

GNU Radio Implementation and Demonstration of MALIN: “Multi-Arm bandits Learning for Internet-of-things Networks”

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Abstract

We implement¹ an IoT network the following way: one gateway, one or several intelligent (learning) objects, embedding the proposed solution, and a traffic generator that emulates radio interferences from many other objects. Intelligent objects communicate with the gateway with a wireless ALOHA-based protocol with no specific overhead for learning needs. We model the network access as a discrete sequential decision making, and using the framework and algorithms from Multi-Armed Bandit (MAB) learning, we show that intelligent objects can improve their access to the network by using load complexity and decentralized algorithms, such as UCB and Thompson Sampling.

1 Objectives and importance

Unlicensed bands are more and more used and considered for mobile and LAN communication standards (WiFi, LTE-U), and for Internet of Things (IoT) standards for short-range (ZigBee, Z-Wave, Bluetooth) and long-range (LoRaWAN, SIGFOX, Ingenu, Weightless) communications [1]. Efficient Medium Access (MAC) policies allow objects to avoid interfering traffic and can significantly reduce the spectrum contention problem in unlicensed bands. As the objects battery life is a key constraint of IoT networks, this leads to IoT protocols using as low signaling overhead as possible and simple ALOHA-based mechanisms. In this demo, we evaluate Multi-Armed Bandits algorithms [2], used in combination with a pure ALOHA-based protocol. We consider the Upper-Confidence Bound

(UCB) [3], and the Thompson-Sampling (TS) algorithms [4]. Both algorithms have already been applied with success, for Opportunistic Spectrum Access [5] and recently for multi-users Cognitive Radio problems [6].

This demo aims at assessing the potential gain of learning algorithms in IoT scenarios. In a simple wireless network, consisting of one gateway (radio access point), and a certain interfering background traffic assumed to be stationary, some dynamic intelligent objects (end-user or autonomous objects), try to access the network, with a low-overhead protocol. To simulate networks designed for the Internet of Things (IoT), we consider a protocol with no sensing, no repetition of uplink messages, and where the gateway is in charge of sending back an acknowledgement, after some fixed-time delay, to any object who succeeded in sending successfully an uplink packet. By considering a small number of wireless channels (10) and one PHY layer configuration (*i.e.*, modulation, waveform, etc), and in case of a non-uniform traffic in the different channels, the object can improve their usage of the network if they are able to *learn* on the fly the best channels to use (*i.e.*, the most vacant).

Following our recent work [7], we propose to model this problem as Non-Stationary² Multi-Armed Bandit (MAB), and suggest to use low-cost algorithms, focusing on two well-known algorithms: a frequentist one (UCB, Upper Confidence Bounds) and a Bayesian one (Thompson Sampling). We use a TestBed designed in 2017 by our team SCEE [8], containing different USRP cards [9], controlled by a single laptop using GNU Radio [10], and where the intelligence of each object corresponds to a learning algorithm, implemented as a GNU Radio block [11] and written in Python or C++.

Our demo can modify dynamically the background traffic in a configurable number of channels, and reset at any time the channel selection algorithms of a End-Users with low duty-cycle, with a second one running the naive uniform access for comparison. This allows to check that in case of uniform traffic, there is nothing to learn and the in-

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¹We propose a demonstration for the French GNU Radio days, in reply of `gnuradio-fr-18.sciencesconf.org` 2018.

²Non-stationarity comes from the presence of more than one dynamic object.

telligent object do not reduce their successful communication rate in comparison to the naive object, and in case of stationary non-uniform traffic, the MAB learning algorithms indeed help to increase the global efficiency of the network by improving the success rate of the intelligent object.

2 Demo layout

Figure 1 shows the layout of our demonstration. Figures 2, 3 and 4 show the GNU Radio Companion (GRC, [11]) schemes corresponding respectively to the *interfering traffic* generator (in charge of generating a random stationary traffic in each channel, with a fixed duty-cycle), the *gateway* (in charge of listening in each channel, detecting incoming messages and replying with an acknowledgement), and one or more objects (dynamic device in charge of emitting in a sequentially chosen channel, receiving an acknowledgement and using the statistics and its learning algorithm to decide which channel to use next). In our demo, the objects try to communicate with the gateway. This communication is hindered by some interfering traffic. This interfering traffic is supposed to be unevenly distributed in channels and is generated by a single USRP. If the gateway receives a message transmitted by an intelligent object and can decode it, it acknowledges it by sending a short ACK message.

The basic blocks (sink, source, FFT) are builtin GRC, but all the other blocks (`demodulator`, `send_ack`, `check_ack` for the gateway, `generator` for the interfering traffic, and `renormalize_ack` and `generator_SU` for the objects) are written in C++ for this demonstration.

3 List of equipment for demo

We require a large-screen TV, but we will bring everything else. Our demo is developed using a large Testbed, as showed in Figure 5, but it can be transported by using only one laptop, connected to a portable switch, to control the different USRP cards and an octoclock for synchronisation.

Our demo operates on the 433.5 MHz band, with a bandwidth of 2 MHz, at low power consumption.

4 Conclusion

Possible extensions of this work include: considering more dynamic objects, implementing a real-world IoT communication protocol (like the LoRaWAN standard), and studying the interference in case of other gateways located nearby.

Acknowledgment

The authors acknowledge the work of two Centrale-Supélec students, Clément Barras and Théo Vanneville, as we took inspiration in the GNU Radio code they wrote during their project in Spring 2017.

This work is supported by the French National Research Agency (ANR), under the projects SO-GREEN (grant coded: *N ANR-14-CE28-0025-02*), by Région Bretagne, France, by the CNRS, under the PEPS project BIO, by the French Ministry of Higher Education and Research (MENESR) and ENS Paris-Saclay.

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Note: the code of our demo is for GNU Radio [10] and GNU Radio Companion [11], and is open-sourced under the GPLv3 License, on Bitbucket at: <https://goo.gl/y6kKH2>.

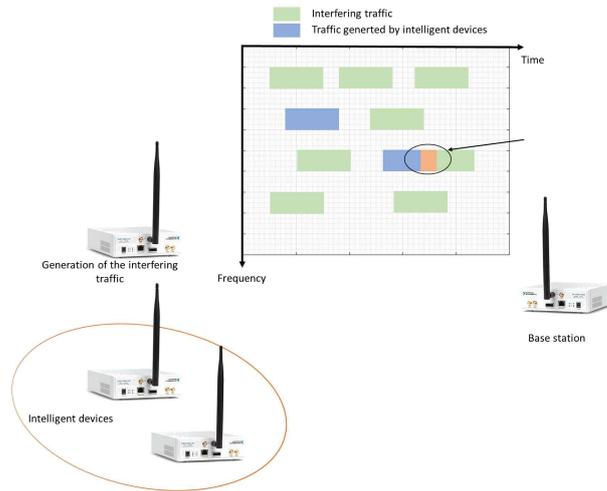


Fig. 1: Layout of the demonstration. Our demo uses one USRP to generate an interfering traffic and one for the base station. Moreover, at least one intelligent device is added in the network and tries to communicate with the base station. The protocol is a pure ALOHA protocol with acknowledgement.

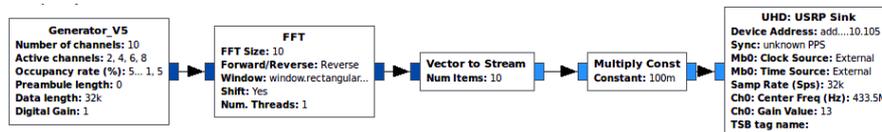


Fig. 2: GRC Scheme for the Interfering Traffic (TX PU): 1 USRP block (sink).

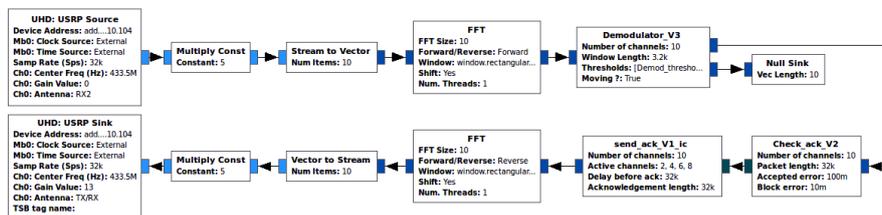


Fig. 3: Base Station (RX/TX BTS): 2 USRP blocks (sink/source) but one card.

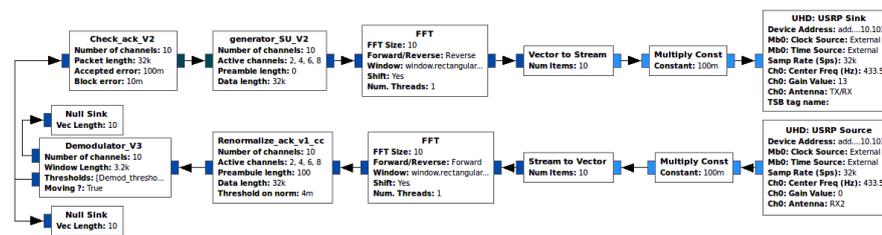


Fig. 4: Dynamic Device (RX/TX SU): 2 USRP blocks (sink/source) but one card.



Fig. 5: Our TestBed, cf. <http://www-scee.rennes.supelec.fr/wp/testbed/>.