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 [19], SigFox [21], IQRF [1], RPMA [2], DASH7 [3], Weightless-N/P [4], Telensa [23] in the ISM band, and EC-GSM-IoT [5], NB-IoT [6], LTE Cat M1 [7, 46], 5G [20] 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 [58–60]. *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 [27]. Previously, they were aimed mostly for broadband access by Microsoft [10, 56], Google [11], standards bodies such as IEEE 802.11af [12], 802.22 [18], 802.19 [17], and in research [22, 27, 28, 33, 36–40, 42, 44, 48, 52, 57, 64, 68, 72, 76, 78–80]. 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 [58–60].

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 [51]. With Comcast recently announcing to add LPWAN radios on set-top boxes, LPWANs will be ubiquitous in the US [50]. Ongoing standardization efforts such as IEEE 802.15.4m [62] (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 [55]. 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 [35, 41]. Another study shows significant throughput reduction when four LoRa networks coexist [67]. Coexistence handling for WiFi, traditional short-range wireless sensor network (WSN), and Bluetooth [61, 70, 71] 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 [58–60]. 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 AN OVERVIEW OF SNOW

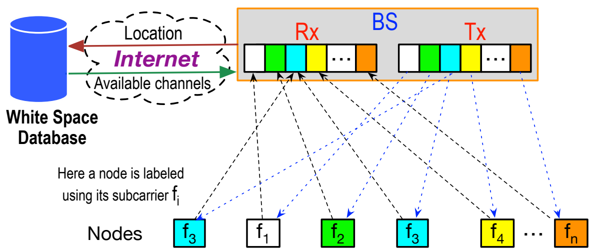

Figure 1: The SNOW architecture.

Here we provide a brief overview of the SNOW PHY that we developed previously [58–60]. Its **full description** is available in [60]. Due to long transmission (Tx) range, the nodes in SNOW are directly connected to the BS, forming a star topology as shown in Fig. 1. We use **'node'** to indicate a sensor node. We assume that the BS knows the locations of the nodes through manual configuration or some existing WSN localization technique [49]. This assumption is relaxed in our proposed research. The BS periodically determines white spaces by providing locations of its own and of all other nodes in a cloud-hosted database through the Internet. The BS uses wide white space spectrum as a single wide channel that is split into narrowband orthogonal subcarriers, each of equal spectrum width (bandwidth). Each node has a single half-duplex narrowband radio. It sends/receives on a subcarrier. The nodes are power-constrained, and do not do spectrum sensing or cloud access. As shown in Fig. 1, the BS uses two radios – one for only transmission (called ***Tx radio***) and the other for only reception (called ***Rx radio***) – to facilitate concurrent bidirectional communication.

A key design goal of SNOW is to achieve high scalability by exploiting wide spectrum of white spaces. Hence, its PHY is designed based on a **D**istributed implementation of **OFDM** for multi-user access, called **D-OFDM**. D-OFDM splits a wide spectrum into numerous narrowband orthogonal subcarriers enabling parallel data streams to/from numerous distributed nodes from/to the BS. A subcarrier bandwidth is in kHz (e.g., 50kHz, 100kHz, 200kHz, or so depending on packet size and needed bit rate). Narrower bands have lower bit rate but longer range, and consume less power [29]. The nodes transmit/receive on orthogonal subcarriers, each using one. A subcarrier is modulated using Binary Phase Shift Keying (BPSK) or Amplitude Shift Keying (ASK). If the BS spectrum is split into *m* subcarriers, it can receive from *m* nodes simultaneously using a single antenna. Similarly, it can transmit different data on different subcarriers through a single transmission. The BS can also use fragmented spectrum. This design is different from MIMO radio adopted in various wireless domains including IEEE 802.11n [43] as they rely on multiple antennas to enable the same. While OFDM has been adopted for multi-access in the forms of OFDMA and SC-FDMA in various broadband (e.g., WiMAX [69]) and cellular (e.g., LTE [81]) technologies [47, 53, 75], they rely on strong time synchronization which is very costly for low-power nodes. We adopted OFDM for the first time in WSN design and without requiring time synchronization. D-OFDM enables multiple packet receptions that are transmitted asynchronously from different nodes which was possible as WSN needs low data rate and short packets. Time synchronization is avoided by extending the symbol duration (repeating a symbol multiple times) and sacrificing bit rate. The effect is similar to extending cyclic prefix (CP) beyond what is required to control inter-symbol interference (ISI). CPs of adequate lengths have the effect of rendering asynchronous signals to appear orthogonal at the receiver, increasing guard-interval. As it reduces data rate, D-OFDM is suitable for LPWAN. Carrier frequency offset (CFO) is estimated using training symbols when a node joins the network on a subcarrier (right most) whose overlapping subcarriers are not used. Using this CFO, it is determined on its assigned subcarrier and compensated for using traditional method to mitigate ICI.

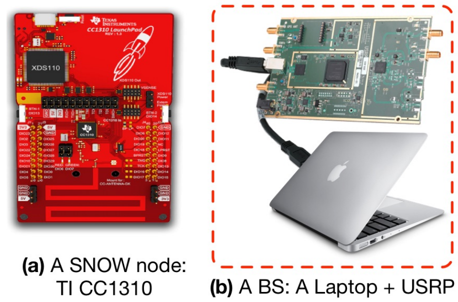

Figure 2: SNOW Hardware.

We implemented SNOW on two hardware platforms – USRP [14] using GNU radio [16] and TI CC1310 [24]. Using a simple CSMA/CA based MAC protocol, our preliminary experiments showed its better scalability and energy efficiency over other LPWANs [58–60]. We observed a Tx range of 8km at 20dBm. CC1310 is a tiny, cheap (<$30), and commercially off-the-shelf (COTS) device with a programmable PHY. We implemented SNOW with CC1310 (using CC-ANTENNA-DK2) as a SNOW node (Fig. 2 (a)) [30]. The BS is a USRP210 with a laptop (Fig. 2 (b)). Since CC1310 allows us to use ASK modulation and up to 15dBm Tx power, we achieved 1.5km Tx range compared to 8km achieved using USRP. We have set a testbed using both USRP and CC1310 devices as SNOW nodes [15]. As the frequencies of SNOW's operating spectrum are close to that (lower ISM band) of most LPWANs, its antenna form factor will be close to those in real production.

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 [66] with no collision avoidance. SNOW currently uses a lightweight CSMA/CA approach. While such lightweight protocols provide

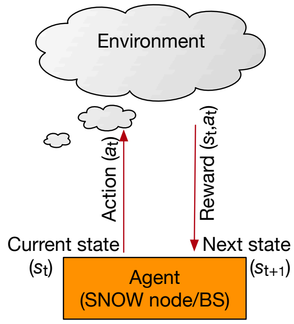

Figure 3: RL visualization

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 [67]. This trivial approach needs more infrastructure support and cost while the gain is marginal. *Choir* [32] 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 [54] 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 [61, 70, 71]), it will not work well for LPWANs. Due to their 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 massive crowds of coexisting networks, the interference pattern can be hard to detect for an LPWAN/SNOW device. Hence, a TDMA (time division multiple access) or traditional CSMA/CA based approach will simply fail. 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 [65]. As shown in Fig. 3, 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.

4.1 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 [73], and in WSN for routing [26, 31, 34, 63], QoS provisioning [25, 77], and resource management [74]. It was also used with RTS/CTS to learn contention and collision with the nodes in the **same** network using a **single channel** [45]. SNOW exploits many subcarriers concurrently and does not rely on energy-consuming RTS/CTS frames. 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. Adopting it for SNOW that features massive concurrent communications on numerous narrowband subcarriers, white space dynamics, PAPR constraints, and very low-power requires a new Q-learning framework.

4.2 Proposed Q-Learning Framework

Both the nodes and the BS in a SNOW will adopt Q-learning. The common purpose of both sides is to learn about the communication pattern of the coexisting networks. On the BS side, this can help determine usable subcarriers and their use pattern. The actions of a BS can also include load balancing among the subcarriers considering its outside utilization (in coexisting users). To each node, we assign prioritized access to multiple subcarriers. The intuition is that if one subcarrier is busy or noisy, another may remain free. A node will start with its first priority subcarrier. If a subcarrier is busy, it will either back-off or hop to its next subcarrier. If Tx fails on one subcarrier, a node can choose to retransmit on the same or the next prioritized subcarrier on a higher Tx power. When a node has chosen a subcarrier it can either transmit on it, or backoff, or hop to the next priority subcarrier, or sleep. If some subcarriers become unavailable due to primary users, the nodes are informed using some backup subcarriers which is a common technique in cognitive radios [27]. Nodes switch to backup subcarriers if no communication happens on their subcarriers for a certain time length. Since the BS can use fragmented spectrum, it can turn on and off some subcarriers based on their noise level. The Q-learning framework on the BS side will take into account the cost associated with PAPR in downlink communication. To reduce PAPR, it uses a subset of the Rx subcarriers on the Tx radio for sending ACKs. A node may need to transmit on one subcarrier and listen for ACK on another. The BS may put multiple ACKs on a subcarrier along with any subcarrier reassignment information.

Reward Function Formulation for Node. Every SNOW node individually adopts Q-learning to make its decision. It adopts *CCA (clear channel assessment)* for carrier sensing. Its set of actions is $\Lambda = \{$*Transmit, Receive, Backoff, Wake up, Subcarrier hop, CCA, Get sleep, null*$\}$. We consider agent (node) states $\Omega = \{$*Tx, Rx, Idle, sleep*$\}$, to indicate its state of transmitting, receiving, idle, sleeping. Fig. 4(a) shows state transitions. Let $s_t \in \Omega$ be the agent state at time t. Its total reward is given by

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

(a) Node states

(b) A BS subcarrier states.

Figure 4: **Agent state diagram.**

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.

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

Based on this idea, we need to formulate all reward functions for a node agent......

Reward Function Formulation for BS. Here we provide an outline to formulate reward functions for the BS. The BS will maintain states and actions for each subcarrier on both Rx radio and the Tx radio. For our preliminary formulation, we consider two states, Rx_OFF and Rx_ON, for each subcarrier on the Rx radio to indicate if it is ON or OFF. The actions are: *Turn Rx ON*, *Turn Rx OFF*, and *null.* We consider similar states and actions for each subcarrier on the Tx radio. A state diagram showing these states and actions is shown in Fig. 4(b) for a subcarrier at the BS. For a subcarrier f_i used in the Rx radio for receiving from the nodes, let $\mathbf{rps}(t, i)$ be packet rate (number of packets received per unit time) per subcarrier at time t if we add subcarrier f_i to the Rx radio. Let $\mathbf{lps}(t, i)$ be loss rate (number of times the BS recognizes high signal strength on a subcarrier but cannot decode packet per unit time) per subcarrier at time t if we add subcarrier f_i to the Rx radio. Thus, $\mathrm{rps}(t, i)$ and $\mathrm{lps}(t, i)$ can be considered *reward* and *cost*, respectively, for turning f_i on at the Rx radio. Let $\mathbf{aps}(t, i)$ be ACK rate (number of ACKs sent per unit time) per subcarrier at time t if we add subcarrier f_i to the Tx radio. Let $m_{\mathrm{tx}}(t)$ be the total number of subcarriers used by the Tx radio for ACK at time t. If the BS's maximum tolerable PAPR is β, then if adding a subcarrier exceeds this value, i.e. if $m_{\mathrm{tx}}(t) + 1 > \beta$, we consider a penalty (cost) as the BS has to dissipate more energy. Considering ν as some normalized cost per subcarrier, R-values for subcarrier f_i can be formulated as follows.

$$R(s_t^i, a_t^i) = \begin{cases} \mathrm{rps}(t,i) - \mathrm{lps}(t,i) & \text{if } s_t^i = \textit{Rx\_OFF},\ a_t^i = \textit{Turn Rx ON} \\ \mathrm{aps}(t,i) - \nu . \max\left(0,\ m_{\mathrm{tx}}(t) + 1 - \beta\right) & \text{if } s_t^i = \textit{Tx\_OFF},\ a_t^i = \textit{Turn Tx ON} \end{cases}$$

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 [65]. 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 [65].

With the above idea, we need to complete our Q-learning framework for both the nodes and the BS to govern the SNOW MAC for handling coexistence.......... 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.

5 CONCLUSION

To Do .....

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