A Deep Reinforcement Learning Approach For LoRaWAN Energy Optimization

Yassine Yazid[1] , Imad Ez-Zazi[2], Mounir Arioua[1] and Ahmed El Oualkadi[1]
[1]Abdelmalk Essaadi University , National school of applied sciences of Tangier (ENSATg)
Laboratory of Information and Communication Technologies (LabTIC)
ENSA Tanger, Route Ziaten, BP 1818, Tangier, Morocco
[2]Sidi Mohamed Ben Abdellah University, National school of applied sciences of Fez (ENSAF), Morocco
y.yazid@uae.ac.ma, imad.ezzazi@usmba.ac.ma, m.arioua@uae.ac.ma, aeloualkadi@uae.ac.ma

2021 IEEE Microwave Theory and Techniques in Wireless Communications (MTTW) | 978-1-6654-2469-1/21/$31.00 ©2021 IEEE | DOI: 10.1109/MTTW53539.2021.9607147

***Abstract*—In almost-majority of IoT (Internet of Things) networks; the wireless sensor nodes are small and low-cost portable devices. Besides, they are typically battery-powered with a finite lifespan duration. In most emerged applications, these nodes are required to remain for the maximum time possible with a standalone performance for large-scale coverage. Therefore, it is important to understand the node's processing before real implementation of any massive long-range IoT networks to assign accurate settings for each node on its positions along with estimating the approximate mean duration of all networks. LoRa (Long Range) is one of the recently emerged Low Power Wide Area Networks IoT networks that is knowing high interest in various applications. In this paper, we propose a Markov Decision Process-based model that aims to estimate the lifespan of LoRa class A end nodes regarding the efficiency in resources allocation and transmission parameter settings. The proposed model has been tested and showed interesting results on the accuracy of lifetime estimation and prediction under different scenarios.**

***Index Terms*—IoT, LoRa, energy estimation, Markov Decision Process, lifespan prediction, resource allocation.**

I. Introduction

As an emerging low-power wide-area network (LPWAN) technology, LoRaWAN has been gaining popularity owing to its flexibility and manageability in deployment. Dissimilar to other LPWAN solutions, it allows the flexibility of a variety of network parameters that affect different network performance metrics, such as energy efficiency, latency, and bandwidth. In principle, allowing the network behavior to be matched to specific applications scenario requirements [1]. Hence, the complex and potentially unenviable interconnections between different network components make it quite challenging to predict the effect of some given parameter settings, which further affect the IoT devices lifetime prediction. [2]. LoRa devices are considered of tiny sizes deployed massively to work autonomously relying only on their batteries for unknown periods. The lifespan of each node in the network depends on the used transmission energy as well as the channel conditions of the long range communication system. Before any transmission, the LoRa end node should adjust its parameters taking into account many features i.e. the range, the packet size and the channel conditions [3]. For this reason, it is quite challenging to predict the approximate lifespan of the post-distributed network due to many random under control conditions. In this regard, we aim at investigating the behavior of LoRa end nodes in long range network where they are supposed to communicate the aggregated data of interest to their Gateway situated at a ranged distance. The concerned nodes should perfectly adapt their communication parameters to succeed any required transmission.

In any uncertain surrounding and dynamic environment, the behavior of the wireless communication system can be modeled using a mathematical framework called Markov Decision Processes (MDP) to optimize the desired objectives of the network. The MDP approach implies that the system has a Markov property. In particularly, the state of the system in the next phase depends only on the current state but not on the past states. More recent developments in MDP solvers have enabled the solution for large-scale systems and introduced new research potentials [4]. MDP modeling offers many advantages to deal with wireless sensor communications and processings [5]. For instance, MDPs have the potential to dynamically optimize the network requirements to be adapted to unpredictable physical stats, thereby significantly improving resource utilization [6]. Furthermore, minimizing energy consumption and maximizing sensing coverage is of paramount importance to achieve the best operational policy for the transmission metrics [4]. In this work, an MDP based model is proposed to find best policies in LoRa transmission parameter settings taking into account the channel condition, energy consumption , the distance of the node from the final destination as well as the size of the transmitted packet length.

The remainder of this paper is structured as follows. In Section II, we first introduce some of the existing works related to energy estimation methods dedicated for the LoRa networks on the state-of-the-art. We present some definitions of LoRa/LoRaWAN functioning notions, and then we detail our proposed energy estimation method based on Reinforcement Learning (RL) in Section IV. We comment and discuss the obtained results in section V. Finally, we provide the conclusion in Section VI.

II. Related work

To understand the energy and resource allocation behavior of LoRa end-nodes (EDs); many academic studies have been devoted to assessing different scenarios [3], [7], [8]. Some works have been devoted to outdoor and indoor scenarios to analyze the limitations of this technology. In [9], the authors have assessed the energy consumption of LoRa transmitters and receivers through the use of diverse radio transmission configurations for star and mesh network typologies. To address the LoRa reliability and energy consumption; the authors have based on several approaches. For instance, some works have assessed the impact of LoRa transmission parameter selection on the performance on the overall network [3]. Moreover, the optimization of the packet error fairness on LoRa networks has been addressed in [8]. In [7] , the effect of spreading factors (SFs) allocation of LoRa End-Nodes (EDs) to optimize the energy consumption constraint is investigated. Authors in [10] have addressed the energy consumption issue in LoRa EDs by deriving an optimal transmitting configuration. In [11], authors assess the optimal allocation of SFs and transmission power to EDs in LoRa networks. In other context, several works have addressed the issue of sensor data collection delay in urban areas focusing on LoRa based gateways [12]. Moreover, in [13], authors have considered the trade-off between energy consumption and reliability where the authors experienced the energy measurement on different LoRa Semtech end devices. In the same context, a prediction model of energy consumption and probabilistic approach based on Markov's chain is provided to estimate the lifetime of the LoRa network using Labview simulation [14]. In [9], authors explored the flexibility of LoRa and provided various strategies to adapt its radio parameters , then calculated the energy consumption using various radio configurations in star and mesh typologies. This work developed a Markov framework to characterize the performance of battery-free LoRaWAN devices for down link and up link transmissions. They have assessed the performance of energy in terms of device configuration, application behavior, and environmental conditions [15]. In addition, a probabilistic approach based on Markov chains has been proposed to predict the system lifetime depending on the size of transmitted data during the day [14]. A dynamic LoRa transmission control (DyLoRa) has been proposed to improve energy efficiency by considering the adjustment of physical layer parameters for optimal energy efficiency from scattered LoRa packets [16]. An EF-LoRa mathematical model has been proposed in [17], to model the energy efficiency and deal with resource allocation problems in multi-gateway LoRa networks. The paper [18] has described a LoRa and LoRaWAN based energy usage model that permits to estimate the power consumed by each IoT device. Within the model, different node unit definitions are introduced, then a comprehensive energy model is proposed for communicating sensors. However, most of the discussed works have neglected the prediction of entire network lifetime. Hence, the aforementioned references considered only certain characteristics for energy consumption metrics which mainly include transmit and receive energy. In this work, we also include the processing energy, as when the packet size is larger, the processing energy consumption increases. An MDP based approach has been proposed to predict the life time of LoRa end nodes regarding the energy efficiency of resource allocations.

III. System Model

LoRaWAN is a newly emerged wireless communication protocol designed to achieve long-range scale along with low power usage. In such networks, the end nodes are deployed easily forming a stare-of-stare topology architecture form over a gateway. This approach allows peer-to-peer communications which are highly demanded by present and future IoT applications. The gateway (GW) may be connected to local or distance network servers (Edge or Cloud servers) then directly with the application users' interfaces through internet protocols; IP, Wi-Fi, 4G [19]. A network may contain one or several GWs and a massive number of EDs which enable the coverage of large areas in urban and suburban places. Three different EDs classes may be encountered; classes A, B, and C [20] . Since we are studying Class A, these types of devices can only receive Down-Links packets directly after an Up-Links transmission. They are more frequent, and after a transmission they only receive during two reception windows (RX1 and RX2), which are respectively 1 s and 2 s after the end of each up-link transmission.

A. Motivation and Problem formulation

In [18], an energy model has been proposed to estimate the energy consumed during different processing tasks in LoRa EDs. Moreover, in [14], only few transmission parameters have been considered. In this work, the channel condition estimation has been taken into account , which is considered random. Herein, the used parameters are typically random which rely on the channel conditions. The data length and the distance separating the concerned node from its GW are dynamic. Therefore, the energy consumption would be dissimilar, if we consider all the energy consumption activities during the up-links and down-link transmissions. In this paper, we introduce an efficient Markov chain-based energy estimation model to predict the lifespan of a given ED by exploiting the most efficient parameter allocation. We assume that the GW distance is known and the packet size and channel state are assumed to be random, which means that the concerned ED must autonomously adapt and perform a selection of the appropriate transmission parameters to use. The selection of parameters should ensure a successful transmission with lower energy usage.

B. Markov Decision Processes model

The designed optimization model under uncertain surroundings for decision-making is known as MDP . Given a specific system or environment where agents are involved, a stochastic decision procedure is described by the MDP [21]. At each decision instant, the system is maintained in a particular state S and the agent elects an action A, existing in the latter state. Once the action A is performed, an intermediate reward R is received by the agent and thus the system is moved to a qualitatively different new state S' based on the transition probability $P(S, A, S')$. In IoT networks, MDP is used to model the interface between an ED and their respective system (surrounding environment) to accomplish specified policy goals. To illustrate, optimizing the energy control or transmission scenarios in LPWAN is efficiently achieved based on MDP modeling. The aim of the MDP to find the optimal policy to either maximize or minimize a certain objective function. An MDP can be either a finite or infinite time frame [4]. Given a finite MDP time horizon, the optimal policy $\pi*$ to maximize the total expected reward is defined as follows:

$$max\ V_{\pi}(S) = F_{\pi,s} \sum_{t=1}^{T} \gamma^t R(s^{'}|s, \pi(a)) \tag{1}$$

Here, γ is the discounting factor and $F[]$ is the expectation function. Furthermore, finite time horizon Markov decision processes are a finite time horizon MDP solution. The performance of the system takes place in a period of time known as the lifetime measure of the end node. In particular, the system starts in state S or the initial state of the node when it is full of energy and continues to operate until the battery is completely discharged. The optimal policy is to maximize $V_{\pi}(S)$. If we denote $V_t^*(S)$ as the maximum achievable reward at state s, then we can estimate the value of $V_t^*(S)$ at each state recursively by solving the following optimal Bellman equations.

$$V_t^*(S) = max_{a\in A}[R_t(s,a) + \sum_{s^{'}\in S}^{T} P(s^{'}|s,a)V_{t+1}^*(s^{'})] \tag{2}$$

$$Q_t^*(s,a) = R(s,a,s^{'}) + \sum_{s^{'}}^{T} P(s,a,s^{'})V_{t-1}^*(s^{'}) \tag{3}$$

Wherein $V_t^*(S)$ is the value of state s and $Q_t^*(\mathcal{S},a)$ is the value of taking action $\mathcal{A}$ in state $\mathcal{S}$.

C. Proposed model

In LoRa network, the EDs perform many activities following the insisted regularities by frequency providers and international regulation according to each regions. For example, in a public LoRa networks the transmission are organized and allowed for specific time duration called duty cycle (DC). This time period differs from one region to another. This means that the node after transmitting a packet (Up-link transmission); it remains on sleep mode for a DC duration. Therefore, there are two different states associated to every ED on the network ; a sleep state S_{slp} and active state S_{act}. During S_{slp} the ED may perform data gathering from its environment and processing tasks but no transmissions can be hold, whereas during S_{act}, it communicates with the GW base and opens predominately listening windows to send and receive exchanged full duplex transmissions with the same GW. In active state, the ED takes many autonomous decisions to adjust transmission settings including transmission power P_{tx} adjustment. The packets are transmitted within packet duration T_{packet} on two different stages; one part holds the preamble and the other holds the information data. Generally, any LoRa ED in the monitored area consumes its energy in a participatory manner by carrying out multiple tasks. The node may generally occupy two active states and a standby state, with a significant amount of energy being consumed in active mode than in standby mode. The overall energy consumed per node taking into account both states can be expressed by :

$$E_{tot} = E_{act} + E_{slp} \tag{4}$$

Where, E_{slp} covers the energy consumed on sleep state which is proportional to P_{slp} within sleep duration T_{slp} as:

$$E_{slp} = P_{slp} \times T_{slp} \tag{5}$$

And E_{act} is the energy consumed during the active state performing multiple principal operations which leads to drain energy passing through different sequences; Radio Frequency (RF), processing tasks, and then circuity and sensing energy. The ED sequentially releases two possible windows to admit a probable feedback from the GW. The node initiates the first listening window for T_{w1}, in case there is no recognition; it tries again by opening a second window of T_{w2} duration. Afterwards, as long as nothing is detected, it re-transmits the preamble for next cycle. Consequently, the approximate consumed energy by the radio communication component is esteemed by:

$$E_{RF} = E_{rx,w1} + E_{rx,w2} + E_{tx} \tag{6}$$

Where :

$$E_{rx,w1} = P_{rx,w1} \times N_{sym} \times T_s \tag{7}$$

And:

$$E_{rx,w2} = P_{rx,w2} \times \left(\frac{2^{SF} + 32}{BW}\right) \tag{8}$$

Where N_{sym} corresponds to the number of symbols associated with up and down links, its value depends on the selected SF (i.e: it values 8 symbols for SF 11 and 12 and 12 for other SFs) and and T_s is the symbol duration. The consumed energy for transmission is proportional to transmission power P_{tx} and packet duration T_{packet} [22]. It can be expressed by :

$$E_{tx}(t) = \frac{T_{packet} \times P_{tx}(t)}{\zeta_a} \tag{9}$$

Where ζ_a is fraction related to the node's antenna amplifier power efficiency. Where P_{tx} is approximated by:

$$P_{tx}(t) = \eta \frac{E_b}{N_0} \times N \times L_{path} \tag{10}$$

Where η, E_b , N_0 denote respectively the system's spectral efficiency, the required minimum energy per bit at the receiver side, N is the noise power spectral density and L_{path} the path loss. MDP optimization has gained momentum attention in IoT networks in various applications for the reason of resource and power optimization especially for dynamic optimization and resource allocation requirements. Here, we base our investigation on this type of reinforcement learning model exploiting the aforementioned energy formulas dedicated to LoRaWAN

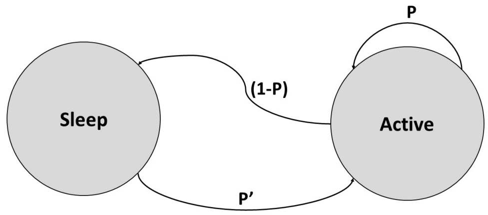

Fig. 1. ED states for Markov chain model

EDs energy drain estimation. Herein, the problem resides on which parameter to be selected to ensure minimum energy usage and efficiency. Moreover, according to LoRa sensor node specification, there are many possibilities assignments between SFs, CRs, and transmission power as well. Therefore, the main aim is to assign the most energy-efficient configuration to the ED while transmitting a given packet from a given distance to the GW. To assign a given transmission parameter, the node has to consider many variances that can affect the quality of transmission like random channel conditions. Therein, the node should adjust its transmission parameters in an efficient manner by using minimum energy dispenses. In our proposed system, the MDP is defined by the tuple ($\mathcal{S}$, $\mathcal{A}$, P_r, $\mathcal{C}(.)$), where $\mathcal{S}$ denotes the state space of the system, $\mathcal{A}$ is the action set space, P_r is the set of transition probabilities of the system state space, and $\mathcal{C}(.)$ is the associated cost function of decision making. Switching from the state $\mathcal{S}$ to the state $\mathcal{S}'$, performing the action $\mathcal{A}$ depends on the efficiency of different available transmission settings. Selecting an action $\mathcal{A}$ is proportional to the transition probability from sleep to active mode and inversely as described in Table I. The probability P_r of selecting a possible action $\mathcal{A}$ is defined by :

$$P_r = (1 - \frac{E(SF_i, CR_j)}{\sum_{i,j=1}^{6,4} E(SF_i, CR_j)})P + (1-P)E_{slp}(S) \quad (11)$$

The cost function implicitly determines the adequate transmission parameter selection decision that minimizes the estimated energy E_{Tot} per transmission using optimal SF and CR. P is the probability when the next state is active. The transition across the state $\mathcal{S}$ to state $\mathcal{S}'$ when action $\mathcal{A}$ is selected based on the probability through the probability of P_r is taken leads to a cost $\mathcal{C}(.)$:

$$C(S, A, S') = E_{Residual} - minE_{Tot}(S, A, S') \qquad (12)$$

When $E_{Residual}$ is the remaining energy in the actual state of the system and $E_{Tot}(S, A, S')$ is the consumed energy by the ED at actual state using optimal selected transition parameters. The node ED is assumed to check and test all the possibilities of transmission settings by surveying the most less energy consumption. This is to assure high bit rate with successful transmission. The transition to the active state is proportion to the action $A(SF, P, CR, P_{tx})$ that is controlled sequentially by the selected transmission parameters and transition probability. The transmission power depends on the ED hardware architecture and is typically comprised between 2 dBm and 20 dBm when the transmission power P_{tx} is higher or lower than these thresholds the transmission can not be carried out efficiently. Therefore, the ED has to open the second window re-transmit again the packet before moving to sleep mode. However, if the packets are not correctly received in the second round, the node will wait for next duty cycle to re-transmit until a correct reception is occurred.

TABLE I
TRANSITION PROBABILITIES BETWEEN ACTIVE AND SLEEP MODE STATES

	S_{slp}	S_{act}
S_{slp}	0	1
S_{act}	p	1-p

IV. RESULTS AND DISCUSSION

In this work, Matlab framework is used to implement and test the MDP proposed model based on LoRa architecture, we have considered an IoT device directly communicating with a GW head, which is located at a distance of 1.5 km. The IoT device senses the environment and transmits the collected data at each duty cycle of DC=1%. The simulation with Matlab is based on the LoRa network module while the channel conditions estimation is described Table II and simulation parameters in Table III. The relevant ED is deemed to use the channel frequency of the 868 MHz ISM band (in Europe) with a bandwidth of 125 kHz. The uplink packets are associated with an 8-byte header and a PHY payload (PL) of different sizes (i.e., 5, 20, 50, 100, and 200 bytes respectively). The channel condition is considered random because at each iteration the path loss α is updated and takes a value in the range of 2.5 to 4. This means at every iteration the transmission parameters must be tailored to the channel condition. To simulate our model, we first considered the scenario of transmitting the same packet from a fixed distance by varying channel conditions and transmission parameters, including SF and CR, and various packet sizes are selected at each iteration. The number of total transmissions that can be held by the dedicated node at a distance d=1.5 away from the GW carrying a message of different payloads is shown in Figure 2. In this scenario, all transmissions are carried out using code rate (CR=4/7). Furthermore, it is observable that the package length affects the total number of transmissions by the ED, as when it is larger, fewer transmissions can be held before the ED dies. The Figure 2 describes also, the energy drain of the node after each transmission until the battery energy is completely consumed

TABLE II
REQUIRED SNR FOR EACH SPREADING FACTOR AT BER $= 10^{-4}$

SF	7	8	9	10	11	12
SNR [dB]	-7	-9.75	-12.5	-15	-17.5	-20.75

TABLE III
SIMULATION PARAMETER VALUES

Parameter	Value
BW	125 KHz
CR	$4/5$, $4/6$, $4/7$, $4/8$
SF	7, 8 , 9 ,10 , 11 ,12
ED type	class A
Path loss exponent	$2.5 < \alpha < 4$
γ	0.5
N_F	8 dBi
DC	1 %
Sensing energy per cycle	0.28 mJ
$I_{leakage}$	10 ηA
I_{rx}	11 mA
I_{sleep}	1.5 μA
Processing frequency	4 MHz
Carrier frequency	868 MHz
Battery Capacity	2600 mAh
Sensor unit voltage	3.6 V
Processing unit voltage	3.3 V

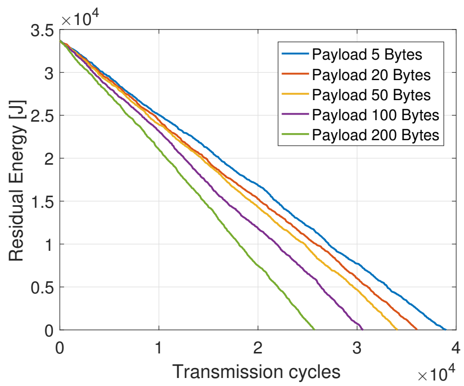

Fig. 2. Energy draining per transmissible cycle for different payload sizes from a distance d=1.5 Km using CR 4/7.

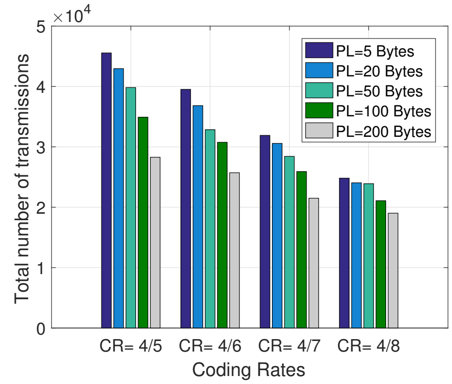

Fig. 3. The total number of possible transmissions occurred by the ED using different CRs settings carrying different payload size from the distance d=1.5 Km.

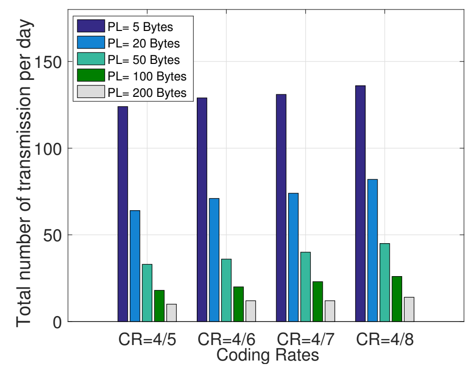

Fig. 4. The total consumed energy average by different possible transmission settings from distance d = 1.5 Km for different CRs settings and payload lengths.

for different packet sizes. The node is initially equipped with a battery with a capacity of 2600 mAh, for each use case, we see that the node can perform more transmissions when the packet size is 5 Bytes. Therefore, the maximum number of transmissions decreases as the payload size of the transmitted messages increases. For example, the node can perform multiple successful transmissions up to 39524, 36823, 32348, 30753 and 25711 for PL=5, PL=20, PL=50, PL=100 and PL=200 bytes respectively. Moreover, Figure 3 shows the behavior of the node when using different CR transmitting the previous payload sizes by the node situated at the same distance d. We notice that the coding rate CR 4/8 allows the node to perform the highest number of transmissions followed respectively by CR 4/7, CR 4/6, and CR 4/5. For instance, when the node uses the CR 4/5, it can handle a transmission of payload size : PL= 5, PL= 20, PL=50, PL=100, and PL=200 Bytes respectively.

Figure 4 shows the total number of possible transmissions per day respecting the duty cycle regulation of total transmission of the total transmission duration of 30 seconds. We can notice that the number of transmission per day is important for small packet sizes using the coding rate (CR=4/5).

In LoRa systems, the number of possible transmissions per day differs between the EDs, since the distant nodes take more time to transmit a message, yet the duty cycle period enlarges. Consequently, only a few packets could be sent to the GW compared to the nearest nodes.

As we already mentioned, our model estimates the energy behavior of the ED after each transmission, knowing the channel medium is random, therein the node has to adjust the transmission parameter to choose the optimal transmission configuration to ensure a high bit rate and minimum energy consumption. In Table IV, the selected parameters are depicted and the consumed energy of a set of first 12 transmissions carrying every cycle a packet of PL=20 Bytes using the configuration with coding rate CR 4/7. As shown the expected parameters like bit rate, the time on air (TOA) of the packet, the quantity of energy consumed by processing units, for reception, and consumed energy in active mode vary at each transmission iteration. More precisely, the value of SF differs from one transmission to another proportional to the path loss exponent that indicates the harsh of the channel medium. For example, the ED uses SF 12 for the first transmission because the path loss exponent is high, which means that the channel condition

TABLE IV
ENERGY ESTIMATION AT FIRST 12 TRANSMISSIONS OF THE ED SITUATED AT D=1.5 KM TRANSMITTING A PL =20 BYTES USING CR 4/7.

Transmission	SF	E_{Tx} [mJ]	E_{proc} [μJ]	E_{Rx} [mJ]	Rb [bit/s]	α	TOA [s]	E_{active} [mJ]
1	12	53.25631	69.18919	0.00883	1464.84375	3.71070	1.58106	92.17276
2	7	0.00897	63.20137	0.00062	27343.75	2.52265	0.07808	30.71122
3	11	23.62713	66.31339	0.01433	2685.546875	3.59957	0.79053	68.04061
4	8	0.54037	63.45557	0.01350	15625	3.08298	0.14182	44.12043
5	9	2.15935	63.91689	0.01521	8789.0625	3.27241	0.25498	47.44825
6	7	0.01625	63.20137	0.00113	27343.75	2.60386	0.07808	31.22286
7	7	0.11030	63.20137	0.00764	27343.75	2.86570	0.07808	37.83309
8	7	0.00771	63.20137	0.00053	27343.75	2.50197	0.07808	30.62267
9	9	1.69844	63.91689	0.01196	8789.0625	3.23958	0.25498	43.74128
10	7	0.01171	63.20137	0.00081	27343.75	2.55906	0.07808	30.90366
11	7	0.14653	63.20137	0.01015	27343.75	2.90453	0.07808	40.37956
12	11	24.26511	66.31339	0.01472	2685.546875	3.60321	0.79053	69.06553

is harsh. After that, it uses SF 7 for the second transmission and SF 11 for the third. From these scenarios, it is accepted that LoRa ED adapts its transmission parameters to successfully transmit an up-link message even sometimes with a low data rate.

V. CONCLUSION

In this paper, we have proposed a probabilistic Markov model for energy consumption estimation and lifetime prediction of LoRa devices in a wide area network. Firstly, the energy efficiency requirement is studied and analyzed in LoRa network context. A mathematical model for energy estimation in LoRa nodes taking into account transmission, reception and processing tasks was formulated and the resource allocation problem for achieving low energy consumption has been derived. The system fundamentals adopt the low energy consumption parameter between SF, CR and data rate in the formulation of optimization transmission parameters. To cope with the randomization of the channel medium, we have considered the random path exponent for each transmission. The simulation results have shown that the lifetime of an ED and the number of transmissions can be predicted by knowing its position around the GW, as well as the length packet expected to be delivered.

ACKNOWLEDGMENT

This work is partially supported by the Moroccan National Center for Scientific and Technical Research (CNRST).

REFERENCES

[1] D. Magrin, M. Capuzzo, and A. Zanella, "A thorough study of lorawan performance under different parameter settings," *IEEE Internet of Things Journal*, vol. 7, no. 1, pp. 116–127, 2019.

[2] J. P. S. Sundaram, W. Du, and Z. Zhao, "A survey on lora networking: Research problems, current solutions, and open issues," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 1, pp. 371–388, 2019.

[3] M. Bor and U. Roedig, "Lora transmission parameter selection," in *2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. IEEE, 2017, pp. 27–34.

[4] M. A. Alsheikh, D. T. Hoang, D. Niyato, H.-P. Tan, and S. Lin, "Markov decision processes with applications in wireless sensor networks: A survey," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 3, pp. 1239–1267, 2015.

[5] A. Kobbane, M.-A. Koulali, H. Tembine, M. El Koutbi, and J. Ben-Othman, "Dynamic power control with energy constraint for multimedia wireless sensor networks," in *2012 IEEE International Conference on Communications (ICC)*. IEEE, 2012, pp. 518–522.

[6] G. K. Atia, V. V. Veeravalli, and J. A. Fuemmeler, "Sensor scheduling for energy-efficient target tracking in sensor networks," *IEEE Transactions on Signal Processing*, vol. 59, no. 10, pp. 4923–4937, 2011.

[7] S. Narieda, T. Fujii, and K. Umebayashi, "Energy constrained optimization for spreading factor allocation in lorawan," *Sensors*, vol. 20, no. 16, p. 4417, 2020.

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

[9] M. N. Ochoa, A. Guizar, M. Maman, and A. Duda, "Evaluating lora energy efficiency for adaptive networks: From star to mesh topologies," in *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, 2017, pp. 1–8.

[10] R. M. Sandoval, D. Rodenas-Herraiz, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "Deriving and updating optimal transmission configurations for lora networks," *IEEE Access*, vol. 8, pp. 38 586–38 595, 2020.

[11] G. Premsankar, B. Ghaddar, M. Slabicki, M. Di Francesco *et al.*, "Optimal configuration of lora networks in smart cities," *IEEE Trans. Ind. Inform*, 2020.

[12] N. J. B. Florita, A. N. M. Senatin, A. M. A. Zabala, and W. M. Tan, "Opportunistic lora-based gateways for delay-tolerant sensor data collection in urban settings," *Computer Communications*, 2020.

[13] X.-C. Le, B. Vrigneau, M. Gautier, M. Mabon, and O. Berder, "Energy/reliability trade-off of lora communications over fading channels," in *2018 25th International Conference on Telecommunications (ICT)*. IEEE, 2018, pp. 544–548.

[14] M. Nurgaliyev, A. Saymbetov, Y. Yashchyshyn, N. Kuttybay, and D. Tukymbekov, "Prediction of energy consumption for lora based wireless sensors network," *Wireless Networks*, pp. 1–14, 2020.

[15] C. Delgado, J. M. Sanz, C. Blondia, and J. Famaey, "Batteryless lorawan communications using energy harvesting: Modeling and characterization," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2694–2711, 2020.

[16] Y. Li, J. Yang, and J. Wang, "Dylora: Towards energy efficient dynamic lora transmission control," in *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*. IEEE, 2020, pp. 2312–2320.

[17] W. Gao, W. Du, Z. Zhao, G. Min, and M. Singhal, "Towards energy-fairness in lora networks," in *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 2019, pp. 788–798.

[18] T. Bouguera, J.-F. Diouris, J.-J. Chaillout, R. Jaouadi, and G. Andrieux, "Energy consumption model for sensor nodes based on lora and lorawan," *Sensors*, vol. 18, no. 7, p. 2104, 2018.

[19] Y. Yazid, I. Ez-Zazi, M. Arioua, and A. E. Oualkadi, "On the lora performances under different physical layer parameter selection," in *2020 International Symposium on Advanced Electrical and Communication Technologies (ISAECT)*. IEEE, 2020, pp. 1–6.

[20] M. A. Ertürk, M. A. Aydın, M. T. Büyükakkaşlar, and H. Evirgen, "A survey on lorawan architecture, protocol and technologies," *Future Internet*, vol. 11, no. 10, p. 216, 2019.

[21] M. L. Puterman, *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, 2014.

[22] I. Ez-Zazi, M. Arioua, and A. El Oualkadi, "Adaptive joint lossy source-channel coding for multihop iot networks," *Wireless Communications and Mobile Computing*, vol. 2020, 2020.