POSTPRINT VERSION. The final version is published here :
Sani, Y., Ouameur, M. A., Massicotte, D. et Martin, T. (2021, 13-15 Oct. 2021). Energy Efficient Exponentially Weighted Algorithm - Based Resource Allocation in LoRa Networks. Communication présentée 2021 IEEE 4th 5G World Forum (5GWF), Montreal, Canada. doi: 10.1109/5GWF52925.2021.00045

Energy Efficient Exponentially Weighted Algorithm - Based Resource Allocation in LoRa Networks

Yalda Sani [*], Messaoud Ahmed Ouameur [*], Daniel Massicotte [*] and Tristan Martin [**]

[*] Laboratoire des Signaux et Systèmes Intégrés,
Université du Québec à Trois-Rivières, Department of Electrical and Computer Engineering,
3351, Boul. des Forges, Trois-Rivières, Québec, Canada.
{yalda.sani, messaoud.ahmed.ouameur, daniel.massicotte}@uqtr.ca
[**] Altus Technologie, 1300 Place du Technoparc, Trois-Rivières, Québec, Canada.
tristan.martin@altus-tech.com

***Abstract*—— Low-power wide-area networks (LPWANs) increasingly attract attention in the IoT community. The provision of long communication ranges with low energy consumption is the main reason behind LPWAN's growing popularity. Energy efficiency is a crucial matter for LPWAN devices that are mostly battery-powered and required to function in a crowded environment. To reduce energy consumption over these networks, minimizing the collision rate in the packet transmission process is one of the possible solutions. However, existing algorithms for radio resource allocation management do not fulfill the energy efficiency required by IoT devices. We propose Energy Efficient Exponentially Weighted Algorithm Based Resource Allocation, which considers energy consumption level and transmission time of each packet in learning the best set of resources to be allocated to each end-device. We achieve 30% lower energy consumption per packet transmission than the base line methods, which is a noticeable amount when considering the whole network packet transmission, at the expense of losing 2% of the successful transmission rate.**

Keywords—IoT, LoRaWAN, resource allocation, energy efficient, reinforcement learning, MAB, EXP3

I. INTRODUCTION

Nowadays Internet of Things (IoT) devices are distributed over wide geographical areas. As Low-power wide-area (LPWA) networks are offering low-cost they have recently gained significant attention [1]. LoRa stands out among other popular LPWAN technologies [2], such as Narrowband IoT, considering its extremely long battery lifetimes and reduced costs. To achieve low-power and robust links, LoRa has a remarkable ability to adjust communication parameters according to a proprietary chirp spread spectrum modulation [3].

Some examples for adjustable communication parameters in LoRa are Spreading Factor (SF), Transmission Power (TP), Carrier Frequency (CF), Coding Rate (CR), and Bandwidth (BW). Adjustment of these parameters would lead to changes in radio coverage, radio interference, energy consumption, error rates, and other aspects of the network performance [9].

Working on pure ALOHA principles, LoRa utilizes different ISM frequencies based on region (using 868, 915, and 433 MHz in Europe, North America, and Asia, respectively). Although, depending on the country, this frequency dedication on a shared wireless medium might result in strict time limitations for LoRaWAN networks, which use the LoRa modulation technique and apply the LoRa Alliance standard when implementing the upper MAC and the Network layers [4].

One of the noteworthy features of LoRaWAN networks is their flexibility in customizing the transmission parameter of each device in the network. This means that there is an optimal configuration for transmission parameters throughout the network. Hence, we can improve the throughput of the network by reducing collision, which can be obtained by intelligent resource allocation management [3].

When two or more LoRa transmissions overlap at the receiver side, a collision occurs. In other words, a collision happens when multiple devices select the same channel and spreading factor (SF), with timing overlap. Moreover, since the orthogonality of SFs is not perfect, inter-SF collisions can occur among signals on the same sub-channel even with different SFs.

The frequent communication of end devices with the network server to ask for a suitable recourse-set per packet would cause an excessive rise in the number of packets on the network. This additional traffic would lead to a continuous increase in the probability of collision happening and energy consumption. Therefore, a distributed self-managed solution for selecting radio resources at the device level seems vital.

Our goal is to decrease energy consumption in IoT devices while keeping reliability as high as possible. To achieve this goal, we present a distributed learning approach in LoRa technology resource allocation and compare the results against the existing solutions. The performance evaluation results indicate a significant decrease (more than 30%) in energy consumption in trading off 2% of the lower successful transmission rate.

The remainder of the paper is as follows. Related works are presented in the next section. We discuss the LoRaWAN based Multi-Armed Bandit (LoRaWAN-MAB) simulator in section III. In Section IV, we present the proposed learning approach. The performance of our distributed learning algorithm is compared against the random and the base line EXP3 policies in Section V, where the simulation results are presented. Finally, in section VI, a conclusion and future works are outlined.

II. RELATED WORKS

There have been different points of view addressing the SF allocation issue in LoRa networks. Authors in [10] and [11] consider mathematically tractable node distributions. Despite the theoretical benefits of mathematical modeling, it has been suggested that mathematical distributions can hardly reflect the scenario when deploying nodes in real life [12].

Utilizing an in-depth analysis of the capture effect and the LoRa modulation scheme, the average per-node throughput of LoRaWAN networks has been mathematically modeled in [3]. This work offers optimal disseminating policies by formulating the updating process as a Reinforcement Learning (RL) problem. However as updating process adds extra downlink traffic, they let LoRa gateway pause updating process which is a weak point in reinforcement learning.

Using machine learning algorithms is a reasonable approach to the resource allocation problem. In order to reach reliable data transmission and maximum energy efficiency, the authors in [6] propose a learning solution for devices to adapt their communication parameters with environmental circumstances. Regardless of the stochastic and adversarial-based distributed learning algorithm for resource allocation in an IoT network, inter-SF and the capture effect have not been considered. Also, MATLAB-based simulators that have been used in this work may not capture all aspects of a real LoRaWAN network [5]

Authors in [5] consider radio resource allocation in LoRaWAN as a Multi-Armed Bandit (MAB) problem [7], [6]. In their presented distributed learning algorithm, each end-device performs as an intelligent agent that uses a fitting rewarding process to choose a given SF and/or channel to improve the trade-off between energy efficiency and reliability, i.e., transmission success rate.

The work in [7] utilizes the stochastic MAB algorithm for frequency selection determination, assuming that all end-devices share the same SF. However, the mutual coupling between intelligent end devices invalidates this assumption in real-world cases. In [5] and [6], receiving acknowledgment is used as a reward in their learning process. Also, to obtain a more energy-efficient solution through the proposed algorithm, relating network parameters such as the amount of energy consumed by each packet transmission can be included in the rewarding process.

III. REINFORCEMENT LEARNING FOR RESOURCE ALLOCATION

A. Network Parameters

The characteristics of LoRa are based on some configurable parameters, such as Bandwidth, Spreading Factor, Carrier Frequency, Transmission Power and Coding Rate. We use three of the following parameters in our learning algorithm:

Spreading Factor: SF is the ratio between the symbol rate and the chip rate, which can be in the range from 7 to 12. Higher SF increases the SNR, transmission range, and packet airtime; but, it decreases the data rate.

- Channels: Depends on geographic region, can be set to 433 MHz, 868 MHz and 900 MHz.
- Transmission Power: Due to hardware limitations, the transmission power in a LoRa network can be configured in steps of 1 dB with a signal power between 2 dBm and 20 dBm [6].

B. LoRaWAN-MAB and EXP3

Reinforcement learning is one of the most suitable algorithms for resource allocation problems. As there are no training samples to learn from, the nodes need to learn by taking actions and receiving rewards related to the action. This kind of learning can be applied through the Multi-Armed Bandit (MAB) problem, which only uses local information available at the LoRaWAN end-device level [5]. EXP3 algorithm (Exponential Weights for Exploration and Exploitation) [13] is one of the most efficient algorithms to solve MAB problems. As previously mentioned, the authors in [5] introduce a lightweight and flexible simulator that uses the popular EXP3 algorithm in LoRa networks, called LoRaWAN-MAB. Each end-device learns to autonomously pick the most suitable set of resources (e.g., spreading factors, sub-channels). The main goal of the algorithm is to minimize energy consumption by reducing the collision rate.

This simulator is a disc-shaped LoRaWAN-like network with one or more gateways and N end-devices uniformly distributed in the network with a radius of R. In the LoRaWAN-MAB simulator have three main components: end-devices, propagation model, and gateways. It is assumed that the network server functions are part of the gateway.

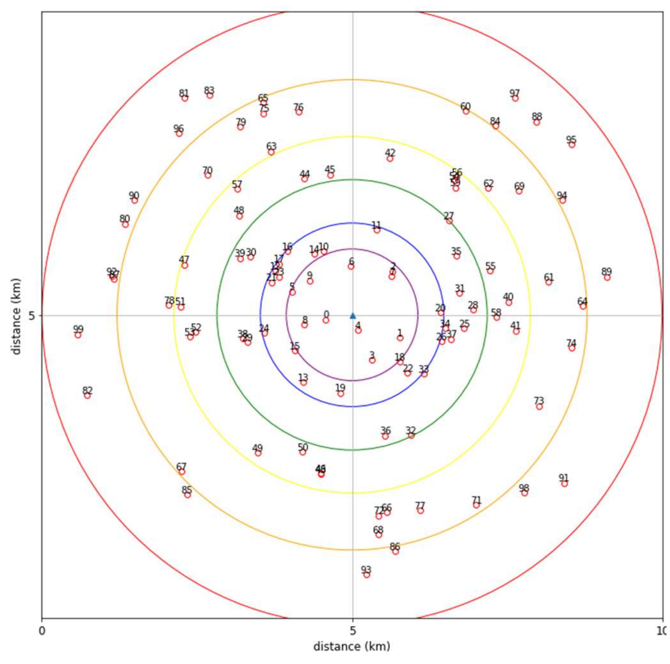


Fig.1. distribution of 100 end devices within a circle with a radius of 5km

In the IoT-MAB simulator, the log-distance path loss model with flat fading is considered, where the reference distance is $d_0 = 40$ m, the path loss at the reference distance is $PL_0 = 107.41$ dB, and the path loss exponent is $\mu = 2.08$.

IV. ENERGY EFFICIENT EXP3 ALGORITHM

To implement the distributed learning for resource allocation in LoRaWAN, we consider the Exponential-weight algorithm for Exploration and Exploitation (EXP3). To enhance the role of the reinforcement learning algorithm in reducing the energy consumption of the network, we start our contribution with classification of end nodes, before the learning process begins. This can speed up and help the learning process at the beginning. Receiving acknowledgement for packet sending is a vital parameter in learning process but it is not the only one. For the next step, during the learning process, we use more parameters in calculating the reward, such as the energy consumption of the taken action for sending a packet and the time it consumes. As a result, the learning is based on the different factors that affect energy consumption of the network, in addition to receiving or not receiving the packets.

A. Classification

Before starting the learning algorithm, we decided to classify the end devices based on their distance from the gateway. At the beginning of the simulation, each class of end devices will have a preferred action instead of random selection among possible choices. Such a distance can be inferred from the measured RSS during initial access.

The spreading factor is a critical variable in LoRa, which significantly influences the range, transmission speed, and power consumption, as it increases and decreases the time and energy used to transmit each bit. LoRa uses spreading factors SF, in the range from 7 to 12 to control the data rate of the transmitted signals [8].

In a LoRa network, an end device located at the network's edge must communicate with the highest spreading factor (SF12) [8]. In our classification, when the deployment of the network is formed for the first time, each end device receives a higher probability for a specific spreading factor based on its distance from the gateway. In this case, the probability of choosing a suitable spreading factor gets higher and not only has an immediate affect on transmitting packet successfully but also increases the speed of learning to allocate a suitable action for each end device which improves the throughput of the network.

Fig.1 shows the network configuration and end devices classification based on their distance from the gateway. Nodes within each circle will use an identical related spreading factor at the beginning of the simulation.

B. eeEXP3 Algorithm

Each end device at time *t* can choose an action $a_i(t)$ to send a packet. The action $a_i(t) \in \mathrm{A}$ where A is a set of resources, $\{\mathrm{sf}_i, \mathrm{ch}_i, \mathrm{tp}_i\}$ where $\mathrm{ch}_i \in \mathrm{CH}$ is a selected channel, $\mathrm{sf}_i \in \mathrm{SF}$ is a selected spreading factor and $\mathrm{tp}_i \in \mathrm{TP}$ is a selected transmission power.

The learning process is based on the energy consumption and transmission time of the packet, and receiving the acknowledgment (ACK) or not receiving the acknowledgment (NACK). After choosing the action $a_i(t)$ at time *t*, device *i* receives the corresponding reward.

Algorithm 1: eeEXP3: Energy Efficient EXP3 algorithm with energy and transmission time updated reward ($e \approx 2.7182...$)

Initialization for each end device *j*

Set initial weights $w_a^j(0) = 1, \forall a \in \mathrm{A}$

Set learning rate $\gamma = \min\left\{1, \sqrt{\dfrac{k\log(k)}{(e-1)T}}\right\}$

Classify the nodes based on their distance

for each end device *j* do

for each sf_i do

if $d(\mathrm{sf}_i) < dist^j \le d(\mathrm{sf}_{i+1})$ and $a[0] = \mathrm{sf}_i$

then $p_a^j(0) = 1$

end if

end for each sf_i

end for each end device *j*

Compute reward, weight and probability at each iteration *t*

for $t = 1$ to T-1 **do**

for each end device *j* **do**

Take an action $a \in \mathrm{A}$ according to the probs.

Calculate/receive reward

if ACK then

$$r_a^j(t) = 1 + \alpha\left(-\mathrm{eng}_a^j(t) - \beta\,\mathrm{trn}_a^j(t)\right)$$

end if

if NACK then

$$r_a^j(t) = 0 + \alpha\left(-\mathrm{eng}_a^j(t)\right)$$

end if

Update weight $w_a^j(t+1) = w_a^j(t)\exp\left(\dfrac{\gamma r_a^j(t)}{k\, p_a^j(t)}\right)$

Compute probability

$$p_a^j(t+1) = (1-\gamma)\left(\frac{w_a^j(t+1)}{\sum_{a=1}^{k} w_a^j(t+1)}\right) + \frac{\gamma}{k}$$

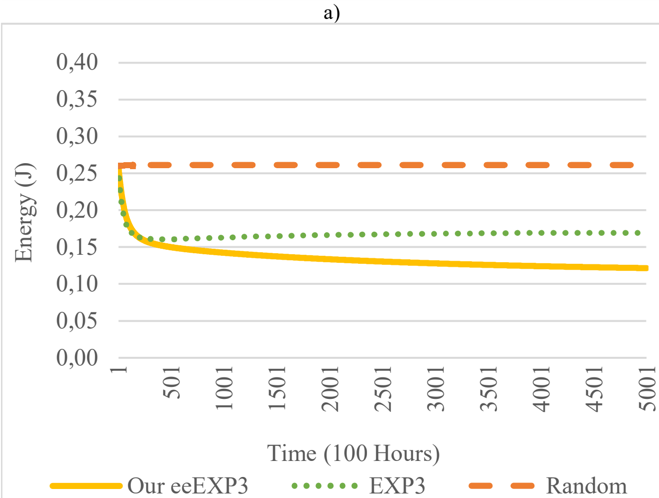
end for

end for

By receiving the reward, the related weight and probability of action $a_i(t)$ is calculated and updated. If choosing the action ends with acknowledgment, the reward will be positive, where the lower energy and time consumption will increase the reward. Thus, between two actions with acknowledgment, the one with lower energy and time consumption will have a higher probability of being picked. As result the most suitable action will be picket. Conversely, if the end device does not get acknowledged, the reward will be negative and accordingly decreases the probability of the action. When an end device wants to send a packet, it will choose an action with a higher probability.

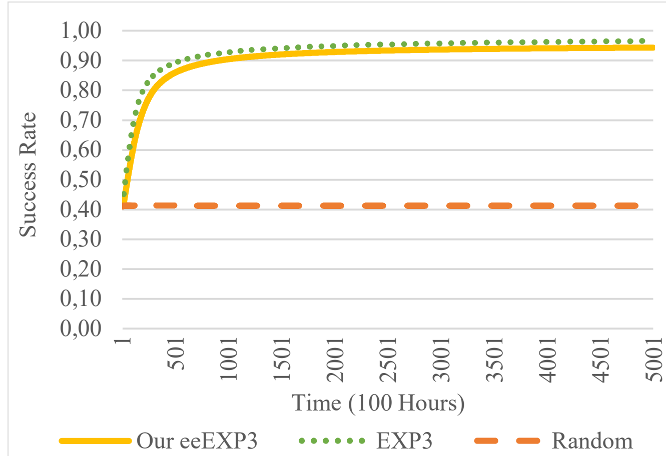
Where $a(t)$ is the chosen action at time *t*, which gives a reward $r_a^j(t)$, $p_a^j(t)$ and $w_a^j(t)$ are the probability and weight of each action.

a)

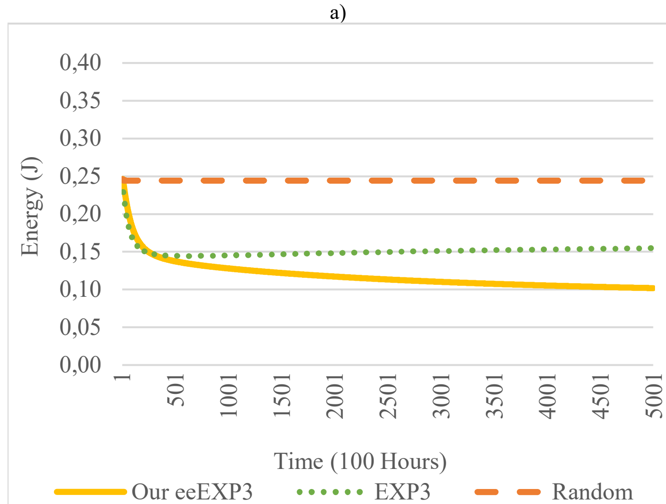


b)

Fig. 2. Scenario 1 a) Successful Transmission Rate and b) Average Energy Consumption per Packet.



a)



b)

Fig. 3. Scenario 2 a) Successful Transmission Rate and b) Average Energy Consumption per Packet.

For calculating the reward, $\mathrm{eng}_a^j(t)$ is the energy consumption of the taken an action a at time t to send a packet from node j, and $\mathrm{trn}_a^j(t)$ is the amount of time it takes to transmit a packet from node j through action a at time t. α and β are parameters for trade off between acknowledgement, energy efficiency and transmission time which $\alpha, \beta \in \{0,1\}$.

By learning progress, each device i chooses the most appropriate set of resources with minimum collision rate and this improve the overall performance of network.

Algorithm 1 shows the pseudo-code of the eeEXP3 (energy-efficient EXP3) algorithm for resource allocation.

V. Evaluation

After importing above mentioned improvements to the LoRaWAN-MAB simulator [14] we evaluate our proposed algorithm. In our evaluation, 100 smart end devices transmit packets to one gateway. After many simulations, we decided that the best value for α and β to achieve a lower energy consumption are respectively 0.5 and 0.1, respectively. The packet generation rate of each end-device is $\lambda = 15$ packet per hour and the packet length is $l = 50$ bytes. The packets are generated through an exponential distribution. End- devices are located in a circle with a radius R = 4.5 km through a uniform distribution.

To evaluate the performance of network we consider different scenarios:

- scenario 1: each end-device can select one of 6 possible SFs from 7 to 12 with one subchannel and the transmission power of {8, 11, 14} dBm.
- scenario 2: each end-device can select one of 6 possible SFs from 7 to 12 with three subchannels and the transmission power of {8, 11, 14} dBm.
- scenario 3: each end-device can select one of 6 possible SFs from 7 to 12 with one sub-channel and the transmission power of 14 dBm.

To assess the performance of the algorithms, we compare our learning algorithm (referred to as eeEXP3) to the base line EXP3 algorithm and random selection policy considering successful packet transmission rate and the average energy consumption per successfully transmitted packet.

Fig. 2 shows the performance of algorithms for scenario 1. Fig.2.a shows that the successful transmission rate of EXP3 is

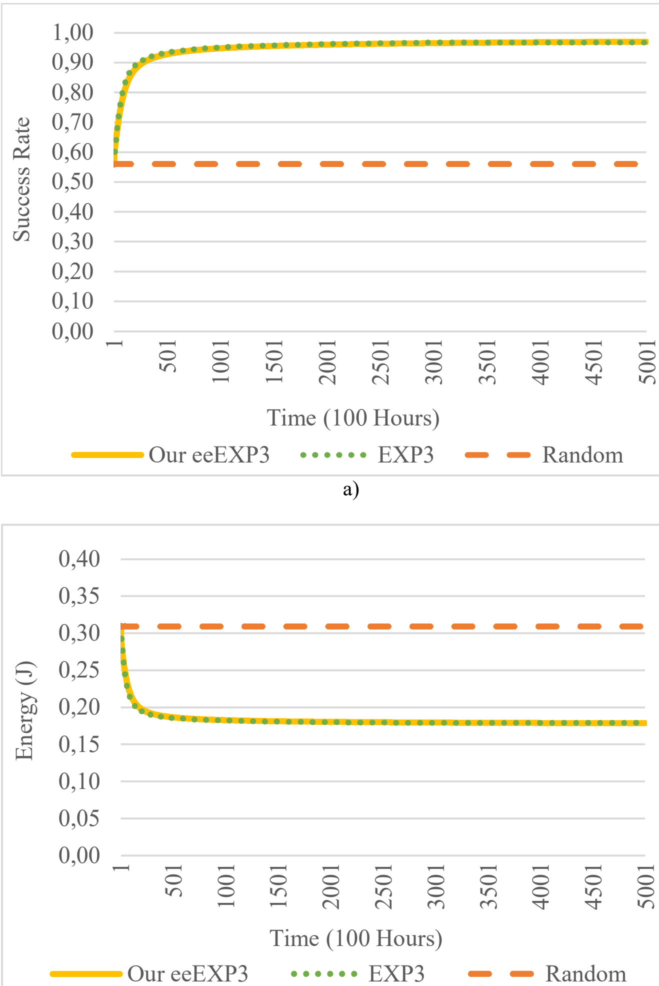


Fig. 4. Scenario 3 a) Successful Transmission Rate and b) Average Energy Consumption per Packet.

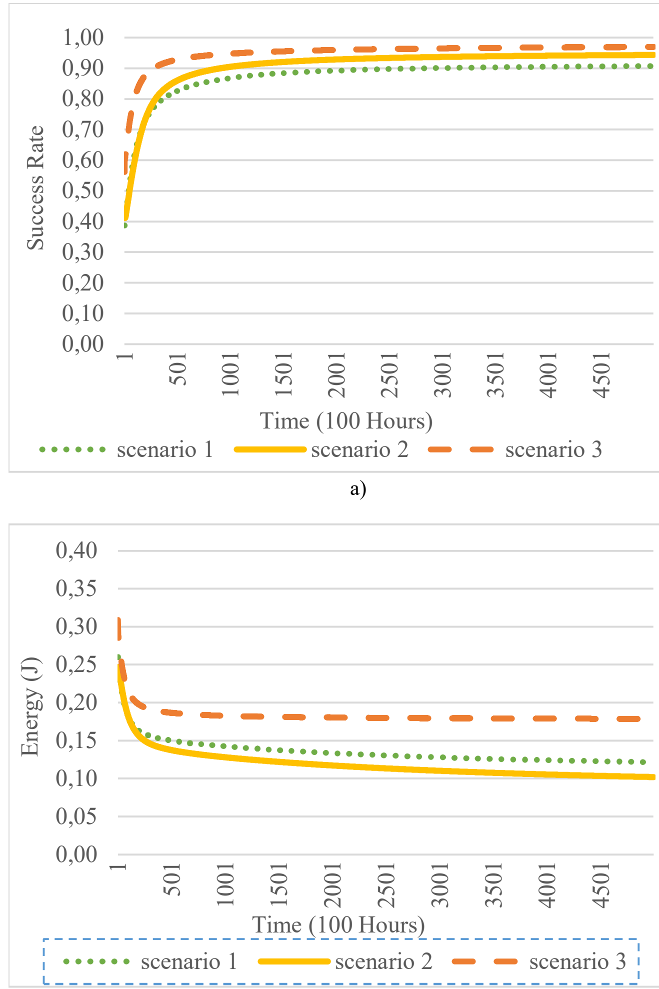


Fig. 5. Scenario 1 to 3 using our eeEXP3 algorithm a) Successful Transmission Rate and b) Average Energy Consumption per Packet.

2% higher compared to the proposed algorithm. However, we can see, in Fig. 2.b, that the network average energy decreased. Both policies show similar performances at the beginning of the simulation. However, after 500 KHours, the energy consumption of each successful packet transmission using eeEXP3 is about 0.121 J which is 28 % lower than energy consumption of EXP3 algorithm.

For scenario 2 with a higher number of resources to choose from, Fig 3.a shows that the successful transmission rate of eeEXP3 and EXP3 is so close, with a negligible loss of 2% (0.94 vs. 0.96). In Fig. 3.b, it is clear that the eeEXP3 algorithm performs remarkably better than the base-line EXP3 and random selection policy. The energy consumption for each packet using the eeEXP3 algorithm is 0.102 J whereas it is 0.154 for the EXP3 algorithm which is 33% lower.

Finally, for scenario 3, Fig. 4.a and Fig. 4.b respectively show the successful transmission rate of LoRaWAN and network average energy consumption. We can see that the system's performance with our eeEXP3 and EXP3 are the same, and both algorithms have a significantly higher success rate than random SF selection policy.

It worth mentioning that we simulate 500 KHours, and the achieved results can still be improved. The successful transmission rate increases, and the energy consumption decreases by exceeding learning time. As a result, the difference between the successful transmission rate of our proposed algorithm and the EXP3 algorithm will be reduced over time. In addition, regarding the average energy consumption for scenarios 1 and 2, the difference will decrease even more.

Fig. 5.a and 5.b compare successful transmission rate and average power consumption of our proposed algorithm in scenario 1 to scenario 3. We can see that scenario 3 has the best performance and a higher success rate. However, the average energy consumption for each packet in scenario 3 is the highest. Scenario 2 has a noticeably lower energy consumption than two other scenarios. We can conclude that our proposed algorithm performs better if there are more resources to consider.

VI. CONCLUSION AND FUTURE WORK

This paper presents a learning algorithm based on the EXP3 algorithm, which uses both energy consumption and transmission time of the packet to calculate the reward. The results show that our algorithm significantly improves the performance of LoRaWAN, especially when the network has a higher number of parameters to allocate. Low energy consumption is one of the most critical features in LoRaWAN networks, and our work notably decreases the energy consumption of each packet which would be a great value if we consider the number of transmitted packets in the whole network.

In our future work, we will use reinforcement learning to learn the behavior of the network and use it to allocate the most suitable and efficient set of resources to each device. The gateway can also have a valuable role in the learning algorithm in the resource allocation process because it has more information about the whole network, which is not available for the end-devices; thus, adding more related parameters in the learning process, we can achieve more efficient network.

As the learning progresses, each device *i* chooses the most appropriate set of resources with a minimum collision rate, which improves the overall performance of the network.

It is worth mentioning that our work uses LoRa-MAB simulator [14] which is a flexible simulator for decentralized learning resource allocation in IoT Networks, but we envision to deploy our algorithm in a real word LoRa WAN after considering backward compatibility with its adaptive data rate (ADR) mechanism.

ACKNOWLEDGMENTS

This work has been funded by the MITACS grant with the collaboration from Altus Technologie.

REFERENCES

[1] Z. Qin, F.Y. Li, G.Y. Li, J.A. McCann, and Q. Ni, "Low-power wide area networks for sustainable IOT," IEEE Wireless communications, Vol. 26, No 3, June2019.

[2] Lora-Alliance. “LoRa” 2017, [Online]. Available: https://www.lora-alliance.org/

[3] R. M. Sandoval, A.-J. Garcia-Sanchez, and J. Garcia-Haro, “Optimizing and Updating LoRa Communication Parameters: A Machine Learning Approach,” IEEE Transactions on Network and Service Management, vol. 16, no. 3, pp. 884–895, sep 2019.

[4] ETSI, “Final draft ETSI EN 300 220-1 V2.4.1 (2012-01),” ETSI, Tech. Rep. REN/ERM-TG28-434, 2012.

[5] D.Tuyen Ta, K. Khawam, S. Lahoud, C. Adjih and S. Martin, “LoRa-MAB: A Flexible Simulator for Decentralized Learning Resource Allocation in IoT Networks”, WMNC 2019- 12th IFIP Wireless and Mobile Networking Conference, Sep 2019, pp.55-62.

[6] A. Azari and C. Cavdar, “Self-organized low-power iot networks: A distributed learning approach,” IEEE Global Communications Conference (GLOBECOM), 2018, pp. 1–7.

[7] R. Bonnefoi, L. Besson, C. Moy, E. Kaufmann, and J. Palicot, “Multiarmed bandit learning in iot networks: Learning helps even in nonstationary settings,” Cognitive Radio Oriented Wireless Networks, 2018, pp.173–185.

[8] E. Aras, G. S. Ramachandran, P. Lawrence and D. Hughes, "Exploring the security vulnerabilities of lora", 3rd IEEE International Conference on Cybernetics (CYBCONF), June 2017, pp. 1-6.

[9] E. Sallum, N. Pereira, M. Alves and M. Santos, “Improving Quality Of-Service in LoRa Low-Power Wide-Area Networks through Optimized Radio Resource Management”, journal of sensors and actuator networks, 2020.

[10] B. Reynders, W. Meert, and S. Pollin, “Power and spreading factor control in low power wide area networks,” IEEE International Conference on Communications (ICC). IEEE, may 2017, pp. 1–6.

[11] D. Zorbas, G. Z. Papadopoulos, P. Maille, N. Montavont, and C. Douligeris, “Improving LoRa Network Capacity Using Multiple Spreading Factor Configurations,” 25th International Conference on Telecommunications, 2018, pp. 3–8.

[12] R. M. Sandoval, D. Rodenas-Herraiz, A. Garcia-Sanchez and J. Garcia-Haro, "Deriving and Updating Optimal Transmission Configurations for Lora Networks," IEEE Access, vol. 8, pp. 38586-38595, 2020.

[13] P. Auer, N. Cesa-Bianchi, and P. Fischer, “Finite-time analysis of the multi- armed bandit problem,” Machine Learning, vol. 47, no. 2/3, pp.235–256, 2002.

[14] D. Ta, K. Khawam, S. Lahoud, C. Adjih and S. Martin, "LoRa-MAB: A Flexible Simulator for Decentralized Learning Resource Allocation in IoT Networks," *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*, 2019, pp. 55-62