Fuzzy Logic Decision Module for LoRa at 2.4 GHz Adaptive Network Deployment

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***Abstract*—Long Range (LoRa) technology is a Low Power Wide Area Network (LPWAN) alternative for IoT applications. It connects devices, things, or node sensors to a gateway and then to the cloud through broadband connections. LoRa technology offers several degrees of freedom on its configuration parameters such as transmission power (PTx), spreading factor (SF), bandwidth (BW), and coding rate (CR) for different applications and use cases. According to the application, the transceiver LoRa parameters must be set up. Moreover, these parameters must be adapted or reconfigured to the current channel state, network deployment state, and optimization policies such as minimizing the node sensors' energy consumption or maximizing the Packet Delivery Ratio (PDR). This paper proposes a fuzzy logic decision module to select the optimal configuration when conditions are changing. Rules are defined based on energy consumption and communication distance simulations using LoRa transceivers SX1280 at 2.4 GHz. We found that the decision module attributes configuration values to fit maximum communication distance while optimizing energy consumption on the node sensor.**

***Index Terms*—Adaptive Networks, LoRa Technology, Energy Consumption, Fuzzy Logic, Spreading Factor, IoT deployments.**

I. Introduction

Technological evolution allows the fast growth of the Internet of Things (IoT). The number of connected node sensors is increasing exponentially. Smart cities and several applications and use cases involve massive node sensor deployments. Wireless communication technologies are now being widely discussed as candidates to address this growth.

Wireless Sensor Networks (WSNs) are formed by tens or even thousands of sensors that are often deployed in difficult access environments. WSNs have a limited power capacity, so proper battery use is crucial. The use of traditional technologies such as Bluetooth, WiFi and cellular networks does not fully meet the needs of WSNs. However, Low Power Wide Area Networks (LPWANs) technologies have emerged to face the exponential growth, and the needs of WSNs (i.e., small data over long distances with minimal energy consumption).

Features of this technology are [1]: low battery consumption allowing a lifetime of up to 10 years, low-cost devices, high penetration coverage, secure connection and security authentication, and network scalability. Narrow Band IoT(NB-IoT) and LTE-M LPWANs operate in licensed bands as they are implemented by mobile operators. Sigfox and LoRa work in unlicensed bands, cheaper than licensed bands [2].

LoRa received a lot of interest as a network choice for the IoT thanks to its long range and low energy consumption [3]. Moreover, LoRa presents flexibility in its parameters configuration allowing to adapt nodes configuration to the current network conditions. These configurations regulate the link efficiency and energy consumption [4].

Large-scale node sensor deployments need to connect to the Internet of Things. It takes into account the constant change of the transmission channel, the number of node sensors communicating, and the mobility of these devices (i.e., a changing deployment). IoT applications need sensor nodes smarter and smarter to be able to adapt their configurations, to reconfigure, according to the changing deployment. For this reason, a decision module based on Fuzzy Logic should be evaluated to adapt sensor node configurations while optimizing energy consumption and communication distance.

Adaptive networks selecting LoRa parameters to reconfigure the transceiver is a challenging research area to optimize energy consumption and maximize communication distance in changing deployment use cases. There are several works on power adaptation in WSNs to optimize energy and communication distance [4]. Link quality is defined over time by bit error rate (BER), PDR, packet error rate (PER), RSSI, SNR, SINR, and link quality indicator (LQI) in general.

Djoudi et al. [4] evaluated a set of LoRa transmission settings based on the measured QoS metrics such as BER, Time on Air (ToA), and RSSI. Their method aims to map a set of LoRa transmission settings that offers the same QoS to the same cluster. They apply the Fuzzy C-Means (FCM) clustering algorithm on the resulting QoS metrics. Results show best-fit application requirements depending on the application payload size and packet rate (e.g., 8 packets/day for water and gas metering). However, we need to evaluate node adaptation for changing deployments, not only for changing payload size.

In this paper, we analyze the link budget and energy consumption for different LoRa parameters (i.e., SF, PTx, and BW). By adapting these parameters to the current environment, we can obtain an optimal configuration with higher link efficiency and energy savings to increase the battery lifetime. In this work, we also define the performance metrics of a LoRa communication and sensor nodes deployment. Then we apply the Fuzzy Logic on these metrics to define the current configuration of the sensor node (i.e., PTx, BW, and SF). Finally, we evaluate by simulation the performance of the decision module and compare it with the adaptive data rate (ADR) of the LoRaWAN specification.

The remainder of the paper is as follows. Section II exposes the LoRa Technology and Fuzzy Logic, Section III describes the system model. Section IV evaluates the decision module performance. Finally, conclusions are drawn in Section V.

II. Technologies Overview

This section presents the most important features according to technical documents [5] [6]. Moreover, we present the principles of the Fuzzy Logic Inference System.

A. LoRa Tecnology

In this section, we present shortly an overview of the LoRa technology. We present LoRa features, LoRa parameters, and LoRa modulation.

1) LoRa Features: The main features of LoRa are:

Coverage: LoRa communication range is up to tens of km. It is reduced for LoRa at 2.4 GHz.

Battery: Up to 10 years depending on the application.

High Network Capacity: It simultaneously receives multiple messages thanks to the modulation.

Modulation: Chirp Spread Spectrum (CSS).

Security: It has AES-128bits end-to-end encryption.

Applications: It is used in different sectors such as home automation, smart cities, smart agriculture, etc [5] [7].

2) LoRa Parameters: The main parameters of the physical layer according to technical documents [5] [8] are:

Bandwidth (BW) is the frequency range of the chirp signal. BW values are 200, 400, 800 and 1600 KHz for SX1280.

Spreading Factor (SF) It is the number of bits in a symbol. It takes values from 5 to 12. The data rate depends on the SF.

Coding Rate (CR) It is the ratio of effective bits with the total (i.e., including redundancy). This gives robustness to interference. CR values are: CR = 4/5, 4/6, 4/7 or 4/8.

3) LoRa Modulation: LoRa modulation is based on CSS. This modulation is a spread spectrum technique that uses linear frequency-modulated chirp pulses. The spread spectrum technique is a method where a signal is spread in the frequency domain. The chirp varies in frequency linearly with time. This modulation adds robustness to reach long-distance [8].

Symbol rate **(R_s):** The R_s is shown by Equation 1 depending on the BW and SF:

$$R_s = BW/2^{\mathrm{SF}} \tag{1}$$

Bit rate *(R_b):* It depends on BW, CR, and SF.

$$R_b = SF \times R_s \times 4/(4 + CR) \tag{2}$$

B. Fuzzy Logic

In order to implement an automatic decision support system for optimizing the LoRa adaptive network configuration, a Fuzzy inference system was developed. This system uses four modules: fuzzification, inference, rules, and defuzzification.

Fuzzyfication transforms numerical quantities into fuzzy sets defined adequately by an expert and according to the problem. The defuzzification block performs the reverse process using the geometric centre method.

The inference process can be implemented following the Mamdani method, which uses numerical information from the inputs and rules. The rule bank can be built from the expert's knowledge through a natural language.

In this way, the fuzzy inference system may be able to abstract the expert's knowledge for the automatic optimization of LoRa adaptive network configurations, as shown in Fig. 1.

The Fuzzy Logic System inputs are the communication distance between nodes and the gateway, and the energy consumption of the packet transmission. The Fuzzy Logic System outputs are the transmission power of the node (PTx), the spreading factor (SF), and the bandwidth (BW). These are the main configuration parameters of LoRa communication.

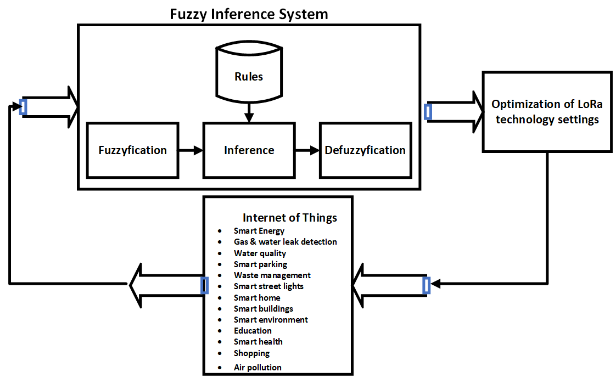

Fig. 1. Fuzzy inference system for optimization of LoRa parameters for Internet of Things.

III. Decision Support Procedure based on Fuzzy Logic

In this section, we present our methodology of the decision module to set up adaptive LoRa networks. We also present propagation models used to evaluate communication distance. Moreover, we present the energy consumption model to evaluate the battery life of nodes as well as the features of the LoRa SX1278. Finally, we present the Fuzzy Logic System.

A. Methodology Block Diagram

In Figure 2 the proposed procedure for the development of the automatic decision support system is illustrated. Initially, it is performed the measurement of the network state characteristics by measuring different metrics. These metrics can be BER, PDR, PER, RSSI, SNR, SINR, and LQI in general. In this work, we consider the communication distance and the energy consumption of packet transmissions as metrics. After that, these metrics are analyzed to improve performance. We analyse all possible LoRa transceiver configurations to obtain the optimal configuration (i.e., less energy consumption while achieving maximum communication distance). In the decision module based on Fuzzy Logic System, we make a decision to adapt the network for a given application profile. The profile could be to optimize energy consumption while maintaining maximum coverage. Finally, a reaction is developed to select and apply the most appropriate configurations of the node transceivers. These configurations are based on PTx, BW, and SF values. We consider a CR of $4/5$.

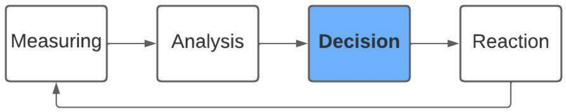

Fig. 2. Metodology to adapt the configuration of the node.

B. Propagation Model

We use the ECC-33 propagation model. It is a modification of the Okumura-Hata model extending communication frequency up to 3 GHz in large and medium cities [10] [11]. We evaluated coverage in large city environments. It is defined in Equation 3.

$$L_P = A_{fs} + A_{bm} - G_b - G_r \tag{3}$$

Where A_{fs} defined in Equation 4 is the free space attenuation, A_{bm} defined in Equation 5 is basic median path loss, G_b defined in Equation 6 is base station gain or in this case, transmitter gain. G_r is receiver gain. Each term is calculated as follows:

$$A_{fs} = 92.4 + 20\log_{10}(d) + 20\log_{10}(f) \tag{4}$$

$$\begin{aligned} A_{bm} = 20.41 + 9.83\log_{10}(d) + \\ 7.894\log_{10}(f) + 9.56(\log_{10}(f))^2 \end{aligned} \tag{5}$$

$$G_b = \log_{10}(\frac{h_B}{200})(13.958 + 5.8(\log_{10}(d))^2) \tag{6}$$

G_r changes depending on the environment type. Equations 7 and 8 correspond to medium cities and large cities respectively.

$$G_r = (42.57 + 13.7\log_{10}(f))(\log_{10}(h_R) - 0.585) \tag{7}$$

$$Gr = 0.759h_R - 1.862 \tag{8}$$

Where d is distance in km and f is frequency in GHz.

C. Energy Consumption Model

The energy consumption analysis is performed for the nodes since we consider that the Gateway is constantly connected to an energy source. Note that we do not consider the consumption in standby mode due to nodes having the most important consumption in transmission mode. The energy of an Uplink communication is calculated as $E_{up} = T_{frame} * PTx$. Where T_{frame}, is the transmission time of the whole packet. It depends on the packet length L_{frame} and the transmission power PTx. Then, we use Equation 9 to calculate the E_{up}.

$$E_{up} = (L_{\text{frame}}/R_b) * PTx, \tag{9}$$

where the L_{frame} is 50 Bytes and PTx is set up according to the datasheet specifications of the sensor node.

D. LoRa Devices

We consider the LoRa Semtech $SX1280$ [9] as the LoRa radio transceiver. The LoRa sensitivity parameter indicates the minimum signal power required for a transceiver to be able to receive and decode a signal. Values vary depending on SF, BW and PT_x configurations. Sensitivity is directly related to received signal indicators or RSSI.

The LoRa SX1280 has 2 operating modes, low power (i.e., LP) and high sensitivity (i.e., HS). Each of these has an impact on device current during reception windows depending on bandwidth as shown in Table I.

TABLE I
RECEIVER CURRENT $[mA]$ DURING RX [9]

Mode/BW (kHz)	203	406	812	1625
HS	6.2	6.7	7.7	8.2
LP	5.5	6	7	7.5

For SX1280, transmission power varies from -18 dBm to 12.5 dBm with 1 dB increments. Datasheet [9] holds current measurements at 0, 10 and 12.5 dBm. Table II shows current variations at different PT_x during transmissions.

TABLE II
TRANSCEIVER CURRENT $[mA]$ DURING TX [9]

PT_x (dBm)	0	10	12.5
I (mA)	10	18	24

E. Fuzzy Logic Decision Module

In this subsection, we present the Fuzzy Logic implementation. We show information about inputs and outputs, fuzzification, rules, and the defuzzification method.

We consider the communication distance between nodes and the gateway, and the energy consumption of packet transmissions as inputs to the Fuzzy Logic decision module. Figure 3 shows the Fuzzy Logic decision module with inputs and outputs. The outputs are the transmission power PTx, the SF, and the BW of the node sensor (i.e., the node configuration).

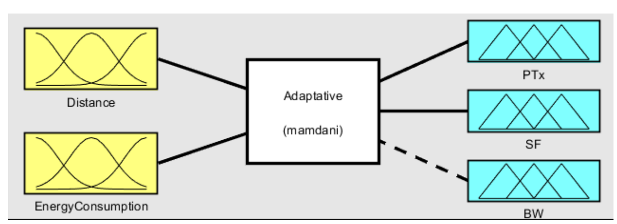

Fig. 3. Fuzzy Logic decision module.

The communication distance is divided into ultra-low (ULow), Low, Low Medium, High Medium, High, and ultra-high (UHigh). Figure 4 shows the membership function Distance. Maximum communication distance in 852 m. We consider Ulow up to 125m, Low up to 250 m, Low Medium up to 375 m, High Medium up to 500, High, up to 625 m, and UHigh up to 852 m. These distances were obtained from simulation using propagation model ECC appropriate for 2.4 GHz and considering LoRa SX 1280 transceiver specification.

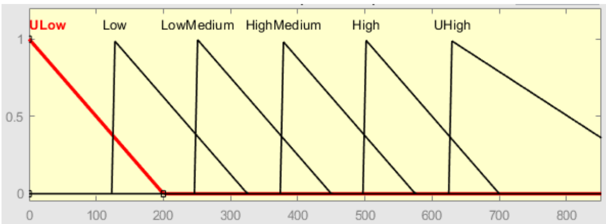

Fig. 4. Membership function Distance[m].

The energy consumption of a packet transmission of 50 Bytes is divided into ultra-low (ULow), Low, Medium, and High. Maximum energy consumption is 34 mJ. We consider Ulow up to 0.1 mJ, Low up to 1 mJ, Medium up to 10 mJ, and High up to 34 mJ. These values are obtained from simulation previously considering consumption in the datasheet LoRa transceiver depending on the LoRa configuration.

We define 24 rules based on previous simulation results of communication distance and energy consumption. The output is the LoRa transceiver configuration (i.e., PTx, BW, and SF). We define low, medium, and high PTx for 0 dBm, 10 dBm, and 12.5 dBm respectively. SF can be set up from 5 up to 12. The BW can be set up among 200, 400, 800, and 1600 kHz.

The SF impacts directly the communication distance. Low values of SF give a small communication distance. High SF values give a large communication distance. However, there is a trade-off between communication distance and the data rate. Then with high SF, we gain in communication distance but we lose in data rate. The SF also impacts directly the energy consumption. Our decision module based on a fuzzy logic system selects the optimal configuration of SF to optimize energy consumption while maintaining communication distance. Figure 5 shows how to select the SF as a function of the communication distance and the energy consumption.

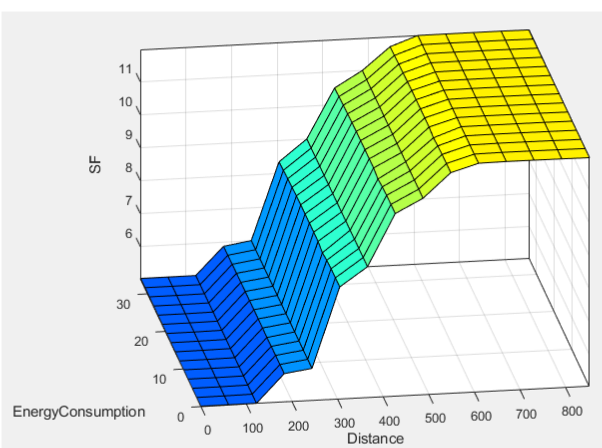

Fig. 5. SF selection according to communication distance [m] and energy consumption [mJ].

Moreover, the BW impacts communication distance. Low BWs give a large communication distance. High BWs give a small communication distance. However, there is a trade-off between communication distance and the data rate. Then with low BW, we gain in communication distance but we lose in data rate. The BW also impacts directly energy consumption. Our decision module based on a fuzzy logic system selects the optimal configuration of BW to optimize energy consumption while maintaining communication distance. Figure 5 shows how to select the BW as a function of the communication distance and the energy consumption.

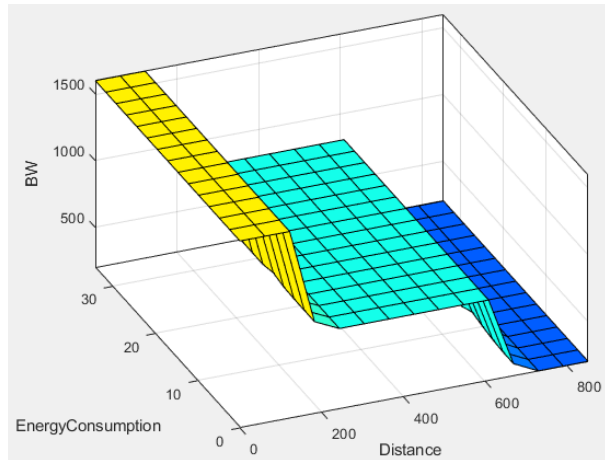

Fig. 6. BW selection according to communication distance [m] and energy consumption [mJ].

IV. Use Case Results

This section presents four scenarios to show the gain using the Fuzzy Logic decision module. We evaluate PDR and energy consumption as performance metrics of the scenarios. We consider each node (SX1280 LoRa transceiver) transmits a single packet of 50 Bytes to analyze energy consumption.

A. Scenario 1: Inicial deployment

Here we have eight nodes deployed and a gateway. These nodes are configured with the adaptive data rate (ADR) of LoRaWAN. Node 0 (N0) is set up with SF5, N1 is set up with SF6, and so on. N7 is set up with SF12. They all are set up with BW=200kHz, PTx=12.5dBm, and CR=4/5. Figure 7 shows the deployment of scenario 1.

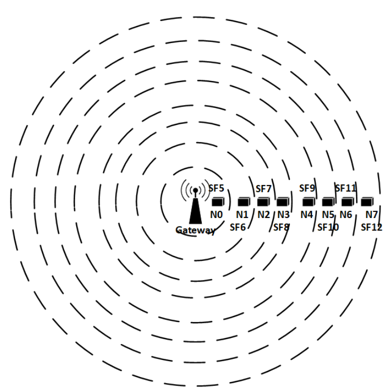

Fig. 7. Deployment of scenario 1.

Then, nodes deployed in scenario 1 are configured as shown in Table III. Nodes close to the gateway are set up with low SF, and nodes far from the gateway are set up with high SF. We deploy this scenario to configure each node with a different SF but the same SF and BW to analyse how the LoRa ADR and our decision module perform when nodes do the self-reconfiguration and adapt the SF, BW, and PTx.

TABLE III
NODES SET UP IN SCENARIO 1.

Node	SF	PTx [dBm]	BW [KHz]
0	5	12.5	200
1	6	12.5	200
2	7	12.5	200
3	8	12.5	200
4	9	12.5	200
5	10	12.5	200
6	11	12.5	200
7	12	12.5	200

B. Scenario 2: Nodes move without reconfiguration

Here we have the same eight nodes and the gateway of the previous scenario but the nodes move to another position. All the nodes do not reconfigure (i.e., they maintain their SF, BW, PTx, and CR configuration). Figure 8 shows this deployment. Note that some nodes will not reach the gateway because they will be out of the range for their current configuration.

On one hand, N0 is configured with SF5 but it is out of the maximum communication range for this configuration. Then, packets transmitted to the gateway will be lost. Node 1 is configured with SF6 but now it is farther than in the previous scenario. Packets transmitted to the gateway will be also lost. We observe that these nodes will not reach the gateway and they also spend energy on packet transmissions. They need to be reconfigured with an optimal set-up to reach the gateway and to consume less energy on transmissions after they move.

On the other hand, N7 now is close to the gateway but it is configured with SF12. First, the data rate is low and it is spending much more energy than it needs to transfer packets. It needs to reconfigure SF to a lower value which consumes less energy but reaches the gateway.

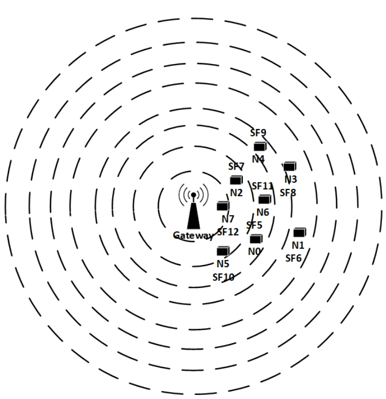

Fig. 8. Deployment of scenario 2.

Then, nodes deployed in scenario 2 are configured as shown in Table III (i.e., no reconfiguration, they have initial set-ups).

C. Scenario 3: Nodes move and reconfigure with ADR

Here we have the eight nodes and the gateway in the same position as scenario 2. The main difference is that all nodes do reconfigure using the ADR algorithm. Figure 9 shows this deployment. We compute PDR and energy consumption to evaluate the deployment performance.

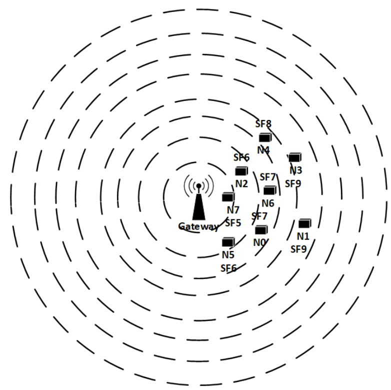

Fig. 9. Deployment of scenario 3.

Table IV shows the set-ups of deployed nodes using ADR.

TABLE IV
NODES SET UP IN SCENARIO 3.

Node	SF	PTx [dBm]	BW [KHz]
0	7	12.5	200
1	9	12.5	200
2	6	12.5	200
3	9	12.5	200
4	8	12.5	200
5	6	12.5	200
6	7	12.5	200
7	5	12.5	200

D. Scenario 4: Nodes move and reconfigure with the Fuzzy Logic decision module

Here we have again the eight nodes and the gateway after they move. In this scenario, all nodes do reconfigure using the Fuzzy Logic decision module. Figure 10 shows this deployment. Here, nodes select the optimal PTx, and SF, but also the optimal BW to minimize the energy consumption of packet transmissions while achieving the gateway (i.e., coverage). We evaluate PDR and energy consumption for performance.

Table V shows the set-ups of all deployed nodes using the Fuzzy Logic decision module. Note that nodes N0, N2, N5, N6, N7 are configured with the same configuration (i.e., SF9, PTx of 12.5 dBm, and BW of 800 MHz). Nodes N1, N3, N4 are configured with SF11, PTx of 10 dBm, and BW of 800 MHz. These are the optimal configurations according to the Fuzzy Logic decision module.

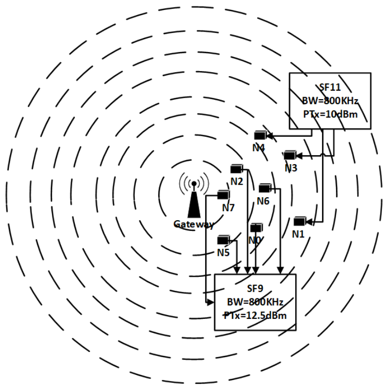

Fig. 10. Deployment of scenario 4.

TABLE V
NODES SET UP IN SCENARIO 4.

Node	SF	PTx [dBm]	BW [KHz]
0	9	12.5	800
1	11	10	800
2	9	12.5	800
3	11	10	800
4	11	10	800
5	9	12.5	800
6	9	12.5	800
7	9	12.5	800

E. Performance Analysis

Here we evaluate the four previously deployed scenarios comparing our proposal with the ADR of LoRaWAN specification. We evaluate the PDR of each node communicating to the gateway in the four scenarios as shown in Table VI. We evaluate PDR by transmitting a few packets. Note that there is no packet loss when they are deployed inside the coverage depending on its LoRa configuration. Main packet loss appears when nodes move to another position (i.e., from scenario 1 to 2) and they do keep their current configuration. When they reconfigure using ADR or the Fuzzy Logic decision module (i.e., scenarios 3 and 4 respectively), they do not have packet losses. Note that these deployments consider 8 nodes. Large-scale deployments will increase interference and packet losses.

TABLE VI
PDR, ENERGY CONSUMPTION, AND BATTERY LIFETIME FOR THE FOUR SCENARIOS.

Scenario	PDR	E_tot [mJ]	Battery lifetime [years]
1	100	147	1.5
2	69	147	1.5
3	100	41	5.6
4	100	34	6.7

We also evaluate the battery lifetime for the four deployed scenarios. We consider a battery of 2000 mAh, 1 packet transmission every 5 minutes and 50 Bytes of the packet payload size. We found a reduction in energy consumption from 147 mJ to 41 mJ using ADR to reconfigure the nodes. However, the Fuzzy Logic decision module outperforms the ADR, it reduces the energy consumption of the 50 Bytes packet transmission to 34 mJ. Moreover, the battery lifetime in the nodes is improved from 5.6 years to 6.7 years. Note that when there is no reconfiguration, the battery lifetime is several impacted by up to 1.5 years.

V. CONCLUSION AND FUTURE WORK

In this paper, we implemented a Fuzzy Logic decision module to select the optimal configuration of nodes depending on the communication distance with the gateway and the energy consumption of the transmission packets. Rules were defined based on simulations of the communication distance and energy consumption for different LoRa configurations (i.e., SF, PTx, and BW). We analyzed the performance of the Fuzzy Logic decision module when nodes move and change position. We evaluated 3 cases (without reconfiguration, reconfiguration with ADR of the LoRaWAN specification, and reconfiguration with Fuzzy Logic). We found the main improvement in the energy consumption and battery lifetime of nodes. Battery lifetime is improved from 1.5 years to 5.6 using LoRa ADR. However, the Fuzzy Logic decision module outperforms the ADR (i.e., improving battery lifetime by up to 6.7 years).

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