Handling Coexistence in LPWAN

ABSTRACT

As an emerging Internet-of-Things (IoT) technology, *Low-Power Wide-Area Network (LPWAN)* enables low-power wireless devices to transmit at low data rates over long distances using narrowband. While many competing LPWAN technologies have been developed recently, they have a number of **major limitations** that make their adoption challenging. Specifically, rapid growth of LPWANs in the limited spectrum raises the challenge of **coexistence**. It will be severe in urban areas where spectrum can be congested due to numerous independent networks. Due to long range, LPWAN devices can be subject to an unprecedented number of hidden nodes. Today, they are not equipped to handle this impending challenge. It is difficult to employ sophisticated MAC for low-power nodes. We address this challenge in LPWAN by developing theoretical foundations and systems for ***SNOW (Sensor Network Over White Spaces)***, an LPWAN architecture that exploits the TV white spaces for scalable IoT. Compared to cellular LPWANs, SNOW does not require wired infrastructure making it suitable in both rural and urban areas. While we focus on SNOW to develop and evaluate the proposed protocols, the approach can be extended to other types of LPWANs for broader impacts on industry. We propose a novel approach based on Reinforcement Learning to handle coexistence with many independent networks. This is done by developing an efficient Q-learning framework that is practical at low-power nodes. This will be the **first** Q-learning approach for LPWAN and for handling coexistence in low-power network.

CCS CONCEPTS

• Networks → Network protocols; **• Computer systems organization → Sensor networks**;

KEYWORDS

White space, LPWAN, Sensor Network, OFDM, MAC Protocol.

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1 INTRODUCTION

As an emerging Internet-of-Things (IoT) technology, *Low-Power Wide-Area Network (LPWAN)* enables low-power (milliwatts) wireless devices to transmit at low data rates (kbps) over long distances (kms) using narrowband (kHz). With the fast growth of IoT, multiple competing LPWAN technologies are currently being developed such as LoRa [16], SigFox [18], IQRF [1], RPMA [2], DASH7 [3], Weightless-N/P [4], Telensa [20] in the ISM band, and EC-GSM-IoT [5], NB-IoT [6], LTE Cat M1 [7, 40], 5G [17] in the licensed cellular band. To avoid the **crowd** in the **limited** ISM band and the **cost** of licensed band, we designed ***SNOW (Sensor Network Over White spaces)***, an LPWAN architecture to support scalable wide-area IoT over the TV white spaces [50–52]. *White spaces* are the allocated but locally unused TV channels [8, 9]. Compared to ISM band, they have much wider, less crowded spectrum in rural and most urban areas, with an abundance in rural areas [24]. Previously, they were aimed mostly for broadband access by Microsoft [10, 48], Google [11], standards bodies such as IEEE 802.11af [12], 802.22 [15], 802.19 [14], and in research [19, 24, 25, 28, 31–35, 37, 38, 41, 45, 49, 56, 60, 63, 66, 68–70]. Our initial design and experiment showed the potential of SNOW for asynchronous, low power, massively concurrent communications between numerous nodes and a base station (BS) over long distances, enabling scalable, wide-area IoT in white spaces [50–52].

Rapid growth of LPWANs in the limited spectrum brings forth the challenge of coexistence. The number of connected devices will exceed 50 billions by 2020 [44]. With Comcast recently announcing to add LPWAN radios on set-top boxes, LPWANs will be ubiquitous in the US [43]. Ongoing standardization efforts such as IEEE 802.15.4m [54] (extending 802.15.4 [13]) and Weightless-W [4] may yield many LPWAN users in white spaces in the future. The coexistence problem will be severe in urban areas where spectrum can be congested due to numerous independent networks. Today, LPWANs are not equipped to handle this impending challenge [47]. It is difficult to employ sophisticated media access control (MAC) protocol for low-power nodes. Studies show a collision probability ≈ 1 if 1000 nodes of LoRa, SigFox, or IQRF coexist [30, 36]. Another study shows significant throughput reduction when four LoRa networks coexist [59]. Coexistence handling for WiFi, traditional short-range wireless sensor network (WSN), and Bluetooth [53, 61, 62] will not work for LPWANs. Due to long range, their devices are subject to an unprecedented number of hidden nodes, requiring techniques that handle such coexistence while being highly energy-efficient.

We shall develop theoretical foundations and systems to address the above challenges for LPWAN. Our preliminary work showed advantages of SNOW over other LPWANs in scalability and energy [50–52]. It allows the BS to receive concurrent transmissions made by the nodes asynchronously. It also allows concurrent downlink communication. LoRa relies on time synchronized beacons and schedules for downlink communication. Compared to cellular LPWANs, SNOW does not need wired infrastructure making it suitable in both rural and urban areas. With the rapid growth of

IoT, LPWANs will suffer from crowded spectrum due to long range, making it critical to exploit white spaces.

We propose a novel approach based on Reinforcement Learning to handle coexistence with many independent networks. This is done by developing an efficient Q-learning framework that is practical at low-power nodes. This would be the **first** Q-learning approach for LPWAN and for handling coexistence for any low-power network. This framework can be adopted for other (non-cellular) LPWANs with minor modification.

The paper is organized as follows. Section **??** describes related work. .... so on.

2 BACKGROUND AND SYSTEM MODEL

In this section we describe the system model and the necessary background for the LPWAN technology we've considered in our design.

2.1 System Model

We consider LPWAN networks consisting of numerous nodes connected directly to one or more gateways. We consider a dense deployment where multiple LPWAN networks are operating in the same spectrum. We assume that the nodes and gateways of these networks do not posses any knowledge about each other and operate independently. Nodes are battery-powered and only wake-up if they have data to send. Nodes do not posses significant computing power and memory. Gateways are line-powered devices and are always active. We assume that the gateways can support concurrent receptions of multiple packets up to some limit. Thus, the gateways are limited by maximum number of simultaneous receptions n which can be controlled by the network manager. If more than n packets arrive at the gateway at the same time, some packets are dropped. Nodes rely on acknowledgements from the gateway to confirm successful reception of data. Nodes retransmit the packet if an acknowledgement is not received. The maximum number of retransmissions is also configured by the network manager. We focus on LoRa as an representative LPWAN technologies and handle coexistence for dense LoRa networks with our q-learning framework. In the following subsection, we describe the necessary background on LoRa.

2.2 An Overview of LoRa

Here we provide a brief overview of LoRa(Long-Range). Detailed description for the physical and link-layer of LoRa networks can be found in [22]. LoRa is the physical layer technology for an LPWAN. It's characteristics include extremely long-range which can be in the range of 3-7 miles depending on the environment and successful reception of packets even at extremely low signal-to-noise ratio. LoRa modulation is derived from *Chirp Spread Spectrum (CSS)*. CSS modulation spreads the signal over the entire bandwidth, thus providing robustness to interference and enabling reception of packet at very low signal-to-noise ratio. The modulated signal consists of symbols/chirps, whose frequency linearly increases or decreases over time. Information is encoded onto each chirp using multiple cyclic shifted chips. The number of chips present in each symbol is controlled by the *spreading factor*. Specifically, spreading factor is the ratio between symbol rate and chip rate. LoRa supports spreading factor in the range [6,12]. Spreading factor (SF) controls the data rate and thus the transmission time and energy consumption. A higher spreading factor reduces the data rate and thus increases the time on air for each packet leading to significant increase in energy consumption. Transmissions on different spreading factors are orthogonal to each other.

LoRa also supports different levels of forward error detection (FEC), called *coding rates* in the range of $\frac{4}{5}$ to $\frac{4}{8}$ A higher coding rate provides resilience against bursts of interference, but increases the duration of each packet. Apart from coding rate and spreading factor, other configurable parameters for LoRa are carrier frequency, channel and bandwidth. Carrier frequency and channels vary from region to region depending on local regulation. For example, in the US band LoRa operates in the range 902-928MHz. For uplink communication in the US, there are 64 channels of bandwidth 125kHz and 8 channels of bandwidth 500kHz. For downlink, there are 8 channels of bandwidth 500kHz.

The MAC protocol used with LoRa physical layer is called LoRa Wide Area Network(LoRaWAN). In LoRaWAN numerous nodes are directly connected to one of more gateways, which forward the data collected from nodes to a central network server. Thus, LoRa forms a star of star network topology. LoRaWAN supports classes of operation, namely class A,B and C. In all classes, nodes transmit using pure ALOHA. In class A, nodes transmit when they have data and open two receive windows after each transmission. In class B, gateway send periodic beacons to synchronize nodes. Between two beacons, the nodes wake up periodically to receive any packets from the gateway. In class C, the nodes are continuously listening for packets from the gateway.

For the rest of the paper, we focus on LoRa as an representative LPWAN technology. We design a framework to handle coexistence in LoRa network, however, our approach can be used to handle coexistence for any LPWAN technologies easily by adjusting some parameters.

3 RELATED WORK AND NEW CHALLENGES

Limited power budget of LPWAN nodes makes it difficult to adopt sophisticated MAC. Hence, SigFox and LoRa resort to ALOHA [58] with no collision avoidance. SNOW currently uses a lightweight CSMA/CA approach. While such lightweight protocols provide energy efficiency, they cannot handle coexistence while low-power transmissions are easily subject to interference. Coexistence study through simulations revealed that using multiple gateways in distant places can improve some throughput in LoRa [59]. This trivial approach needs more infrastructure support and cost while the gain is marginal. *Choir* [27] is a reactive and PHY-layer approach for handling dense deployment of LoRa in urban areas which leverages on resolving the collided packets. In an uncoordinated environment where packets from many unknown networks can collide, such an approach will not work. The study in [46] uses Poisson cluster process to model LoRa dense networks but does not propose coexistence handling. While there exists much work on wireless coexistence considering WiFi, WSN, and Bluetooth (see surveys [53, 61, 62]), it will not work well for LPWANs. Due to their

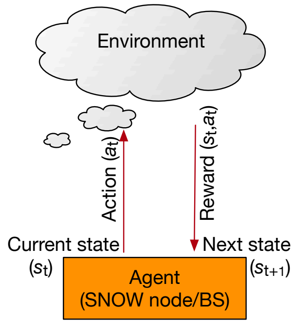

Figure 1: RL visualization

large coverage domains, LPWAN devices can be subject to an unprecedented number of hidden terminals. With their rapid growth while the spectrum is limited, coexistence will be a severe problem and new techniques that are both energy efficient and capable of handling coexistence must be developed.

4 HANDLING COEXISTENCE IN LORA

4.1 Performance of LoRa under Co-existence

In massive crowds of coexisting networks, the interference pattern can be hard to detect for an LPWAN device like LoRa. Hence, a TDMA (time division multiple access) or traditional CSMA/CA based approach will simply fail.

4.2 A learning-based approach to co-existence handling

As the wireless environment is largely unknown due to the coexistence of a massive number of unknown devices/networks, a *learning* based approach becomes more effective to make actions (e.g, transmit, sleep, backoff) according to the environmental conditions. However, a learning process usually can be time and computation extensive while the nodes are power-constrained and battery-operated. Hence, we propose to adopt a lightweight machine learning approach. Specifically, as the SNOW nodes may have no knowledge of the coexisting networks, we will adopt ***Reinforcement Learning (RL)*** that enables an *agent* (e.g., a node) to learn by interacting with its environment [57]. As shown in Fig. 1, an agent regularly updates its achieved *rewards* based on the taken action at a given *state*. It will learn to take the best actions that maximize its long-term rewards by using its own experience. This would be the **first RL approach** for LPWAN and for handling coexistence for any low-power network.

4.3 Rationale for Reinforcement Learning

We adopt *Q-learning*, a widely-adopted RL technique, which is well-suited for coexistence handling because it is useful in decision making under unknown network conditions. It has *low memory requirements* and *low computation*, and learns near-optimal or even *optimal* solution under certain conditions. Q-learning can be *efficiently* implemented in a distributed platform like WSN, where each node chooses actions to maximize rewards. It has been efficiently used in cognitive radios [64], and in WSN for routing [23, 26, 29, 55], QoS provisioning [21, 67], and resource management [65]. It was also used with RTS/CTS to learn contention and collision with the nodes in the **same** network using a **single channel** [39]. We aim to adopt RL to handle its coexistence with numerous unknown and uncoordinated networks. RL has not yet been adopted to handle such coexistence. LPWAN technologies like LoRa has unique features which require a new Q-learning framework. For example, LoRa networks enable multiple concurrent transmissions by dynamically adjusting multiple transmission parameters. Thus, adopting Q-learning for low-power LoRa devices requires a novel Q-learning framework.

4.4 Challenges for Q-learning in LoRa

Like other LPWAN technologies, LoRa devices are extremely low-power and do not possess high computation power. Although Q-learning has low memory and computation requirement compared to other RL approaches, we have to be cautious in designing the Qlearning agent. Specifically, the memory and computation requirement of an Qlearning agent is dependent on the size of the set of actions and agent states. Thus, these parameters need to be chosen carefully to not overwhelm the low-power LoRa devices.

5 DESIGN OF THE LORA Q-LEARNING AGENT

Every LoRa node will use a Q-learning agent locally for uplink communication. Each Q-learning agent aims to learn the communication pattern of other co-existing networks and take intelligent decisions to increase the network performance. We consider agent (node) states $\Omega = \{Tx, Rx, Idle, sleep\}$, to indicate its state of transmitting, receiving, idle, and sleeping. Each node will start transmitting on a randomly selected channel from the set of enabled channels in the operating band. After each transmission, the Q-learning agent updates it knowledge about the network through the acknowledgment received from the gateway.

5.1 Action Set Formulation

Is Back-off Advantageous under Coexistence?
In traditional LoRa networks, whenever nodes have data, they transmit immediately . However, that might lead to the transmission being failed. Thus,it might be better to introduce a backoff period before transmissions. Based on the received acknowledgements each Q-learning agent tries to learn the best backoff period which increases the *throughput* and decreases the *energy consumption* under *tolerable* latency.

Is Channel Hopping Advantageous under Coexistence?
In traditional LoRa, the nodes randomly hop between 64 channels before each transmission. However, our q-learning agent can learn which channel has better probability of making a successful transmission with less number of transmission attempts.

Is Changing SF Advantageous under Coexistence?
LoRa networks usually rely on Adaptive Data Rate(ADR) control from the network server for assigning spreading factor to the nodes. The network server tries to increase the network capacity through th ADR algorithm. However, when there are multiple co-existing networks, the network server of one network can not anticipate the interference caused by other networks. Thus, transmissions on the spreading factor assigned by the network server may not be

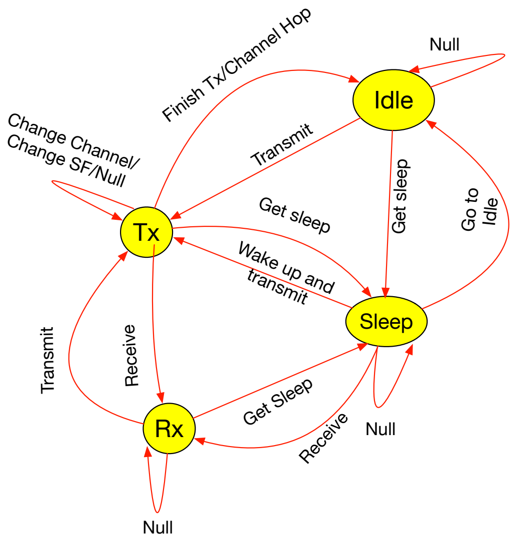

Figure 2: Agent state diagram.

successful. However, the q-learning agent can learn the best spreading factor which has higher probability of ensuring a successful reception at the gateway.

Thus, the set of actions is

$$\Lambda = \{\textit{Transmit, Receive, Backoff, Wake up, Channel hop, Change SF, null}\}$$

5.2 Reward Function Formulation

Let $s_t \in \Omega$ be the agent state at time t. Its total reward is given by

$$R(s_t, a_t) = r(s_t, a_t) + c(s_t, a_t),$$

where $r(s_t, a_t)$ is the *immediate reward* and $c(s_t, a_t)$ is the *cost* of taking action $a_t \in \Lambda$ at state s_t. Considering both energy consumption and throughput, we can assign some numerical values indicating rewards and costs. As an example, we can consider total reward for a successful packet *transmission* or *reception* by considering 2 units of immediate reward and 1 unit of cost. Thus, a failed transmission will incur only a cost of 1 unit. We can also consider 1 unit of cost in *idle* state (as the radio consumes energy almost similar to Tx/Rx). From s_t =*Idle*, important reward functions can be given as follows.

$$R(s_t, a_t) = \begin{cases} 2-1=1 & \text{if } s_t = \textit{Idle},\ a_t = \textit{Transmit} \text{ and ACK received} \\ 0-1=-1 & \text{if } s_t = \textit{Idle},\ a_t = \textit{Transmit} \text{ and ACK not received} \\ 2-1=1 & \text{if } s_t = \textit{Idle},\ a_t = \textit{Receive} \\ -1 & \text{if } s_t = \textit{Idle},\ a_t = \textit{Null} \\ 0 & \text{if } s_t = \textit{Idle},\ a_t = \textit{Get sleep} \end{cases}$$

$$R(s_t, a_t) = \begin{cases} 2-1=1 & \text{if } s_t = \textit{Sleep},\ a_t = \textit{Transmit} \text{ and ACK received} \\ 0-1=-1 & \text{if } s_t = \textit{Sleep},\ a_t = \textit{Transmit} \text{ and ACK not received} \\ 2-1=1 & \text{if } s_t = \textit{Sleep},\ a_t = \textit{Receive} \\ 0 & \text{if } s_t = \textit{Sleep},\ a_t = \textit{Null} \\ -1 & \text{if } s_t = \textit{Sleep},\ a_t = \textit{Wake up} \end{cases}$$

$$R(s_t, a_t) = \begin{cases} 2-1=1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Finish Tx} \text{ and ACK received} \\ 0-1=-1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Finish Tx} \text{ and ACK not received} \\ -1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Backoff} \\ -1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Channel hop and remain Idle} \\ 2-1=1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Channel hop, transmit and ACK received} \\ -1=1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Channel hop, transmit and ACK not received} \\ 2-1=1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Change SF, transmit and ACK received} \\ -1=1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Change SF, transmit and ACK not received} \\ -1 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Null} \\ 0 & \text{if } s_t = \textit{Tx},\ a_t = \textit{Get Sleep} \end{cases}$$

$$R(s_t, a_t) = \begin{cases} 2-1=1 & \text{if } s_t = \textit{Rx},\ a_t = \textit{Finish Rx} \\ 2-1=1 & \text{if } s_t = \textit{Rx},\ a_t = \textit{Transmit} \text{ and ACK received} \\ 0-1=-1 & \text{if } s_t = \textit{Rx},\ a_t = \textit{Transmit} \text{ and ACK not received} \\ -1 & \text{if } s_t = \textit{Rx},\ a_t = \textit{go to idle} \\ -1 & \text{if } s_t = \textit{Rx},\ a_t = \textit{Null} \\ 0 & \text{if } s_t = \textit{Rx},\ a_t = \textit{Get Sleep} \end{cases}$$

5.3 Q-Values and Action Selection Approach

Let the Q-value associated with action a_t and state s_t be $Q(s_t, a_t)$. It represents the currently expected total future reward and is initialized to zero. Through trial and experience, the agent learns how good some action was. The Q-values of the actions change through learning and finally represent the absolute value function. After convergence, taking the actions with the greatest Q-values in each state guarantees taking an optimal decision. The new Q-value of pair $\{s_{t+1}, a_t\}$ in state s_{t+1} after taking action a_t in state s_t is computed as the sum of old Q-value and a correction term as

$$Q(s_{t+1}, a_t) = Q(s_t, a_t) + \gamma(R(s_t, a_t) - Q(s_t, a_t)).$$

The learning constant, γ, prevents the Q-values from changing too fast and thus oscillating. The nodes take actions and update the Q-values up to a certain time length. After completion, a new episode begins, repeating until the Q-values no longer change. Always taking the actions with maximum Q-value (greedy policy) may result in finding locally minimal solutions. On the other hand, selecting always randomly implies ignoring prior experience and spending too much energy to learn the complete environment. We shall adopt by combining and weigthing both which is a prominent approach in machine learning [57]. Specifically, we shall use ϵ-**greedy**: with probability ϵ the agent takes a random action and with probability $(1-\epsilon)$ it takes the best available action, which is known to yield quick and high quality solutions [57].

Note that every node runs as a single-agent whose Q-table size is $O(|\Omega|.|\Lambda|)$, where $|\Omega|$ is the number states and $|\Lambda|$ is the number of actions. Since these numbers are small for a node, the memory needed is feasible for it. The Q-learning procedure stops after T iterations, called the time *horizon*, having time complexity $O(T)$. An optimal policy can be achieved as the number of iterations goes to infinity. The framework can be adopted to other LPWANs by revising the actions and rewards.

6 EVALUATION

6.1 Experiments

Experiment Plan We will test the Qlearning MAC under the following setups:

- Interference caused by co-existing LoRa networks, where the nodes are LoRa class A and B end devices following Pure ALOHA mac protocol.
- Interference caused by LoRa networks(Class A and B) using slotted ALOHA mac protocol.
- Interference caused by a combination of above three

The metrics for evaluating the Qlearning MAC are energy consumption, latency and reliability. We will test the energy consumption and latency for convergecast from 25 nodes. Each node in the network other than the base station will generate a packet after some fixed interval, we will measure the total energy consumption for successfully transmitting all packets to the base station. We will measure latency by measuring the time to collect all packets at the base station. For reliability we will measure the ratio of successfully decoded packets at the gateway to the number of packets transmitted .

We can measure the above metrics under varying number of interfering nodes, Q-learning MAC nodes and at various distances.

We can also measure the learning performance by introducing periodic interference.

6.2 Simulation

We conducted Simulations using NS-3. In our implementation we used the LoRawan module for NS-3 proposed in [42]. We use a custom-build Q-learning agent following our framework and the MAC protocol is also governed by this agent. For a network with 100 co-existing nodes, traditional LoRa suffers in throughput as only 8% of the total sent packets generated a successful acknowledgement, and most of the nodes were not able to send any packets at all. On the other hand, using Q-learning MAC we could ensure 30% of the packets were acknowledged by the gateway and none of the nodes were suffering from starvation.

7 CONCLUSION

To Do .....

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