum allocation. This scheme prioritizes users and distributes resources based on their needs and priorities. In this scheme, low-priority users have sufficient access to the spectrum. The proposed scheme ensures quality of service, as it focuses on user heterogeneity and priority.
- The ESA addresses several problems (e.g., receiver accessibility, reliability, and utilization of the unlicensed spectrum) that are ignored in most existing literature on CR-IoT. Thus, the ESA presents more practical and reliable analyses and simulations.

III. SYSTEM MODEL AND IMPLEMENTATION

A. SYSTEM MODEL AND SPECTRUM ALLOCATION

Fig. 1 shows the system model of the proposed scheme (i.e., ESA), where a primary network and a secondary network (i.e., cognitive network) coexist. There are three users in the primary network, which are known as primary users

TABLE 2. Summary and comparison of the selected articles in CR-IoT.

References	Key Criteria	Constraints	Comparison with this study
[25], [26]	• Channels are ranked according to their past states. • A few QoS parameters are considered.	• Do not address certain crucial QoS parameters, such as SINR, channel capacity, etc. • Prioritization among the users is also not considered.	• This study considers many QoS parameters, such as throughput, collision probability, SUE, link reliability, SPT probability, sensing time, and energy. • ESA classifies and prioritizes users, such as PU, SU-A, and SU-B.
[27], [28]	• The schemes focus on the channel availability. • Channel ranking is performed by addressing a few QoS parameters. • The schemes address the QoS parameters independently.	• Ignores the impact of the Valid Channel Obsolescence (VCO) problem. • The schemes do not study the imperfect spectrum sensing for performance analysis.	• Includes three novel algorithms for ESA to distribute channels efficiently to different users. • The system model focuses on spectrum sensing mechanisms. • Many QoS parameters are considered for performance analysis, including spectrum sensing time and energy.
[29], [30]	• Channel availability, along with channel quality, is considered to rank the idle channels. • Critical QoS parameters are considered for channel ranking.	• The effect of channel failures is not considered. • Priority and heterogeneity of the users are not addressed.	• Priority and heterogeneity of the users are addressed. • Channel failure is addressed by efficient spectrum management and traffic prioritization.
[5]	• Channel failure is considered for channel assignment and ranking. • Employs multiple parameters of a channel simultaneously to analyze suitability for channel assignment and ranking. • Considers multitier users' heterogeneity and priority and ensures the QoS.	• Receiver accessibility is not considered before data transmission. • Poor performance in terms of spectral sensing time and sensing energy.	• Channel failure is significantly reduced by user scheduling and traffic prioritization. • ESA algorithms check the receiver accessibility before data transmission. • Shows good results in sensing time and energy compared with the state-of-the-art.
[32], [33]	• Employ static channel reservation schemes. • Improve the capacity of the network and the blocking probability of the users.	• The schemes ignore the fairness and spectrum reservation tradeoffs. • Receiver accessibility is not considered before data transmission.	• The algorithm employs dynamic spectrum allocation techniques that improve throughput and reduce collisions significantly. • Checks the receiver accessibility before data transmission, which validates the performance analysis.
[34], [35]	• These papers employ dynamic spectrum reservation for spectral efficiency. • Improves certain QoS parameters remarkably.	• The schemes ignore the fairness and receiver accessibility of the users. • Priority and heterogeneity of the users are not efficient.	• All of the criteria of [27] and [28] are focused on designing the ERA scheme. • The scheme improves most of the QoS parameters remarkably.
[36]–[38]	• Propose priority-based channel reservation methods for the users. • Improve the QoS of the CRN efficiently.	• Low-priority users do not meet the required QoS.	• The proposed scheme considers priority among the users. • Improves overall performance significantly, where low-priority users meet the QoS parameters.
[39], [40]	• Introduce a new paradigm of IoT termed 'Social-IoT'. • Focus on users' heterogeneity, utilization of the network's spectrum, and QoS parameters. • Requires a substantial amount of bandwidth as well as a rigid QoS service.	• Receiver accessibility is not considered before data transmission. • Reservation tradeoffs are not studied.	• This study is also appropriate for Social-IoT. • Huge bandwidth is available to the users as the study involves both the licensed and unlicensed spectrums. • Other limitations and advantages of [32] and [33] are also addressed effectively.
[22]	• Receiver accessibility is considered and elaborately studied for performance measurement. • Presents a mathematical model for analyzing performance using a continuous-time Markov Chain.	• Does not evaluate several important performance metrics in simulation (e.g., throughput, collision probability). • The effect of channel failures is not considered.	• This study covers most of the prominent features of the article [17]. • Also presents a mathematical model using a continuous-time Markov Chain. • The complexity of the ESA algorithms is studied.
[18], [19], [45]	• Focus on critical and delay-sensitive IoT systems.	• Several performance metrics are ignored. • The schemes do not emphasize reliability dimensions.	• Improves SPT rate and throughput along with other performance metrics.

TABLE 2. *(Continued.)* **Summary and comparison of the selected articles in CR-IoT.**

	• Improve several metrics, such as the SPT rate.	• Throughput is not remarkable.	• Link reliability is analyzed through mathematical modeling and simulations.
[7]	• In addition to the SPT rate, it focuses on link reliability. • Multiple copies of a packet are sent to ensure link reliability. • The scheme formulates several mathematical expressions by utilizing CTMCs.	• Receiver accessibility is not considered in the scheme. • Throughput is low due to sending multiple copies of a packet.	• Most prominent features of [6] are emphasized in this study. • ESA outperforms [6] in many aspects, such as throughput, collision reduction, SUE, etc.

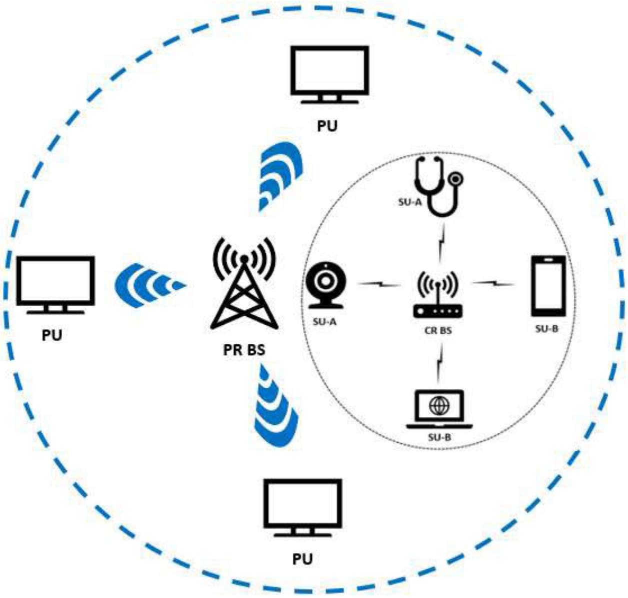

FIGURE 1. System model of the proposed scheme.

(PUs). PUs communicate through the corresponding base station known as the primary radio base station (PR BS). The secondary network (i.e., cognitive network) has a Cognitive Radio Base Station (CR BS) and four users known as secondary users (SUs). SUs communicate with each other and outside the network through the CR BS. The primary network can operate only in the licensed spectrum, and the cognitive network can operate in both licensed and unlicensed spectra.

In the ESA, we have classified SUs into two types (SU-A and SU-B) based on their communication data types. The SU-A is required to transmit critical and sensitive information. This information can include sensitive medical/healthcare data, real-time surveillance/monitoring, and time-critical systems/applications. SU-Bs are ordinary users who usually communicate general data, such as social media, web searching, and file transfer. Thus, the ESA ensures a higher priority for SU-A devices than for SU-B devices. Thus, in the proposed model, there are three types of users are exist, namely, the PU, SU-A, and SU-B, with the priority values 1, 2, and 3, respectively, where the low priority value indicates the higher priority in accessing the radio channels. In the system model shown in Fig. 1, there are three PUs (e.g., televisions) in the primary network, two SU-A (e.g., an IoT-based CCTV and a smart stethoscope), and two SU-B (e.g., a mobile and a laptop).

Two types of spectra are available in the ESA scheme: licensed spectrum (Ω_L) and unlicensed spectrum (Ω_U). According to CR-IoT, PUs have prerogative access to the licensed spectrum and SUs can access only the white spaces (i.e., free spectra) in the Ω_L. The SUs must release their acquired channels (spectra) as soon as any PU enters the network for data transmission. As PUs monopolize access to the spectrum in Ω_L, there are no provisions to access Ω_U for PUs. Thus, in our model, the PU can access only the Ω_L, and the SU can access both the Ω_L and Ω_U. As the PU possesses the highest priority, it can remove any SUs from Ω_L and acquire its channels to transmit data. Similarly, SU-A can remove SU-Bs from the Ω_L owing to its higher priority. Thus, a PU can access the Ω_L at any time if an idle channel is available. An idle channel is required because a PU cannot remove other existing PUs.

Again, the unlicensed spectrum (Ω_U) is only accessible to SUs if no spectrum is available in the licensed spectrum (Ω_L) for those. Moreover, no priority rules are applied to access the unlicensed spectrum. Therefore, SU-B cannot be replaced with SU-A in an unlicensed spectrum. This provides low-priority users with sufficient access to the spectrum. Previously, most research has ignored this issue, and low-priority users have suffered from severe spectrum scarcity and inefficiency.

Fig. 2 illustrates the channel accessibility and priority of different users, namely, PU, SU-A, and SU-B. ∂_{ICL}, ∂_{SU-A}, and ∂_{SU-B} are three binary decision variables that represent the availability of idle channels, SU-A, and SU-B, respectively. $\partial_{ICL} = 1$ indicates that an idle channel is available, whereas $\partial_{ICL} = 0$ indicates that no idle channels are available. Likewise, $\partial_{SU-A} = 1$ means that SU-A is available, whereas $\partial_{SU-A} = 0$ indicates that SU-A is not available. Similarly, $\partial_{SU-B} = 1$ denotes that SU-B is available, whereas $\partial_{SU-B} = 0$ denotes that SU-B is unavailable. A PU can access the licensed spectrum if an idle channel ($\partial_{ICL} = 1$), SU-A ($\partial_{SU-A} = 1$), or SU-B ($\partial_{SU-B} = 1$) is available. The phenomena can be mathematically expressed using the Boolean equation.

$$\partial_{ICL} + \partial_{SU-A} + \partial_{SU-B} = 1. \tag{1}$$

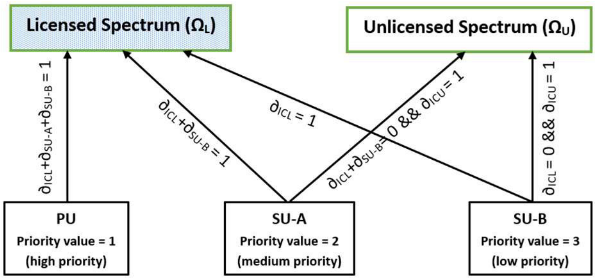

FIGURE 2. Spectrum accessibility and priority of different users.

Remember that a new PU can remove existing SUs from the primary network to acquire the channels released by SUs. Following the above procedure and adhering to the priority rules, SU-A can access the licensed spectrum if

$$\partial_{\mathrm{ICL}} + \partial_{\mathrm{SU-B}} = 1. \tag{2}$$

We observe the absence of the decision variable $\partial_{\mathrm{SU-A}}$ in the above Boolean equation, because SU-A cannot replace another existing SU-A. If SU-A has not been granted access to the licensed spectrum, it holds the opportunity to access the unlicensed spectrum if there exists any idle channel, that is, $\partial_{\mathrm{ICU}} = 1$. Thus, SU-A can access the Ω_{U} if it satisfies the following equation.

$$\partial_{\mathrm{ICL}} + \partial_{\mathrm{SU-B}} = 0 \ \ \&\& \ \ \partial_{\mathrm{ICU}} = 1. \tag{3}$$

Following the above procedure and adhering to the priority rules, an SU-B can access the licensed spectrum if

$$\partial_{\mathrm{ICL}} = 1. \tag{4}$$

If an SU-B does not have access to the licensed spectrum, it has the opportunity to access the unlicensed spectrum if there exists any idle channel, that is, $\partial_{\mathrm{ICU}} = 1$. Thus, SU-B can access the Ω_{U} if it satisfies the following equation.

$$\partial_{\mathrm{ICL}} + \partial_{\mathrm{SU-B}} = 0 \ \ \&\& \ \ \partial_{\mathrm{ICU}} = 1. \tag{5}$$

B. SPECTRUM SENSING MECHANISMS

Whenever a station or user wants to communicate with another user, both the sender and the receiver must be connected to the network. Although PUs must connect through a base station (BS) (i.e., PR BS), IoT devices (SUs) need not necessarily connect through any BS. SUs can communicate directly with each other without a BS by forming an ad hoc network [53], [54]. However, to communicate outside the network, SUs must be connected through a base station (i.e., CR BS), as shown in Fig. 1.

To communicate in a network, all users must sense the channels in order to check whether a free channel is available. If a free channel is available, the user transmits or receives the data using the channel. After transferring the data, the user releases its channel, which can be acquired by subsequent users. Several techniques can be used to determine whether a channel is busy. Among these techniques, evaluating the strength and periodicity of a signal are two well-known mechanisms currently used by most transmitters [55], [56]. Measuring signal strength is a popular and flexible technique that can easily distinguish noise from a signal. In our model, we use the signal strength technique to implement the transceiver. When a sender wants to transmit data, it senses the channels to find a free channel. The sender analyzes the received signal and makes a decision (i.e., busy or free) by employing the following hypothesis [55]:

$$r\,(t) = \begin{cases} w\,(t)\,, & H_0 \\ h(t) \times s\,(t) + w\,(t)\,, & H_1 \end{cases} \tag{6}$$

In Equation (6), $r(t)$ denotes the received signal strength from the sensing device that wants to transmit data, $s(t)$ denotes the sending signal strength by the current user of the channel, $h(t)$ denotes the channel gain of the sensing channel, and $w(t)$ denotes the zero-mean Additive White Gaussian Noise (AWGN). Hypothesis H_0 represents an empty or free channel and H_1 represents a busy or occupied channel. Thus, a new user intends to send data when a channel is idle (i.e., a free channel). Equation (6) indicates that the sensing device senses the high-energy signal of the currently occupied device. The sensing device senses low energy (i.e., noise only) if another device does not occupy the channel.

C. CHANNEL ACCESS PROCEDURES

The availability of a free channel is not the only requirement for sending data to the receiver. The receiver must also be ready to accept the data simultaneously. The receiver may not be ready for different reasons, such as it may be currently communication with another device, channel failure, or device failure. This phenomenon is carefully considered when designing the algorithms and flowcharts for the ESA scheme. Unfortunately, many previous studies have not considered this issue or explicitly mentioned it. Although some papers mention this issue, they do not consider it when measuring the system performance and efficiency [22].

Because the ESA prioritizes different users based on their information, the channel-access mechanisms of various users (i.e., PU, SU-A, and SU-B) are different. The flowchart in Fig. 3 illustrates the channel-access procedure for primary users. When a PU arrives for communication, it first checks whether SU-A is available in the network. If so, the current SU-As stop transmission and release their acquired channels. The PU then checks whether the receiver is ready to accept this information. If the receiver is inaccessible, the system blocks the PU. If the receiver is accessible, the sender (i.e., PU) adds all free channels, as in Equation (7), and sends its data using TA channels.

$$\mathrm{TA} = \mathrm{IC} + \mathrm{SUAC}. \tag{7}$$

where TA represents the total available channels, IC represents the idle channels, and SUAC represents the channels released by SU-As. The PU sends the data to the receiver using all TA channels in the licensed spectrum, Ω_{L}. We notice that there is no provision for accessing the unlicensed spectrum Ω_{U} by primary users.

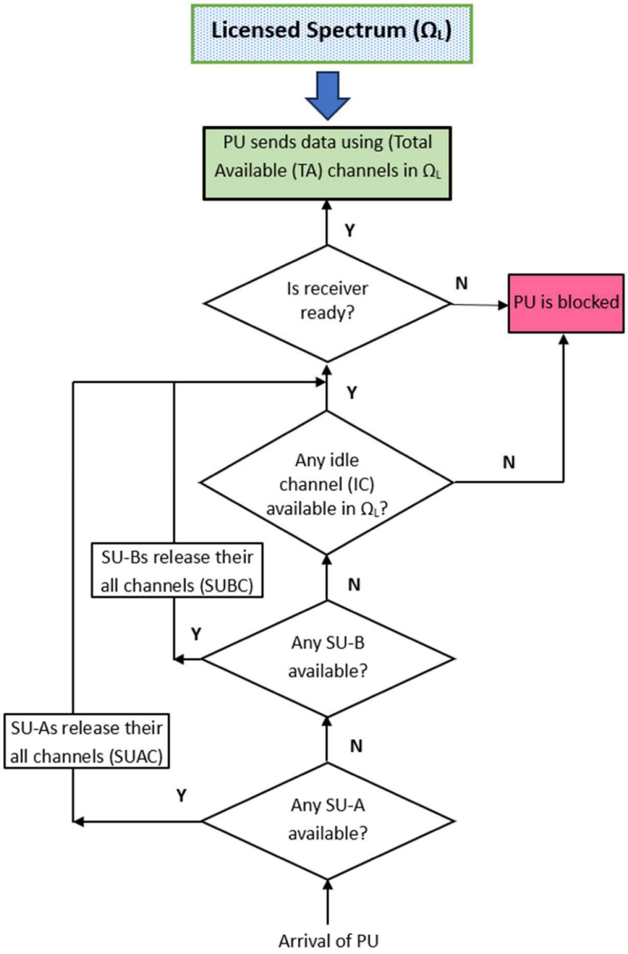

FIGURE 3. **Channel access mechanism of the PU.**

Fig. 3 shows that the PU does not need to check whether SU-B is available in the network when SU-A is detected. Because SU-A is detected by the PU, it ensures that there is no SU-B in the network because the existing SU-A already removes SU-B (if any) because of its priority over SU-B. If there is no SU-A in the network, the PU must check if any SU-B is currently available in the network. If so, the PU removes the SU-Bs from the network and acquires their released channels. The PU counts the total available channels (TA), as shown in Equation (8), and sends data using TA channels if the receiver is accessible.

$$\mathrm{TA} = \mathrm{IC} + \mathrm{SUBC}. \tag{8}$$

In Equation (8), SUBC represents the channels released by the SU-Bs. If there are no SU-B in the network, the PU checks whether idle channels are available in the network. If no, the PU is blocked by the system. If an idle channel is available and there are no SU-Bs, the PU counts TA as follows:

$$\mathrm{TA} = \mathrm{IC}. \tag{9}$$

Algorithm 1 states the steps of the spectrum allocation strategy of the primary users.

Algorithm 1 Spectrum Allocation Strategy of PU in $\mathbf{\Omega_L}$

```
01. Arrival of a PU
02. PU senses all the channels in $\Omega_L$
03. IF SU-A is available
04.     PU removes SU-A from the network
05.     PU computes $TA = IC + SUAC$ in $\Omega_L$
06.     Go to Step 21
07. ELSE
08.     IF SU-B is available
09.         PU Removes SU-B from the network
10.         PU computes $TA = IC + SUBC$ in $\Omega_L$
11.         Go to Step 21
12.     ELSE
13.         IF IC is available
14.             PU computes $TA = IC$ in $\Omega_L$
15.             Go to Step 21
16.         ELSE
17.             Go to step 25
18.         END
19.     END
20. ENDS
21. IF Receiver is accessible
22.     PU sends data to the Rx using the TA channels in the corresponding spectrum
23.     Exit algorithm //Data transmission is successful
24. ELSE
25.     System blocks the PU
26.     Exit algorithm //Data transmission is unsuccessful
27. END
```

Fig. 4 shows the channel access procedure for SU-A. After arriving at the network, it looks for SU-B to acquire its channels. Unlike in Fig. 3, it does not look for an SU-A, because an incoming SU-A does not replace an existing SU-A, because it has the same priority. If no SU-B is available in the network, the user (SU-A) searches for an idle channel. If neither an SU-B nor an idle channel is available in Ω_L, the user has the provision to access the Unlicensed Spectrum (Ω_U). SU-A checks whether an IC is available in Ω_U. Otherwise, SU-A is blocked by the system. If so, it must check whether the receiver is accessible or not. If the receiver is accessible, then the user (SU-A) sends its information to the destination. However, if the receiver is inaccessible, then the user is blocked. Algorithm 2 describes the channel access procedure for SU-A.

The channel mechanism of the SU-B is shown in Fig. 5. SU-B follows the same procedure as SU-A, except that it does not need to be checked for the presence of SU-B. Algorithm 3 describes the spectrum access mechanism of the SU-B.

IV. PERFORMANCE ANALYSIS

A. COMPLEXITY ANALYSIS

We aim to determine the complexities of the algorithms presented in Section III. Algorithm 1 is designed to distribute the spectrum to the PU, as illustrated in Fig. 3. The algorithm

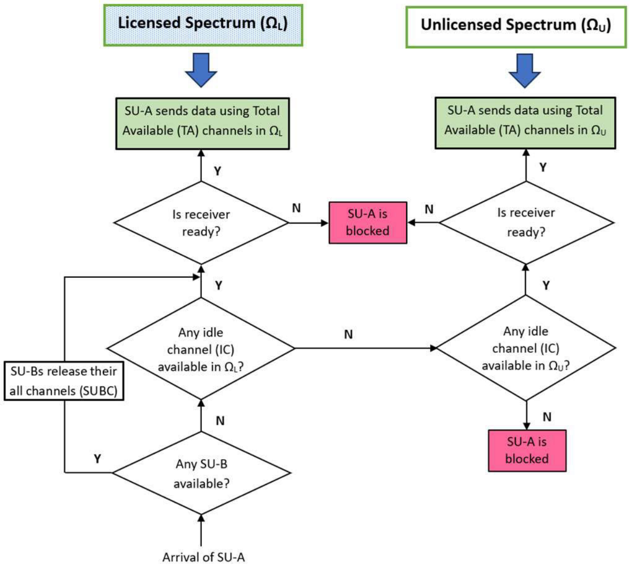

FIGURE 4. **Channel access mechanism of the SU-A.**

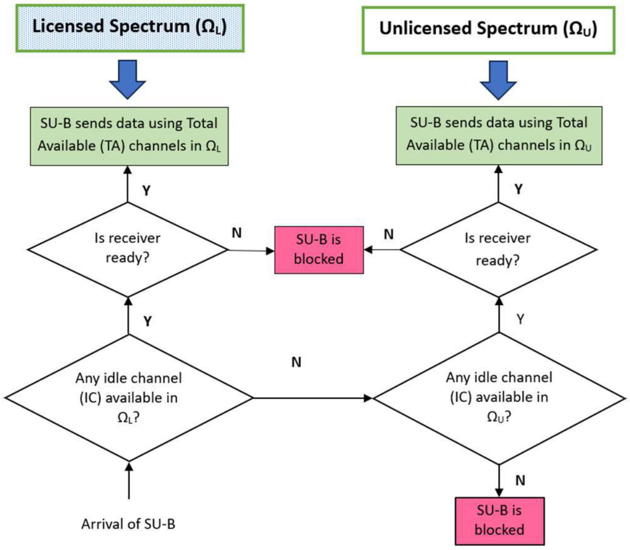

FIGURE 5. **Channel access mechanism of the SU-B.**

Algorithm 2 Spectrum Allocation Strategy of SU-A in $\mathbf{\Omega_L}$ and $\mathbf{\Omega_U}$

```
01. Arrival of an SU-A
02. SU-A senses all the channels in $\Omega_L$
03. IF SU-B is available
04.     SU-A removes SU-B from the network
05.     SU-A computes TA = IC + SUBC in $\Omega_L$
06.     Go to Step 21
07. ELSE
08.     IF IC is available in $\Omega_L$
09.         SU-A computes TA = IC in $\Omega_L$
10.         Go to Step 21
11.     ELSE
12.         SU-A senses all channels in $\Omega_U$
13.             IF IC is available in $\Omega_U$
14.                 SU-A computes TA = IC in $\Omega_U$
15.                 Go to step 21
16.             ELSE
17.                 Go to Step 25
18.             END
19.     END
20. END
21. IF Receiver is accessible
22.     SU-A sends data to the Rx using the TA channels in the corresponding spectrum
23.     Exit algorithm //Data transmission is successful
24. ELSE
25.     System blocks the SU-A
26.     Exit algorithm //Data transmission is unsuccessful
27. END
```

Algorithm 3 Spectrum Allocation Strategy of SU-B in Ω_L and Ω_U

```
01. Arrival of an SU-B
02. SU-B senses all the channels in $\Omega_L$
03. IF IC is available in $\Omega_L$
04.     SU-B computes TA = IC in $\Omega_L$
05.     Go to Step 15
06. ELSE
07.     SU-B senses all channels in $\Omega_U$
08.         IF IC is available in $\Omega_U$
09.             SU-B computes TA = IC in $\Omega_U$
10.             Go to step 15
11.         ELSE
12.             Go to Step 19
13.         END
14. END
15. IF Receiver is accessible
16.     SU-B sends data to the Rx using the TA channels in the corresponding spectrum
17.     Exit algorithm //Data transmission is successful
18. ELSE
19.     System blocks the SU-B
20.     Exit algorithm //Data transmission is unsuccessful
21. END
```

must find idle channels for a newcomer (i.e., PU). In the worst case, all channels must be verified for availability, leading to the upper bound of the complexity, which is $O(n)$. This is a linear time complexity, as spectrum sensing/searching occurs in all channels. However, searching/sensing can be significantly reduced if SU-A or SU-B are detected the network earlier. In a real network, it is very likely to have SU-A or SU-B, which eliminates the need to sense all channels, thereby significantly improving network performance. Thus, the complexity of Algorithm 1 is $O(n)$ which indicates excellent performance.

Algorithm 2 is developed to distribute channels to SU-A. Algorithm 2 searches for resources in both the licensed and unlicensed spectra. Examining the algorithm and

TABLE 3. **Key notations used in the paper.**

Notation	Description
Ω_{L}	licensed spectrum
Ω_{U}	unlicensed spectrum
$I^{(m)}$	mean idle time of the channel m
$B^{(m)}$	mean busy time of the channel m
$a^{(m)}$	probability of availability of the channel m
$u^{(m)}$	probability of unavailability of the channel m
L	length of a packet in bits
$t^{(m)}$	transmission time over a channel m
r	data rate
$S^{(m)}$	probability of successful packet transmission
$U^{(m)}$	probability of unsuccessful packet transmission
Ψ	a set of channels that formed a link
R^{Ψ}	reliability of the link
T	throughput
R_c	link capacity in bps
P_l	packet loss ratio
η	efficiency factor
C	channel capacity
$\bar{T}$	normalized throughput
τ	sensing time
T_t	transmission time
T_f	total frame time
T_τ	total sensing time to sense δ number of channels
M	total number of channels
T_{max}	maximum sensing time
T_N	normalized sensing time
E_S	sensing energy
P_S	sensing power
E_T	total sensing energy to sense δ number of channels
E_{max}	maximum sensing energy
E_N	normalized sensing energy
λ_{SU}	number of secondary users
λ_{PU}	number of primary users

corresponding flowchart in Fig. 4, we observe that the complexity is $O(n)$ for searching channels in the licensed spectrum (Ω_{L}). Again, better results can be obtained if the SU-B is detected earlier. After searching for the licensed spectrum, the algorithm searches for the unlicensed spectrum (Ω_{U}), if no idle channel is found for SU-A. The cost of the complexity of searching in Ω_{U} is another $O(n)$. Thus, the total complexity of Algorithm 2 is $O(n) + O(n) = O(n)$.

Algorithm 3 is designed to assign resources to the SU-B. The algorithm can be easily evaluated by observing the flowchart in Fig. 5. Again, the searching/sensing complexity of both licensed and unlicensed spectra is $O(n)$. The total complexity of Algorithm 3 is $O(n) + O(n) = O(n)$. TABLE 3 lists the key notation used in this study. In summary, we observe that all three algorithms have the same complexity, that is, $O(n)$. Moreover, Algorithms 1 and 2 may have shown a better performance in a few cases.

B. TRAFFIC MODELING

We consider a two-state continuous-time Markov Chain (CTMC) to model several performance matrices of the proposed ESA scheme. Each wireless channel (m) has two states: busy (State 1) and idle (State 0). An SU pair (transmitter and receiver) can access the channel when it is idle. According to a two-state CTMC [51], [52], the *availability* of channel m can be represented as

$$a^{(m)} = \frac{I^{(m)}}{I^{(m)} + B^{(m)}} \tag{10}$$

where $I^{(m)}$ represents the mean idle time and $B^{(m)}$ represents the mean busy time of channel m. Therefore, the *unavailability* of channel, $u^{(m)}$ can be expressed as

$$u^{(m)} = 1 - a^{(m)}. \tag{11}$$

Let the length of a packet be denoted by L (bits), packet transmission time t, and data rate r; then the *transmission time* over a channel m be represented as

$$t^{(m)} = \frac{L}{r^{(m)}}. \tag{12}$$

The SPT (Successful Packet Transmission) probability, $S^{(m)}$ over channel m is represented as follows [47]:

$$S^{(m)} = e^{-\frac{t^{(m)}}{I^{(m)}}}. \tag{13}$$

Therefore, the probability of unsuccessful packet transmission, $U^{(m)}$ would be,

$$U^{(m)} = 1 - S^{(m)}. \tag{14}$$

Let Ψ denote the set of channels that forms a link for an SU pair. For a single channel, where $\Psi = \{1\}$, link reliability is $R^{\Psi} = 1 - u^{(1)}$. If two channels form a link (i.e., $\Psi = \{1, 2\}$), then the reliability is $R^{\Psi} = 1 - u^{(1)}u^{(2)}$. Thus, the *reliability of link* can be computed using the following formula:

$$R^{\Psi} = 1 - \prod_{i=1}^{|\Psi|} u^{i}. \tag{15}$$

We now investigate the system throughput. Owing to the nature of packet loss and overhead in wireless systems, the *throughput* (T) can be expressed as [57], [58]:

$$T = R_c \times (1 - P_l) \times \eta \tag{16}$$

where R_c denotes the link capacity in bps, P_l denotes the packet-loss ratio, and η denotes the efficiency factor. If the channel capacity is expressed as C, then the *normalized throughput* is:

$$\bar{T} = \frac{T}{C}, \text{ where } 0 \leq \bar{T} \leq 1. \tag{17}$$

Finally, the sensing time and energy are investigated. *Sensing time* (τ) refers to the period during which a device listens to the channel to determine whether it is free or occupied before transmitting data. Equation (6) can be used to determine whether a channel is busy (i.e., occupied) or free (i.e., idle). The *transmission time* (T_t) is the duration required to send a certain amount of data over a channel once transmission starts. The *total frame time* (T_f) is expressed as

$$T_f = \tau + T_t \tag{18}$$

If an IoT node senses δ channels (where $\delta \leq M$) to find an idle channel, the *total sensing time* is:

$$T_\tau = \delta \times \tau. \tag{19}$$

Similarly, we can get *maximum sensing time* to sense all channels as follows,

$$T_{max} = M \times \tau. \tag{20}$$

The *normalized sensing time* (T_N) is the ratio of the total sensing time to the maximum sensing time and can be expressed as follows:

$$T_N = \frac{T_\tau}{T_{max}}. \tag{21}$$

In IoT communication, *sensing energy* (E_S) refers to the amount of energy consumed by an IoT device to perform sensing operations (e.g., sensing a wireless channel to determine whether it is free or occupied). This can be expressed as follows.

$$E_S = P_S \times \tau. \tag{22}$$

where E_S represents the sensing energy in Joules, P_S represents the sensing power in watts, and τ represents the sensing time in seconds. The *Total sensing energy* to sense δ number of channels (where $\delta \leq M$) to find an idle channel is:

$$E_T = \delta \times E_S. \tag{23}$$

Similarly, we can have *maximum sensing energy* to sense all channels as follows,

$$E_{max} = M \times E_S. \tag{24}$$

The *Normalized sensing energy* (E_N) is the ratio of the total sensing energy to the maximum sensing energy and can be expressed as follows:

$$E_N = \frac{E_T}{E_{max}}. \tag{25}$$

V. SIMULATION AND RESULTS

A. SIMULATION SETUP

Simulations are conducted using MATLAB [59] to evaluate the performance of the proposed ESA scheme. We have compared ESA with three promising schemes: FMCPR [5], HRT [7], and RS [5]. The details of these schemes are discussed in Section II-B. TABLE 4 lists the simulation parameters and their default values. These values are treated as default values throughout all experiments unless otherwise specified. The simulation parameters are chosen such that they comply with the IEEE 802.22 WRAN standard [12]. All communication occurs in the data link layer. Sensing information is collected every 2 s and communicates periodically to the base station. Each simulation is iterated 100 times, and the average values are plotted in the graphs. We have used the Rayleigh propagation model with a path loss exponent (n) of four for the simulation. The received power (P_r) is given by the following formula [60], [61].

TABLE 4. Simulation parameters with default values.

Parameter	Value
frequency band	54 MHz
number of PUs	1-10
number of SUs	1-10
total number of channels (m)	10
packet size (l)	4 KB
area	200×200 m^2
carrier frequency (f)	900 MHz
channel bandwidth (b)	1 MHz
transmitting power (p_t)	1 W
modulation	16-QAM
path loss exponent (n)	4
number of simulation iterations	100
transmission attempts per iteration	1000

$$P_r = P_0(\frac{d}{d_0})^{-n} \times X \tag{26}$$

where n denotes the path loss exponent, d denotes the distance between the transmitter and receiver, d_0 denotes the close-in distance ($d \geq d_0$), and X denotes an exponential random variable with a mean of one that models the Rayleigh fading power gain. P_0 is the power received at a close-in distance (d_0) and is measured as follows:

$$P_0 = \frac{P_t G_t G_r C^2}{(4\pi d_0 f)^2} \tag{27}$$

where P_t is the transmission power, G_t is the transmitting antenna gain, G_r is the receiving antenna gain, C is the velocity of light, and f is the carrier frequency. We set $G_t = G_r = 1$, and $P_t = 1W$.

B. SIMULATION RESULTS

Fig. 6 shows the normalized throughput $\bar{T}$ (defined in Eq. (17)) of the protocols. We calculate the average normalized throughput of the SUs (where $\lambda_{\text{SU}} = 10$) with respect to the number of PUs (λ_{PU}), which varied from one to ten. It is observed that the ESA scheme provides the highest throughput, followed by the FMCPR scheme. When $\lambda_{\text{PU}} = 1$, all schemes provide the maximum throughput as the secondary users obtain the maximum number of channels to deliver data. As the number of PUs increases, the throughput declines gradually because incoming PUs force existing SUs to release their channels. When λ_{PU} reaches 10, the normalized throughput reaches a minimum, which is nearly zero. Because the number of channels is 10, no channels are left to be used by secondary users.

Among the schemes, ESA provides the highest normalized throughput, which is approximately .91, followed by FMCPR, RS, and HRT. The ESA employs spectrum allocation algorithms that check the receiver accessibility before data transmission, thereby avoiding packet collisions between the sender and receiver. FMCPR also ensures a good normalized throughput of .87. The scheme concurrently

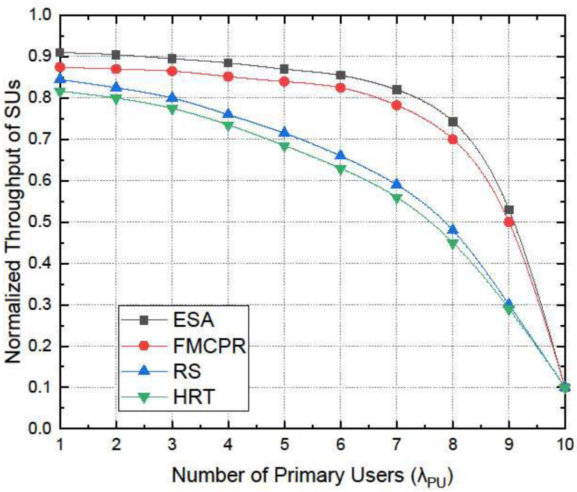

FIGURE 6. **Normalized throughput w.r.t. the number of primary users (λ_{PU}).**

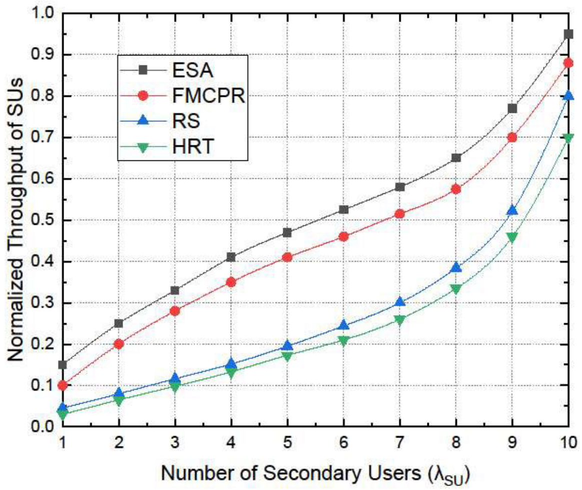

FIGURE 7. **Normalized throughput w.r.t. the number of secondary users (λ_{SU}).**

considers several performance parameters to determine the quality of channels and ranks them accordingly. RS provides a comparatively low throughput (i.e., a maximum of approximately .84) than ESA and FMCPR, but higher than that of the HRT scheme. RS is a WRAN-compliant method that randomly selects channels and provides a meager throughput. HRT provides the lowest throughput among all the schemes, which is approximately.82. The scheme ensures maximum reliability by compromising the system throughput.

Fig. 7 shows the normalized throughput with respect to the number of secondary users. The average normalized throughput of SUs is calculated in the absence of primary users (i.e., $\lambda_{PU} = 0$). As expected, ESA ensures the highest throughput, followed by FMCPR, RS, and HRT. The reasons for this are the same as those shown in Fig. 6. The highest normalized throughput of the protocols is approximately .95, .88, .8, and .7 for ERS, FMCPR, RS, and HRT, respectively. It is observed that λ_{SU} reaches its maximum (i.e., $\lambda_{SU} = 10$), as all SUs properly utilize all channels (i.e., M = 10). Subsequently, the arrival of an SU increases the collision between stations and significantly decreases the throughput.

Fig. 8 illustrates the impact of the collision probability of a secondary user ($\lambda_{SU} = 1$) with an increase in the number of primary users. The collision probability of the schemes is extremely low when the number of primary users is only one. As λ_{PU} increases, the number of available channels for the secondary user decreases, leading to an increase in collision probability. Again, the ESA shows the best performance by minimizing the collision probability among all the schemes. The ESA checks the receiver accessibility before data transmission, thereby minimizing the probability of collision between the sender and the receiver. The FMCPR scheme also exhibits a good performance because it selectively chooses channels for suitable users. HRT shows better results than RS and worse results than the other two protocols. As a random scheme, the collision probability of RS is poor. In this simulation, the comparative performance of different schemes (except RS) is almost the same at the beginning ($\lambda_{PU} = 1$) and end ($\lambda_{PU} = 10$).

Fig. 9 presents the collision probability versus the number of secondary users. In this experiment, the number of PUs is kept constant (i.e., $\lambda_{PU} = 4$) to examine the behavior of the collision probability of secondary users in the presence of some prime users. We observe that, initially, the collision probability increases slowly with an increase in secondary users, as there are many idle channels available. However, when λ_{SU} reaches six, all channels (i.e., M = 10) are used by 10 users, leaving no channels to be used by upcoming secondary users. As such, after $\lambda_{PU} = 6$, the collision probability increases significantly as the number of secondary users increases. Again, we can see that the ESA exhibits the best performance by ensuring fewer collisions between the stations. The FMCPR and HRT schemes also perform well, whereas the RS could not. The reasons for the variations in the performance of the different schemes are the same as those in the previous experiment, as shown in Fig. 8.

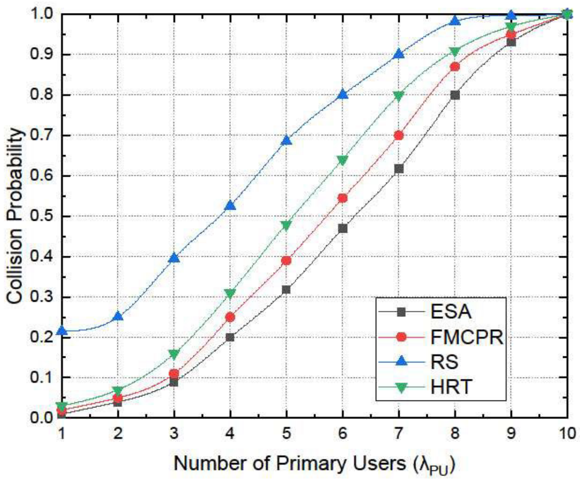

FIGURE 8. **Collision probability w.r.t. the number of primary users (λ_{PU}).**

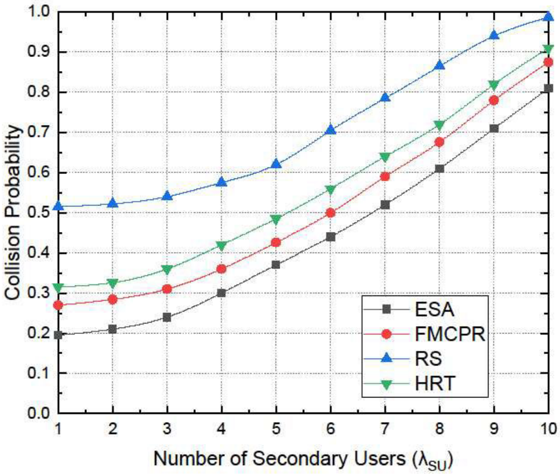

FIGURE 9. Collision probability w.r.t. the number of secondary users (λ_{SU}).

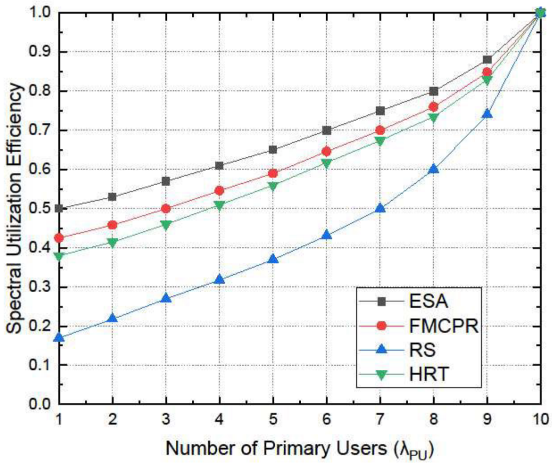

FIGURE 10. SUE w.r.t. the number of primary users (λ_{PU}).

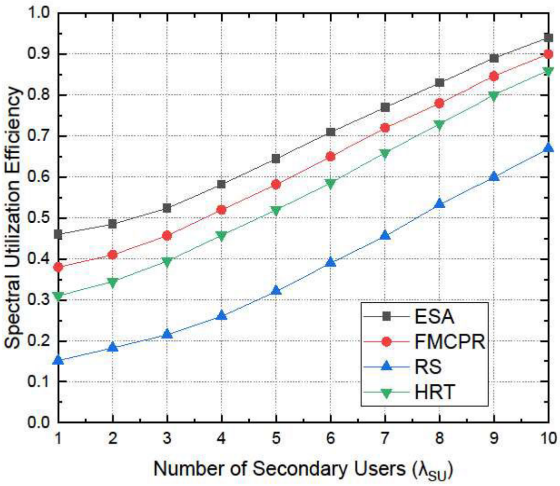

FIGURE 11. SUE w.r.t. the number of secondary users(λ_{SU}).

Fig. 10 shows the spectral utilization efficiency (SUE) of an SU with respect to the number of PUs. In this simulation, we want to observe the SUE of a single secondary user (i.e., $\lambda_{SU} = 1$) while varying the number of primary users ($\lambda_{PU} =$ 1 to 10). We observe that SUE is initially very low; subsequently, it gradually increases with an increase in the number of PUs. Initially, there is only one PU and SU in the network, enabling a large number of free channels to be available to the SU. A single SU cannot utilize many idle channels, leading to a low SUE of the system. As the number of PUs gradually increases, the number of free channels decreases. That is why the SUE of the secondary user increases steadily with an increase in the arrival of PUs in the network. The SUE of all schemes reaches a maximum (i.e., SUE $= 1$) when the number of PUs reaches ten. Among the competing schemes, ESA shows the best results, followed by FMCPR, HRT, and RS. When ($\lambda_{SU} = 1$), ESA shows a 13.95% performance improvement over FMCPR, 28.94% over HRT, and 188.2% over RS.

Fig. 11 shows the SUE of secondary users, which varies between 1 and 10 in the presence of a single primary user ($\lambda_{PU} = 1$). It is observed that SUE gradually increases as the number of secondary users increases. Initially, the SUE is low because a large number of channels (i.e., M $= 10$) could not be utilized by a small number of users. As more secondary users enter the network, the spectrum is efficiently consumed by users, leading to an increase in spectral utilization efficiency. In all cases, the ESA proves its superiority over the other schemes by ensuring the best efficiency. The ESA provides the highest efficiency (approximately 94%), followed by FMCPR (approximately 90%), HRT (approximately 86%), and RS (approximately 67%).

Fig. 12 shows a comparison of the link reliability, R^{Ψ} (defined in Eq. (15)) between the competing schemes. In this simulation, the average link reliability of two secondary users is computed in the presence of a primary user (i.e., $\lambda_{PU} =$ 1). It is observed that HRT ensures the highest reliability (i.e., approximately .97) among the schemes. To achieve high reliability, HRT sends multiple copies of a packet through multiple channels. The HRT scheme is specially designed to provide higher reliability and SPT, thereby compromising other performance parameters. ESA and FMCPR provide comparatively low link reliability (i.e., approximately .90 and .88) as the schemes do not focus on link reliability. Scheme RS provides the worst reliability (i.e., approximately .67) among all protocols, as expected.

Fig. 13 shows the performance of the SPT probability $S^{(m)}$ (defined in Eq. (13)), for different schemes. As in the previous simulation, the average SPT probability of two secondary users is measured in the presence of a primary user ($\lambda_{PU} =$ 1). In this simulation, the proposed ESA scheme performs slightly better than the HRT scheme because of its innovative design and protocols, as described earlier. The successful packet transmission probability of the ESA and HRT is approximately .925 and .92, respectively. HRT shows better performance than FMCPR and RS, as it considers reliability to be an important performance criterion.

Fig. 14 depicts the normalized spectrum sensing time (T_N) (defined in Eq. (21)) versus the number of primary users.

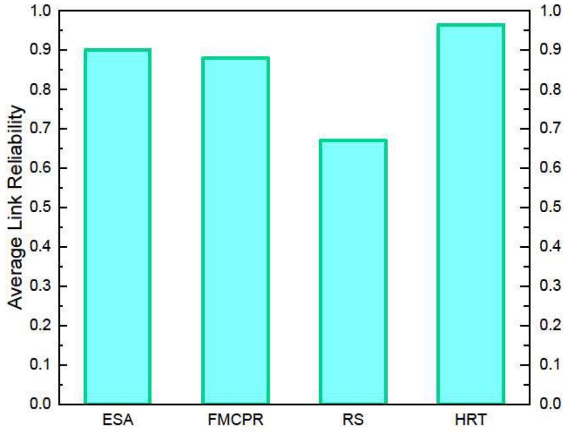

FIGURE 12. Comparison of link reliability between different schemes.

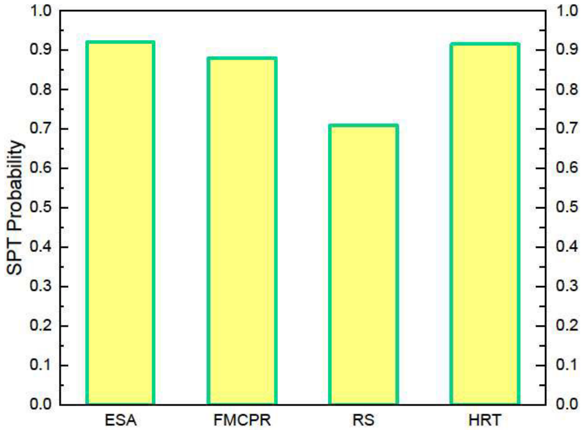

FIGURE 13. Comparison of SPT probability between different schemes.

Here, we observe the normalized sensing time of a secondary user ($\lambda_{SU} = 1$) where the number of primary users varies from 1 to 10. Initially, the SU can quickly choose an idle channel because many channels are available for use. Therefore, the sensing time is very low, providing good results at the beginning of all protocols. As λ_{PU} increases, the idle channels decrease for the SU, leading to an increase in the cumulative sensing time. Interestingly, in this simulation, the RS scheme shows the best results among all protocols. This is because the RS, which is a random scheme, acquires an idle channel without considering any quality or criteria. The sensing time of the FMCPR scheme is the worst among the schemes and increases linearly with the number of primary users. The ESA scheme shows better results than FMCPR and HRT. It should be noted that when $\lambda_{PU} = 10$, all schemes have the highest sensing time, leading to a normalized cumulative sensing time of 100 percent. At this stage, all channels (i.e., M=10) are used by all primary users ($\lambda_{PU} = 10$), and the primary user must search for all channels for availability.

Fig. 15 shows a comparison of the normalized sensing energy (E_N) (defined in Eq. (25)) for the four schemes. The parameters of this simulation (e.g., λ_{PU}, λ_{SU}) are the same as those in the previous simulation in Fig. 14. As the sensing energy is proportional to the sensing time, the behavior of the graphs in Fig. 15 is similar to that of the graphs in Fig. 14. Hence, the interpretation and cause of the results of the previous simulation are applicable to this case.

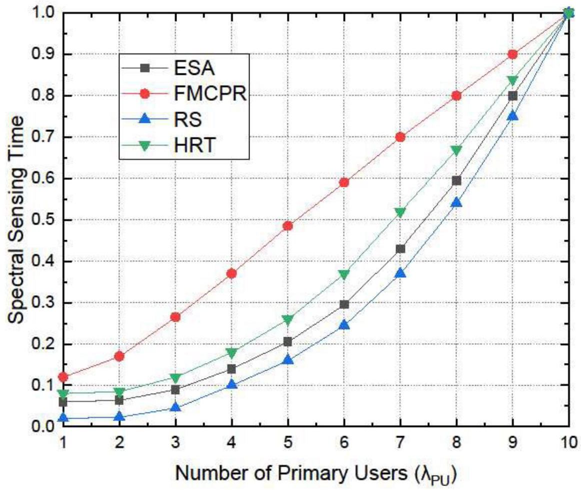

FIGURE 14. Spectral sensing time w.r.t. the number of primary users (λ_{PU}).

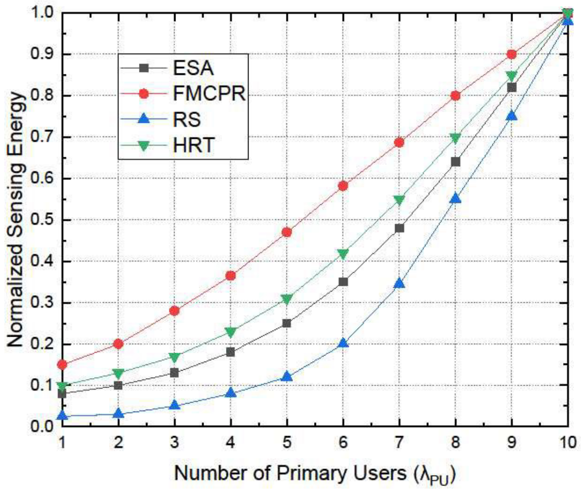

FIGURE 15. Sensing energy w.r.t. the number of primary users (λ_{PU}).

VI. CONCLUSION AND FUTURE DIRECTIONS

The drastic growth of IoT has been severely hindered by the lack of available radio spectrum. CR-IoT has paved the way to mitigate spectrum scarcity to a large extent and has significantly improved the overall efficiency of cognitive radio-based IoT. In this paper, we present a novel CR-IoT scheme termed 'ESA' that enhances the performance of the cognitive radio network remarkably. The complexity and performance of the relevant algorithms are analyzed, and a traffic analysis is performed using the CTMC model. Exhaustive simulations are conducted using MATLAB to validate the robustness (throughput improvement 4%–21%, collision reduction of up to 32%, spectrum efficiency 8%–31%, and successful packet transmission of up to 21%) of the proposed scheme.

By efficiently allocating both licensed and unlicensed spectra and considering user heterogeneity and priority, ESA enables more scalable and fair IoT deployments. The algorithms also reduce collisions and improve link stability, making CR-IoT more suitable for mission-critical applications such as healthcare, smart cities, and industrial automation. Overall, this study supports the development of practical, efficient, and robust CR-IoT networks. Future research on the CR-IoT based on the ESA scheme can explore several promising directions. First, the algorithms can be extended to incorporate advanced machine learning or reinforcement learning techniques for adaptive and predictive bandwidth/channel distributions in highly dynamic environments. Investigating the integration of the CR-IoT with emerging technologies, such as 5G/6G, edge computing, and AI-driven optimization, could improve scalability and real-time decision-making. Further studies should focus on integrating unlicensed spectrum bands and hybrid spectrum-sharing models to improve scalability. A large-scale testbed implementation in real-world CR-IoT scenarios can validate the practical effectiveness of the proposed scheme. Finally, real-world deployments in domains such as smart cities or industrial IoT would provide deeper insights into the practical feasibility and performance of ESA.

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GAZI ZAHIRUL ISLAM (Member, IEEE) received the B.Sc. degree in computer science and engineering from Chittagong University of Engineering and Technology (CUET), Bangladesh, the M.Sc. degree in wireless communications systems engineering from the University of Greenwich, U.K., and the Ph.D. degree from Bangladesh University of Professionals.

He has been teaching as an Associate Professor at Southeast University, Bangladesh, since August 2022. He is currently doing his post-doctoral research at International Islamic University Malaysia (IIUM), on the Internet of Things. He has published many research papers in renowned journals and conferences. He reviewed many reputed journals, including *IET Communications*, IEEE ACCESS, *Transactions on Emerging Telecommunications Technologies*, *Complex and Intelligent Systems*, *Ad Hoc Networks*, *Journal of King Saud University—Computer and Information Sciences*, *Microprocessors and Microsystems*, *Journal of Communications*, *Internet of Things*, and *Cyber-Physical Systems*. He conducted research and several projects on Wi-Fi networks, wireless communications, computer networking, the Internet of Things, software/app development, e-governance/e-commerce, and machine learning. He has also contributed to many academic conferences, such as the track chair, the session chair, a committee member, and a reviewer.

S. M. A. MOTAKABBER (Senior Member, IEEE) received the B.Sc. (Hons.) and master's degrees from Rajshahi University, in 1986 and 1987, respectively, and the Ph.D. degree from the National University of Malaysia (UKM), in 2011.

He was the Scientific Officer of Bangladesh Atomic Energy Commission and Bangladesh Scientific and Industrial Research, two renowned national research institutes in Bangladesh, from 1991 to 1992 and 1992 to 1994, respectively. He started his teaching and academic research career in 1994 as a Lecturer with the Department of Applied Physics and Electronics, Rajshahi University. He was an Associate Professor with the Department of Applied Physics and Electronic Engineering, Rajshahi University, from 2008 to 2012. He joined International Islamic University Malaysia (IIUM) as an Academic Faculty Member with the Department of Electrical and Computer Engineering, in 2012, and is currently a Professor with the Department. He has published over 150 indexed journal articles and conference proceedings, including two textbooks. His research interests include VLSI, microelectronics, electronic control and automation, embedded systems, wireless communication, microwave and satellite communication, RFID and NFC, the IoT, renewable energy, and green technology. He is a member of IET and a Chartered Engineer of U.K.

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