POLITECNICO DI TORINO

Master Degree Course in Communication and Computer Networks Engineering

Master Degree Thesis

Resource Allocation and Mobility Management in LoRaWAN

Supervisors:

Prof. Roberto GARELLO

Prof. Sahar HOTEIT

Prof. Veronique VEQUE

Candidate:

Hiba HOJEIJ

ACADEMIC YEAR 2020/2021

Acknowledgement

In the name of GOD, who has gave me the strength and blessing to finish this project. I take this opportunity to express my deepest sense of gratitude and sincere thanks to everyone who helped me to complete this work successfully. I express my sincere thanks to my supervisors in L2S Prof. Veronique VEQUE and Prof. Sahar HOTEIT for providing me with all the necessary facilities and support. I would like to express my sincere gratitude to Prof. Roberto Garello, my supervisor at Politecnico di Torino for his guidance and co-operation. Finally I thank my family and friends who contributed to the successful fulfilment of this thesis work.

Abstract

The Low Power Wide Area Networks (LPWANs) represent a new trend in the evolution of the wireless communication technologies that target static and mobile Internet of Things (IoT) applications requiring energy efficiency, scalability and coverage. One of the most successful technologies in the LPWAN is Long Range Wide Area Networking (*LoRaWAN*).

LoRaWAN uses an adaptive data rate (ADR) mechanism at the network server (NS) to meet the requirements of IoT-enabled applications. By controlling the spreading factor (SF) and transmit power (TP), ADR seeks to provide end devices (EDs) with the efficient resources for reliable and energy saving transmission. However, such algorithm may have high convergence period because of the scalability of LoRaWAN network and variable channel conditions. Thus we propose an ADR mechanism which combines NS-managed ADR with ED-managed one aiming to reduce the convergence period along with providing better performance indicators such as packet success rate as well as less energy consumption.

Contents

List of Figures

List of Tables

LIST OF ABBREVIATIONS

LPWANs Low Power Wide Area Networks

IoT Internet of Things

LoRaWAN LOng RAnge Wide Area

ADR Adaptive Data Rate

NS Network Server

BS Base Station

ED End Device

SF Spreading Factor

TP Transmission Power

CSS Chirp Spreading Spectrum

GW GateWay

ACK Acknowledgement

S Sensitivity

ISM industrial Scientific and Medical

DR Data Rate

ToA Time on Air

DER Data Extraction Rate

GADR Guassian Adaptive Data Rate

LoRaSim LoRa Simulator

LoRaMAB LoRa Multi Armed Bandit

EXP3 Exponential Weights for Exploration and Exploitation

ISFA Initial SF Allocation

PSR Packet Success ratio

DER Data Extraction Rate

MAC Media Access Control

QoS Quality of Service

Chapter 1

Introduction

1.1 Technology Backgroud

LoRa, stands for Long Range, is a proprietary physical layer for LPWAN connectivity. LoRa is based on Chirp Spread Spectrum modulation that allows long ranges of transmission (up to 10km in rural areas) and is robust against multipath and fading effects. Long Range Wide Area Network *LoRaWAN* [1] [6] is a an open standard defining architecture and layers above the LoRa physical layer proposed by LORA alliance group. *LoRaWAN* is a promising technology for the IoT devices providing more effective and flexible solutions than other technologies like sigfox, weightless, ingenu... toward meeting a wide range of IoT application requirements [2]. An important characteristicy of LoRaWAN is that there is no need for compatibility with other technologies. LoRaWAN is based on acknowledged transmissions, This give it a huge plus guaranteeing successful packets reception with a high probability. As a consequence, LoRaWAN intervene in many use case scenarios such as personal IoT applications, smart metering, remote control, industrial and agriculture monitoring, etc.

1.2 Research Problem

When dealing with IoT networks, low cost of transmission and high success rate are the main criterion of the performance. Thus, especially LoRaWAN, where chirp spread spectrum (CSS) modulation is adopted, transmission parameters are crucial for realizing the required performance. In current LoRaWAN deployments, an Adaptive Data Rate (ADR) scheme that controls the uplink transmission parameters (spreading factor, bandwidth, coding rate and transmission power) for static LoRa devices is adopted. In ADR, static nodes can communicate by selecting the minimum spreading factor that permits the correct reception by the intended Gateway; this scheme is shown to be inefficient in terms of collision and air time [6]. This thesis work focuses on implementing an intelligent power control and spreading factor allocation algorithm that reduces interference and improves total network capacity for both static and mobile devices.

1.3 Organization

The rest of the report is organized, as follows: a brief overview of the technology in question in Section 2. Section 3 provides an overview of related work. Section 4 elaborates on the proposed schemes. Simulation Frame work is detailed in Section 5. Section 6 presents the experimental results and an analysis of the proposed schemes. Section 7 presents some concluding remarks.

Chapter 2

LoRaWAN Description

2.1 Network Architecture

LoRaWAN network is composed of base stations (BS) and end devices (ED) as shown in Figure 2.1. EDs are connected to and served by the BS, and the data flow is between ED and BS thus no ED-ED traffic. It is important to notice that the uplink traffic dominates in such networks. *LoRaWAN* networks are organized in a star-of-stars topology for the purpose of bringing huge energy saving advantages. The BS is connected to a centralized network server (NS) via backbone internet protocol (IP) based link. NS is responsible for traffic management, collecting data from the gateway (GW) and sending them to appropriate applications.

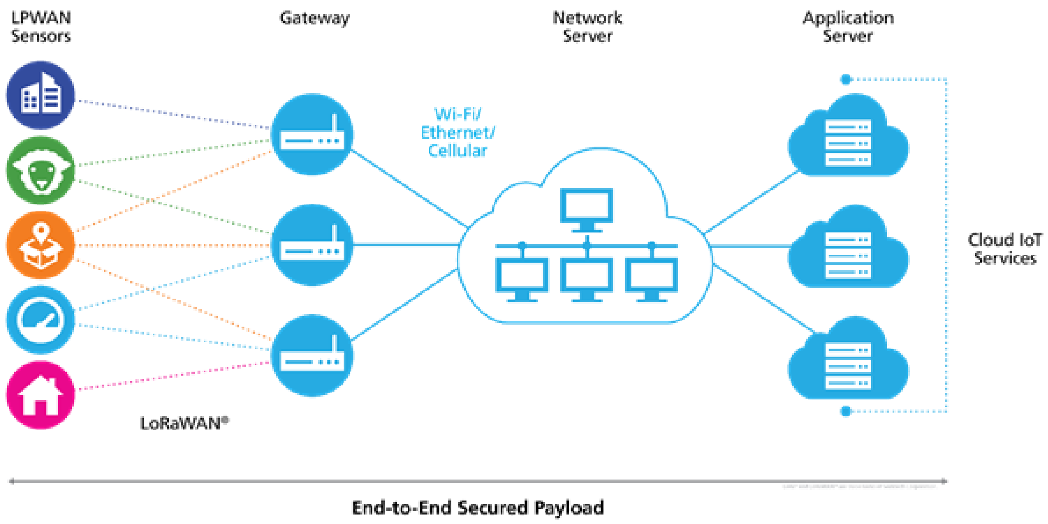


Figure 2.1: LoraWAN Network Architecture [11]

This network is optimized specifically for energy-limited EDs by using an ALOHA-based protocol, a random access MAC protocol in which end devices transmit without doing any carrier sensing. The simplicity of ALOHA is thought to keep the design of the transceiver simple and low cost, also end devices do not need to peer with specific gateways. Thus LoRaWAN does not use the clear channel assessment (CCA) mechanisms and relies exclusively on the ED duty cycle-based channel access mechanism. LoRa network operates in license-free sub-gigahertz bands, mainly the industrial, scientific and medical (ISM) band, aiming at reducing the cost to network operators for not licensing new spectrum. As a consequence, the transmission from a device should account for the imposed restrictions.

End Device Classes

LoraWAN is an acknowledged-based transmission technology, reliability is achieved through the acknowledgment of frames in the downlink. For managing the acknowledgment reception by the ED, the LoRaWAN specification defines three device types: Class A, Class B, and Class C. The implementation of class A functionality is obligatory, whilst classes B and C are optional. This description is referenced from LoRaWAN specifications [3].

For the EDs of class A each uplink transmission is followed by the two receive windows (RX1 and RX2) where acknowledgment can be transmitted on the downlink. The devices of class B open, in addition to RX1 and RX2, special receive windows at scheduled times, it is used by beacons transmitted by the gateway for time-synchronization purposes. Finally, EDs of class C stay in receive mode all the time unless they are transmitting.

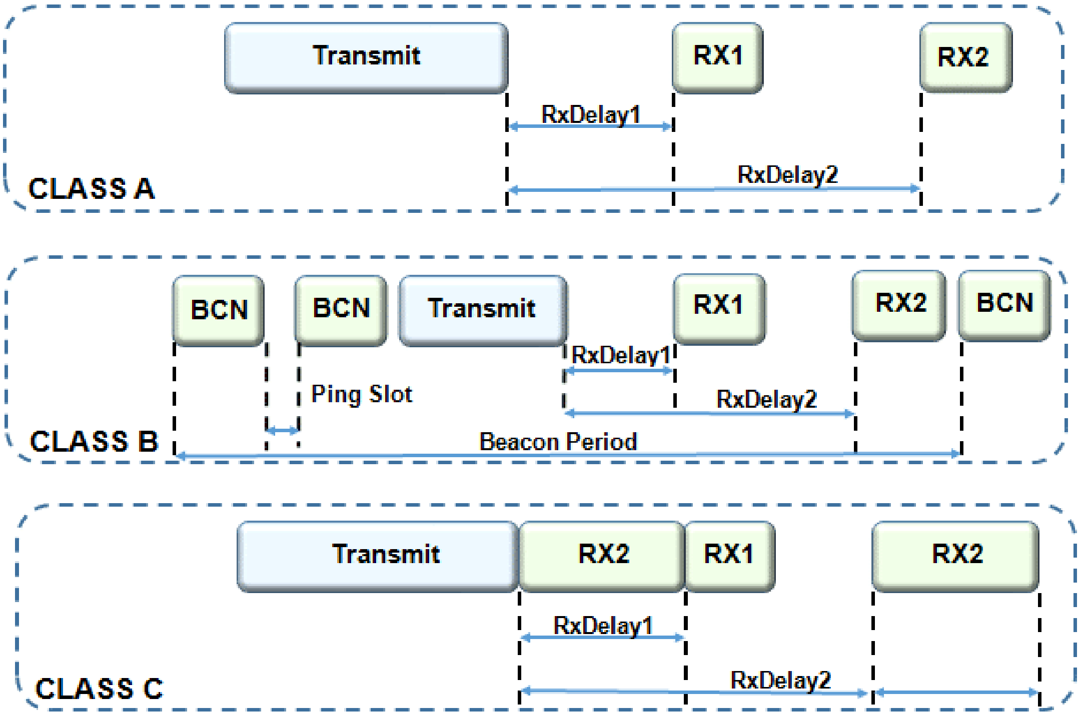


Figure 2.2: Frame encoding in LoRaWAN [5]

Thus, Class A has the lowest power consumption, Class B is adopted for applications with additional downlink traffic needs and lastly Class C are always listening devices.

2.2 LoRa Modulation

The modulation scheme in LoRaWAN is the Chirp Spread Spectrum (CSS) making it work well with channel noise, multipath fading, and doppler effect, even at low power [14]. In figure 2.3, an example of encoded LoRaWAN frame is shown. The frame consists of up and down chirps, formed as follows: the first 6 chirps are the preamble, the next 2 chirps represent the synchronization bits, and finally the payload.

2.3 Data Rate and Airtime

The resulting data rate depends on the used bandwidth and spreading factor. LoRaWAN can use channels with a bandwidth of either 125 kHz, 250 kHz, or 500

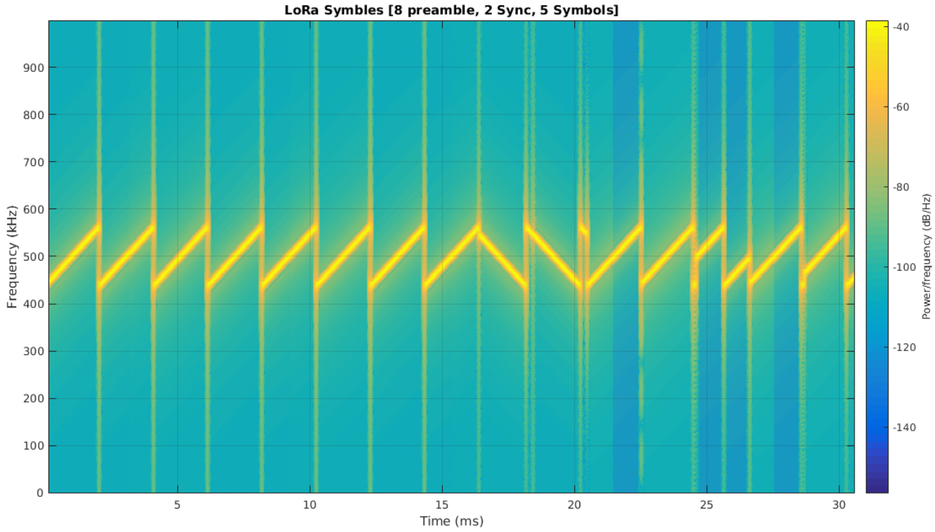


Figure 2.3: Frame encoding in LoRaWAN [13]

kHz, depending on the region. The spreading factor is chosen by the end device and influences the time it takes to transmit a frame known as Time on Air (ToA). ToA is computed as a sum of the time of the preamble plus the time of the Payload frame as in [12], T_{frame} or ToA is shown in formula 2.1.

$$T_{frame} = T_{preamble} + PL_{sys} * T_{sys} \tag{2.1}$$

$$T_{sys} = 2^{SF}/BW \tag{2.2}$$

where PL_{sys} is the payload size in bytes, and T_{sys} indicates symbol duration in ms.

2.4 Transmission Parameters and ADR

The two main transmission parameters in LoRaWAN are Transmission Power (TP) and Spreading factor (SF).

The TP is the power used by the LoRa End Device to transmit the packet and it ranges between -4 and 20 dBm. The Higher its value, the higher the range of transmission, however, the more energy consumption is needed by the transceiver.

In order to improve the spectral efficiency and increase the capacity of the network, LoRa modulation features six orthogonal spreading factors defined as 2.3:

$$SF = log_2(Rc/Rs) \tag{2.3}$$

where Rc is the code rate and Rs is the symbol rate, resulting in the different data rates. SF describes the length of a chip which is 2^{SF} and divided by SF to give the length of a code. Lower spreading factors provide higher bit rates resulting in a shorter time on-air TOA (channel occupation time). Shorter TOA results in longer battery life because the radio transceiver is active for a shorter period. In contrast, the higher the SF, the higher the signal-to-noise ratio, the sensitivity, and range, but also the ToA. Accordingly, there is a trade-off between SF and the communication range. Orthogonality of SFs enables multiple spread signals to be transmitted at the same time on the same frequency channel without degrading the communication performance and trading the on-air time for the communication range. In essence, multiple spreading factors provide a third degree of diversity after time and frequency.

Moreover, When two signals using the same spreading factor (SF) arrive at the same time, with one signal stronger than the other by a certain threshold, the so-called capture effect [6] causes the stronger signal to drown the weaker. Even when the signals use different spreading factors, Inter-SF interference can be observed, because the spreading codes are not perfectly orthogonal [8]. Here arise the proposal, ADR, an Adaptive Data Rate algorithm for *LoRaWAN*. The ADR [10] algorithm manages the allocation of SFs and TPs to EDs, aiming at fair collision probability and high Data Extraction Rate (DER) based on distance from the gateway.

For static end devices, the ADR is managed by the network server, based on the history of the uplink packets received. This is referred to as Network-managed ADR or Static ADR. In addition, an ED-managed ADR can be adopted on all Nodes provoking a distributed learning over the whole network in order to optimize the transmission parameters.

Chapter 3

Related Works

The scalability and reliability of LoRa-based networks is an active research topic, especially for smart city scenarios. In terms of scalability, the findings in [4] show that a single LoRaWAN cell can serve millions of people. Only a few bytes of data are sent per day by these devices. Despite this, just a small percentage of these devices can be located far from the base station. The majority of the devices, particularly those with a high upload traffic should be located in the vicinity of the base station. This necessitates better data rate management by end nodes, i.e ADR. Thus, the main question is how exactly the performance of a LoRaWAN network depends on the resource allocation policy and how improvements in ADR can significantly affect network performance.

The recent ADR Deployed in LORA is described by Semtech in [10]. This ADR is managed by the network server, based on the history of the uplink packets received. It is referred to as **Network-managed** ADR or Static ADR. The network server receive ADR-Enabled uplinks from the ED. Following the next uplink, a MAC command to change the data rate is sent down to the end device, as appropriate. The problem is that downlink transmissions such as acknowledgements and ADR commands, are expensive when compared with uplinks. A LoRaWAN network can support much fewer downlink transmissions from a gateway to a node than uplink transmissions. For this reason, adding a **Self-managed** ADR allowing each node to allocate optimal resource is the best solution in terms of minimizing the downlink traffic in a LoRaWAN network.

Although LoRAWAN has been released in 2015, with the specifications of ADR described above, Many studies have been conducted in order to solve the problems of ADR scheme that controls the uplink transmission parameters in terms of the convergence period, scalability, and packet success ratio. In particular, the literature focused on the enhancement and convergence period reduction of a typical ADR [15] [16], [17], [18], [19].

Authors in [19] propose simple algorithms for SF allocation in LoRaWAN networks based each on Received Signal Strength Indicator (RSSI) and time on air (ToA). The lowest available SF is given to EDs having the highest RSSI. On the other hand, the time-on-air is equalized between different nodes in a way that the number of nodes assigned to each SF is inversely proportional to its time on air. Such changes make improvements over the ADR in [10].

In paper [18] authors propose an enhanced LoRaWAN ADR. The proposed method is based on NS-managed ADR using called Gaussian ADR (G-ADR) and aims to allocate the best SF and TP to EDs reducing the convergence period of the acknowledged mode LoRaWAN. Based on their simulations, G-ADR scheme shows a promising results in terms of convergence time.

In paper [16] they show that using distributed learning algorithms, such as Multi Armed Bandit (MAB), is beneficial when all end-devices are intelligent and the network status is dynamically changing. In their studied scenario, the scalability of the network is improved as well as the reliability. Another paper [17] also studied the performance of the same distributed learning solution for adapting the communication parameters of devices to the environment for maximizing successful data transmission probabilities.

Concerning LoRa implementations found in the literature, ADR schemes are implemented and evaluated using different approaches such as mathematical models and simulation, since large scale real-time network deployment would be prohibitively expensive. Mainly, simulators such as LoRaSIM [6] and LoRaMAB [9], based on Python with SimPy library, are sensible to conduct simulation-based studies to evaluate the network design as well as protocol parameters for several LoRaWAN applications.

3.1 LoRaSim Simulator

LoRaSim is the most popular simulator for LoRaWAN [6]. It is a discrete-event simulator implemented with SimPy to build a radio propagation model based on the log-distance path loss model [?]. In [6], authors investigate the capacity limits of LoRa networks using some simulations done on LoRaSim, mainly by studying the collision between packets. For this reason, and to parameterise the collision behaviour, the following radio parameter settings are studied: spreading factor (SF), bandwidth (BW), power and timing. Finally, the simulator reports the corresponding packet delivery ratio and total energy consumption of the network. However, the main limitation of this simulator is due to neglecting some realistic physical setting such as Inter-SF interference and Capture effect. More importantly, no intelligent is introduced in either part of the network under study.

3.2 LoRaMAB Simulator

Paper [15] extends the work of [16] and [17] and builds a simulation framework based on MAB problem using a distributed learning algorithm called EXP3, which stands for Exponential Weights for Exploration and Exploitation. The simulator is named LoRaMAB and it shows its relevance against the fair centralized solution and basic heuristics, without neglecting Inter-SF interference and Capture effect.

Each ED in this simulator is considered as an intelligent agent which aims at minimizing the collision rate in a distributed manner by choosing the best radio resources Ai = {si, ci, pi}, where ci, si and pi are the selected channel, spreading factor and transmission power respectively. After choosing the action a(t) at time t, device i receives the corresponding reward, denoted by r(t) {0,1}, where 1 stands for a successful transmission (ACK) and 0 represents a lost packet (NACK). Each end device follows a set of rules that steers its decision and allows it to make a balance between (i) Exploiting the cumulative knowledge by choosing the most appropriate resources {si, ci, pi} and transmitting on them, and (ii) Exploring other resources that could be interesting to exploit.

Chapter 4

Proposed Algorithm - GADR with EXP3 Algorithm

4.1 Distributed Learning: EXP3 Algorithm

As mentioned in section 3.2, LoRaMAB simulator proposes a self-managed solution by each ED using distributed learning algorithm EXP3 (Exponential Weights for Exploration and Exploitation). It steers autonomously the decision of LoRa end-devices towards the most suitable resources (e.g. spreading factors, sub-channels) with the impact of the capture effect and inter-SF collision not being neglected.

This algorithm is considered to be state of the art in terms of optimization of resource allocation relying on how good was the previous packet transmission(reward based on ACK). But, here is a but, the study of the convergence period for static EDs under variable conditions reveals that the proposed ADR in [9] suffers from a high convergence period in the order of 20 kHours.

Therefore, to reduce the convergence period and to improve the ASTR (average successful transmission ratio) as well as the energy consumption, we propose some updates during the learning process causing a warm up in EXP3 algorithm. Our proposal is mainly to enhance the role of the gateway in the learning process so that it can, beside the intelligence at the end-devices, intervene and improve the resource selection process. This is done with the aid of Gaussian filter-based ADR (G-ADR) [18] as will be discussed in the following section.

4.2 NS-managed ADR: G-ADR

In addition to the previously described EXP3 distributed algorithm implemented at each node, we added Gaussian ADR Algorithm (G-ADR), described in [18], to be deployed at the Network Server component helping in the resource allocation process. Authors in [18] build their proposal relying on the evaluations revealed in [20] showing that the signal strength received at the GW can be seen to have a Gaussian distribution. Therefore, it is possible to use a Gaussian filter in order to estimate the value of the SNR of the next transmission by smoothing the SNR every M packets being received at the BS, then, computing the convenient SF and TP that are SNR-dependent parameters. The G-ADR scheme is described in algorithm 2. It involves 2 main steps:

1. The network server tracks every M received packets from ED in order to compute the mean and variance of their SNR.

2. The algorithm obtains SNR_{th} which is the SNR threshold for a given receiver sensitivity and current Data Rate according to table 4.1. Receiver sensitivity is a measure of the minimum signal strength that a receiver can detect and process successfully. It is expressed in dBm and is described as follows

$$S = -174 + 10log(BW) + NF + SNR \tag{4.1}$$

   where BW is the receiver bandwidth and NF is the receiver noise figure that is fixed for a given hardware implementation. Then computes N_{step} which represents the number of executions required to reach the optimal parameters.

Notice that, GADR tends to decrease the SF-value, while ED-managed ADR is responsible for increasing it. This will give GADR an energy saving advantage over EXP3.

Algorithm 1 Gaussian filter-based adaptive data rate (G-ADR) scheme

Data: $TP = 10 - 14, SF = 7 - 12, M, SNR_{\text{req}}, device_{\text{margin}}$
Result: $SFandTP$
for $i \leftarrow 0$ *to* M **do**
    $SNR = getSNR(i)$
    if $SNR > LPF$ *and* $SNR < HPF$ **then**
        $insertSNRintoSNRlist$
    end
end
$SNR_m = Sum/SizeofSNRlist$

`/* Server-Managed ADR */`
$SNR_{req} = demodulationfloor(currentdatarate)$
$device_margin = 10$
$SNRmargin = (SNRm - SNRreq - devicemargin)$
$steps = int(SNRmargin/3)$
while $steps > 0 andSF > SF_{min}$ **do**
    $SF = SF - 1$
    $steps = steps - 1$
end
while $steps > 0 andTP > TP_{min}$ **do**
    $TP = TP - 2$
    $steps = steps - 1$
end
while $steps < 0 andTP < TP_{max}$ **do**
    $TP = TP + 2$
    $steps = steps + 1$
end
$NStransmitsLinkADRReq$

SF	GW Sensitivity (Sg) [dBm]	ED Sensitivity (Se) [dBm]	SNR [dB]
12	−142.5	−137.0	−20
11	−140.0	−135.0	−17.5
10	−137.5	−133.0	−15
9	−135.0	−130.0	−12.5
8	−132.5	−127.0	−10
7	−130.0	−124.0	−7.5

Table 4.1: Sensitivity and required signal-to-noise ratio (SNR) of EDs and GW with BW = 125-kHz [22] [6]

4.3 EXP3 with G-ADR Algorithm

To better understand how both algorithms are combined, algorithm **??** describes the detailed operation of signaling or superposition between EXP3 with GADR. Our benchmark was EXP3 algorithm which is ED-managed ADR. Simultaneously, NS-managed ADR is added and it works to aid the learning process of optimizing the transmission parameters.

Our main contribution is that each algorithm rely on a different interpretation to take the decision of resource parameters to be used in the next packet transmission. EXP3 searches probabilistically for the best parameters based just on the good reception of a packet (reward based on ACK or NACK), while GADR sends a request to the ED to update the transmission parameters based on the SNR values of every M packet received from each node at the NS side]. When GADR sends this downlink request to the ED, the ED will listen and deploy the updates on SF and TP accordingly. However, in the meanwhile of NS tracking the M SNR values, ED will be trying to optimize over the GADR previous decision using EXP3 and so on.

Algorithm 2 EXP3 with G-ADR Algorithm

Data: T= SimTime, TP = 10-14, SF = 7-12, M, N_tx = 0, $w_a(0) = 1, a \in A = setofactions, K = numberofactions, \gamma = \min(1, \sqrt{\frac{k\log(k)}{(e-1)T}})$

Result: SF and TP

```
// Algorithm to be running on Each ED
```

initialization;

for $t \leftarrow 1$ *to* T **do**

Transmit Packet with configurable SF and TP

N_tx++

```
/* ED-Managed ADR */
```

Receive reward

$$r_a(t) = \begin{cases} 1 & \text{if ACK is received,} \\ 0 & \text{otherwise.} \end{cases}$$

Update Prob and weight of each action according to the reward

$$w_a(t+1) = w_a(t)\exp(\frac{\gamma r_a(t)}{K.p_a(t)})$$

$$p_a(t+1) = (1-\gamma)\frac{w_a(t+1)}{\sum_{a=1}^{K} w_a(t+1)} + \frac{\gamma}{K}$$

draw strategy $a \in A$, according to the distribution $p_a(t)$

```
/* NS-Managed ADR */
```

if $N\_tx < M$ **then**

$SNR = getSNR(i)$

$insertSNRintoSNRlist$

else

Estimate SNR_{req} of the next packets

Optimize the configurable parameters SF & TP ; `//SNR-dependent parameters`

NS transmit downlink packet ; `//telling ED to update SF & TP`

$N\_tx = 0$

end

end

Chapter 5

Simulation Framework

In this project, we aim to study the performance of resource allocation mechanisms in *LoRaWAN* network. Our simulation framework are done using the LoRa-MAB simulator [9], build in Python with Simpy library.

5.1 Simulation Model

The modeled communication range is around 4.5 km composed of 1 Base Station (Sink or Gateway) and 200-800 End devices (Nodes). All EDs are supposed to be Class A devices. It is likely that, for a LoRaWAN Network, high number of nodes would have to be supported within the given range. For this reason, we will study the performance of the network with an increasing number of smart Nodes.

There exists 6 regions around the BS, each specifying the minimum SF that can be used by the node when transmitting a packet to the BS, according to a sensitivity matrix shown in table 4.1. More nodes are supposed to be located near to the Gateway, so we specify a nodes matrix distribution = [0.1, 0.1, 0.3, 0.4, 0.05, 0.05] as supposed in [9], see Fig. 5.1.

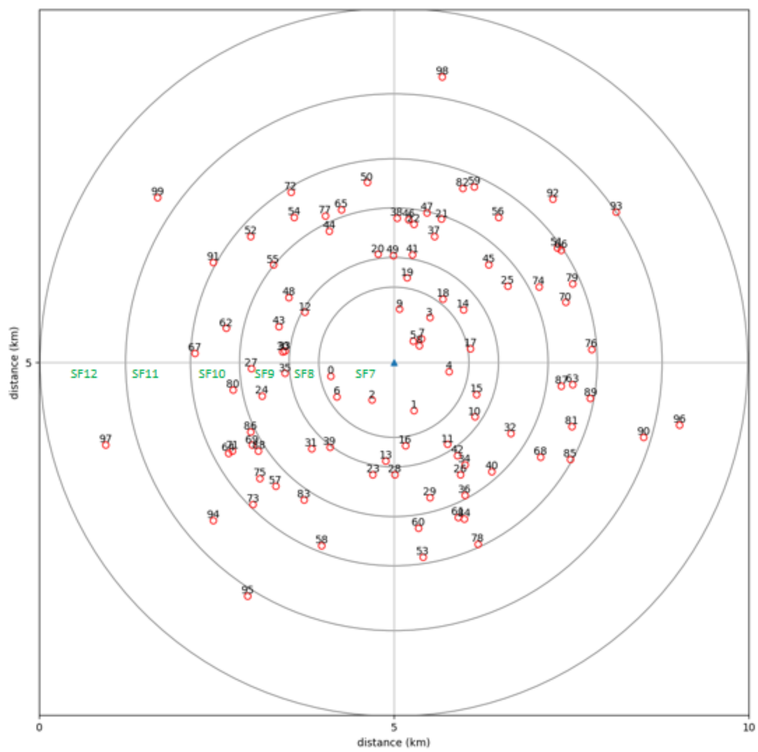


Figure 5.1: Network Configuration

5.2 Duty Cycle Restriction and Packet Generation Rate

The packet generation rate must satisfy the duty cycle restriction, 1% in Europe for the ISM band [3] . Every ED transmits a 50 byte packet with an exponential inter generation time of 16.7 minutes representing a realistic application [6] during 10 kHrs of total simulation time.

5.3 Propagation Model

Our radio propagation model is based on the well known log-distance path loss model, which is presented in [**?**]. This model describe the path loss as follows:

$$L_{pl}(d) = L_{pl}(d0) + 10\gamma log(d/d0) + X_{\sigma} \tag{5.1}$$

where $L_{pl}(d0)$ is the mean path-loss at the reference distance d0, γ is the path loss exponent, and X_σ is the normal distribution of shadowing, with zero mean and σ^2 variance.

5.4 Simulation Parameters

The SF to be selected ranges from 7 to 12. As initial deployment, each node has SFset = [SF_{min}, . . . , 12], SF_{min} is the minimum allowed SF depending on its corresponding region (sensitivity). This is referred to as an initial SF allocation mechanism (I-SFA) during the start-up of the running process, it is used also by authors in [18]. The main goal is reducing the available choices of SF at each node and thus decreasing the learning time. I-SFA is adopted in all the following experiments.

Also, Capture Effect and Inter-SF interference are taken into account in all experiments.

As a result of the above model descriptions, Table 5.1 presents all the simulation parameters adopted.

Parameter	Value
Simulation time [Khrs]	10
lambda[packets/hour]	4
GW	1
Packet length [bytes]	50
Spreading Factor	7 to 12
Transmit power [dBm]	10 to 14
Frequency region	EU-868
Channel bandwidth [kHz]	125
Propagation model	log-distance
Path loss exponent	2.08
Coding Rate (CR)	4/5

Table 5.1: System Parameters

Chapter 6

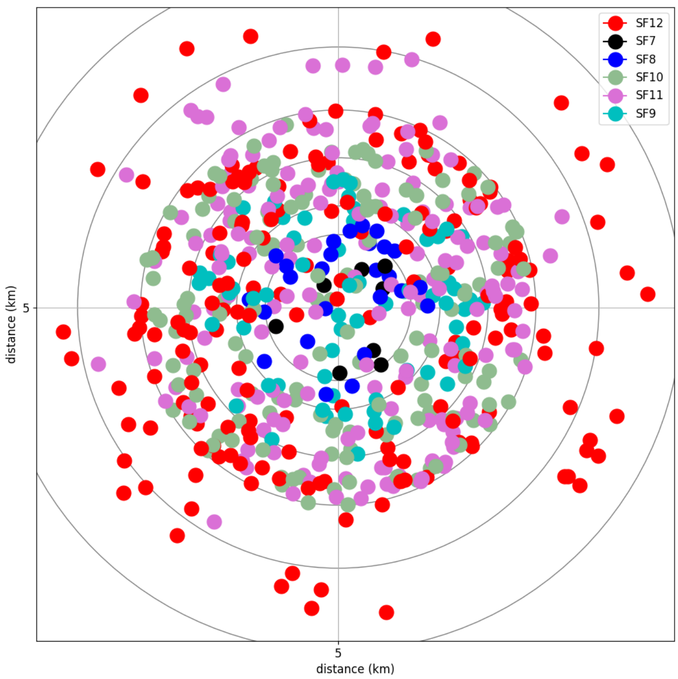
Experimental Evaluation

In this section, we demonstrate the power of this combination of algorithms by presenting a comprehensive performance description of the proposed scheme EXP3-GADR, which is examined in comparison to a simple network and EXP3-alone scenarios. Simple mode is described to be an all non-intelligent nodes scenario, by which all nodes select randomly the resources, keeping the acknowledged-based transmission technology. For the sake of simplicity, simple mode is considered to resemble the typical ADR described in [10].

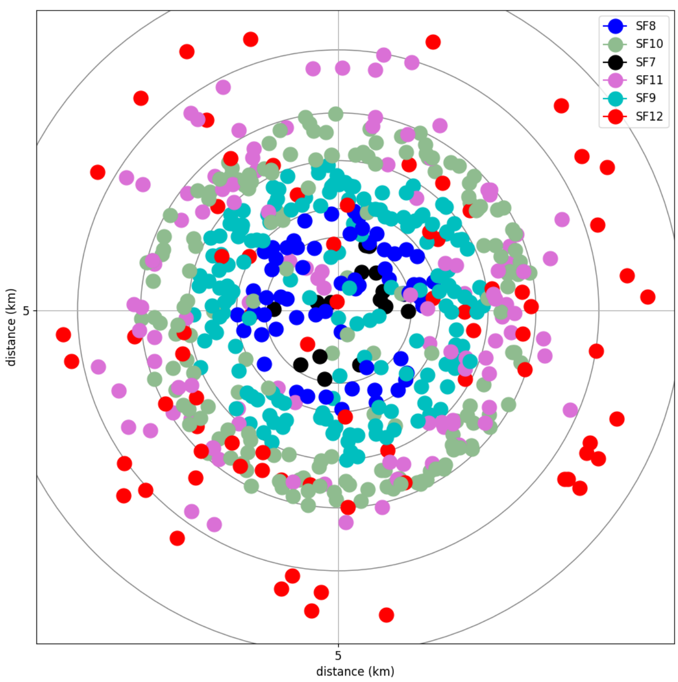
The analysis is investigated in terms of packet successful transmission rate, energy consumption, and convergence period in static EDs scenarios. And lastly, fairness interpretation is done to illustrate the performance of different algorithms over the whole network. Simulations are performed using LoRaMAB simulator.

6.1 Convergence Period Analysis

Convergence period is defined to be the time needed by the EDs in the network to reach a steady average successful transmission rate. Fig 6.1 shows the network topology view of 600 EDs and 1 BS, where EDs are colored according to the SF value selected during transmission. In the initial network, most of the nodes were transmitting using SF=12, this makes the BS reachable by all nodes, however, an increase in the inter-SF collision and also the energy consumption will be inevitable. Thus, certainly, one can notice the convenient SF selection mechanism achieved in the final topology where SF percentages at convergence are more suitable as will be seen in the next sections.



(a)



(b)

Figure 6.1: (a) Initial network topology in case of static EDs with N = 600 (b) Final network topology after applying EXP3-GADR in the case of static EDs with N = 600

6.1.1 Static EDs Network

Figure 6.2 reveals a convergence time order of 2 khrs in the case of the proposed Algorithm(EXP3 + GADR). This convergence time is roughly the same even when increasing the number of nodes to 800 nodes. The convergence of EXP3 algorithm alone is in order of 20 khrs, thus adding GADR is considered to owe an enhancement up to 90% in the convergence period advantage. This improvement can be anticipated in a way that the NS_managed ADR implemented will assist the resource allocation mechanism at the ED level where self-managed ADR takes place. Therefore, the proposed algorithm shows a very important improvement in the convergence period. It is a result of deploying, experimenting and comparing extensive simulation scenarios in order to come up with such a result. Table 6.1 highlights the detailed convergence periods of different EDs in khrs for static EDs.

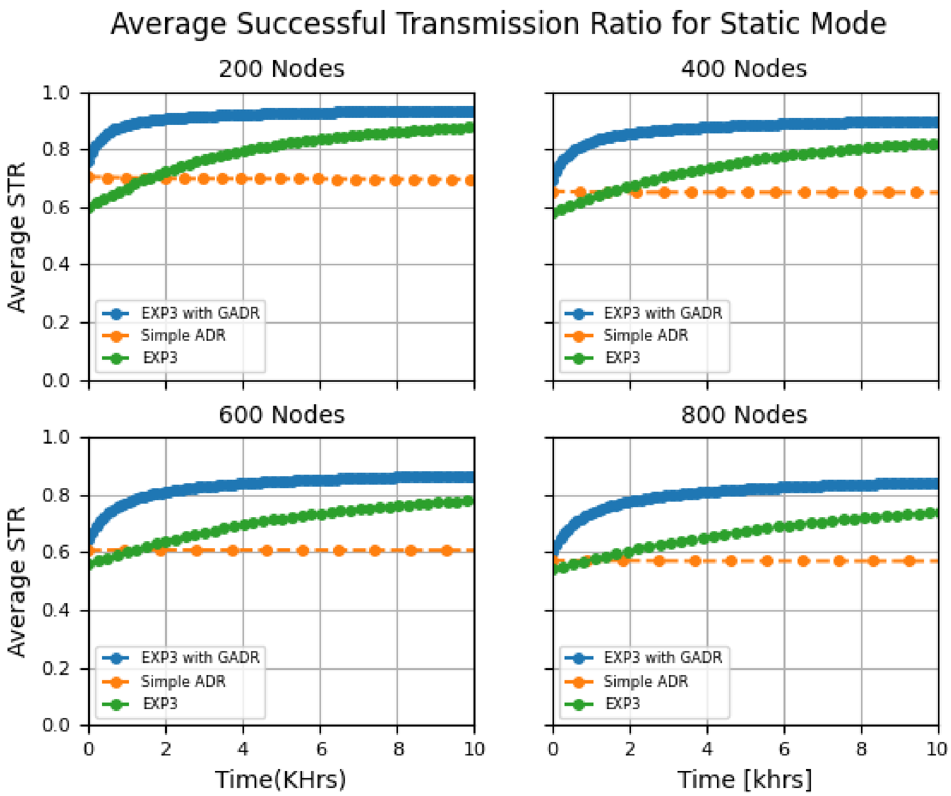


Figure 6.2: Average successful transmission rate of static EDs during simulation time under three different algorithms

Number of EDs N	EXP3	EXP3-GADR
200	11	2
400	14	3
600	13	4
800	19	6

Table 6.1: Convergence period in KHrs for static EDs (with total simulation time = 20Khrs days)

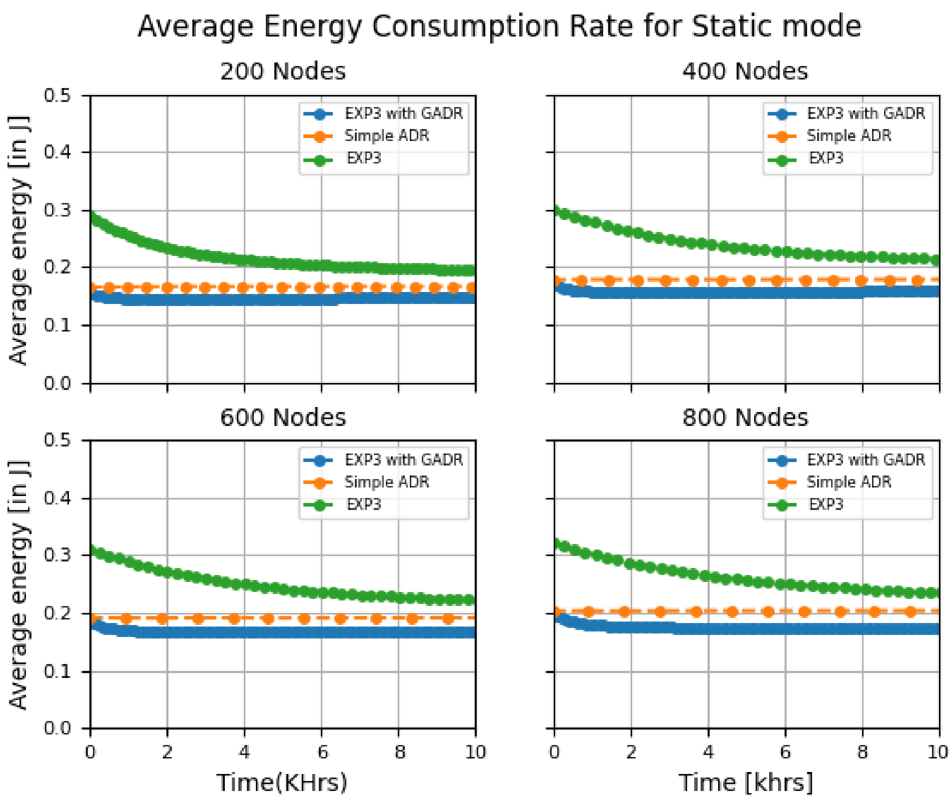


Figure 6.3: Average energy consumption rate of static EDs during simulation time under the three different algorithms for an increasing number of Nodes

6.1.2 Mobile EDs Network

Taking mobility of the EDs into consideration, which is a possible use case of LoRa devices, we will study the performance of the proposed algorithm under this scenario. The motion model is implemented as in [18]. Each node chooses a speed between 0.5 and 1.5 m/s (higher speed is selected for the outdoor positioning [23]). In our case, where we are running a simulation time order of khrs and in order not to make the learning process dump and useless, we reduced the speed to a value between 0.05 and

0.15 m/s. Also, to force the learning process not to start again during each movement of an ED, we proposed a distant threshold set to 100 meters after which the node should update its learning process, meaning the set of actions to be taken including the SF and TP chosen, depending on its new current position with respect to the BS.

As for expectations in mobile network case, normally, the maximum average STR shall be less, since the time during motion will not have enough for the node to choose its best resources (as seen previously in 6.1.1, convergence is reached after 2 kHrs of learning). Figure 6.4 shows our anticipation was correct, a decrease in the maximum STR value is recorded compared to the static mode. We can notice a very slight improvement of GADR over EXP3, but this improvement becomes more important with a higher number of EDs (> 800), for N=800 nodes, an increase of 3% in the average STR is recorded.

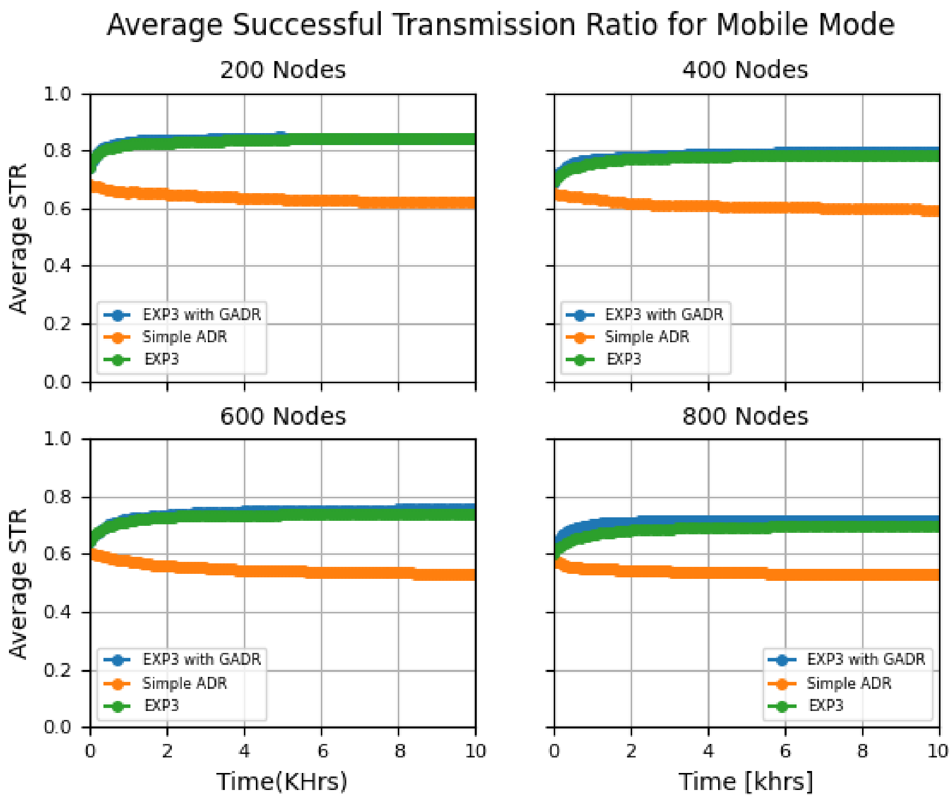


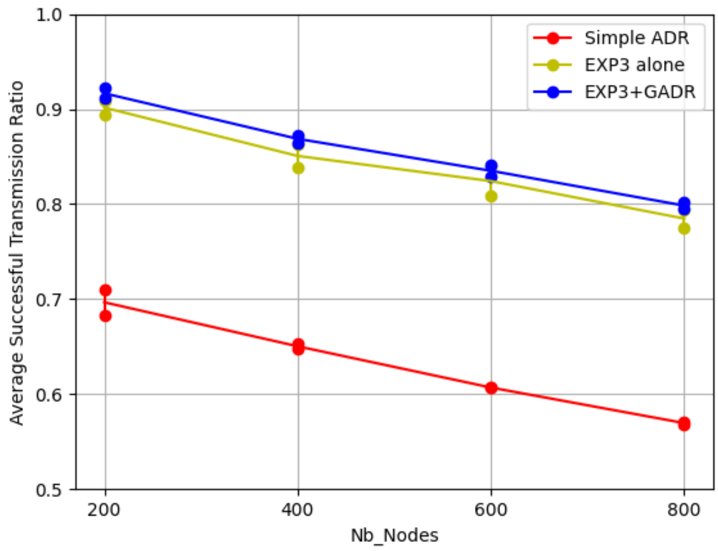
Figure 6.4: Average successful transmission rate of mobile EDs during simulation time under the three different algorithms

6.2 Average STR and Energy Analysis

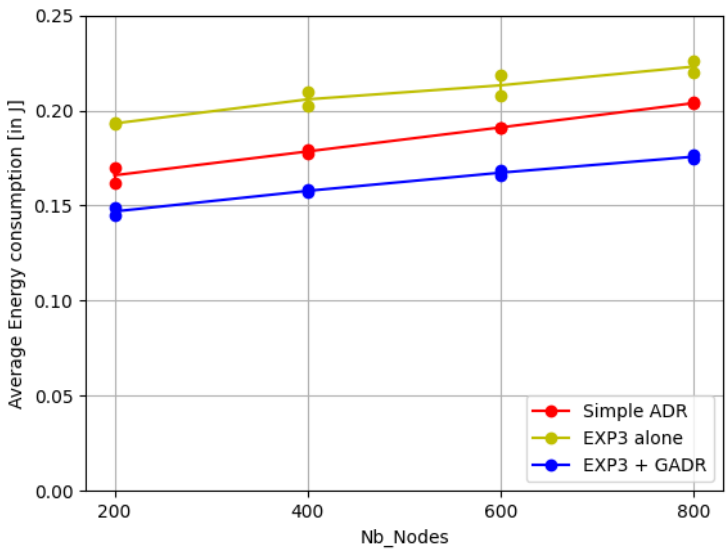
In this study, the STR is defined as the number of uplink packets that are correctly received in one of the available Gateways, i.e., the rate of successfully received packets, while the average energy consumption is the energy consumed per successfully transmitted packets by all EDs. The results are generated using a confidence interval of 5 simulations with different seeds. The confidence intervals of average STR and average energy for a different number of static EDs under 3 different scenarios are presented in Figure 6.5. Results in the case of GADR along with EXP3 algorithm show high STR values($\tilde{0}.85$) with a decreasing trend when increasing the number of EDs. EXP3-alone deployment has a high STR performance as well, but to attain such a record it requires much more running time (high convergence discussed in section 6.1). On the other hand, the simple ADR scenario (yellow plot) has the least performance in terms of STR ($\tilde{0}.6$). This is due to high interference among the random SFs chosen when packets are transmitted. The influence of intelligence (GADR-EXP3) achieves an enhancement up to 20% in successful transmission rate (STR) with respect to an all simple nodes scenario and 4-5% over EXP3-alone algorithm.

In addition, the lowest energy consumption is recorded for the case of both NS and ED intelligence (EXP3-GADR) with a slight increase as the number of nodes increase. however, the energy consumption in the EXP3-algorithm study is even more than that of simple node scenario. The energy is reduced by 25% using our algorithm. A 0.05 Joules difference in the energy consumption is not negligible when working with large-scale LoRaWAN devices which is energy-saving oriented. And as mentioned before, this enhancement is referred to the working methodology of GADR where it decrements SF in the mean while of probabilistic searching of SF done by EXP3. so decreasing SF will result a less ToA and thus less energy (Energy = ToA*TP , refer to ToA in formula 2.1).

Summing up, Table 6.2 illustrates quantitatively the performance of the algorithms showing that EXP3-GADR outperforms EXp3-alone algorithm and simple mode, providing even better performance in case of the highly loaded system with an average of Packet Success Rate of roughly 0.85 and energy consumption of 0.16 joules. Much better STR values with even less energy consumption than previous situations make the combination of node-managed ADR and sever-manged ADR surpass previous results. Thanks for the intelligence added to the EDs and BS.



(a)



(b)

Figure 6.5: (a) Confidence Interval of Average successful transmission rate (b) Confidence Interval of Average Energy consumption

Number of EDs N	Simple Mode	EXP3	EXP3-GADR
200	-	30.4%	34.7%
400	-	30.7%	33.8%
600	-	36.0%	38.5%
800	-	36.8%	39.0%

Table 6.2: ASTR improvements for static EDs

6.3 Fairness of the algorithm

As LoRaWAN is based on Aloha, it is supposed to be a fair MAC protocol. However, various effects such as Capture Effect and Node location introduce unfairness, favouring transmissions from nodes closer to the gateway and by those using lower spreading factors. To verify the impact of the fair data rate distribution, we compute the fairness of proposed algorithm using Jain's fairness index [21] as in the formula 6.1:

$$\zeta = (\sum_{i=1}^{N} DER_i)^2 / (N * \sum_{i=1}^{N} DER_i^2) \tag{6.1}$$

where N is the Number of Nodes, and Data Extraction Rate (DER) is the ratio of the number of packets that arrive at least at one gateway without corruption over the total number of transmitted packets during a given period of time. Jain's index [24] is a quantitative fairness index lying between 0 and 1, where a higher index means higher fairness. It is adopted in resource allocation scenarios. It does not consider individual fairness but rather gives an intuitive view of fairness distribution of the algorithm under study.

As the number of nodes increases, the Fairness index slightly decreases as seen in plot 6.6. This stability with an increasing number of nodes in the network is caused by the nodes distribution supposed initially in our network topology for which there are not numerous nodes far away from the BS. Thus, unfairness introduced by Node location almost vanishes and the distortion is proportional to all nodes.

Comparing the results for EXP3 and GADR with the case of simple node, one can observe an improvement up to 7%. This is mainly because the distributed algorithm EXP3 makes the learning process feasible for all nodes interactively with the situation of the simulation environment (all nodes will learn the best available resources simultaneously) reducing the capture effect and collision. A slight enhancement in the index is recorded using GADR algorithm with a more constant value of the index as well, this gives us an intuition that the DER in this scenario is constant even when increasing the number of nodes. This fact can be related to GADR at BS that is enhancing the SF and TP of each node while transmitting, based on the last M received packets reception power and thus reducing the distortion fairly for all nodes.

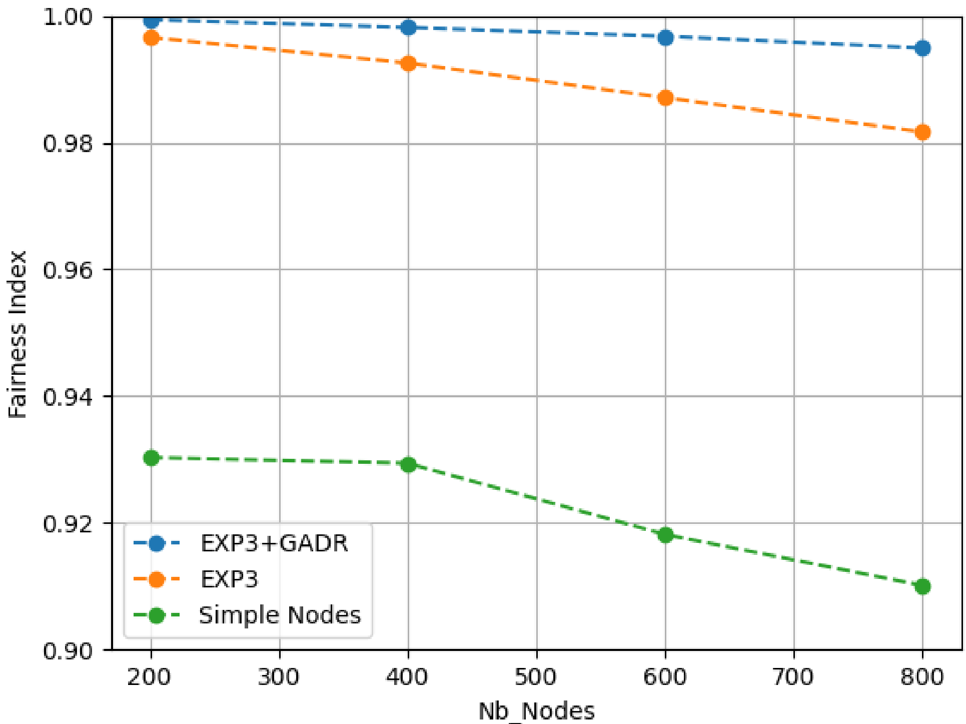


Figure 6.6: Fairness Index for the three different scenarios

Chapter 7

Conclusion and Perpectives

In this paper, we considered LoRaWAN networks with static and mobile nodes operating in the acknowledged mode under three different resource allocation algorithms. We have developed a simulation model of an algorithm to be used for resource allocation during data transmission in LoRaWAN networks. In contrast to previous works, our model combines NS-managed ADR with self-managed one for an optimal resource selection process. It shows important improvements based on the performance evaluation metrics such as packet success ratio, energy consumption rate, and fairness index.

For static EDs, the suggested method when compared to benchmark EXP3 algorithm, have reduced significantly the convergence duration by up to 90%, reduced the energy consumption by up to 25%, and improved the successful transmission rate by almost 8%. However, the improvements are shortened for mobile devices. The scalability of the network was limited since the simulation times were relatively high while in LoRa we expect thousands of end devices in the network. This limits the generality of our approach. Working also on networks with nodes having different priorities or packet size parameters would make insights for the reliability of LoRawAN network to satisfy different QoS Requirements, which can further help in improving the performance of the network.

To sum up, LoRaWAN has shown key success stories as network infrastructure for low-power Internet of Thing devices. Nevertheless, the scalability and resource allocation schemes determine if the ALOHA-based network can fit any use case.

References

[1] *L. Alliance. [Online]. Available: https://www.lora-alliance.org/*

[2] *U. Raza, P. Kulkarni and M. Sooriyabandara, "Low Power Wide Area Networks: An Overview," in IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 855-873, Secondquarter 2017, doi: 10.1109/COMST.2017.2652320.*

[3] *Nicholas Sornin et al., LoRaWAN 1.1 Specifications, Tech. rep. 2017*

[4] *K. Mikhaylov, -. Juha Petaejaejaervi and T. Haenninen, "Analysis of Capacity and Scalability of the LoRa Low Power Wide Area Network Technology," European Wireless 2016; 22th European Wireless Conference, 2016, pp. 1-6.*

[5] *https://emanuelepagliari.it/2020/10/13/what-is-lorawan-internet-of-things-protocol/*

[6] *M. C. Bor and et al, "Do lora low-power wide-area networks scale?" in Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, ser. MSWiM'16. New York, NY, USA: ACM, 2016, pp. 59–67.*

[7] *T. S. Rappaport et al. Wireless communications: principles and practice, volume 2. Prentice Hall PTR New Jersey, 1996.*

[8] *D. Croce and et al, "Impact of spreading factor imperfect orthogonality in lora communications," Communications in Computer and Information Science, pp. 165–179, 2017.*

[9] *D.-T. Ta, K. Khawam, S. Lahoud, C. Adjih, and S. Martin, "Lora-mab: A flexible simulator for decentralized learning resource allocation in iot networks," 12th IFIP Wireless and Mobile Networking Conference (WMNC), 2019.*

[10] *Semtech. Understanding the LoRa Adaptive Data Rate. 2019.*

[11] *https://info.semtech.com/hubfs/image-18.png*

[12] *https://www.rfwireless-world.com/calculators/LoRaWAN-Airtime-calculator.html*

[13] *Sakshama Ghoslaya, LoRa, Chirp Spread Spectrum, in 2017, http://www.sghoslya.com/p/lora-is-chirp-spread-spectrum.html*

[14] *https://www.thethingsnetwork.org/docs/lorawan/modulation-data-rate/*

[15] *D. -T. Ta, K. Khawam, S. Lahoud, C. Adjih and S. Martin, "LoRa-MAB: Toward an Intelligent Resource Allocation Approach for ," IEEE Global Communications Conference (GLOBECOM).*

[16] *R. Bonnefoi and et al, "Multi-armed bandit learning in iot networks: Learning helps even in non-stationary settings," Cognitive Radio Oriented Wireless Networks, pp. 173–185, 2018.*

[17] *A. Azari and C. Cavdar, "Self-organized low-power iot networks: A distributed learning approach," in 2018 IEEE Global Communications Conference (GLOBE-COM), 2018, pp. 1–7.*

[18] *Farhad, A.; Kim, D.-H.; Subedi, S.; Pyun, J.-Y. Enhanced LoRaWAN Adaptive Data Rate for Mobile Internet of Things Devices. Sensors 2020, 20, 6466.*

[19] *Cuomo F., Campo M., Caponi A., Bianchi G., Rossini G., Pisani P. EXPLoRa: Extending the Performance of LoRa by Suitable Spreading Factor Allocations; Proceedings of the 2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob); Rome, Italy. 9–11 October 2017; pp. 1–8.*

[20] *Aernouts, M.; BniLam, N.; Podevijn, N.; Plets, D.; Joseph, W.; Berkvens, R.; Weyn, M. Combining TDoA and AoA with a particle filter in an outdoor LoRaWAN network. In Proceedings of the 2020 IEEE/ION Position, Location and Navigation Symposium (PLANS), Portland, OR, USA, 20–23 April 2020; pp. 1060–1069.*

[21] *R. Jain, D.-M. Chiu, and W. R. Hawe, A quantitative measure of fairness and discrimination for resource allocation in shared computer system. Eastern Research Laboratory, Digital Equipment Corporation Hudson, MA, 1984, vol. 38.*

[22] *Semtech. AN1200.13 SX1272/3/6/7/8: LoRa Modem-Designer's Guide, Revision 1, July 2013.*

[23] *Podevijn, N.; Plets, D.; Trogh, J.; Martens, L.; Suanet, P.; Hendrikse, K.; Joseph, W. TDoA-based outdoor positioning with tracking algorithm in a public LoRa network. Wirel. Commun. Mob. Comput. 2018*

[24] *Huaizhou Shi, R. Venkatesha Prasad, Vijay Rao, I. Niemegeers. A Fairness Model for Resource Allocation in Wireless Networks. Networking Workshops (NETWORKING), May 2012*