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RESEARCH ARTICLE

Radio Resource Management Framework for Energy-Efficient Communications in the Internet-of-Things

Deepak G. C.*[1] | Faycal Bouhafs[2] | Alessandro Raschellà[2] | Michael Mackay[2] | Qi Shi[2]

[1]School of Computer Science and Mathematics, Kingston University, London, United Kingdom
[2]Department of Computer Science, Liverpool John Moores University, Liverpool, United Kingdom

Correspondence
*Corresponding author, Email: d.gc@kingston.ac.uk

Summary

The Internet-of-Things (IoT) is the vision of a global network that connects various physical world objects to the IT infrastructure through a wireless medium. Despite the availability of a number of mature Radio Access Technologies (RATs) such as GSM, LTE, Wi-Fi and due to the current progress made in developing 5G technology, more and more IoT operators are opting to use Low Power Wide Area (LPWA) technologies due to their low cost and easy deployment. However, recent studies show that the radio resource allocation used in these technologies is not scalable. This limitation often results in packet collisions, retransmission and unnecessary waste of scarce energy resources. In this paper, we propose a Radio Resource Management (RRM) framework, based on Software-Defined Networking (SDN), to overcome the inefficient radio resource allocation of LPWA technologies. This is possible through the centralized nature of SDN, which allows collecting network monitoring information in order to analyze and calculate the optimal channel assignment configuration across the IoT network. We perform software-defined radio based spectrum monitoring within the real IoT network platform in 868 MHz bands in which the latest IoT technologies, i.e., *LoRa* and *SigFox*, operate. We demonstrate, through extensive simulations, that the proposed approach provides a better radio resource allocation for LPWA, reduces the number of packet collisions, and significantly improves the energy efficiency of the IoT communications.

KEYWORDS:
Low power wide area network, LoRaWAN, spectrum mapping, Internet-of-Things, 5G

1 | INTRODUCTION

The overwhelming success of the Internet is built in part on the availability of numerous edge communication solutions ranging from wired technologies such as optic fiber and ADSL to wireless communication technologies such as Wi-Fi. This diversity of communication technologies is, in reality, a reflection of the heterogeneity of users and applications requirements. As mobility is a major requirement for many users, wireless communication has unsurprisingly become the most popular technology in many cases. The rise of wireless communications is mainly due to the introduction of smartphones and tablets which allowed users to access the Internet and interact with online services while moving. Since wireless communication technologies rely on the availability of a finite radio spectrum, it becomes important to optimize the utilization of this scarce resource as much as possible.

Until recently, the design of wireless communication solutions and architectures has always been motivated by the need to improve ubiquitous connectivity between people and interaction with online services. The latest progress made in Micro-Electromechanical Systems (MEMS) has enabled new types of applications that rely mostly on wireless communication to interact with physical objects and platforms such as appliances, cars, power supply networks, etc. This concept, often referred to as the Internet-of-Things (IoT), promises to revolutionize the way we interact with everyday objects and services [1].

Wireless communications have an important role in the IoT, as wired connections are often not possible or in many cases not economically viable. Due to their unique data traffic characteristics, IoT applications have different requirements than current Internet applications. Data traffic in these applications consists generally of small uplink data transmissions, with very little or no mobility of IoT devices and the need for high energy efficiency [2]. The data rate requirement in IoT is also very low in comparison to cellular communications because the data transmission occurs less frequently, e.g., from once every hour to a few updates per day. Moreover, the IoT network has to support a diversity of applications within the same energy constraints. For instance, alarm signal applications need highly reliable communication with a guaranteed minimum Quality of Service (QoS), whereas in smart metering applications packet delays could possibly be acceptable [3]. Moreover, the energy efficiency of the IoT devices should be maximized due to the fact that the battery on such distributed IoT devices cannot be easily replaced in which case the efficient energy harvesting techniques are also needed [4].

A number of wireless communication technologies have been designed to address these requirements with cellular technologies such as GPRS, Narrow-Band IoT and the upcoming Fifth Generation (5G) being proposed for IoT connectivity. However, for many IoT applications that rely on a sheer deployment of sensors, RATs operating in the unlicensed bands represent a much cheaper and more practical alternative. In this context, a number of low power wide area (LPWA) technologies such as *LoRa*, *SigFox*, and *Ingenu* have recently emerged. Typically, operating on the license-free Industrial, Scientific, and Medical (ISM) bands, LPWA solutions use a duty cycle access mode, in which a device can only access the subchannel during a fixed time period.

Although the purpose of the duty cycle access mode is to provide fair access to the subchannel among IoT devices, recent studies have shown that it does not scale well when used in dense deployments [5]. This limitation is due to the lack of coordination to access the radio channels. In a scenario where a sizable number of devices are deployed in close proximity, each device will be competing for access to the subchannel, resulting in packet collisions and retransmissions [6,7]. This situation not only affects the performance of the network but also results in spectrum congestion and reduction of available energy on the device.

Motivated by these issues, in this paper, we address the problem of spectrum congestion and energy-inefficiency in LPWA IoT networks by proposing a Radio Resource Management (RRM) framework based on Software-Defined Network (SDN) [8]. The use of SDN allows us to centralize the network management operations in a single entity referred to as a Controller, which in turn enables the programming of large networks through the *OpenFlow* protocol [9]. Moreover, the proposed RRM framework relies on spectrum monitoring information in order to analyze and calculate the optimal subchannel assignment configuration across the IoT network overcoming the above-mentioned limitations of LPWA technologies. In the proposed RRM framework, access to time frames and frequency subchannel resources are devised according to the rate of traffic generated by IoT devices which often follows a random pattern.

The remainder of the paper is organized as follow. In Section 2, we provide a comprehensive analysis of the state-of-the-art on radio access schemes for IoT and the contributions of the paper. In Section 3, we analyze the LPWA communication system for IoT including the radio access scheme and spectrum usage pattern in ISM bands. In Section 4, we present the proposed RRM framework for LPWA technologies in IoT. In Section 5, we evaluate our RRM approach and analyze its performance results. Finally, our conclusions are presented in Section 6.

2 | STATE-OF-THE-ART AND PAPER CONTRIBUTIONS

The main factor in the realization of the IoT is ubiquitous connectivity among the devices at minimal cost and configuration [10]. The maturity of wireless communication technologies along with their easy and often cheap deployment makes them the best candidate for IoT applications. These wireless communication technologies can be classified into three categories according to their connectivity approach: cellular communication, Wireless Personal Area Networks (WPAN), and LPWA networks. In addition to their connectivity approach, these technologies can also be differentiated in terms of the way wireless devices access the radio medium [11]. In this section, we first present the currently available technologies to realize IoTs in practice which is followed by the contributions of the paper.

Following the current trends, IoT will exponentially expand the use of cellular communication beyond traditional smartphones and computers to a large number of applications and devices. Therefore, one of the pillars of the fifth generation of mobile networks (5G) is the massive machine type communications (MTC). To address the demands of massive MTC connectivity in 5G, 3GPPP proposed the Long Term Evolution for MTC (LTE-M) and NarrowBand-IoT (NB-IoT) standards. The mobile service providers can leverage the existing LTE and 5G infrastructures to support extraordinarily wide availability of IoT devices thereby reducing the capital expenses (CAPEX) for operators.

On the other side, novel IoT technologies and protocols have been recently emerged as an alternative to the cellular technology for short range and indoor connectivity. In this context, WPAN technologies often operate on unlicensed 2.4 GHz, 915 MHz and 868 MHz bands which are characterized by higher energy efficiency and short transmission range [12] as is the case with Bluetooth Low Energy [13], Z-Wave [14] and ZigBee [15], which are already used for smart homes and appliance management applications. However, these characteristics make the application of these WPAN technologies to outdoor IoT services very limited.

2.1 | Low Power Wide Area Technologies

Also operating mostly on unlicensed ISM bands, the LPWA technologies as discussed above exhibit certain characteristics that make them attractive to many IoT services. LPWA technologies are specifically designed for M2M connectivity with low power consumption and low bit rate requirements [16]. The transmission range of LPWA typically depends on the radio propagation environment. For instance, *LoRa* typically provides long-range communication up to 10-40 km in rural areas and 1-5 km in urban areas [10]. These characteristics make them more suitable than cellular networks and WPANs for many IoT services where thousands of devices that generate small data traffic need to be connected. Furthermore, the relatively small operational cost makes LPWA a popular alternative to cellular technologies.

There are two main LPWA technologies which are acting as an enabler of IoT, *SigFox* and *LoRa*, which operate on ISM 868 MHz in Europe and 902 MHz in the US [17]. Furthermore, *SigFox* devices can transmit on a bandwidth of 100 Hz with less than 30 seconds in an hour, i.e., 1% duty cycle, at a data rate of 100 bits/s. *LoRa* is the spread spectrum based protocol with the maximum data rate of 50 kbps, at a maximum bandwidth of 125 kHz, which is suitable for applications requiring higher data rates. It is designed based on a 'star of stars' network architecture which supports mobility of the users. Both technologies are highly energy efficient in which batteries are expected to last more than ten years with 20 dBm maximum output power.

In [18], the authors provide a detailed analysis of coverage and capacity for *SigFox* and *LoRa*, together with GPRS and Narrow-Band IoT. In detail, they focus on the performance study of collisions and blocking probabilities in indoor and outdoor environments. While in [19] the authors assess the *LoRa* scheme through a system-level simulator in *ns-3* consisting in tens of thousands of end devices. Their results show that the *LoRa* access scheme outperforms with respect to a basic ALOHA solution in terms of throughput due to the partial orthogonality between its spreading factors.

2.2 | Radio Access in the Internet-of-Things

In general, the nature of network connectivity adopted in a wireless communication dictates the radio access scheme for the devices trying to transmit through the wireless medium. Accordingly, we can classify the radio access schemes for IoT wireless communication technologies into two categories: coordinated and uncoordinated.

Coordinated access approaches typically rely on a central entity to manage access to the wireless medium by IoT devices. This category of access schemes is applicable for communication technologies that operate on the licensed radio, as is the case with cellular systems. Since cellular communication technologies operate on dedicated radio bands, access to the spectrum is therefore coordinated, centralized and provisioned according to the size of the network. The drawback of cellular communication, however, is the cost as this access mode will limit the number of devices that could transmit. In addition, radio access schemes in current cellular systems do not consider the energy constraints that often characterize many IoT devices. The upcoming 5G mobile networks promise to address these challenges by offering low cost, low energy wireless communication [20] but specific details have yet to emerge.

In contrast, uncoordinated access schemes rely on a distributed management approach without the intervention of a central entity [21]. This usually applies to IoT technologies that operate on unlicensed radio bands, as is the case with WPANs and LPWA. Obviously, the use of unlicensed bands will reduce the cost of the radio spectrum, and this uncoordinated access mode will also help to simplify the implementation of communication software in often computationally limited devices. Uncoordinated access schemes could, therefore, yield efficient communication for limited size and short transmission IoT networks as is the case for applications using WPANs. However, in cases where IoT applications are deployed in large networks that require long-range transmissions using LPWA technologies, such uncoordinated access could result in interference and spectrum congestion, thus, degrading the reliability of communication links [22].

This situation is similar to the spectrum congestion problems often observed in densely deployed residential Wi-Fi networks. As Wi-Fi networks also operate on unlicensed bands, the popularity of this technology has resulted in dense deployments with a lack of coordination among Wi-Fi Access Points (APs) which has resulted in interference and congestion that affects the quality of connectivity for many wireless users.

Many research initiatives are currently trying to address the spectrum congestion problem in Wi-Fi networks by introducing novel inter-AP cooperation solutions based on SDN[23,24].

2.3 | Our Motivations and Novel Contributions

From the analysis of the state-of-the-art, it emerges that LPWAs technologies are more suitable for dense environments including thousands of IoT devices. On the other hand, as we have mentioned in the introduction, the main shortcoming in LPWA IoT networks is the lack of coordination among devices that can cause spectrum congestion and energy inefficiency. The main contributions of this paper can be then summarized as follows:

> The proposed SDN-based IoT framework, to the best of our knowledge, is the first solution that provides subchannel sensing information to the IoT nodes through a centralized controller. Such subchannel sensing and monitoring techniques enable us to analyze and calculate the optimal subchannel assignment configuration across the IoT network, therefore the proposed method efficiently minimizes the limitations of uncoordinated LPWA radio access schemes. The existing radio access technologies in the IoT domain are not optimal and impact higher packet loss and round trip delay. Our novel RRM framework is proposed based on a new parameter, i.e., the number of subchannel reallocation attempts, which will be explained in Section 4. We will demonstrate how the proposed method outperforms the existing *SigFox* and *LoRa* standard schemes, assessed in [18], [19], in terms of packet collision rate and energy consumption.

The next section presents an overview on the LPWA communication system where our RRM framework can be applied to improve the performance of *SigFox* and *LoRa* standard schemes.

3 | LPWA COMMUNICATION SYSTEMS FOR IOT

3.1 | Radio Access Scheme for LPWA

In general, LPWA technologies use specific base stations to allow long-range communication with IoT devices deployed in a specific network. As illustrated in Fig. 1, the base station provides wireless connectivity and acts as a gateway between IoT and the backend infrastructure where the collected data is processed and stored. Here, the base station can be connected to the SDN infrastructure by means of optical fiber or cable connection where the transmission delay is negligible. Since it is envisaged that wireless IoT devices will be deployed in large numbers, the method of radio access becomes very important as this will dictate the performance of the IoT network and the quality of the wireless connections. Moreover, in many IoT applications, wireless devices may operate on battery power without recharging or replacement for many years. Therefore, the radio access scheme needs to be energy efficient such that the lifetime of IoT devices is extended[25].

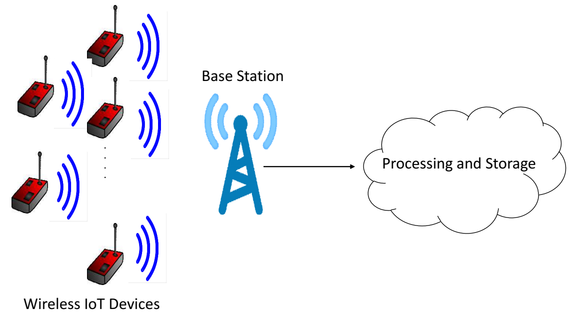

FIGURE 1 The architecture of LPWA communication for IoT.

There are broadly two possible techniques to access the subchannel in LPWA networks, namely: Listen-Before-Talk (LBT) and Duty Cycle[26]. In LBT, a device listens for communication on the subchannel before transmitting and waits for an acknowledgment after each transmission. If no acknowledgment is received after a predefined delay, the device retransmits after a random back-off time. This process is repeated until the transmission is successful. LBT is effective in reducing interference, however, it is only suitable for applications where devices are not energy-constrained, as the listening and retransmission process can result in costly energy usage[27].

The Duty Cycle restriction scheme, on the other hand, restricts the network access of IoT devices to a fixed total duration thus dispensing them from continuously listening to the subchannels. In this scheme, a device is assigned a time duration per hour that indicates the maximum sum of time the device can occupy the specific subchannel. For example, when a subchannel is restricted to a 1% duty cycle, a device is allowed 36 seconds of transmission per hour, in which such 36 seconds can be divided in any random or periodic order depending on the application and device requirements. Many LPWA solutions available in the market today, such as *LoRa* and *SigFox*, have adopted this access approach due to its optimized energy efficiency.

In both approaches, access to time frames and frequency channels is devised according to the rate of traffic generated by IoT devices which often follows a random pattern. This is largely due to the large number and heterogeneous functionality of these devices which makes it difficult to organize access. As a result, the probability of simultaneous access to the subchannel both in time and frequency domains increases as the number of IoT devices increases, which often results in transmission collisions. Therefore, our work considers duty cycle radio access for uplink transmissions as it is the most challenging issue in LPWA IoT communications.

3.2 | Spectrum for IoT in ISM Bands

In order to devise an efficient radio resource allocation approach for LPWA communication technologies, it is also necessary to assess the available spectrum and utilization on the ISM bands used by these technologies. For that, we focus on *SigFox* and *LoRa*, which both operate on the frequencies ranging from 868 MHz to 868.6 MHz for uplink transmissions with a maximum transmit power of 25 mW. For downlink transmissions, *SigFox* and *LoRa* use 869.40 MHz to 869.65 MHz with a maximum transmit power of 500 mW.

The availability of free subchannels in such ISM bands can be estimated by using spectrum sensing techniques, such as an energy detection method [28]. By comparing the received signal energy to the threshold energy level, which is a system defined parameter, the idle subchannels can be estimated. Such statistical information can be grouped in space and time to obtain the *Radio Environment Mapping*. In an IoT framework, such a radio database could help to coordinate uplink communications thereby significantly reducing the contention for resources [29].

4 | RADIO RESOURCE MANAGEMENT FRAMEWORK FOR IOT LPWA COMMUNICATION

The main challenge addressed in this paper is the uncoordinated allocation of subchannels and subframes to IoT devices for uplink communications. In cases the radio resource allocation strategy is not properly designed it may result in interference and severe transmit packet collisions. Therefore, we propose an RRM framework based on SDN which is implemented in the Radio Access Network (RAN). In this framework, the centralized SDN controller accesses and uses a set of IoT gateways to allocate each IoT device a specific subchannel through which it transmits without interfering with other devices as illustrated in Fig. 2.

The components of the proposed framework include the IoT devices, the IoT gateways and the SDN-based controller and, therefore, our implementation includes a modification in the RAN and SDN controller for the execution of our algorithm. In this paper, we analyze the proposed radio resource allocation framework for IoT devices within isolated IoT network scenario.

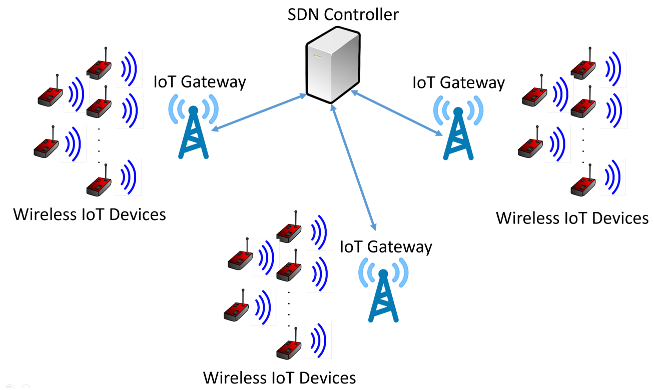

FIGURE 2 A centralized radio resource management framework to enable efficient IoT.

The design of this RRM framework follows a strategy that defines three essential components: a Spectrum Sensing Module, a Channel Status Database and a Channel Allocation Module. All three network components are located on top of the SDN controller as illustrated in Fig. 3. In this framework, the SDN controller gathers subchannel sensing information through the uplink control channels. The information is then processed at the SDN controller to evaluate the idle and busy subchannels. The available subchannels pool is then provided to the IoT gateway which schedules the subchannels with a low probability of interference to the IoT devices for uplink transmissions. The SDN controller and IoT gateway are either collocated or connected through wired or optical networks. This avoids the network congestion issue when there are a very large number of IoT devices. The subchannel availability computation, subchannel monitoring and allocation techniques are discussed in detail in this section.

Note that the radio band, duty cycle restrictions, physical and MAC layer technologies are according to the standards used by the *SigFox* and *LoRa* protocols. The details of the implementation of these LPWA protocols are out of the scope of this paper, see [6] for the details. The proposed RRM framework improves over the random subchannel allocation to individual IoT devices included in these communication technologies [18,19].

The strategy used in this RRM framework can be described using Algorithm 1 below. As shown in line 1, the number of subchannel allocation attempts, N, is set, which allows an IoT device to repeat the subchannel selection process if the previous attempt has resulted in choosing a busy subchannel, where the subchannel allocation is based on the Duty Cycle restriction approach.

According to this strategy, the status of each subchannel C that is highly likely to be idle is maintained and the IoT gateways allocate them with an optimal number of attempts

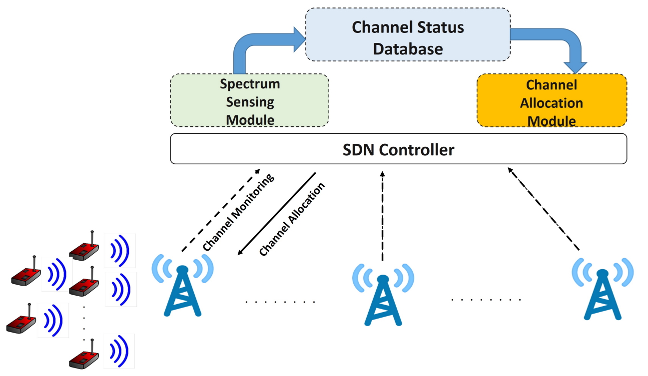

FIGURE 3 The proposed radio resource management framework and associated components.

TABLE 1 Symbols used in the paper.

Symbols	Descriptions
$x[K]$	Transmit signal sample
$y[K]$	Received signal sample
$w[k]$	AWGN sample (variance σ_w^2)
E_c	Received energy level
E_{th}	Threshold energy level
f_s	Sampling frequency
$\mathbb{P}_f$	False alarm probability
$\mathbb{P}_m$	Miss detection probability
$T_{s,c}$	Sensing duration
H_0, H_1	Null and alternative hypothesis
N	Channel reallocation attempt
D	Number of IoT devices

to the end IoT devices. When the subchannels are used, the related information is stored and updated in the Channel Status Database following a predefined time interval, which depends on the type of applications. For instance, home security and utility monitoring will have extremely low updates in comparison to road monitoring IoT devices in the busy road.

To assess the availability of each subchannel in each IoT gateway managed by the controller, the strategy relies on the Spectrum Sensing Module which executes the sub-Nyquist sampling as described in the following. Let the transmitted signal by an IoT device be $x = [x(0), x(1), \dots, x(K-1)]$, where $x(k)$ is the k^{th} sample in the sequence for $k = \{0, 1, \dots, K-1\}$. The sub-Nyquist sample of signal is $x(k) = x(kT_s)$ where $f_s = 1/T_s$ is the sampling rate and T_s is the symbol duration. If $w[k]$ is the received noise vector of the same size K, then the received signal monitored by spectrum sensor is $y[k] = x[k]+w[k]$ when the subchannel is occupied, or $w[k]$ when the subchannel is free. Then, the controller obtains a set of received signal $y = [y(0), y(1), \dots, y(K-1)]$ through the IoT gateway and in the Spectrum Sensing Module defines the received energy level E_c on subchannel c, where $c = \{1, \dots, C\}$, which is computed by averaging over k observed samples and is defined as follows:

$$\mathrm{E}_c = \frac{1}{K}\sum_{k=0}^{K-1} |y_c[k]|^2, \forall c. \tag{1}$$

Hence, the energy levels E_c are first obtained for all the C subchannels (line 2 of Algorithm 1). Then, $\mathrm{E}_c, \forall c$, is compared to the detection threshold, E_{th}, which is a system controlled parameter, that depends on the QoS requirements and subchannel conditions. For instance, when higher channel QoS is required, the system will be able to raise the E_{th} value correspondingly. As a result, the set of available subchannels, i.e., any subchannel c with $\mathrm{E}_c < \mathrm{E}_{th}$, with minimum detection errors are obtained (lines 3-5). Afterward, the Spectrum Sensing Module orders the subchannels according to their probability of interference, which is the weighted sum of probabilities of the false alarm, i.e., $\mathbb{P}_f$, and the miss detection, i.e., $\mathbb{P}_m$. Specifically, we can define $\mathbb{P}_f$ and $\mathbb{P}_m$, as follows:

$$\mathbb{P}_f = \Pr(E_c \geq E_{th}|H_0), \tag{2}$$

$$\mathbb{P}_m = \Pr(E_c < E_{th}|H_1), \tag{3}$$

where, H_0 (H_1) is the hypotheses of subchannel c is idle (busy). It can be demonstrated that for a large value of K, $\mathbb{P}_f$ and $\mathbb{P}_m$ can be computed under hypotheses H_0 and H_1 through the Q-function as follows[30]:

$$\begin{aligned}\mathbb{P}_f &= \Pr(\mathrm{E}_c \geq E_{th}|H_0)\\ &\approx \mathrm{Q}\left(\left(\frac{E_{th}}{\sigma_w^2} - 1\right)\sqrt{T_{s,c} f_s}\right),\end{aligned} \tag{4}$$

$$\begin{aligned}\mathbb{P}_m &= \Pr(\mathrm{E}_c < E_{th}|H_1)\\ &\approx \mathrm{Q}\left(\left(\frac{E_{th}}{\sigma_w^2} - \gamma_c - 1\right)\sqrt{\frac{T_{s,c} f_s}{2\gamma_c + 1}}\right).\end{aligned} \tag{5}$$

Here, σ_w^2 is the variance of additive white Gaussian noise (AWGN), $T_{s,c}$ is the sensing duration on subchannel c, and γ_c is the average Signal to Noise Ratio (SNR) of the received signal y_c and defined as follows:

$$\gamma_c = \frac{\mathrm{E}[|y_c|^2]|h_c|^2}{\sigma_w^2}, \tag{6}$$

where, $E[\cdot]$ indicates expected value and h_c is the channel gain of subchannel c. Furthermore, E_{th} is the energy detection threshold, which varies from 0 to ∞, and decides whether the subchannel is busy or idle. It primarily depends on thresholds for miss detection and false alarm probabilities. In this paper, we consider E_{th} when maximum tolerable probabilities of miss

Algorithm 1 RRM allocation algorithm in the considered IoT framework

1: *Set* N the number of subchannel allocation attempt
2: *Obtain* the subchannel information E_c for subchannel $\mathbf{c} = \{1, \dots, C\}$ from Spectrum Sensing Module
3: **if** $E_c < E_{th}, \forall c$ **then**
4:     *Get* the available channel set $X \in \mathbf{c}$
5: **end if**
6: *Order* the subchannels X for uplink according to lower probability of interference, i.e., $\mathbb{P}_m \mathrm{Pr}(H_1) + \mathbb{P}_f \mathrm{Pr}(H_0)$, as a channel quality indicator
7: *Obtain* the subchannel status, C_s, for each X, and update the Channel Status Database
8: **for** $i = 1, 2 \dots, N$ **do**
9:     *Select* random slot and subchannel
10:     **if** slot(i) = idle and $C_s(i)$ = available **then**
11:         *Exit* for loop
12:     **end if**
13:     *Update* the Channel Status Database
14: **end for**
15: **for** each device $d = 1, 2 \dots, D$ **do**
16:     **if** IoT device has packet to transmit **then**
17:         *Execute* RRM for *LoRaWAN* and *SigFox*
18:     **end if**
19: **end for**

detection and false alarm are 0.1 and 0.2, respectively, according to the IEEE 802.22 standard. Similarly, the probabilities of states H_0 and H_1 are denoted by $\mathrm{Pr}(H_0)$ and $\mathrm{Pr}(H_1)$, respectively, and their initial distributions are assumed according to $\mathrm{Pr}(H_0) + \mathrm{Pr}(H_1) = 1$.

The Spectrum Sensing Module then updates the Channel Status Database with the information about the probability of interference, i.e., $\mathbb{P}_m \mathrm{Pr}(H_1) + \mathbb{P}_f \mathrm{Pr}(H_0)$, as a subchannel quality indicator for uplink transmissions (lines 6-7). Note that such information may not be completely accurate due to the inevitable probabilities of false alarm and miss detection in the spectrum sensing process.

Since the number of available subchannels is limited, the value of N depends on the end-to-end delay requirement, number of IoT devices competing for the subchannel which is denoted in Algorithm 1 as D, and the number of available subchannels. When the number of IoT devices is relatively small, it will be reasonable to set N to a small number. On the other hand, this value should be larger if the size of the IoT network is relatively big. In such a case, however, a very important trade-off will need to be made: a large value for N might result in a device that keeps attempting to access an available subchannel for a long time, thus, affecting the performance of the communication in terms of end-to-end delay or QoS. Moreover, it is also possible that the subchannels allocated at $t = 0$ may become invalid at $t > 0$ when a large N is set due to unavoidable sensing errors, $\mathbb{P}_m$ and $\mathbb{P}_f$.

In addition, and as explained previously in Section 3, both *SigFox* and *LoRa* do not use the listen-before-talk protocol due to the energy constraints. The IoT devices, therefore, select a random slot and subchannel to connect to the gateway following the predefined duty cycle. In our proposed framework, however, when the IoT device tries to initiate the transmission of a data packet, the SDN controller triggers the Channel Allocation Module which accesses the Channel Status Database to find a suitable subchannel, as shown in lines 8-14 in Algorithm 1. Note that a chosen subchannel needs to be exclusively used by the transmitting IoT device and its status will be updated as busy in the Channel Status Database.

The Channel Allocation Module has the specific task of channel reallocation attempts which is a system defined parameter and primarily depends on the network size and QoS requirements. When this module detects that the chosen subchannel is being used by another device, it will repeat the process up to a maximum N times. If the allocation of a free subchannel to the IoT device proves unsuccessful after N attempts, it will then forcefully allocate a subchannel randomly to the device, which may or may not be in idle state. If the allocation of available subchannels to the IoT device is successful, the LPWA communication protocol (i.e., *SigFox* or *LoRa*) is executed, thus allowing the transmission of the data packet, as described in lines 15-19 of Algorithm 1. In Section 5, we will discuss the obtained results for different values of N.

5 | PERFORMANCE EVALUATION

To evaluate our system, we analyze the performance of the subchannel monitoring functionality of the proposed method against the standard *SigFox* and *LoRa* schemes based on random access allocation and assessed in [18] and [19].

5.1 | Subchannels Monitoring

In this subsection, we present the subchannel monitoring scheme introduced in Section 4. We deployed *RealTek RTL2832U* radio receivers [31] as spectrum sensors at uniform locations to monitor the status of all $c = \{1, \dots, C\}$ subchannels, each of 125 kHz, used by the existing two LPWA technologies. The sampling frequency of 2.4 MHz is chosen and it is decimated by a factor of 12 so that only one of 12 samples are obtained at the signal processor. The receiver tuner gain is set to 25 dB.

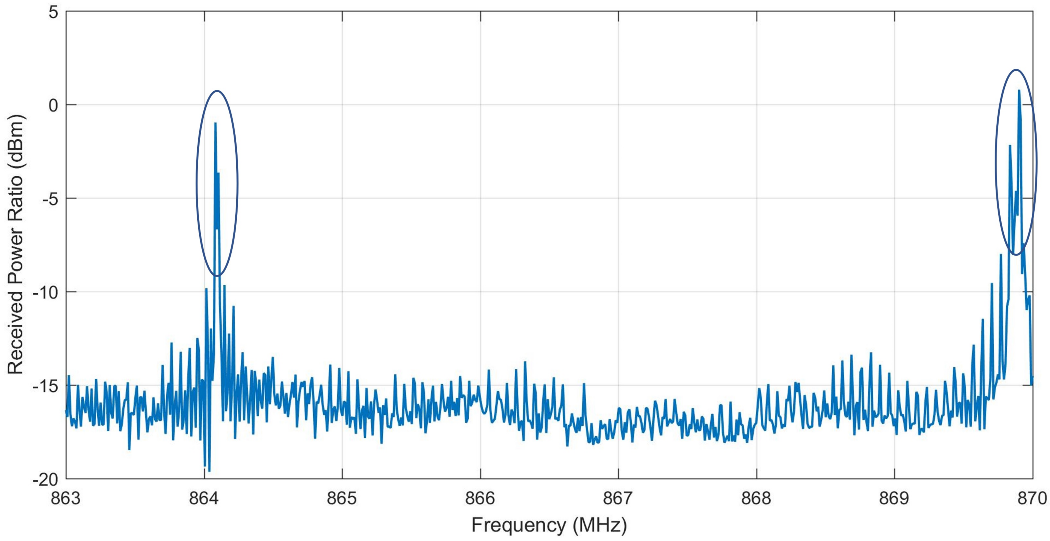

FIGURE 4 The instantaneous signal measurement in ISM 868 MHz band in the monitored area.

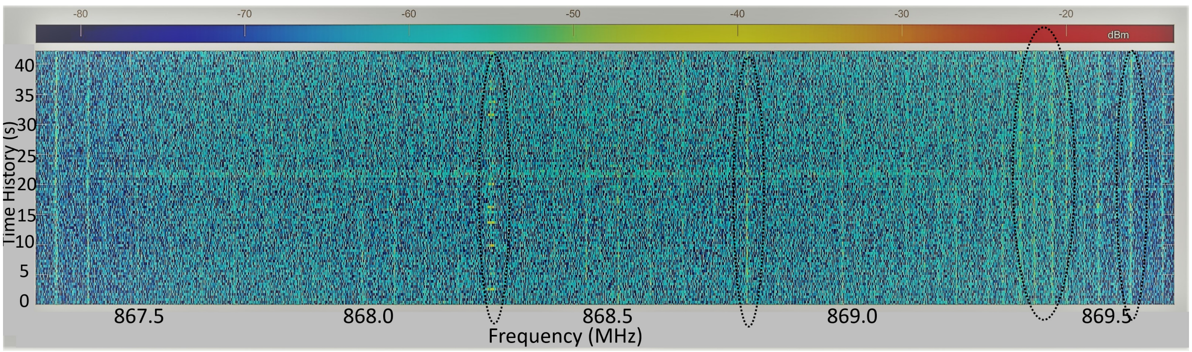

FIGURE 5 The time-frequency diagram of received signal showing both uplink and downlink subchannels for *LoRa* and *SigFox* in the monitored area.

The computing of subchannel power is facilitated by the Software-Defined Radio (SDR) package available in MATLAB. The spectrum sensors perform the subchannel sensing and measurement within a gateway transmission range to improve the spatio-temporal sensing results. The SDR sensor was deployed at ten different locations in the monitored area to create the subchannel database. It is true that a larger number of radio receivers would lead to more accurate results but this would be at the expense of increasing the computational complexity. In a real deployment, however, we need a large number of sensors to consider the tolerable probabilities of miss detection and false alarm within 0.1 and 0.2, respectively, as mentioned in Section 4.

The deployed spectrum sensors determine the subchannel information of the 868 MHz ISM bands by using (1) and the measurements of access of these bands are shown in Fig. 4. Here, $k = 1, \dots, N$ samples are taken periodically for the energy detection method to measure the energy profile of subchannels. The information is then transmitted to a MATLAB-based SDN controller for further processing and to fine-tune the subchannel states. As shown in the figure, a subset of radio channels is being accessed in the range of 868 MHz bands which are observed as two spikes of observed signal power.

As a matter of fact, such transmissions cannot be easily observed due to the fact that a very small duty cycle is imposed on those bands, typically 10% in the downlink and 1% in the uplink subchannels. In addition, when very limited numbers of *SigFox* and *LoRa* devices are installed in the measurement area, the instantaneous signals in uplink and downlink are difficult to trace. For instance, an instantaneous packet transmission, i.e., high energy detection, has been observed at the 864 MHz bands at the time of measurement.

Fig. 5 shows the time-frequency plot for the uplink and downlink frequencies that can be used in *LoRa* and *SigFox*. We can observe from this figure that the 868.25 MHz channel in the uplink band is being continuously accessed, as we notice high levels of power ratio, denoted by a high received signal in the range from approximately -50 dBm to -10 dBm. We also notice that within 40 seconds of observation, there are still available subchannels to be used for the uplink and downlink communications in our proposed framework. Moreover, larger the number of measurement, higher will be the accuracy but at the cost of increasing the computational complexity and power consumption on the IoT devices. The channel has been monitored for 40 seconds to create the subchannel database in order to handle a trade-off between complexity and accuracy.

Based on the subchannel monitoring result illustrated in Fig. 4 and Fig. 5, the Spectrum Sensing Module orders the subchannels according to (1) - (6) and stored them in the *Channel Status Database*. Furthermore, the *Channel Allocation Module* assigns the subchannels to the IoT devices based on different values of channel allocation attempts N set during the simulation campaign.

5.2 | Simulation Setup

The performance of the proposed channel assignment algorithm was measured by counting the number of collisions, i.e., when two IoT devices transmit at the same time and the same subchannel. This is measured for various user densities, i.e., number of IoT devices which contend for the scarce radio resources. It is important to note that higher system capacity, longer battery life, and wider coverage are the fundamental goals of LPWA technologies [32]. To achieve this, the proposed RRM framework addresses the lack of coordination among IoT devices in order to reduce collisions thereby optimizing network capacity and reducing battery consumption [33]. Therefore, we obtain the success rate of packet transmissions among IoT devices to measure the relative performance gain of the proposed resource allocation framework.

To assess the performance of the proposed RRM framework, we simulated an IoT network where a number of devices varying from 50 to 1000 are deployed randomly within the transmission range of the IoT gateway. The IoT devices perform the channel sensing by means of the energy detection method to find the available subchannels based on the obtained channel QoS. The information is then transmitted to the IoT gateway using Pure ALOHA access due to the fact that both *LoRaWAN* and *SigFox* have adopted it for uplink communication [34]. ALOHA is an asynchronous protocol where the end devices communicate when they have data ready to send, either scheduled or event-driven. Since ALOHA operates well under low-traffic loads, only subset of IoT devices takes part in the spectrum sensing phase in the proposed method so that there are no uplink collisions while transmitting the channel sensing information.

The subchannel sensing information is then provided to the SDN controller through the simulated backhaul channels for further processing. A pool of subchannels for the data transmission is then obtained as explained in the previous section. When the SDN controller receives the data transmission notification, it creates a user subchannel pair, which are then logically allocated to the IoT devices through the IoT gateway as described in Algorithm 1. By the time IoT device transmits the data packets, the subchannel may no longer be valid. This problem can be tackled, as proposed, by allowing the IoT device to transmit on orthogonal channels up to the maximum number of reallocation attempts value, i.e., N.

The evaluation of the proposed method is focused on the two most popular LPWA technologies: *LoRa* and *SigFox* [17], where we assessed the performance of both protocols with and without the proposed RRM framework. In these simulations, we assume that IoT devices can transmit at the maximum power of 10 dBm and 14 dBm and that both the IoT devices and the gateway use an omnidirectional antenna, as is the case in *LoRa* and *SigFox* [18].

The number of packets in each device is randomly selected between 1 or 2. Therefore, every device has at least one packet to transmit, i.e., the minimum numbers of packets on the considered IoT network scenario is equal to the number of devices. This emulates the highly similar scenario to the majority of real IoT applications where a very limited number of packets per hour are generated. Moreover, we consider 60 seconds of simulation duration in which the proposed algorithm runs. Therefore, this is equivalent to long duration in real IoT system models.

5.3 | Performance Evaluation under *LoRa*

For the evaluation of *LoRa*'s performance in a dense IoT environment with and without our RRM framework, we simulate three scenarios according to the method followed by IoT devices to access the subchannel:

- **Scenario 1**: In this scenario, IoT devices access the subchannel following a 2% duty cycle where there is no listen-before-talk as is the case with the *LoRa* protocol.
- **Scenario 2**: In this scenario, the proposed RRM framework is implemented to coordinate IoT device access to the subchannel, with the number of attempts $N = 2$, while keeping the 2% duty cycle of *LoRa*.
- **Scenario 3**: In this scenario, the proposed RRM framework is implemented to coordinate IoT device access to

the subchannel, with the number of attempts $N = 5$, while keeping the 2% duty cycle of *LoRa*.

Due to the nature of the proposed system model where IoT devices go to sleep mode unless they have something to transit and the *LoRa* server, i.e., IoT gateway, schedules the transmit and receive resources, class A *LoRa* nodes are considered in this paper. However, the proposed subchannel sensing and resource allocation method are equally applicable for all type of *LoRa* nodes because it aims to distribute the available resources optimally based on some criteria, e.g., channel quality.

Fig. 6 shows the obtained results in terms of the number of unsuccessful transmissions when the number of IoT devices trying to access the subchannels is increased for the three simulation scenarios. The results show that the number of unsuccessful transmissions in scenario 1 (blue-dotted graph) increases linearly as the number of devices competing to access the subchannel increase. Such results are expected because the lack of coordination will result in collisions among device transmissions and this will increase as the number of devices increases. The figure shows a significant improvement under the proposed RRM framework in both scenario 2 (red-dotted graph) and scenario 3 (yellow-dotted graph). These improvements indicate that our RRM framework helps to maximize the probability of IoT devices accessing unoccupied subchannels, thus decreasing the number of collisions. These improvements, however, come at a price as the allocation of subchannels to devices might increase their waiting time and incur more communication delay. Therefore, although most IoT applications are delay-tolerant, it will be important to use this framework to develop trade-offs between packet collisions and delay.

Similarly, the performance of the proposed resource allocation technique is studied when the transmit power is 10 dBm and 14 dBm. It can be observed that when transmit power is increased from 10 dBm to 14 dBm, the performance gain is not significantly high due to the fact that higher transmit power increases the interference and channel reallocation will further limit the performance. Therefore, for the energy efficiency point of view, the optimal transmit power of 10 dBm is chosen for further simulations.

Next, we repeated the experiment above for the three scenarios while decreasing the duty cycle ratio from 2% to 0.9% and took the same measurements as previously, which are shown in Fig. 7. The obtained results show that reducing the duty cycle ratio reduces the number of collisions for the three scenarios in comparison to the results shown in Fig. 6. Such results are again expected as reducing the duty cycle, in turn, reduces the number of times an IoT device tries to access the subchannel. The obtained results show that under the RRM framework in both scenario 2 (red-dotted graph) and scenario 3 (yellow-dotted graph), the number of collisions is almost the same. This

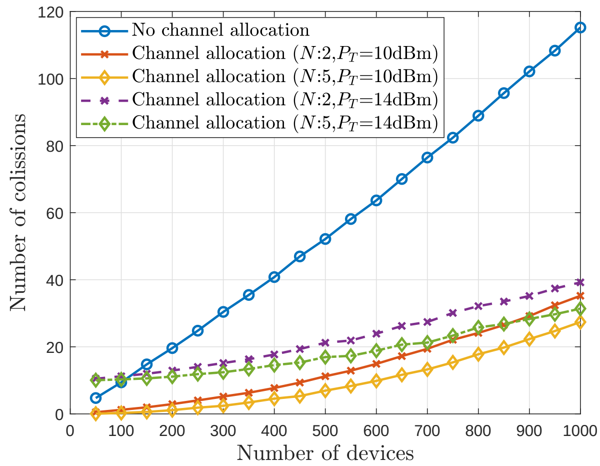

FIGURE 6 Evaluation of number of collisions *vs.* the number of devices in *LoRa* for various numbers of resource allocation attempts at higher duty cycle (2%).

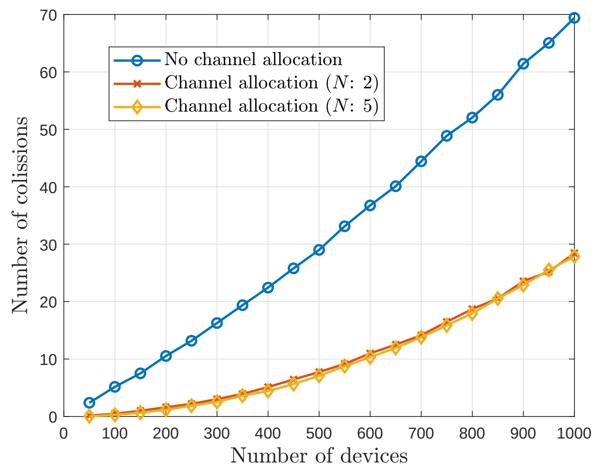

FIGURE 7 Evaluation of number of collisions *vs.* the number of devices in *LoRa* for various numbers of resource allocation attempts at lower duty cycle (0.9%).

is due to the fact that the reduction of the duty cycle ratio will result, as mentioned previously, in fewer attempts to access the subchannel simultaneously. Therefore, the number of attempts to access the channel, defined in Algorithm 1 as N, will have almost no effect on the performance of the proposed RRM framework.

5.4 | Performance Evaluation under *SigFox*

Unlike *LoRa*, a device communicating using *SigFox* needs to transmit each data packet three times on three randomly chosen subchannels, following the duty cycle constraint below 1%.

Therefore, the probability of collision with another transmitting device not only depends on the chosen subchannels but also on the size of the data packet transmitted.

To assess the performance of *SigFox* in a dense IoT environment, with and without our RRM framework, we simulated four scenarios according to the method followed by the IoT devices to access the subchannel and data packet size:

- **Scenario 1:** In this scenario, IoT devices transmit on three randomly chosen subchannels, with the data packet size set to 6 Bytes, which is a relatively small packet size in *SigFox*.
- **Scenario 2:** In this scenario, IoT devices transmit on three randomly chosen subchannels, with the data packet size set to 12 Bytes, which is the maximum packet size in *SigFox*.
- **Scenario 3:** In this scenario, IoT devices transmit on the three best possible subchannels, i.e., with a lower probability of interference, using the proposed RRM framework, with the data packet size set to 6 Bytes.
- **Scenario 4:** In this scenario, IoT devices transmit on the three best possible subchannels, i.e., with a lower probability of interference, using the proposed RRM framework, with the data packet size set to 12 Bytes.

The obtained results, shown in Fig. 8, indicate that the measured number of collisions are higher for scenario 1 (yellow-dotted graph) and scenario 2 (blue-dotted graph) in comparison to the number of collisions for scenario 3 (purple-dotted graph) and scenario 4 (red-dotted graph), respectively.

The number of collisions in scenario 2 is the highest in comparison to scenario 1 due to the fact that when the packet size is doubled, i.e., from 6 Bytes to 12 Bytes, it will take a longer frame duration to transmit a packet. This will result in higher number of packet collisions shown in Fig. 8. Furthermore, when the number of IoT devices increases, the collision rate also increases significantly both when using the random subchannel selection and when using the proposed RRM framework. These results are caused by the three simultaneous packet transmissions approach used in *SigFox*. The results obtained in scenario 4 show that, despite the use of the RRM framework, the measured number of collisions is higher than in scenario 1 primarily due to the larger packet size. However, when the RRM framework is applied for the same packet size, i.e., either 6 Bytes or 12 Bytes, as it is the case in scenarios 3 and 4, respectively, there is a significant improvement in terms of the number of collisions. These results indicate that in addition to the use of a robust RRM strategy in *SigFox*, it is very important to optimize the packet size, in order to achieve better performance.

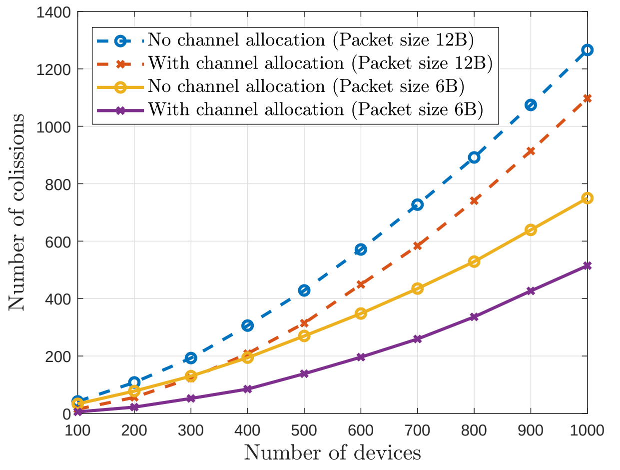

FIGURE 8 Evaluation of number of collisions *vs.* the number of devices in *SigFox* for various numbers of resource allocation attempts and packet sizes.

As with *LoRa*, a similar scenario has been further investigated where the duty cycle is restricted to 0.9% and 2% in *SigFox*. Since the duty cycle indicates how long an IoT device can transmit during the 24 hours period, there would be a significant reduction of packet collisions when this parameter is restricted. In Fig. 9, we can observe an improvement in terms of the number of collisions (purple-solid graph *vs.* yellow-solid graph) when the proposed RRM framework is used with the duty cycle fixed to 2%. Therefore, similar to the *LoRa* network scenario, the packet collision rate can be improved in the proposed framework by optimally selecting the number of subchannel allocation attempts, N.

A similar performance improvement can be observed in Fig. 9 for the case of the duty cycle set to 0.9% (red-dotted graph *vs.* blue-dotted graph). However, the improvement is not as significant as in the packet size study in Fig. 8. This is primarily due to the mechanism of three identical packet transmissions which have an effect on the number of collisions. Therefore, it can be concluded that the proposed RRM framework improves the *SigFox* performance for a high duty cycle, larger packet size as well as higher network density.

The end-to-end delay is not a very critical parameter in many IoT applications. However, for the higher the value of N we set, it is obvious that the delay performance starts degrading. Here, the simulation setup may not provide the accurate delay profile, so a real *LoRa* network with the proposed resource allocation algorithm needs to be deployed to study the end-to-end delay performance which is some future work under consideration.

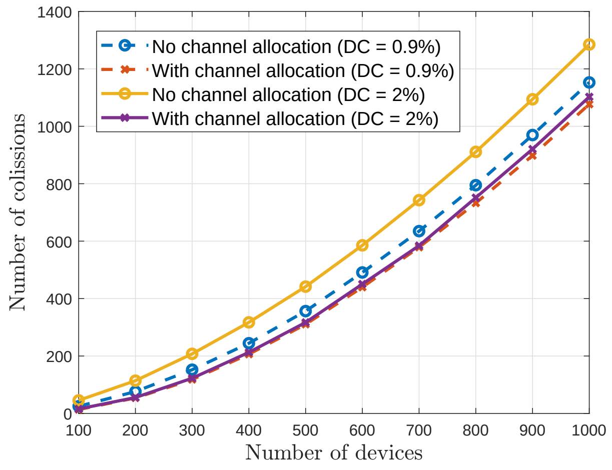

FIGURE 9 Evaluation of number of collisions *vs.* the number of devices in *SigFox* for various numbers of resource allocation attempts and duty cycles.

5.5 | Analysis of Energy Efficiency

In this section, we analyze the energy efficiency (EE) and energy consumption model of the proposed resource allocation technique against the standard *LoRa* protocol. First of all, the energy consumption by a *LoRa* node to transmit one data packet is evaluated. Here, the selection of the transmission parameters directly impacts the energy consumption of the device. Such parameters are, for instance, the transmit power, coding rate, bandwidth and duty cycle, amongst others. For various selection of radio parameters, the energy consumption per packet transmission is evaluated based on the software *LoRa Calculator*[35]. The selection of radio parameters, unless otherwise stated, is as shown in Table 2, which closely follows the specifications for LoRa physical and MAC layer standards. In such a case, the average energy consumption for transmitting one packet of data is approximately 48.68 mJoule.

As mentioned in the previous section while describing *LoRa* performance, two different duty cycles have been considered, i.e., 2% and 0.9%, for performance comparison purposes. In this section, the EE is evaluated by calculating the number of packets that are successfully transmitted for the whole network divided by total energy consumption. Since a data packet of 6 Bytes is selected, we finally obtain EE as the number of bits that are successfully transmitted using 1 mJoule of Energy.

The analysis of EE, when the duty cycle is set to 2%, is shown in Fig. 10 both for no subchannel allocation and the proposed technique of subchannel allocation while varying the number of subchannel allocation attempts, $N = 2$ and $N = 5$. As it can be observed in the figure, the EE deteriorates almost linearly when the number of LoRa devices competing for the radio resources are increased in all cases. However,

TABLE 2 *LoRa* radio parameter selection for energy consumption model.

Radio Parameters	Selected Values
Operating frequency	868 MHz (Europe)
Transmit power	10 dBm
Packet payload	6 Bytes
Bandwidth	125 kHz
Packet header	Disabled
coding rate	4/5
Battery capacity	1.8 v, 1000 mAh
Spreading factor	8
Preamble length	10 symbols
ACK length	2 Bytes

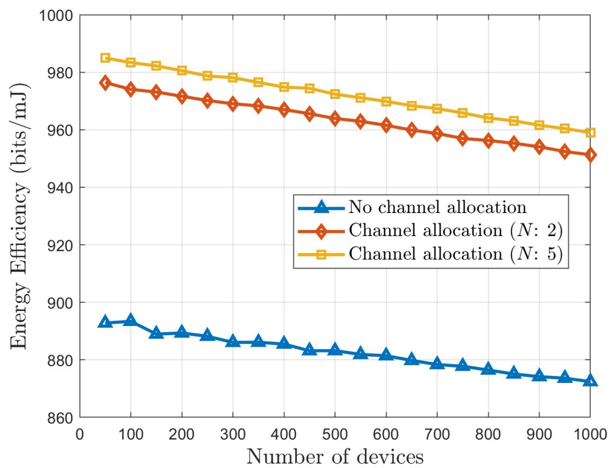

FIGURE 10 Evaluation of energy efficiency *vs.* the number of *LoRa* nodes for the proposed method and no subchannel allocation under duty cycle of 2%.

The proposed subchannel allocation technique improves the EE thereby successfully transmitting almost 90 more bits per mJoule than the case of no subchannel allocation. On the other hand, we can still improve the EE by increasing the number of channel attempt (N), but the improvement is not significantly higher. This also shows that optimal N should be selected to reduce the computational complexity while keeping the performance within the same level.

Within a similar *LoRa* network where the duty cycle is reduced to 0.9%, the EE gain is slightly lowered than in cases of higher duty cycle as shown in Fig. 11. This is due to the fact that there is a lower probability of packet collision or packet drop. However, by implementing the proposed subchannel allocation scheme, the EE is significantly higher than the case of no

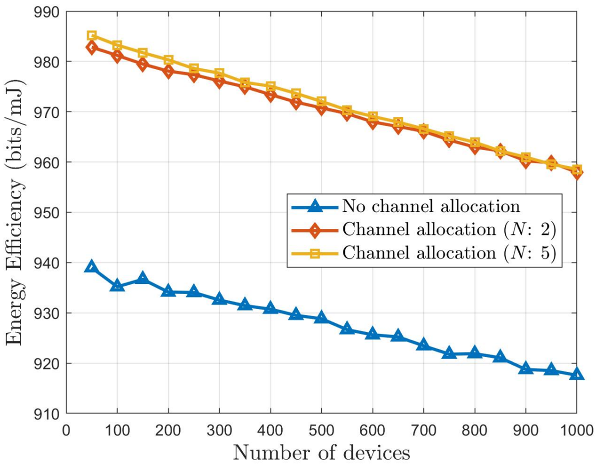

FIGURE 11 Evaluation of energy efficiency *vs.* the number of *LoRa* nodes for the proposed method and no subchannel allocation under duty cycle of 0.9%.

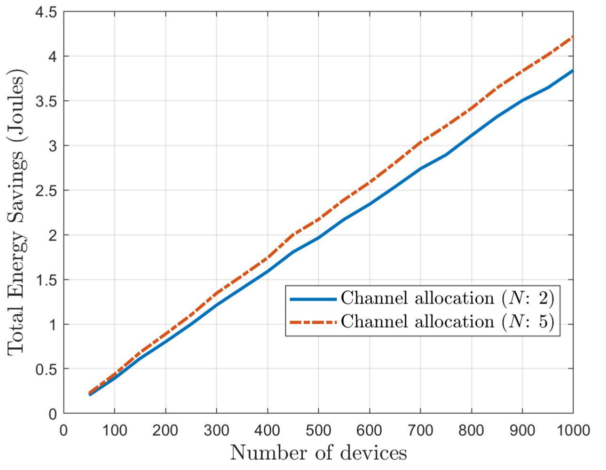

FIGURE 12 Evaluation of energy savings of the proposed method of subchannel allocation in *LoRa* networks in comparison to the case of no subchannel allocation.

channel allocation method. In such a case of low duty cycle, the choice of N does not play a vital role, as shown in Fig. 11, due to the availability of a slightly large number of vacant subchannels.

Since the proposed resource allocation technique improves the packet collision rate and energy efficiency, it apparently consumes lower energy from the battery source. In Fig. 12, total energy saving in the *LoRa* network has been shown for channel allocation attempt, i.e., N to be 2 and 5. It is increasing proportionally according to the number of *LoRa* devices because it is simply the sum of energy saving in each device. However, the optimal choice of the number of attempts, i.e., N, is necessary because even a higher selection of N does not significantly save energy. Therefore, it can be observed that even the large *LoRa* network will save energy proportionally when the proposed resource allocation technique is implemented.

6 | CONCLUSIONS

Wireless connectivity is a major requirement for the realization of the vision of the Internet-of-Things. Although a number of radio access technologies are being considered to satisfy this requirement, LPWA networks technologies are gaining increased popularity as their low cost and easy deployment make them ideal for many IoT applications. However, due to the unlicensed nature of the spectrum used by LPWA, radio resource allocation should be considered a critical task, especially as the size of IoT networks keeps growing.

In this paper, we addressed the problem of spectrum congestion in LPWA IoT networks by proposing an RRM framework based on SDN. The proposed framework consists of three components, a spectrum sensing module, a channel status database and a channel allocation module, to cooperatively function for the time slot and frequency subchannel allocation to IoT devices. The main aim of this framework is to minimize the number of packet collisions during uplink transmissions from the IoT devices to the gateway. We evaluated our RRM framework by simulating two IoT technologies, namely *LoRa* and *SigFox*, upon which we implemented the proposed method. The simulation results demonstrate that the proposed resource allocation significantly improves the packet collision rate, energy efficiency and energy consumption in various IoT network conditions. As future work, we will further investigate the impact of the proposed RRM approach on transmission delay as well as explore, implement and test the framework by deploying the SDN-based *LoRa* network in a real network environment. We will also consider the inclusion of compressive sensing in the Spectrum Sensing Module, which is a suitable option for IoT applications because of its reduced sampling rate and computational complexity[29].

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Conflict of interest

The authors declare no potential conflict of interests.

References

1. Gubbi Jayavardhana, Buyya Rajkumar, Marusic Slaven, Palaniswami Marimuthu. Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems.* 2013;29(7):1645 - 1660.

2. Hou Z., Chen H., Li Y., Vucetic B.. Incentive Mechanism Design for Wireless Energy Harvesting-Based Internet of Things. *IEEE Internet of Things Jour..* 2017;PP(99):1-1.

3. Cao Y., Duan D., Cheng X., Yang L., Wei J.. QoS-Oriented Wireless Routing for Smart Meter Data Collection: Stochastic Learning on Graph. *IEEE Transactions on Wireless Communications.* 2014;13(8):4470-4482.

4. Ju Q., Li H., Zhang Y.. Power Management for Kinetic Energy Harvesting IoT. *IEEE Sensors Journal.* 2018;18(10):4336-4345.

5. Vejlgaard B., Lauridsen M., Nguyen H., Kovacs I. Z., Mogensen P., Sorensen M.. Interference Impact on Coverage and Capacity for Low Power Wide Area IoT Networks. *2017 IEEE Wireless Communications and Networking Conference (WCNC).* 2017;:1-6.

6. Lauridsen M., Vejlgaard B., Kovacs I. Z., Nguyen H., Mogensen P.. Interference Measurements in the European 868 MHz ISM Band with Focus on LoRa and SigFox. *2017 IEEE Wireless Communications and Networking Conference (WCNC).* 2017;:1-6.

7. Bouzouita Meriam, Hadjadj-Aoul Yassine, Zangar Nawel, Rubino Gerardo. Estimating the number of contending IoT devices in 5G networks: Revealing the invisible. *Transactions on emerging telecommunications technologies.* 2018;:e3513.

8. Robertazzi Thomas G.. Software-Defined Networking:81–87. Cham: Springer International Publishing 2017.

9. McKeown Nick, Anderson Tom, Balakrishnan Hari, et al. OpenFlow: Enabling Innovation in Campus Networks. *SIGCOMM Comput. Commun. Rev..* 2008;38(2):69–74.

10. Centenaro M., Vangelista L., Zanella A., Zorzi M.. Long-range communications in unlicensed bands: the rising stars in the IoT and smart city scenarios. *IEEE Wireless Communications.* 2016;23(5):60-67.

11. Vannieuwenborg Frederic, Verbrugge Sofie, Colle Didier. Choosing IoT-connectivity? A guiding methodology based on functional characteristics and economic considerations. *Transactions on Emerging Telecommunications Technologies.* 2018;29(5):e3308.

12. Zhang X., Zhang M., Meng F., Qiao Y., Xu S., Hour S.. A Low-Power Wide-Area Network Information Monitoring System by Combining NB-IoT and LoRa. *IEEE Internet of Things Journal.* 2019;6(1):590-598.

13. Bluetooth Core Specification 4.2: Bluetooth SIG https://www.bluetooth.org/DocMan/handlers/DownloadDocAccessed: Dec. 2014; 2014.

14. Cao H., Leung V., Chow C., Chan H.. Enabling technologies for wireless body area networks: A survey and outlook. *IEEE Communications Magazine.* 2009;47(12):84-93.

15. IEEE Standard for Low-Rate Wireless Networks. *IEEE Std 802.15.4-2015 (Revision of IEEE Std 802.15.4-2011).* 2016;:1-709.

16. Yang Z., Xu W., Pan Y., Pan C., Chen M.. Energy Efficient Resource Allocation in Machine-to-Machine Communications with Multiple Access and Energy Harvesting for IoT. *IEEE Internet of Things Journal.* 2017;PP(99):1-1.

17. Nolan K. E., Guibene W., Kelly M. Y.. An evaluation of low power wide area network technologies for the Internet of Things. *2016 International Wireless Communications and Mobile Computing Conference (IWCMC).* 2016;:439-444.

18. Vejlgaard B., Lauridsen M., Nguyen H., Kovacs I. Z., Mogensen P., Sorensen M.. Coverage and Capacity Analysis of Sigfox, LoRa, GPRS, and NB-IoT. *2017 IEEE 85th Vehicular Tech. Conf. (VTC Spring).* 2017;:1-5.

19. Magrin Davide, Centenaro Marco, Vangelista Lorenzo. Performance evaluation of LoRa networks in a smart city scenario. *Communications (ICC), 2017 IEEE International Conference On.* 2017;:1–7.

20. Palattella M. R., Dohler M., Grieco A., et al. Internet of Things in the 5G Era: Enablers, Architecture, and Business Models. *IEEE Journal on Selected Areas in Communications.* 2016;34(3):510-527.

21. Zucchetto D., Zanella A.. Uncoordinated Access Schemes for the IoT: Approaches, Regulations, and Performance. *IEEE Communications Magazine.* 2017;55(9):48-54.

22. Adelantado F., Vilajosana X., Tuset-Peiro P., Martinez B., Melia-Segui J., Watteyne T.. Understanding the Limits of LoRaWAN. *IEEE Communications Magazine.* 2017;55(9):34-40.

23. Seyedebrahimi M., Bouhafs F., Raschellà A., Mackay M., Shi Q.. Fine-Grained Radio Resource Management to Control Interference in Dense Wi-Fi Networks. *2017 IEEE Wireless Communications and Networking Conference (WCNC).* 2017;:1-6.

24. Seyedebrahimi M., Bouhafs F., Raschellà A., Mackay M., Shi Q.. SDN-based channel assignment algorithm for interference management in dense Wi-Fi networks. *2016 European Conference on Networks and Communications (EuCNC).* 2016;:128-132.

25. Mikhaylov K., Petaejaejaervi .. Juha, Haenninen T.. Analysis of Capacity and Scalability of the LoRa Low Power Wide Area Network Technology. *European Wireless 2016; 22th European Wireless Conf..* 2016;:1-6.

26. din M. Qutab, Hazmi A., Carpio L. F. Del, et al. Duty Cycle Challenges of IEEE 802.11ah Networks in M2M and IoT Applications. *European Wireless 2016; 22th European Wireless Conf..* 2016;:1-7.

27. Laya A., Kalalas C., Vazquez-Gallego F., Alonso L., Alonso-Zarate J.. Goodbye, ALOHA!. *IEEE Access.* 2016;4:2029-2044.

28. Raschellà Alessandro, Umbert Anna. Implementation of Cognitive Radio Networks to evaluate spectrum management strategies in real-time. *Computer Communications.* 2016;79(Supplement C):37 - 52.

29. Qin Z., Liu Y., Gao Y., Elkashlan M., Nallanathan A.. Wireless Powered Cognitive Radio Networks With Compressive Sensing and Matrix Completion. *IEEE Transactions on Communications.* 2017;65(4):1464-1476.

30. C. D. G., Navaie K.. A Low-Latency Zone-Based Cooperative Spectrum Sensing. *IEEE Sensors Journal.* 2016;16(15):6028-6042.

31. Sergienko A. B.. Software-defined radio in MATLAB Simulink with RTL-SDR hardware. *2014 International Conference on Computer Technologies in Physical and Engineering Applications (ICCTPEA).* 2014;:160-161.

32. Yang W., Wang M., Zhang J., et al. Narrowband Wireless Access for Low-Power Massive Internet of Things: A Bandwidth Perspective. *IEEE Wireless Communications.* 2017;24(3):138-145.

33. FerrÃľ G., Simon E. P.. Packet collision analysis when heterogeneous unlicensed IoT technologies coexist. *IET Networks.* 2018;7(6):384-392.

34. Adelantado Ferran, Vilajosana Xavier, Tuset-Peiro Pere, Martinez Borja, Melia-Segui Joan, Watteyne Thomas. Understanding the limits of LoRaWAN. *IEEE Communications magazine.* 2017;55(9):34–40.

35. LoRa Calculator https://www.semtech.com/uploads/documents/SX1272LoRaCalculatorSetup1_1.zip[Accessed: June 2018]; 2018.

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