Exploring Partially Overlapping Channels for Low-power Wide Area Networks

LU WANG, Shenzhen University, China
XIAOKE QI, China University of Political Science and Law, China
RUIFENG HUANG, Shenzhen University, China
KAISHUN WU, The Hong Kong University of Science and Technology (Guangzhou), Shenzhen University, China
QIAN ZHANG, The Hong Kong University of Science and Technology, China

Supporting a massive amount of Internet of Things applications requires a large pool of spectrum. DSM is a promising ecosystem to improve the spectrum efficiency. In the era of LoRaWAN, the physical hardware constraints, along with the bandwidth-hungry applications pose new challenges. In this article, we investigate a novel deep-reinforcement-learning-based spectrum-sharing paradigm, termed Intelligent Overlapping, that explores partially overlapping channels for concurrent spectrum access in LoRaWAN. Our key insight is to leverage the coding redundancy to expand the available spectrum without complicated data processing algorithms. In particular, we learn the extra coding redundancy from the data on the non-overlapping spectrum via a deep-Q-learning network, and we apply such redundancy to recover the data on the overlapping spectrum. In the Media Access Control layer, we predict the channel condition and strategically learn and assign the appropriate overlapping portion to the concurrent access end devices. In the Physical layer, we harness interleaving to randomize the mutual interference to ensure that all the data remains decodable. Simulation results demonstrate that Intelligent Overlapping greatly improves the spectrum efficiency with a fast convergence rate compared to the conventional DSM mechanisms.

CCS Concepts: • **Networks** → **Network protocols**; **Network architectures;**

Additional Key Words and Phrases: LoRaWAN, dynamic spectrum management, partially overlapping channel, deep learning

ACM Reference format:
Lu Wang, Xiaoke Qi, Ruifeng Huang, Kaishun Wu, and Qian Zhang. 2023. Exploring Partially Overlapping Channels for Low-power Wide Area Networks. *ACM Trans. Sensor Netw.* 18, 4, Article 63 (March 2023), 20 pages.
https://doi.org/10.1145/3546075

The research was supported in part by the China NSFC (Grants No. 61872246, No. U2001207, and No. 61872248), Shenzhen Science and Technology Foundation (Grants No. ZDSYS20190902092853047 and No. R2020A045), the Project of DEGP (Grants No. 2019KCXTD005 and No. 2021ZDZX1068), and the Guangdong Pearl River Talent Recruitment Program under Grant No. 2019ZT08X603. RGC under Contract CERG 16203719, 16204820, and Contract R8015, FS112.

Authors' addresses: L. Wang and R. Huang, CSSE Department, Shenzhen University, Shenzhen, Guangdong Province, China; emails: wanglu@szu.edu.cn, huangruifeng2020@email.szu.edu.cn; X. Qi, China University of Political Science and Law, 27 Xuefu Road, Changping District, Beijing, China; email: qixiaoke@cupl.edu.cn; K. Wu (corresponding author), DSA Thrust and IoT Thrust, Information Hub, Hong Kong University of Science and Technology (Guangzhou), Guangzhou, Guangdong Province, China; email: wuks@ust.hk; Q. Zhang, CSE Department, Hong Kong University of Science and Technology, Clear Water Bay, New Territories, Hong Kong, China; email: qianzh@cse.ust.hk.

1550-4859/2023/03-ART63 $15.00
https://doi.org/10.1145/3546075

1 INTRODUCTION

Recently, **Low-power Wide Area Networks (LPWAN)** becomes a promising networking paradigm for connecting billions of low-power **Internet of Things (IoT)** devices. It allows long-range communications at a low bit rate. Among which, **Long-range WAN (LoRaWAN)** is one of the most representative LPWAN technologies, which serves a large volume of coexisting IoT devices, and thus gained tremendous attention from both academy and industry. Accordingly, more and more innovative applications are emerging, such as smart metering, machine-to-machine communication, road traffic monitoring, face recognition, which introduce an ever-increasing demand for large pool of spectrum resource [8] in LoRaWAN. It is forecasted that there will be 41.6 billion connected IoT devices by 2025, generating 79.4 ZB of data annually. Moreover, benefiting from long communication range, the IoT devices can send data over one-hop uplink to an LoRaWAN gateway, resulting in more collisions in a larger coverage area within the same spectrum. Therefore, to support the increasing demand for ubiquitous connectivity in LoRaWAN, we are in the midst of a spectrum management revolution [27].

With the paradox between the spectrum scarcity problem and the underutilization of the static spectrum allocation strategy, a paradigm shift has been introduced from the fixed spectrum allocation towards **dynamic spectrum management (DSM)** [21]. DSM plays an increasingly important role to improve spectral efficiency. In DSM, unlicensed users that were not allowed to transmit before can now access the licensed spectrum along with the licensed users. The access mode can be either opportunistic spectrum access or concurrent spectrum access. In the former mode, the unlicensed users access the licensed spectrum only when the licensed users are inactive. While in the latter mode, the unlicensed users coexist with the licensed users, as long as they keep their transmission under the interference margin of the licensed users.

Conventional DSM rarely adopts **partially overlapping channels (POC)** for concurrent spectrum access [22]. Assigning appropriate POC for concurrent transmissions requires complicated power control and interference cancellation algorithms, which is challenging and impractical for low-power IoT devices with hardware constraints. Moreover, as the environments of the IoT devices are highly dynamic, it is intractable to measure the complete and accurate channel information for POC assignment [25]. Benefiting from long communication range, the IoT devices can send data over one-hop uplink to an LoRaWAN gateway, resulting in more collisions in a larger coverage area. Therefore, the use of POC becomes inevitable and exhibits great potential to fully utilize the spectrum efficiency in LoRaWAN.

Last decade has witnessed a significant achievement in **artificial intelligence (AI)** [40]. Accordingly, AI techniques have been applied to DSM to meet various technical challenges, including channel selection [31], spectrum occupancy analysis [4], cooperative spectrum sensing [28], and so on. Instead of establishing a DSM model based on complete and accurate information, AI techniques can help to learn or explore the access strategy from the surroundings, and adjust the strategy periodically to the dynamic environment. Recent studies have demonstrated that AI techniques are effective to improve system robustness and spectrum efficiency in practice [38]. Despite the surging interest in AI-based DSM, when it comes to POC assignment, there still exist some challenges. For example, how to leverage the characteristics of POC transmissions for concurrent spectrum access with lightweight computational overhead remains a concern. Moreover, as the surroundings for connected IoT devices are highly dynamic, agility and adaptiveness are also required in the POC assignment architecture.

In this article, we investigate the potential solutions to cope with these challenges, and we propose a novel deep-learning-based spectrum sharing paradigm that explores POC for concurrent spectrum access in LoRaWAN. A primary concern upon concurrent spectrum access on POC is the unbalanced channel condition caused by the partially overlapping interference. Possible solutions include complicated power control or interference cancellation algorithms, which is not suitable for IoT devices with physical hardware constraints. In this article, we aim to leverage the extra coding redundancy in the existing **error correcting codes (ECC)** to enable coexistence on POC. The existing ECCs add redundancy to the transmitted signal, so that errors caused by noise during transmission can be corrected at the receiver. Normally, such protection is beyond the decoding capacity. As the channel condition is unbalanced in POC, we can leverage the extra coding redundancy from the clean data on the non-overlapping spectrum to recover the collided data on the overlapping spectrum. Specifically, we propose an **Intelligent Overlapping (IO)** paradigm to strategically randomize the interference among the entire spectrum. In this way, a uniform error distribution is created for further data recovery. As different POC portions have distinct impact on the coding redundancy, Intelligent Overlapping tries to learn the coding redundancy and select the appropriate overlapping portion according to the channel condition. Through IO, IoT devices can coexist on POC without complicated power control and interference cancellation. We further propose a deep-learning-based channel prediction algorithm to estimate the dynamic environments for POC assignment.

We have implemented Intelligent Overlapping with Matlab and Python. Our experiments show that compared with traditional fixed spectrum allocation paradigm, intelligent interleaving achieves higher spectrum usage efficiency under different channel conditions. In summary, our main contributions over existing works are:

- We have proposed an Intelligent Overlapping paradigm for LoRaWAN to improve the spectrum usage efficiency. To the best of our knowledge, this is the first work of its kind in the literature to strategically leverage the extra coding redundancy in the existing ECC to enable low-power IoT device coexistence on POC.
- We have presented the entire design of Intelligent Overlapping based on a **Deep-Q-learning network (DQN)**. Compared to the traditional fixed spectrum allocation paradigm, Intelligent Overlapping unleashes the potential of POC and achieves a more intelligent spectrum access paradigm.
- We have demonstrated the feasibility of Intelligent Overlapping through extensive simulations in Matlab and Python. Numerous experimental results show that Intelligent Overlapping outperforms competitive spectrum allocation paradigm with a fast convergence rate.

2 RELATED WORK

Intelligent Overlapping builds on top of extensive research works in overlapping channel transmissions, interference cancellation and machine-learning-based spectrum management. In this section, we briefly introduce the research works that closely relate to Intelligent Overlapping.

2.1 Collision Resolution in LoRaWAN

Deploying large-scale LoRaWAN is promising yet challenging. To simplify the network design, ALOHA protocol is adopted for media access control in LoRaWAN, and **Chirp Spread Spectrum (CSS)** is adopted for **Physical (PHY)** modulation. Each IoT device transmits data without trying to detect whether the LoRaWAN channel is idle or busy. The long communication range enables concurrency for a large volume of IoT devices, yet also leads to frequent collisions among the coexisting devices.

Recent advances in media access control as well as concurrent transmission methods mitigate the collision problem. Choir [9] is the first work of its kind to resolve collisions for LoRaWAN, which harnessed hardware imperfections of LoRaWAN devices to recover the collided packets.

In Reference [33], the authors proposed mLoRa to resolve collision in time domain. It estimates the collided samples and subtracting them from collisions, and thus gains the collision-free packets. In Reference [36], the authors proposed Ftrack to separate collided transmissions by jointly considering both the features in both time domain and frequency domain. They extended their work and proposed PCube, a phase-based parallel packet decoder for concurrent transmissions of LoRa nodes [35]. In Reference [29], the authors proposed NScale to decompose concurrent transmissions by leveraging subtle inter-packet time offsets for low SNR LoRa collisions. In Reference [30], the authors discovered that the collided pattern remains unchanged during a transmission. Thus they proposed CoLoRa to recover the collided packets through successive demodulation windows. In Reference [26], the authors proposed **Concurrent Interference Cancellation (CIC)**, which enables concurrent decoding of multiple collided LoRa packets. [15] proposed NELoRa, a DNN model that exploits the amplitude and phase features of chirp symbols and recovers these chirp symbols under collision.

Besides the above research, researchers tried to solve the collisions from the data link layer perspective. In Reference [2], the authors proposed a **time-division multiple access (TDMA)**-based media access protocol for LoRaWAN. In Reference [10], the authors explored the PHY indicator termed **Channel Activity Detection (CAD)**, to enable **carrier sense multiple access (CSMA)** for LoRaWAN. Unlike the above-mentioned research, our proposed Intelligent Overlapping tries to make little change to the PHY layer to enable concurrent transmissions for LoRaWAN.

2.2 Overlapping Channel Transmission

The growing demand for high speed wireless services overburdens the spectrum usage, and leads to dense deployed wireless networks. As evidenced by previous measurement studied [3], many 802.11 access points in range of each other use overlapping channels. Therefore, researchers put their efforts into concurrent transmission in partially overlapping channels. In Reference [22], the authors first promoted the idea that simultaneous use of partially overlapping channels is not always harmful. This contra-intuitive design demonstrated significant improvements by a careful use of some partially overlapping channels in 802.11b WLAN with **direct sequence spread spectrum (DSSS)** at physical layer. The authors of Reference [37] further proposed a complete design in wireless sensor networks to encourage non-orthogonal transmissions, which was also built atop DSSS modulation. The above feasibility cannot be directly applied to 802.11g/n. The reason stems from the distinct PHY layer. Unlike DSSS that spread every single bit information over an entire spectrum, OFDM adopted by 802.11g/n divides the spectrum into multiple subcarriers. The overlapping portion has a much lower **signal-to-interference and noise ratio (SINR)** compared with that in DSSS modulation. Thus, it is very difficult to recover the collided portion.

In Reference [5], the authors tried to enable the partially overlapping transmissions in TV white space with different channel widths. Remap in Reference [16] took a detour to leverage the partially concurrent transmissions, which exploit collision-free subcarriers for decoding through multiple retransmissions. However, MPAM [12] and ASN [39] directly nulled the overlapping portion used by neighboring WiFi subcarriers, and utilized spectrum fragments for partially concurrent transmission. Unlike previous works, our proposed Intelligent Overlapping aims to exploit extra coding redundancy from the collided spectrum, and leverage it for partially concurrent transmission in IoT networks.

2.3 Interference Cancellation

Our work also relates to existing interference cancellation techniques in wireless communications. Traditionally, when two or more packet transmissions arrive at a receiver simultaneously, only the strongest signal can be decoded. However, **successive interference cancellation (SIC)** [7] facilitates recovery of even the weaker signal. Extensive research has been proposed to demonstrate the effectiveness of SIC, such as ANC [14], ZigZag [11], and Full-Duplex [13]. However, SIC requires tight synchronization and has certain computational overhead. Meanwhile, References [32, 34] utilized pre-defined interference pattern to produce an extra control panel. The control information obtained by interference cancellation is limited, yet the computational overhead is also reduced. Compared with References [32, 34], our design simply utilizes the coding redundancy to recover the collided symbol. Although we share the similar methodology, our design purpose is quite different.

2.4 Machine-learning-based Spectrum Management

With the development of machine learning techniques in recent years, researchers' attention are diverted towards intelligent techniques to access the spectrum dynamically and efficiently. In Reference [24], the authors addressed the dynamic spectrum access problem in multichannel wireless networks based on **deep reinforcement learning (DRL)**. To estimate the accurate state with partial observation, they integrated an **long short-term memory (LSTM)** into a DQN. The experiment results demonstrated that the proposed scheme doubled the spectrum utilization only with ACK signals. In Reference [19], the authors studied anti-jamming communications without the estimation of jamming patterns. A **convolutional neural network (CNN)** was incorporated with a DQN, where the DQN agent learned the dynamic environment with limited prior knowledge. To improve the spectrum usage in a highly dynamic environment, the authors of Reference [18] investigated a fingerprint-based DQN for **vehicle-to-vehicle (V2V)** networks. The V2V links were acting as agents to interact with the environment. The results showed that with proper training, the V2V agents were able to learn the cooperation strategy distributively, and thus improve the overall capacity of V2V networks. Compared with the existing-state-of-the-art, our work leverages the POC to improve the spectrum usage efficiency, and tries to learning the appropriate POC portion by interacting with the environment.

3 POC ASSIGNMENT FOR LORAWAN: CHALLENGES AND DESIGN PRINCIPLES

In this article, we envision a typical LoRaWAN environment with **mobile edge computing (MEC)**, serving a large amount of IoT devices [1]. As demonstrated in Figure 1, the network is consisted of multiple hierarchies, including access layer, mobile edge and the central cloud. IoT devices are connected to the network through gateways. The gateways act as the mobile edge with computation and communication ability. The central cloud contains data resources and a centralized controller. We choose a software defined MEC architecture for illustration as the data packet and control information can be separated. The access network can be abstracted to better cater the connectivity of IoT devices. The mobile edge and the cloud, however, is responsible for computation tasks and network management.

3.1 Design Challenges

With the dense deployment and long transmission range of IoT devices, the limited spectrum resources turn out to be the bottleneck to fulfill the ever-growing transmission demand. It is inevitable that multiple IoT devices within a same range have to use overlapping spectrum. Concurrent spectrum access is promising to enhance the spectrum utilization in this backdrop. While conventional approaches focus more on power control or interference cancellation, which is not easy to realize on IoT devices with hardware constraint. Lightweight and intelligent spectrum sharing paradigm is critical to fully utilize the spectrum efficiency. To be specific, we ask the following questions as the design issues regarding the spectrum sharing technique:

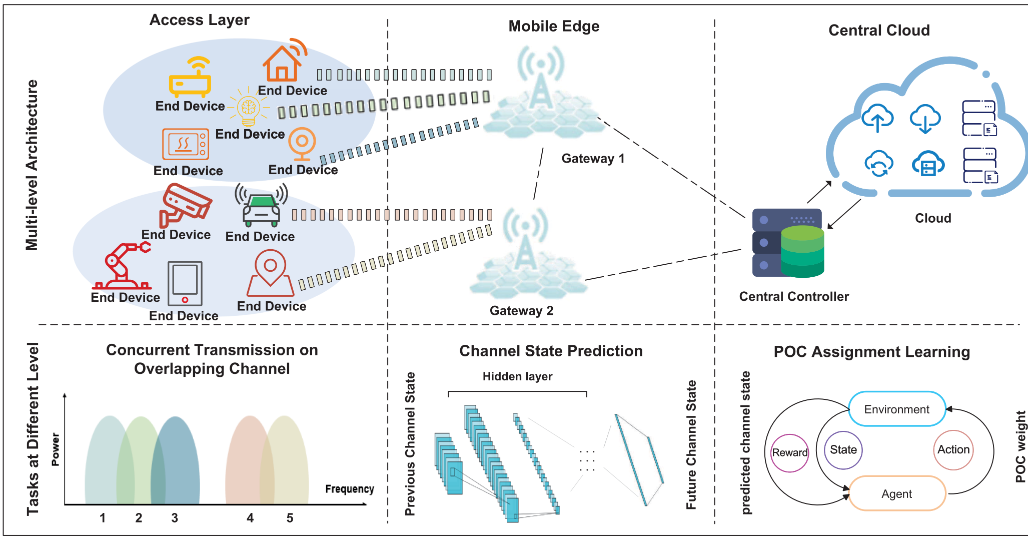

Fig. 1. A hierarchy of LoRaWAN to explore partially overlapping channel (POC) for concurrent spectrum access, including (a) access layer, to enabled concurrent transmission on POC; (b) mobile edge, to conduct channel prediction; and (c) central cloud, to intelligently learn the POC assignment strategy.

- Question 1: Whether there exists a lightweight concurrent transmission method, without complicated computation, e.g., with little signal or data processing overhead for LoRaWAN?
- Question 2: If yes, then can we design an intelligent spectrum access strategy based on the proposed transmission method, which can automatically learn and evolve itself according to the environments?
- Question 3: The mobile networks are sensitive to the surroundings, resulting in dynamic and unstable channel state, how can we cope with the complex and dynamic environments to realize a practical current spectrum access architecture?

3.2 Motivation

To answer these questions, we dive into the network architecture down to the PHY layer. We observe that concurrent transmissions on POC have unique characteristics. The data on the overlapping spectrum are almost corrupted and cannot be decoded due to the mutual interference from the coexisting transmissions. While the data on the non-overlap portion are clean and easy to be decoded. With such diverse decoding capacity, we aim to utilize the data on the non-overlapping spectrum to “help” the data on the overlapping portion. It is known that the existing ECCs, e.g., **Bose-Chaudhuri-Hocquenghem codes (BCH)** or **low-density parity-check (LDPC)** adopted by IoT devices, have sufficient coding redundancy. Thus careful use of such redundancy has the potential to help recovery the corrupted data without jeopardizing the clean data.

To realize such capacity, we utilize an interleaver after the PHY layer coding process [6]. An interleaver is commonly used in standard LoRa encoder/decoder to reduce the effect of burst errors. By reordering the data that is to be transmitted, we can distribute the consecutive bytes of data over a larger sequence of data. Traditional interleavers are designed fixed and pseudo-random, so that the busted errors can be corrected by ECC under all circumstances. However, the fixed pseudo-random interleaver cannot deal with the collision upon different overlapping ratios, as the SINR would be below the decodable threshold. In case of concurrent spectrum access using POC, the interleaver should be interference-aware when we leverage the clean data to help the corrupted data. As different overlapping portions have diverse impact on the coexisting transmissions, the interleaver should adapt its reordering strategy according to the overlapping pattern to better utilize the coding redundancy.

Recently, DRL has drawn extensive attention from both academia and industry. By combining **reinforcement learning (RL)** and **deep learning (DL)**, DRL agents can interact with the surroundings and learn their actions similar to the way humans learn from experience. To be specific, RL guides an agent to reach a certain goal by interacting with the environments, observing the reward and updating its knowledge. This exploring process helps it to find an optimal policy of taking certain actions under particular system states. The value of state-action function is so called Q-value, and an optimal policy will maximize the cumulated Q-value in a long term. RL works fine when the state-action space is limited. Yet when the system has a large number of states and actions, which is typical in communication systems, the computation usually becomes complex and takes long time to converge. To tackle this issue, **deep neural network (DNN)** is introduced in RL to approximate the Q-values. The state is given as the input and the Q-value of all possible actions is generated as the output. Also, the data are randomly sampled in minibatches from the target network to break the correlation in a sequence of observation. As DRL is model-free, and data samples are not necessary from an external supervisor, it is considered a promising tool to make intelligent decisions. Furthermore, with extensive offline training, the online learning overhead can be greatly reduced. In this article, we incorporate DRL to learn the reordering strategy according to overlapping portion, and intelligently assign POCs to IoT devices for concurrent spectrum access.

Another crucial issue is that, as the mobile networks are very sensible to environment dynamics, the channel state may experience sudden change and affect the POC assignment [20]. The assignment needs to be reconsidered once the channel condition changes. For instance, three mobile devices are transmitting concurrently on POC as their channel conditions are good. In the next time slot, the channel of one or more devices may change due to interference, shadowing, or blockage. At this moment, the assignment may exacerbate the interference and damage all the transmissions. On the contrary, if the channel state is poor currently and becomes good in the next time slot, then the POC assignment may waste the concurrent transmission opportunity. Therefore, in a dynamic IoT environment, channel prediction is a critical component and may affect the network performance. We refer to a LSTM for channel prediction. LSTM is more capable of extracting inherent features underlying the channel matrix from the large amount of data. We adopt parallel computing to speed up the neural network training and obtain the network weights. At the gateway, data from multiple end devices are also computed paralleled to obtained the final results. With the help of channel prediction, POC assignment can be more intelligent according to the predicted channel.

3.3 Design Principle

The concurrent spectrum access architecture we envisioned in this article should be able to facilitate the IoT network in the following directions: (1) to embrace concurrent spectrum access with little computational overhead; (2) to automatically learn the access strategy according to the environments; and (3) to guarantee the spectrum access quality and efficiency against systems dynamics. To be more specific, the concurrent spectrum access architecture should provide the following capacities:

- **Lightweight concurrent transmission upon POC:** The network should have the capability to embrace concurrent transmission on POC with little computational or data processing overhead, to facilitate the concurrent spectrum access for LoRaWAN.

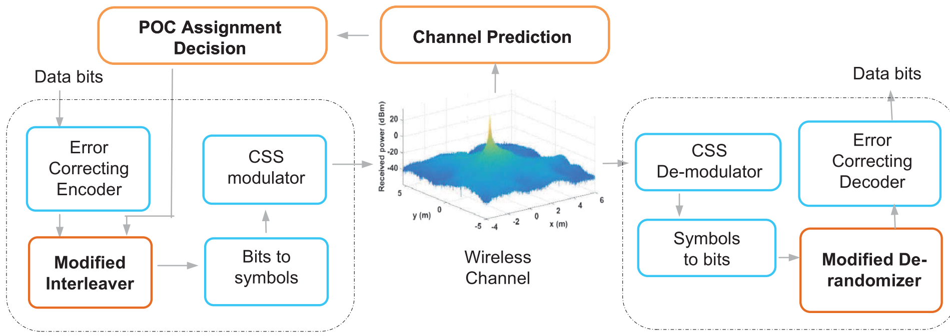

Fig. 2. The building blocks of intelligent overlapping architecture for LoRaWAN.

- **Intelligent redundancy learning and POC assignment:** The network should have the ability to automatically learn the existing coding redundancy and intelligently assign the POC to encourage appropriate concurrent spectrum access according to the environments.
- **Robustness to network dynamics:** To cope with channel dynamics and user mobility, the network should have the capacity to predict the channel variance, and guide the POC assignment to maximize the spectrum usage efficiency.

4 A DEEP-LEARNING-BASED SPECTRUM SHARING UPON POC

To realize the design principles discussed in Section 3, we need to review the network architecture down to the PHY layer. Exploring POC for concurrent spectrum access is promising, yet an appropriate design of the POC assignment technique is necessary to maximize the spectrum usage and ensure the service quality for IoT devices. This section introduces a potential system-level solution. We borrow the wisdom of PHY layer interleaving to exploit the ECC coding redundancy. In the upper layer, we incorporate DRL to automatically learn the POC assignment based on the proposed PHY layer interleaving, and leverage LSTM to predict the channel dynamics. Together, we achieve an efficient concurrent spectrum access architecture using POC for IoT devices in LoRaWAN.

4.1 Design Overview

Figure 1 illustrates a spectrum access scenario in LoRaWAN. The IoT devices, or the end devices, are accessing the network via gateway. By enabling intelligent spectrum sharing, the end devices can be served by the gateway simultaneously via POC. The gateway, as the mobile edge computing resource, is responsible for channel prediction. However, POC assignment learning is placed at the central cloud, which is much resourceful and has high computational capacity. Each time a gateway choose one or more end devices to transmit according to the POC assignment strategy. For instance, in Figure 1, gateway 1 chooses three end devices for concurrent transmission on overlapping channels 1, 2, and 3, and gateway 2 chooses two end device for concurrent transmission on overlapping channels 4 and 5. Instead of performing complex signal processing or interference cancellation, the end device only needs to modify its interleaver and deinterleaver, which is simply a mapping after ECC, and can be easily implemented without extra computational overhead. The prediction and learning process, which require computational resources, are at the mobile edge and central cloud. Therefore, the proposed current spectrum access architecture is feasible in practice and can fully unleash the potential of POC in LoRaWAN.

Figure 2 outlines the building blocks of the proposed architecture. The orange-colored blocks are the extensions to the conventional transmission structure. In the upper layer, the channel prediction block at the gateway estimates the **channel state information (CSI)** in the next time slot according to the history. The prediction results then are fed into the POC assignment learning block at the central controller to select the most appropriate POC strategy and feedback the decision to the transmitter and receiver (e.g., the gateway and the end device). To reduce extra control message exchange in LoRaWAN, the end devices can append their transmit request on uplink frame, and the gateway can piggyback the POC assignment decision through downlink messages or time-synchronized beacons during broadcast window. In the PHY layer, the modified interleaver at the transmitter (e.g., the gateway or the end device) reorders the transmit data to create uniform error distribution according to the overlapping portion, and the deinterleaver at the receiver (e.g., the end device or the gateway) performs the inverse reordering defined by interleaver. Specifically, the role of each network component is described as follows:

- **end device at access layer.** An UE accesses the spectrum following the conventional protocol. No additional operations are required except a modification to the interleaving procedure. When partially overlapping channels are adopted for concurrent transmissions, the UE simply adapts its interleaving strategy according to the POC assignment.
- **gateway at mobile edge.** A gateway has the duty to provide spectrum access to the end devices as in the existing mobile networks. Besides, since it is close to the end devices, the channel prediction is conducted at the gateway. The prediction results are reported to the central controller for POC assignment.
- **Central controller at the cloud.** The central controller at the cloud is responsible for network control and management. With rich computational capacity, it is responsible for the offline and online POC assignment learning. The learning results are feedback to the access network for spectrum access.

4.2 Concurrent Transmission upon POC

The concurrent transmission ability upon POC is built on the wisdom of PHY layer interleaving. In the existing communication systems, interleaving is an essential component to reduce the effect of burst errors, and it is simple to implement. By reordering the transmitted data, the consecutive bytes of data are distributed over a larger sequence of data to fight against the interference. Existing communication systems normally use fix reordering strategy [17]. When it comes to POC, the situation is quite diverse. Different overlapping portions have different interference levels upon ongoing transmissions. Therefore, the reordering strategy has to adapt according to the overlapping portion. The basic idea is simple, yet realizing a practical interleaving strategy for POC still needs careful design to reduce the computational overhead. Here, we do a little modification to the existing interleaving method, to make it compatible with the existing communication systems. The purpose is align with the original design, which creates a uniform error distribution among the entire spectrum, but different in the way that the interleaving conducts the reordering according to the overlapping portion.

The basic idea of the modified interleaver is demonstrated in Figure 3 for illustration. A basic LoRaWAN channel is divided into seven blocks of channel spectrum as a toy example. Each block contains several meta-blocks. The overlapping spectrum contains one block according to the assignment from the central cloud. To uniformly distribute the data on the overlapping blocks among the entire blocks, two reordering functions are adopted. The first one is block-level permutation. The goal is to separate two adjacent overlapping blocks. The second one is meta-block level, aiming to isolate the meta-blocks with interference and uniformly distributed them among the entire spectrum. A row-by-column interleaver is used to create such uniform interference distribution. We assume that the interleaver matrix is with length $N = N_{row} \times N_{col}$, which writes the input bits row-wise and reads the output bits column-wise. The number of the reshaped groups is N_{row}, and

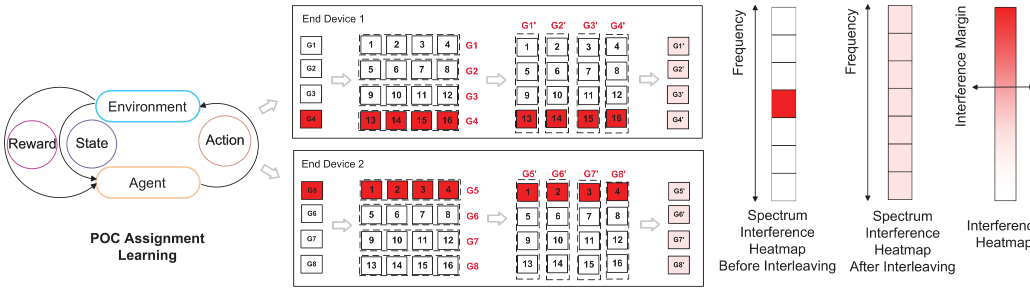

Fig. 3. Illustration of a deep-Q-learning-network-based interleaving strategy to exploit coding redundancy.

the number of subcarriers in each reshaped group is N_{col}. We can use the following equation to denote the the permutation π,

$$\pi(i) = k = N_{col}(i \bmod N_{row}) + \left\lfloor \frac{i}{N_{row}} \right\rfloor, \tag{1}$$

where $i = 0, 1, \ldots, N$ is the bit location before interleaving, and k is the bit location after interleaving. mod donates the modulo operation, and $\lfloor x \rfloor$ represents the floor operation that returns the greatest integer not exceeding x.

As for the deinterleaver at the receiver side, we define a two-step interleaver that performs the inverse rotation,

$$\pi^{-1}(k) = i = N_{row} \times k - (N-1) \times \left\lfloor \frac{k}{N_{col}} \right\rfloor. \tag{2}$$

In one way, the interference can be interpolated into the non-overlapping clean data blocks. In the other way, the resulting interference on the non-overlapping data blocks does not exceed the interference margin, ensuring that all the data blocks is decodable. Therefore, the POC weight (POC portion) is critical. We need to strategically make the decision to fully utilize the coding redundancy according to the channel states. We will introduce the detailed design in the next subsection.

4.3 Intelligent POC Assignment

To find the optimal POC assignment under different channel states, we first formulate the problem. Assume that the IoT system has a set $\mathcal{N} = \{1, 2, \ldots, n\}$ end devices within the collision domain of a gateway with the number of end devices n.

We consider a typical spectrum access scenario with POC, where two or more end device are allowed to transmit on the same blocks of a channel. Our goal is to maximize the overall throughput with an optimal POC assignment of different end device.

The traditional approaches to the assignment problem commonly rely on optimization theory. Here, we employ a DQN to find the optimal strategy under different system states, that is, the optimal POC assignment under different channel states. Each end device's CSI is fed into DQN as the input. The action of the agent is the POC weight assigned to each end device (i.e., the overlapping portion designated to each end device). It is assumed that the agent is employed for interacting with the environment with the objective to find the optimal actions that can maximize the accumulated rewards R_t at time slot t within a sequence of states,

$$R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}, \tag{3}$$

where $\gamma\in[0,1]$ is the discount factor. r_t is the reward at time slot t. To be specific, the state, the action, and the reward are defined as follows:

(1) State $\mathcal{S}$: the state of the agent has two components.
  (a) The end device's channel state information (CSI). Considering that channel is time-varying, we use a LSTM neural network to predict, since LSTM performs well at modeling time series data. The detail will be presented in Section 4.4.
  (b) The end device's signal to interference plus noise ratio (SINR). The POC assignment influences SINR of online end device and then if the transmission is successfull. Thus, SINR also feeds back to the optimal POC assignment.
(2) Action $\mathcal{A}$: We define the action as the overlapping ratio that two or more agents are assigned when they transmit concurrently on POC. The action space $\mathcal{A}$ includes all the appropriate POC weight assignments.
(3) Reward r_t: The reward r_t at time slot t is related to the state s_t and the action a_t at the time slot t. The reward function is designed to express the overall throughput. To this end, we integrate the theoretical system utility U_T and the practical system performance U_P under the selected action to define the reward at time slot t as

$$r_t = \lambda_1 U_T + \lambda_2 U_P, \tag{4}$$

where λ_1 and λ_2 are coefficients to balance the two indexes. U_T and U_P are expressed as follows.

First, let P_i and ρ_i denote the transmission power and overlapping indicator assigned to end device i with $\rho_i = 1$ if end device i reuses the spectrum of other end devices and $\rho_i = 0$ otherwise. h_i is the channel gain for end device i. The SINR of end device i can be expressed as

$$\mathrm{SINR}_i = \frac{P_i h_i}{\sigma^2 + \sum_{k\in\mathcal{N},k\neq i} \rho_k P_k h_k}, \tag{5}$$

where σ^2 is the noise power. P_k denotes the transmission power of other concurrent transmitting end devices and h_k is the channel gain of other concurrent transmitting end devices. Note that when there is no overlapping among all the users, the SINR is the SNR of end device. Thus, the system utility U_T for all n end devices is

$$U_T = \sum_{i=1}^{n} W_i \log(1 + \mathrm{SINR}_i), \tag{6}$$

where W_i is the bandwidth of end device i.

Then, we measure the practical system performance U_P by the system **bit error rate (BER)**, expressed as

$$U_P = \sum_{i=1}^{n} (\eta_i + \nu_i \gamma_i) \frac{1}{pb_i + 1}, \tag{7}$$

where η_i is the ratio of the bandwidth of end device i to the total bandwidth. ν_i is the overlapping portion assigned to end device i. p is the penalty of BER b_i for end device i.

Figure 4 depicts the architecture of the DQN, where we adopt the same architecture for the policy network and the target network. The policy network takes the CSI of each end device as the system input, and returns the approximated POC weight of each end device as the system output. As for the training process, we adopt the experience replay to reduce the correlation between training samples [23]. The agent first sends the state s_t at time slot t to the policy network, which generates

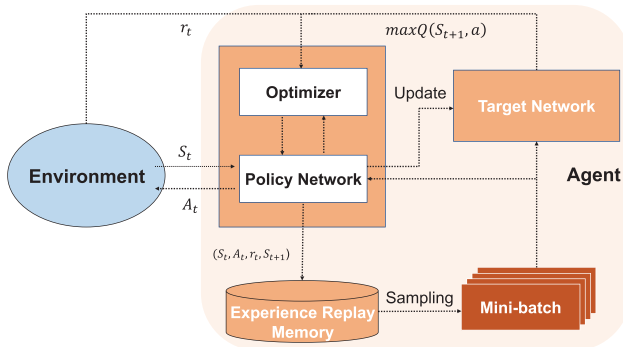

Fig. 4. The DQN architecture for POC assignment learning.

the Q-values $Q(s_t, a)$ of any action a in $\mathcal{A}$. Based on the Q-values and following an ε-greedy policy, the optimal action a_t is generated. Further, we can improve the policy by taking the action as

$$a_t = arg \max_{a \in \mathcal{A}} Q(s_t, a). \tag{8}$$

Afterwards, the reward r_t is obtained from the environment s_t. As for the the transition, which consists of (s_t, a_t, r_t, s_{t+1}), is then stored into an experience replay memory. For each optimization step, we collect minibatch of 32 transitions to update the policy network, and we use the policy network state to update the target network for every 100 iterations. With the proposed DQN, the agent at the central controller collects all the CSI from the end devices, and takes different actions (i.e., selecting different POC weights) to get the Q-values. A certain action is chosen if it leads to a maximized Q-values for a long term.

4.4 Channel Prediction

Although DQN has certain ability to observe the channel dynamics and take appropriate actions, in IoT networks, as the environment always dynamics, the POC assignment decisions will be affected due to the fast-varying channel state. Hence, **channel prediction (CP)** is also critical. Considering that the channels are time series, we utilize a LSTM neural network to conduct channel prediction before the POC assignment. The deep LSTM has two primary building blocks, including high-dimensional CSI extraction and channel generation. To be specific, high-dimensional CSI extraction contains two bidirectional LSTM layers and three full-connected layers. The purpose is to extract the features of the input CSI. Afterwards, the extracted CSI features are fed into the channel generation, and gone through multiple fully connected layers. The generated channel are returned as the final prediction results. We train the network using the **mean-squared error (MSE)** as the loss function, which is calculated as

$$\mathrm{MSE}_i = \frac{1}{F} \sum_{j=1}^{F} \left| CSI_j^{pred} - CSI_j^{actual} \right|^2, i \in \mathcal{N}, \tag{9}$$

where CSI_j^{pred} and CSI_j^{actual} denote the predicted and actual channel state of end device i at the jth frequency bin, respectively.

As we mentioned in Section 3, the CSI of each end device is collected by the gateway, either by measured via the preamble, pilots or reported via the end device. Initially the gateway conduct offline training to predict the channel state using the CSI history. Specifically, a sliding window of size K is leveraged as the input. That means we use the CSI in previous K time slots to predict the

Table 1. Configuration Parameters

Module	Parameters	Values
Channel	Channel model	Rician Fading
	Doppler spectrum	Jake's model
	Max Doppler shift	20Hz/50Hz
	Sample rate	1MHz/3.84MHz
LSTM	BiLSTM layers	2
	Linear layers	3
	Training algorithm	Adam
	Activation function	ReLU
	Cost function	MSE
	Dataset size	20,000
	Batch size	128
	Learning rate	1e-4
DQN	CNN layers	2
	Linear layers	2
	Training algorithm	RMSprop
	Activation function	ReLU
	Cost function	Huber Loss
	Capacity of ER buffer	10,000
	Mini-batch	32
	Update Frequency	32
	Learning rate	5e-3
	Discount factor	0.9

channel in the next time slot. After offline training, online training helps the gateway to adjust the prediction weight matrices to generate the predicted channel as the output. Then the prediction results are reported to the central controller to help make POC assignment decisions.

5 EVALUATION

In this section, we conduct extensive simulations to evaluate the performance of the proposed Intelligent Overlapping paradigm for LoRaWAN. We assume that each gateway is located at the center of a cell and IoT devices are randomly distributed around BS. We adopted a typical LoRaWAN environment with **mobile edge computing (MEC)**. A gateway is associated with 50 LoRa nodes. There are total of 16 CH/SF combinations used. Each time a gateway chooses one or more LoRa nodes to transmit with the same spread factor according to the POC assignment strategy. For each transmission, the settings are with 10-chirp preamble, 16-byte payload, and 2 dB transmission power. The wireless system is deployed in Matlab R2020a. To train the network, we integrated Pytorch 1.9.0 with Matlab. The detailed configuration parameters are shown in Table 1. We divide the evaluation into two parts: a) validation of channel prediction and b) performance of intelligent overlapping. We also present the performance of fixed POC assignment and spectrum access without POC as comparisons.

5.1 Performance of Intelligent Overlapping

In this subsection, we first evaluate the performance of the proposed Intelligent Overlapping paradigm, which consists of the following two parts: the feasibility of concurrent transmission upon POC and the capacity of intelligent POC assignment to learn the optimal POC weight given certain channel information.

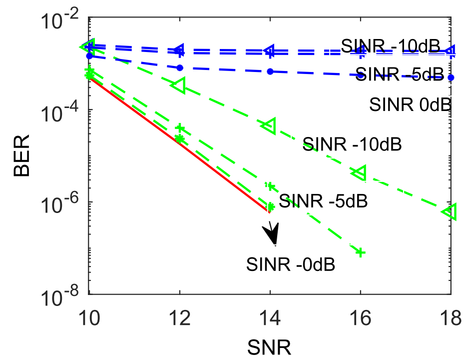

Fig. 5. Decoding capacity of the modified interleaver. Blue lines represent the BER with modified interleaver, while green lines represents the BER with standard interleaver. The red line is the BER without POC.

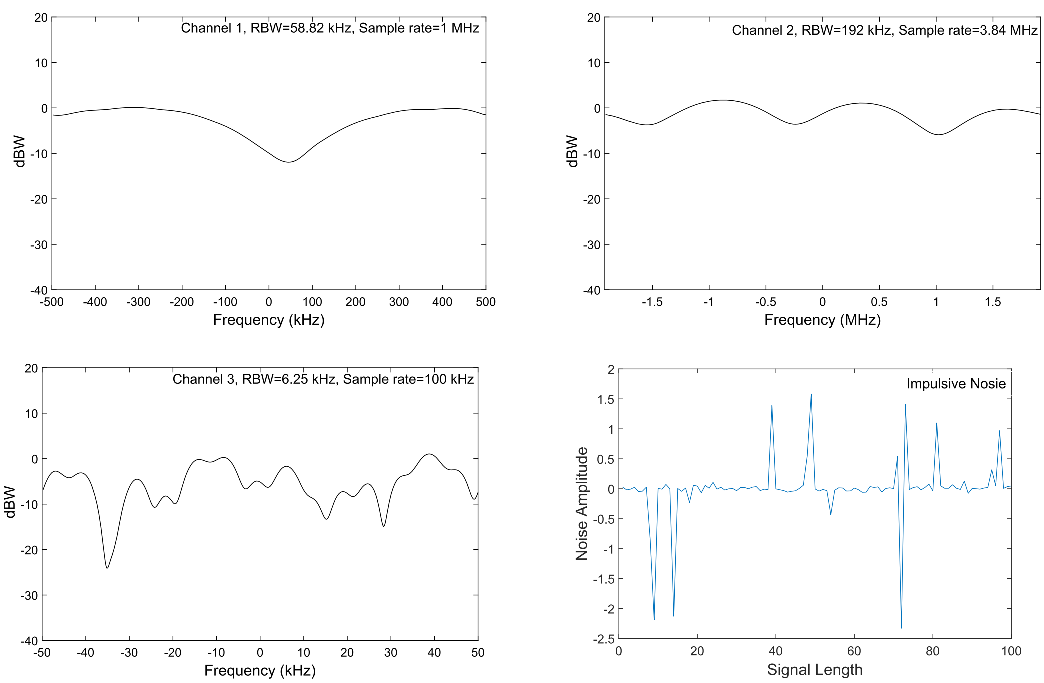

Fig. 6. The channel responses of three representative channel models and the impulsive noise.

First, as shown in Table 1, we deploy two convolution layers and two fully connected hidden layers with six neurons. RMSprop is used to optimize the model. DQN takes in the current channel responses, and tries to predict the expected overlapping ratio of different end devices. During training loops, the policy network weights are updated at each iteration while the target network has its weights kept frozen and only updates every 100 iterations.

Then, we depict the decoding capacity with standard (blue lines) and modified interleaver (green lines) given a certain overlapping scenario in Figure 5. With higher POC weights, the SINR becomes higher. The red line is set as benchmark, which is the transmission without POC. As shown in the figure, the standard interleaver constantly has high BER even the SINR is low, indicating that it is

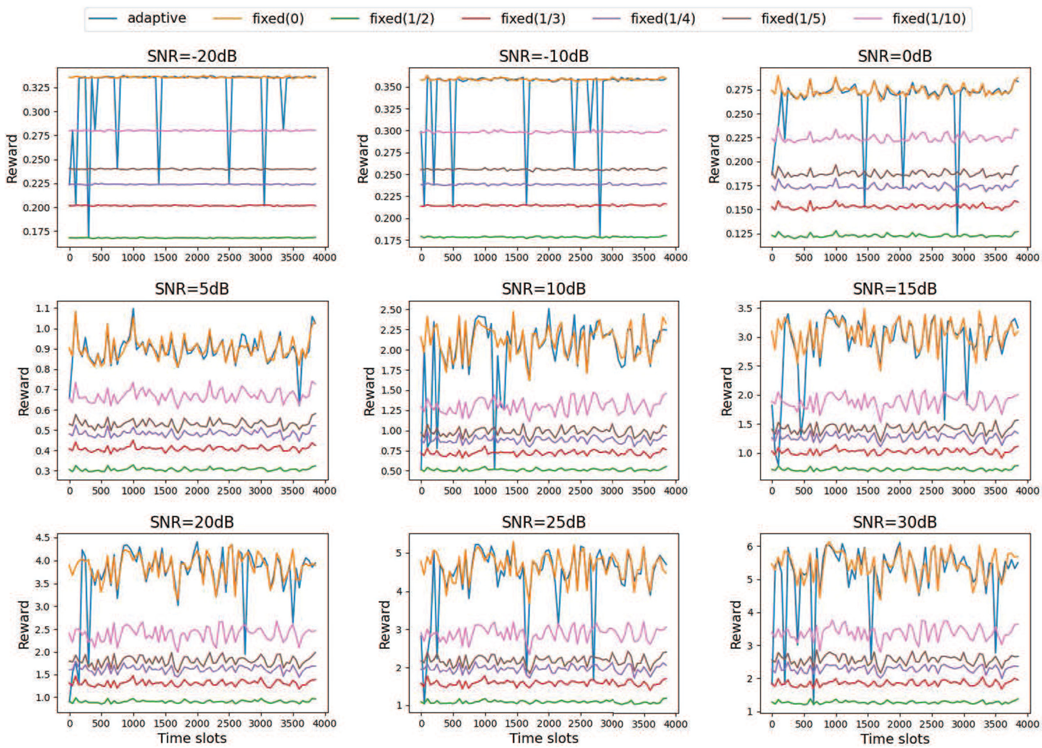

Fig. 7. The performance of different POC assignment strategies under channel 1. IO always learns and traces the best curve.

not capable of dealing with POC. Meanwhile, our modified interleaver has relatively low BER as the SINR decreases, e.g., below 10^{-5}, which is good enough for IoT communications. The modified interleaver even approaches the baseline when two transmission parties have equal transmission power (SINR = 0 dB). Therefore, the modified interleaving is capable of supporting concurrent transmission upon POC for IoT networks.

In the next step, we evaluate the performance of intelligent POC assignment. To make the evaluation more convincing, we add impulsive noise to emulate the unexpected interference in practice. We verify the effectiveness of intelligent POC assignment under three representative channel models. The channel responses are shown in Figure 6.

Figures 7–9 depict the system reward in terms of the training steps under different channel conditions. It is not surprised that with lower SNR, the reward is higher with less POC weight, indicating that when the channel condition is poor, it is better to transmit with less POC. As the SNR grows, the reward is higher with more POC weight, which means we can use more POC for concurrent transmissions when the channel condition is good. Under all circumstance, IO traces the best curve after a certain step, which demonstrates that the proposed DQN-based POC assignment strategy is able to learn the optimal POC weight given certain channel information.

Figure 10 shows the bandwidth efficiency performance for data subcarriers under different SNRs using DQN-based approach, non-overlapping, fixed 1/8-overlapping, and fixed 1/4-overlapping methods. We assume that two end devices transmit data at the same time with different overlapping ratios. It is shown that the proposed DQN-based approach achieves best performance over the other ones under the same SNRs, and the bandwidth efficiency gets higher as SNR increases.

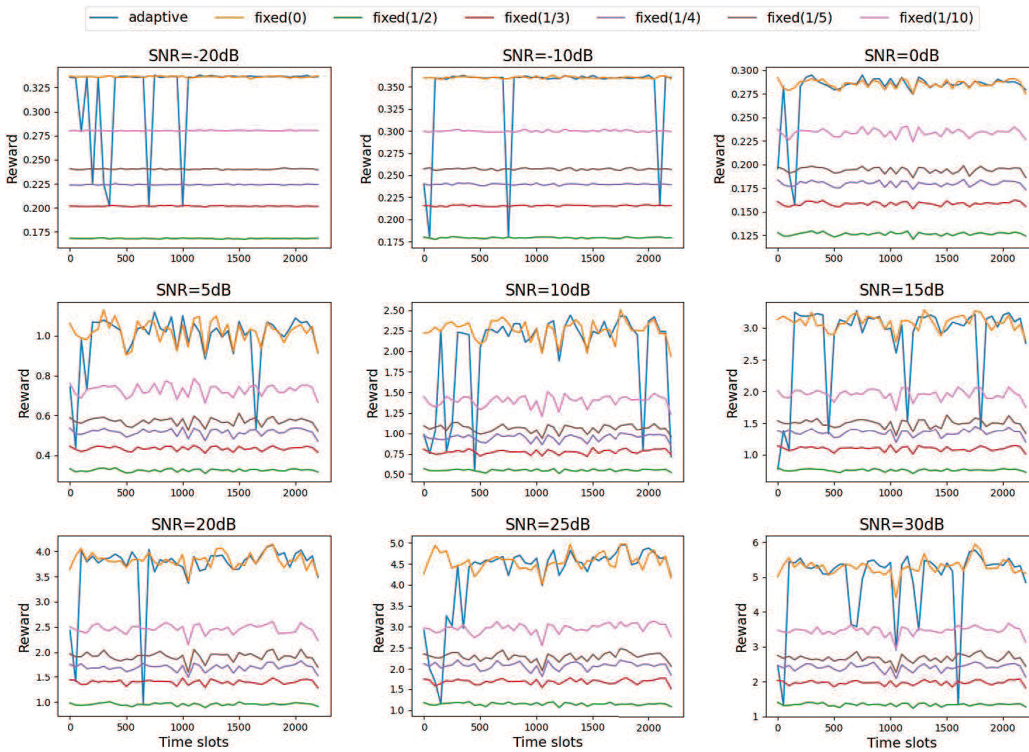

Fig. 8. The performance of different POC assignment strategies under channel 2. IO always learns and traces the best curve.

The reason lies in the ability for BS of predicting the channel variation and choosing the optimal overlapping ratio to maximize the channel utilization. When the channel condition is bad, DQN-based approach gives a low overlapping ratio to make sure the data from a single end device can be resumed. As the channel condition gets better, DQN can output a higher overlapping ratio to fully utilize the bandwidth. In addition, as SNR increases, the non-overlapping and fixed overlapping methods reach to maxima, while DQN can learn a higher overlapping ratio to increase the bandwidth efficiency.

5.2 Validation of Channel Prediction

In this subsection, we validate the training effect of the channel prediction. As shown in Table 1, we choose the loss function of MSE, and the channel is modeled as Racian Fading channel with Jake's Doppler spectrum. The max doppler shift is 20Hz. We collect 20,000 CSIs from the Rician fading channel model, and use a regression model with two bidirectional LSTM layers and three full-connection layers to predict the channel states. At each time slot, the CSIs of all the end devices are stored. We use 10 continuous time slots CSI as the input to predict the CSI of the next time slot. In particular, 80% of the data is allocated for training and the remaining 20% is as validation data.

Figure 11 depicts the training loss against the iteration steps. It is shown that the loss value decreases rapidly as the training steps increase, indicating that the channel prediction becomes stable and converges after certain steps (e.g., 150 steps). It is seen that our proposed approach can predict CSI at the next time slot and give a proper overlapping ratio. For instance, at the time slot

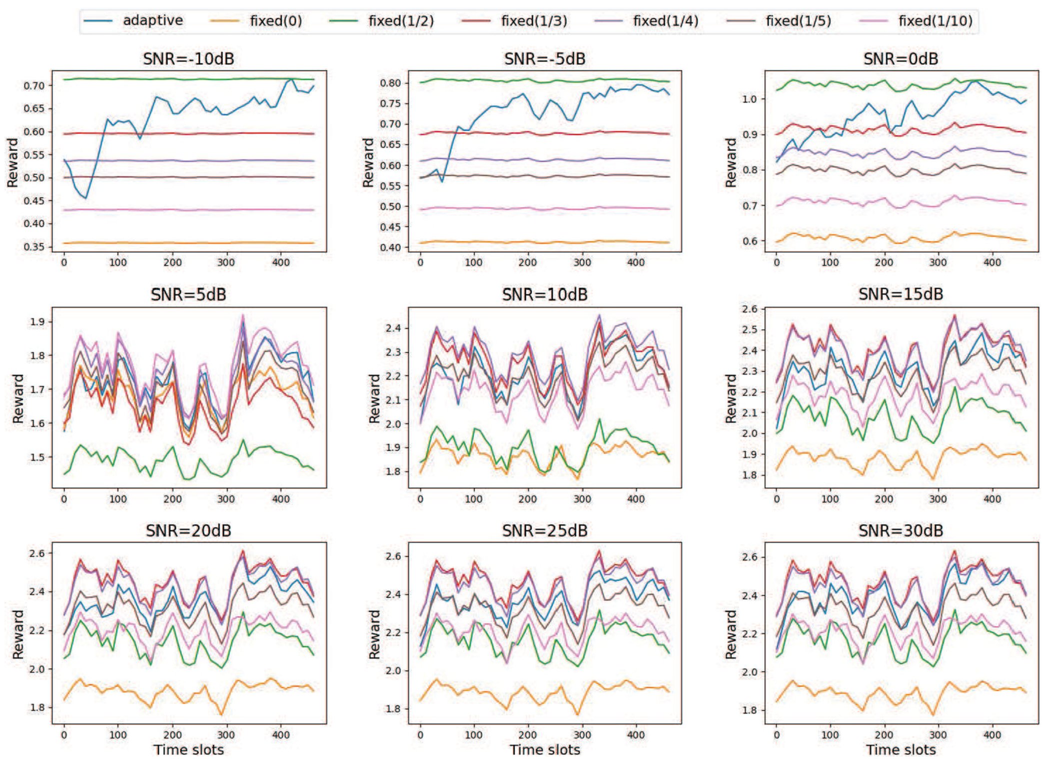

Fig. 9. The performance of different POC assignment strategies under channel 3. IO always learns and traces the best curve.

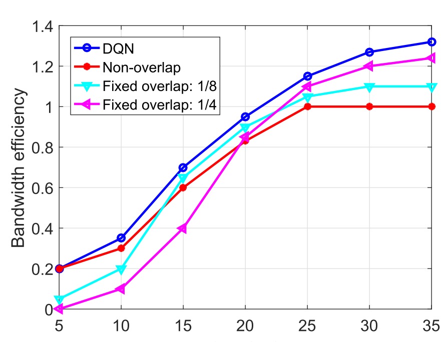

Fig. 10. Performance comparison for bandwidth efficiency performance for data subcarriers in terms of SNRs.

28, channel prediction obtains the estimated CSI at the time slot 29. Based on CP, we predict the overlapping ratio at the next transmission.

Figure 12 compares the performance of bandwidth efficiency under the situations of CP and without CP. It is shown that our DQN-based approach with CP can achieve significant gain over the approach using CSI at the current time slot. From the time slot 33 to 34, the channel condition changes from 30 to 25 dB. When generating data package using the overlapping ratio learned from the channel condition at the time slot 33, it cannot be successfully reconstructed under a worse

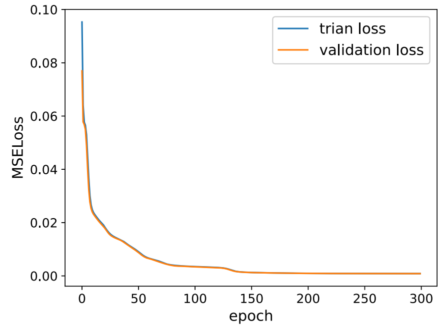

Fig. 11. Training effect of channel prediction in terms of iteration steps.

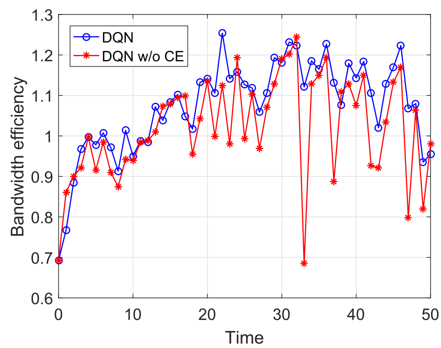

Fig. 12. Bandwidth efficiency with and without channel prediction.

channel condition at the time slot 34. Therefore, the bandwidth efficiency becomes very low and a big gap occurs between DQN-base approach with CP and without CP.

5.3 Complexity Discussion

Our proposed Intelligent Overlapping tries to make little change to the PHY layer, which only requires modification to the interleaver at the end devices and the gateway. The learning and prediction process is also designed with low complexity for LoRaWAN. In this part, we use **Multiply Accumulate Operations (Mac)** and **floating-point operations (FLOPs)** to measure the complexity. Mac is a common step that computes the product of two numbers and adds that product to an accumulator. While a flop serves as a basic unit of computation, which could denote one addition, subtraction, multiplication or division of floating point numbers. According to the simulation results, the computational complexity of channel prediction is 64.24K Mac with 32.12K FLOPs, and the POC assignment learning is 19.62 K Mac with 9.81K FLOPs. As shown in Table 2, comprising with the state-of-the-art machine learning models (such as ResNet), which has G Mac level computations, our proposed channel access methods is suitable for LoRaWAN.

6 CONCLUSION AND FUTURE DIRECTIONS

In this article, we have discussed the potential of using POC for occurrent spectrum access in LoRaWAN, and we investigated design challenges and principles. We have presented a novel deep-learning-based concurrent spectrum access architecture upon POC, termed IO, which automatically learns the extra coding redundancy from the data on the non-overlapping spectrum and applies such redundancy to recover the data on the overlapping spectrum. We have

Table 2. Computational Complexity

System Component	Model	Params	Macs	FLOPs
Channel Prediction	BiLSTM	17.95K	64.24K	32.12K
POC Assignment	DQN	3.94K	19.62K	9.81K
Comparison	ResNet18	11.69M	1.82G	—
Comparison	ResNet50	25.56M	4.12G	—

presented a system-level case study as an illustrated architecture at both the PHY layer and Media Access Control (MAC) layer. We have demonstrated the high performance of the proposed scheme. We believe that the envisioned spectrum sharing architecture facilitate the spectrum usage efficiency in LoRaWAN.

To fully unleash the potential of POC for spectrum sharing, there still exists a bundle of future directions. One primary concern is the energy consumption of IoT devices, which calls for novel designs with a low computational overhead. What is more, multi-user selection needs to be carefully designed to guarantee the service quality. Last, a complete network structure with such spectrum sharing capability is essential for LoRaWAN, including computation offloading, spectrum slicing, and so on.

REFERENCES

[1] Nasir Abbas, Yan Zhang, Amir Taherkordi, and Tor Skeie. 2017. Mobile edge computing: A survey. *IEEE Internet Things J.* 5, 1 (2017), 450–465.

[2] Khaled Q. Abdelfadeel, Dimitrios Zorbas, Victor Cionca, and Dirk Pesch. 2019. FREE—Fine-grained scheduling for reliable and energy-efficient data collection in LoRaWAN. *IEEE Internet Things J.* 7, 1 (2019), 669–683.

[3] Aditya Akella, Glenn Judd, Srinivasan Seshan, and Peter Steenkiste. 2007. Self-management in chaotic wireless deployments. *Wireless Netw.* 13, 6 (2007), 737–755.

[4] Freeha Azmat, Yunfei Chen, and Nigel Stocks. 2015. Analysis of spectrum occupancy using machine learning algorithms. *IEEE Trans. Vehic. Technol.* 65, 9 (2015), 6853–6860.

[5] Paramvir Bahl, Ranveer Chandra, Thomas Moscibroda, Rohan Murty, and Matt Welsh. 2009. White space networking with wi-fi like connectivity. *ACM SIGCOMM Comput. Commun. Rev.* 39, 4 (2009), 27–38.

[6] S. Cao, J. Chen, J. N. Damask, C. R. Doerr, L. Guiziou, G. Harvey, Y. Hibino, H. Li, S Suzuki, K.-Y. Wu, et al. 2004. Interleaver technology: Comparisons and applications requirements. *J. Lightwave Technol.* 22, 1 (2004), 281.

[7] Imre Csiszár and Janos Korner. 1978. Broadcast channels with confidential messages. *IEEE Trans. Info. Theory* 24, 3 (1978), 339–348.

[8] I. B. F. de Almeida, L. L. Mendes, J. J. P. C. Rodrigues, and M. A. A. da Cruz. 2019. 5G waveforms for IoT applications. *IEEE Commun. Surveys Tutor.* 21, 3 (2019), 2554–2567. https://doi.org/10.1109/COMST.2019.2910817

[9] Rashad Eletreby, Diana Zhang, Swarun Kumar, and Osman Yağan. 2017. Empowering low-power wide area networks in urban settings. In *Proceedings of the Conference of the ACM Special Interest Group on Data Communication.* 309–321.

[10] Amalinda Gamage, Jansen Christian Liando, Chaojie Gu, Rui Tan, and Mo Li. 2020. LMAC: Efficient carrier-sense multiple access for LoRa. In *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking.* 1–13.

[11] Shyamnath Gollakota and Dina Katabi. 2008. *Zigzag Decoding: Combating Hidden Terminals in Wireless Networks.* Vol. 38. ACM.

[12] Yong He, Ji Fang, Jiansong Zhang, Haichen Shen, Kun Tan, and Yongguang Zhang. 2011. MPAP: Virtualization architecture for heterogenous wireless APs. *ACM SIGCOMM Computer Commun. Rev.* 41, 4 (2011), 475–476.

[13] M. Jain, J. I. Choi, T. Kim, D. Bharadia, S. Seth, K. Srinivasan, P. Levis, S. Katti, and P. Sinha. 2011. Practical, real-time, full duplex wireless. In *Proceedings of the ACM MobiCom.* 301–312.

[14] Sachin Katti, Shyamnath Gollakota, and Dina Katabi. 2007. Embracing wireless interference: Analog network coding. In *ACM SIGCOMM Computer Communication Review*, Vol. 37. ACM, 397–408.

[15] Chenning Li, Hanqing Guo, Shuai Tong, Xiao Zeng, Zhichao Cao, Mi Zhang, Qiben Yan, Li Xiao, Jiliang Wang, and Yunhao Liu. 2021. NELoRa: Towards ultra-low SNR LoRa communication with neural-enhanced demodulation. In *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems.* 56–68.

[16] L. E. Li, K. Tan, H. Viswanathan, Y. Xu, and Y. R. Yang. 2010. Retransmission≠ repeat: Simple retransmission permutation can resolve overlapping channel collisions. In *Proceedings of the ACM Mobicom.*

[17] Yingxue Li and Prabhakar R. Chitrapu. 2010. Wireless communication method and system for bit interleaved coded modulation and iterative decoding. U.S. Patent 7,802,171.

[18] Le Liang, Hao Ye, and Geoffrey Ye Li. 2019. Spectrum sharing in vehicular networks based on multi-agent reinforcement learning. *IEEE J. Select. Areas Commun.* 37, 10 (2019), 2282–2292.

[19] Xin Liu, Yuhua Xu, Luliang Jia, Qihui Wu, and Alagan Anpalagan. 2018. Anti-jamming communications using spectrum waterfall: A deep reinforcement learning approach. *IEEE Commun. Lett.* 22, 5 (2018), 998–1001.

[20] Zhihong Liu, Jiajia Liu, Yong Zeng, and Jianfeng Ma. 2020. Covert wireless communication in IoT network: From AWGN channel to THz band. *IEEE Internet Things J.* 7, 4 (2020), 3378–3388.

[21] Zhi-Quan Luo and Shuzhong Zhang. 2008. Dynamic spectrum management: Complexity and duality. *IEEE J. Select. Topics Signal Process.* 2, 1 (2008), 57–73.

[22] Arunesh Mishra, Vivek Shrivastava, Suman Banerjee, and William Arbaugh. 2006. Partially overlapped channels not considered harmful. In *Proceedings of the Joint International Conference on Measurement and Modeling of Computer Systems.* 63–74.

[23] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, et al. 2015. Human-level control through deep reinforcement learning. *Nature* 518, 7540 (2015), 529–533.

[24] Oshri Naparstek and Kobi Cohen. 2017. Deep multi-user reinforcement learning for dynamic spectrum access in multichannel wireless networks. In *Proceedings of the IEEE Global Communications Conference (GC'17).* IEEE, 1–7.

[25] Priyabrata Parida and Suvra Sekhar Das. 2014. Power allocation in OFDM based NOMA systems: A DC programming approach. In *Proceedings of the IEEE Globecom Workshops (GC'14).* IEEE, 1026–1031.

[26] Muhammad Osama Shahid, Millan Philipose, Krishna Chintalapudi, Suman Banerjee, and Bhuvana Krishnaswamy. 2021. Concurrent interference cancellation: Decoding multi-packet collisions in LoRa. In *Proceedings of the ACM SIGCOMM Conference.* 503–515.

[27] Manikantan Srinivasan and C. Siva Ram Murthy. 2019. Efficient spectrum slicing in 5G networks: An overlapping coalition formation approach. *IEEE Trans. Mobile Comput.* 19, 6 (2019), 1299–1316.

[28] Karaputugala Madushan Thilina, Kae Won Choi, Nazmus Saquib, and Ekram Hossain. 2013. Machine learning techniques for cooperative spectrum sensing in cognitive radio networks. *IEEE J. Select. Areas Commun.* 31, 11 (2013), 2209–2221.

[29] Shuai Tong, Jiliang Wang, and Yunhao Liu. 2020. Combating packet collisions using non-stationary signal scaling in LPWANs. In *Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services.* 234–246.

[30] Shuai Tong, Zhenqiang Xu, and Jiliang Wang. 2020. Colora: Enabling multi-packet reception in lora. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'20).* IEEE, 2303–2311.

[31] Pavithra Venkatraman, Bechir Hamdaoui, and Mohsen Guizani. 2010. Opportunistic bandwidth sharing through reinforcement learning. *IEEE Trans. Vehic. Technol.* 59, 6 (2010), 3148–3153.

[32] Lu Wang, Kaishun Wu, and Mounir Hamdi. 2012. Combating hidden and exposed terminal problems in wireless networks. *IEEE Trans. Wireless Commun.* 11, 11 (2012), 4204–4213.

[33] Xiong Wang, Linghe Kong, Liang He, and Guihai Chen. 2019. MLoRa: A multi-packet reception protocol in LoRa networks. In *Proceedings of the IEEE 27th International Conference on Network Protocols (ICNP'19).* IEEE, 1–11.

[34] Kaishun Wu, Haochao Li, Lu Wang, Youwen Yi, Yunhuai Liu, Dihu Chen, Xiaonan Luo, Qian Zhang, and Lionel M. Ni. 2012. hJam: Attachment transmission in WLANs. *IEEE Trans. Mobile Comput.* 12, 12 (2012), 2334–2345.

[35] Xianjin Xia, Ningning Hou, Yuanqing Zheng, and Tao Gu. 2021. PCube: Scaling LoRa concurrent transmissions with reception diversities. In *Proceedings of the 27th Annual International Conference on Mobile Computing and Networking.* 670–683.

[36] Xianjin Xia, Yuanqing Zheng, and Tao Gu. 2020. FTrack: Parallel decoding for LoRa transmissions. *IEEE/ACM Trans. Netw.* 28, 6 (2020), 2573–2586.

[37] Xing Xu, Ji Luo, and Qian Zhang. 2010. Design of non-orthogonal multi-channel sensor networks. In *Proceedings of the IEEE 30th International Conference on Distributed Computing Systems (ICDCS'10).* IEEE, 358–367.

[38] Alessio Zappone, Marco Di Renzo, and Mérouane Debbah. 2019. Wireless networks design in the era of deep learning: Model-based, AI-based, or both? *IEEE Trans. Commun.* 67, 10 (2019), 7331–7376.

[39] Xinyu Zhang and Kang G. Shin. 2011. Adaptive subcarrier nulling: Enabling partial spectrum sharing in wireless LANs. In *Proceedings of the 19th IEEE International Conference on Network Protocols (ICNP'11).* IEEE, 311–320.

[40] Fuhui Zhou, Guanyue Lu, Miaowen Wen, Ying-Chang Liang, Zheng Chu, and Yuhao Wang. 2019. Dynamic spectrum management via machine learning: state of the art, taxonomy, challenges, and open research issues. *IEEE Netw.* 33, 4 (2019), 54–62.

Received 25 February 2022; revised 20 May 2022; accepted 5 June 2022