Lightweight Learning for smart resource allocation in LPWAN

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Outline

IoT Scenarios

Internet of Things

The Internet of Things (IoT) generally refers to scenarios where network connectivity and computing capability extends to devices, sensors, and everyday items (ISOC IoT Overview, 2015).

Scenario	Example
Human	Wearables for health monitoring
Home	Heating, security automation
Retail	Self-checkout, inventory optimization
Vehicles	Condition-based maintenance
Cities	Traffic control, environmental monitoring

Evolution of IoT Devices

The largest growth is expected for devices connected to a wide-area network.

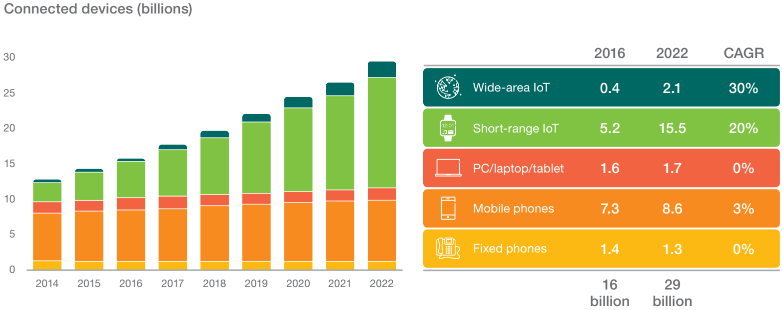


Figure 1: Source: Ericsson mobility report, 2017

Constraints on the Device and Network Layers

- Difficult physical accessibility and limited access to power sources
  - Wireless communications
  - Autonomy and long battery life operation
- Wide area coverage with a large number of communicating devices
  - Scalable deployment
  - Cost efficient devices
- Very loose bandwidth and latency constraints
  - Adaptive radio and access mechanisms

LPWAN Scenarios

Low Power Wide Area Networks

Low power refers to the ability of an IoT device to function for many years on a single battery charge, while being able to communicate from locations where shadowing and path loss would limit the usefulness of more traditional cellular technologies [a]

[a] 3GPP Low Power Wide Area Technologies, GSMA White Paper, 2016

Typical scenarios for LPWAN [2]

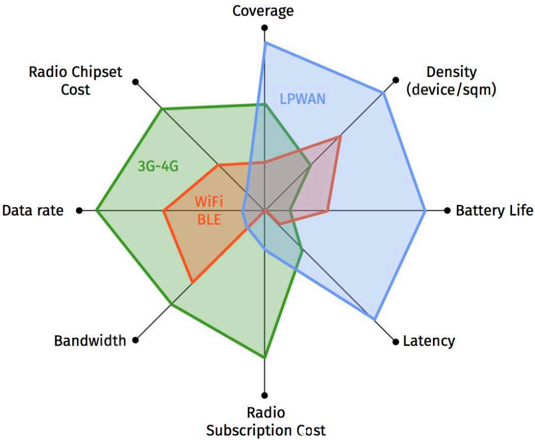
- Smart grid
- Industrial asset monitoring
- Critical infrastructure monitoring
- Agriculture

[2] U. Raza et al., Low Power Wide Area Networks: An Overview, IEEE Communications Surveys and Tutorials, 2017

LPWAN Sweet Spot

Challenge

Do existing wireless networking technologies satisfy these constraints?



Outline

Revisiting LPWAN Requirements

- Low device complexity and cost
- Reliability under extreme coverage conditions
- Low power consumption: long battery lifetime
- High capacity: support for massive number of low-rate devices
- Simplified network topology and deployment

Objectives and Approaches

- Develop a *clean-slate* technology that meets the LPWAN requirements
  $\Rightarrow$ LoRaWAN
- Adapt and leverage existing 4G technology to meet the LPWAN requirements
  $\Rightarrow$ NB-IoT

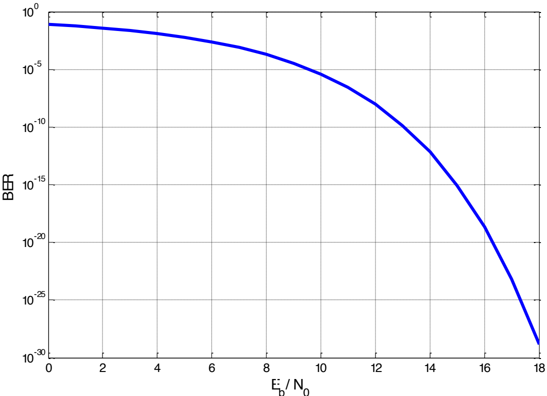
Low Device Complexity and Cost

- Devices are mainly composed of:
  - a processing unit: usually a microcontroller with a limited amount of memory
  - a sensing unit: sensors and analog to digital converters
  - a radio unit: usually a transceiver capable of bidirectional communications
- To limit the complexity of the radio unit:
  - limiting message size: maximum application payload size between 51 and 222 bytes, depending on the spreading factor
  - using simple channel codes: Hamming code
  - supporting only half-duplex operation
    - not using a duplexer
  - using one transmit-and-receive antenna
  - on-chip integrating power amplifier (since transmit power is limited)

Reliability under extreme coverage conditions

Radio Quality

- Reliability $\Rightarrow$ bit error rate (BER) $\leq$ target BER
- The energy per bit to noise power spectral density ratio (E_b/N_0) is defined as the ratio of the energy per bit (E_b) to the noise power spectral density (N_0)



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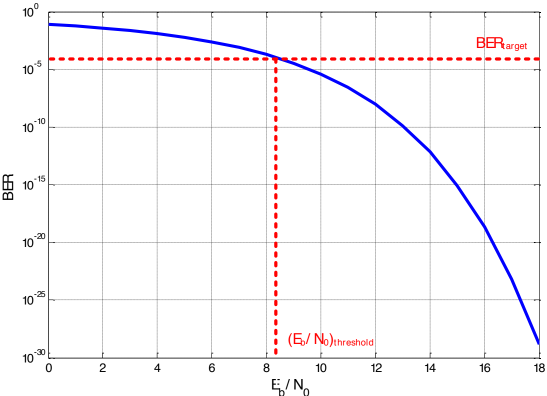


Radio Quality

$$BER \leq BER_{target} \Leftrightarrow \frac{E_b}{N_0} \geq \left(\frac{E_b}{N_0}\right)_{threshold}$$

- $(E_b/N_0)_{threshold}$ does not depend on the signal bandwidth and bit-rate
- The SNR is defined as the ratio of the received signal power C to the power of the noise N within the bandwidth of the transmitted signal

$$SNR = \frac{C}{N} = \frac{E_b/T_b}{N_0 B} = \frac{E_b}{N_0}\frac{R_b}{B}$$

where B is the signal bandwidth in Hz, and R_b is the bit-rate in b/s.

Receiver Sensitivity

$$BER \leq BER_{target} \Leftrightarrow SNR \geq \underbrace{\left(\frac{E_b}{N_0}\right)_{threshold} \frac{R_b}{B}}_{SNR_{threshold}}$$

$$\Leftrightarrow S(dBm) \geq \underbrace{SNR_{threshold}\ (\mathrm{dB})\ + N\ (\mathrm{dBm})}_{\text{Receiver sensitivity}}$$

- N (dBm) is the background noise power at the receiver: $= TN$ (dBm) $+NF$ (dB)
- TN is the thermal noise caused by thermal agitation of charge carriers: $-174 + 10\log_{10}(B)$
- NF is the noise figure caused by RF components

How to Improve Coverage?

- Increasing P_{Tx}, or lowering NF, leads to higher device complexity and cost $\Rightarrow$ inadequate solutions
- Reducing B leads to lower network capacity $\Rightarrow$ inadequate solution
- Reducing $SNR_{threshold}$: optimised radio modulation that uses spread spectrum $\Rightarrow$ LoRa

Why Spread Spectrum?

Spread spectrum compensates for the SNR degradation

$$SNR = \frac{E_b}{N_0}\frac{R_b}{B} \Rightarrow \left(\frac{E_b}{N_0}\right) dB = (SNR)dB + G_p$$

where G_p is the processing gain given by: $G_p = 10\log_{10}(\frac{B}{R_b})$

$$SNR_{threshold} = \left(\frac{E_b}{N_0}\right)_{threshold} - G_p$$

- The higher G_p is
  - the lower $SNR_{threshold}$ is $\Rightarrow$ larger radio coverage
  - the lower R_b is
- SS is robust to interference, multipath fading, and Doppler effect

High Capacity

Support for Massive Number of Low-Rate Devices

- Trading off data rate for coverage
- How to increase network capacity?
  - LoRaWAN uses multiple orthogonal spreading factors simultaneously on the same channel

Simplified Network Topology and Deployment

- LoRaWAN has a simple network architecture and operates in license-free bands ⇒ low-cost deployment

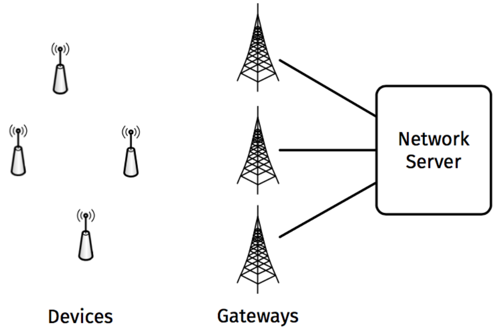


Figure 3: Star of Stars

Outline

What is LoRa?

Definition of LoRa

LoRa is a wireless modulation technique that uses Chirp Spread Spectrum (CSS) in combination with Pulse-Position Modulation (PPM).

- Processing gain given by $g_p = BT$
- Spreading factor SF given by $\log_2(g_p)$
- Considering a coding rate CR, the bit-rate is given by:

$$R_b = SF \cdot \frac{B}{2^{SF}} \cdot \frac{4}{4 + CR}$$

with $1 \leq CR \leq 4$

LoRa Spreading Factors?

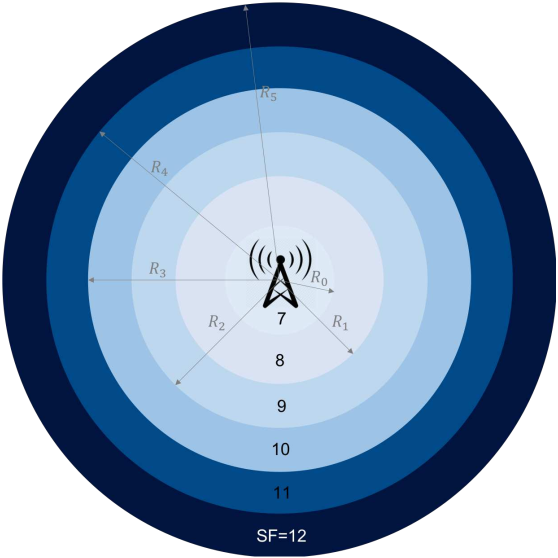
LoRa uses spreading factors from 7 to 12.

Spreading Factor	Bit Rate (kb/s)	Sensitivity (dBm)
7	5.468	-123
8	3.125	-126
9	1.757	-129
10	0.976	-132
11	0.537	-134.5
12	0.293	-137

($CR = 1$ and $B = 125$ kHz)

- Operates in license-free bands all around the world
  - 433, 868 (EU), 915 MHz
- EU 863-870MHz ISM Band
  - Default radiated transmit output power by devices: 14 dBm
  - Minimum set of three channels, maximum of 16 channels

SF spatial distribution



Outline

Intelligent resource management

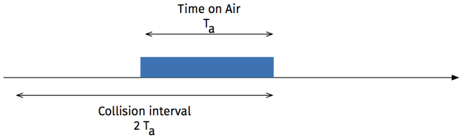
How to reduce collision rate:

- ALOHA-based communication (without sensing):
  - Collision if more than one device selects the same SF and channel.
- Given their strict energy and capacity constraints, devices should avoid signalling with the network:
  - Privilege distributed resource allocation (Reinforcement Learning)

Capacity of LoRaWAN

Pure ALOHA Model

- The start times of the packets in an ALOHA channel is modeled as a Poisson point process with parameter λ packets/second



- If each packet in the channel lasts T_a seconds, the normalized channel traffic can be defined as

$$G = \lambda T_a$$

- The normalized throughput of the ALOHA random access channel is given by

$$S = G \exp(-2G)$$

Capacity Formula for LoRaWAN

- We consider a LoRaWAN network with N end-devices and one gateway
  - One spreading factor s and one sub-channel are available
  - Transmit attempts are done according to a Poisson distribution
  - All end-devices have the same packet generation rate $\lambda(s)$
  - All packets have the same length of l bytes
- The normalized throughput of the LoRaWAN network is:

$$S = G\exp(-2G) = N\lambda(s)T_a(l,s)\exp(-2N\lambda(s)T_a(l,s))$$

- The total number of successfully received packets per second is obtained by:

$$\frac{1}{T_a(l,s)} \times S$$

Centralized Resource Management Problem

- We suppose that we have an external traffic (*e.g.* devices belonging to a different operator) of intensity λ_s^e packets per second on spreading factor s.
- Let p_s be the ratio of devices using SF s.
- We can write the normalized channel traffic on SF s as follows:

$$G_s = (\lambda \cdot N \cdot p_s + \lambda_s^e) T_s \tag{1}$$

The normalized total throughput $\overline{G}$ of the network is given by:

$$\begin{aligned} \overline{G} &= \sum_{s=1}^{S} G_s \exp(-2G_s) \\ &= \sum_{s=1}^{S} (\lambda \cdot N \cdot p_s + \lambda_s^e) T_s \exp(-2(\lambda \cdot N \cdot p_s + \lambda_s^e) \cdot T_s) \end{aligned}$$

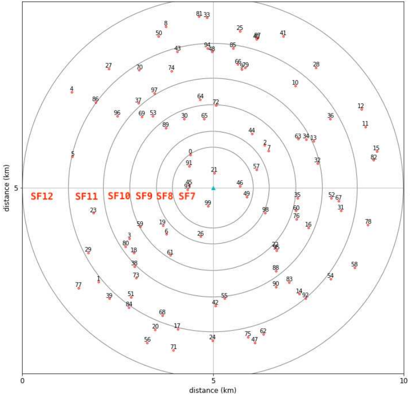
Centralized Problem

The optimization problem is as follows:

$$
\begin{aligned}
(\mathcal{P}): \quad & \max_{p_s} \sum_{s=1}^{S} \left(G_s(p_s) \exp(-2G_s(p_s)) \right) \\
\text{subject to} \quad & \sum_{s=1}^{S} p_s \le 1, && \text{(2a)} \\
& p_i \le \frac{N_i}{N}, \forall s = 1, \ldots, S. && \text{(2b)}
\end{aligned}
$$

Geographical SF distribution

Parameters	Values
Disc of radius	4.5 km
N	100
Packet length	50 bytes
Bandwidth (BW)	125 kHz
Code rate	4/5
Frequency set	868.100 KHz
Capture Effect Threshold	6 dB
Transmission Power	14 dB



Distributed resource management Problem

Reinforcement learning based algorithms are lightweight and particularly adapted to LoRaWAN

- Any end-device is an intelligent agent that chooses a convenient spreading factor SF_i or strategy $s = \{SF_i\}$.
- Let $\mathcal{S} = \{7, \ldots, 12\}$ be the set of spreading factors.
- Realistic setting: devices are unaware of their position and channel conditions.
- At each iteration t (at packet arrival), any device selects a strategy $s(t)$ which renders a reward $r_s(t) \in \{0, 1\}$.
  - Successful packet transmission (acknowledged by the GW) yields $r_s(t) = 1$.
  - In case of packet loss, $r_s(t) = 0$.

Distributed resource management Problem: MAB

- Multi-Armed Bandit (MAB) problem makes use of local information available at the LoRaWAN end-device level (received ACK).
- The result of the devised algorithm in each device will be a set of SFs that suffers the least from collisions.
- To reduce the resource occupation of the neighboring devices, each device follows a set of rules to strike a good balance between:
  - (i) Exploiting the cumulated knowledge by choosing the most appropriate SF s to transmit, and
  - (ii) Exploring other SFs that could be interesting to exploit.

Which MAB?

There are two widely considered MAB types [1]:

- For stochastic MAB, the reward of each strategy is drawn according to a given probability density function (PDF)
- For non-stochastic MAB, no statistical assumptions are made about the generation of rewards.

As the distributed selection of the best radio resources by uncoordinated devices is appropriately modeled by the adversarial MAB problem, we resort to the popular EXP3 algorithm (Exponential Weights for Exploration and Exploitation) [2].

[1] Bubeck, N. Cesa-Bianchi, et al., Regret analysis of Stochastic and Non-Stochastic Multi-Armed Bandit Problems, Foundations and Trends in Machine Learning, vol. 5, no. 1, pp. 1-122, 2012

[2] P. Auer, N. Cesa-Bianchi, and P. Fischer, Machine Learning, vol. 47, no. 2/3, pp. 235-256, 2002

EXP3

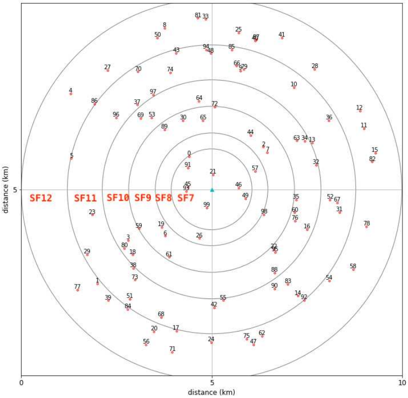
- Set the initial weights $\omega_s^j(0) = 1, \forall s \in \mathcal{S}, \forall j \in \mathcal{N}$.
- Set the uniform distribution of actions per device $p_s^j(0) = \frac{1}{S}$.
- Set the horizon time T and the learning rate $\gamma = \min\left\{1, \sqrt{\frac{S\log(S)}{(e-1)T}}\right\}$.
- For t=1 to T, for each device $j \in \mathcal{N}$ at time t,
  - Draw strategy $s \in \mathcal{S}$ according to $p_s^j(t)$ and Transmit;
  - Receive reward $r_s^j(t) \in \{0, 1\}$
    - 1 if ACK is received,
    - 0 otherwise
  - Update the weights and distributions of available strategies as follows:

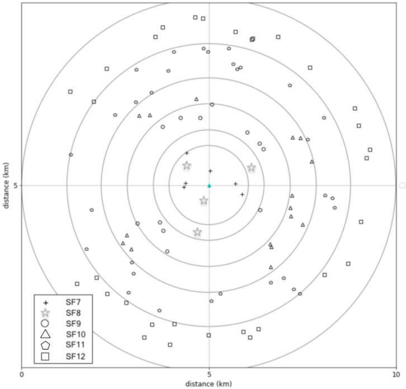
$$\omega_s^j(t+1) = \omega_s^j(t)\exp\left(\frac{\gamma r_s^j(t)}{S \cdot p_s^j(t)}\right)$$

$$p_s^j(t+1) = (1-\gamma)\frac{\omega_s^j(t+1)}{\sum_{s=1}^{S}\omega_s^j(t+1)} + \frac{\gamma}{S}$$

EXP3 SF Selection

Uniform Distribution





EXP3 SF Selection

Strategy Evolution

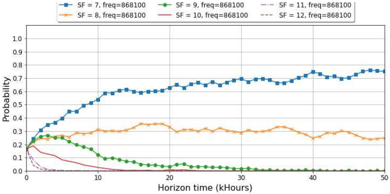


Figure 4: Impact of closeby devices

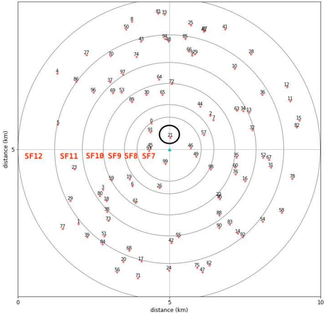
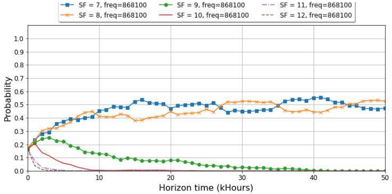


Figure 5: SF Distribution

EXP3 SF Selection

Strategy Evolution



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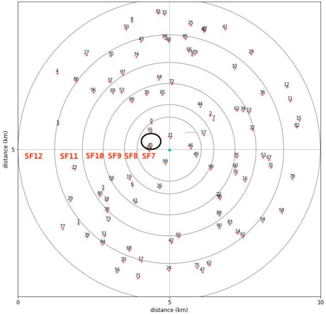

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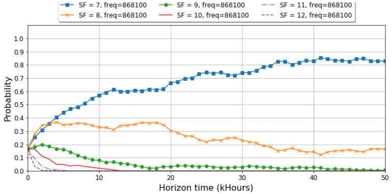

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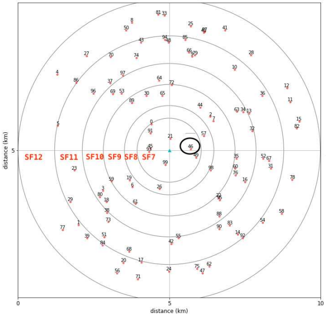


Figure 5: SF Distribution

EXP3 SF Selection

Devices in outer regions:

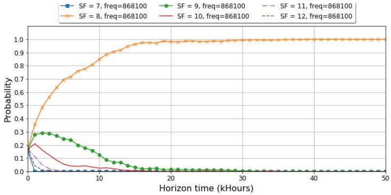


Figure 6: In region with $SF = 8$

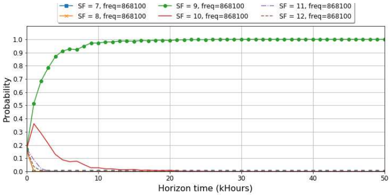
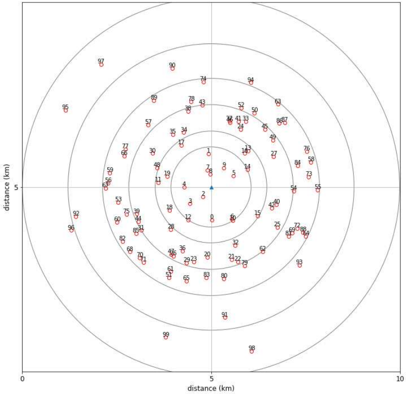
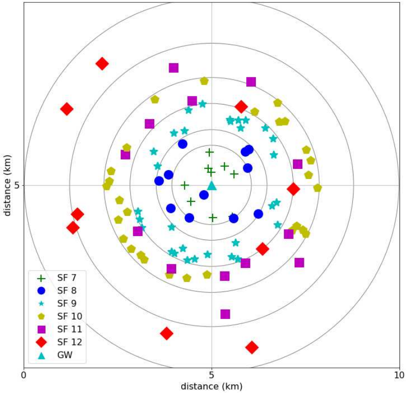


Figure 7: In region with $SF = 9$

EXP3 SF Selection

Non-Uniform Distribution





EXP3 SF Selection

Impact of Capture Effect

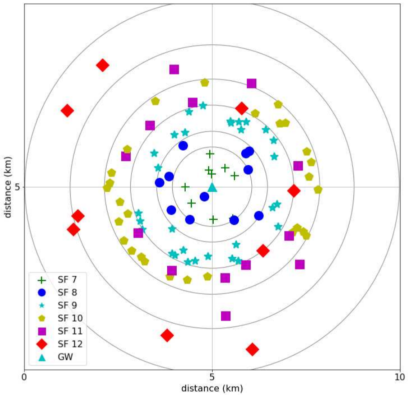


Figure 8: with CE

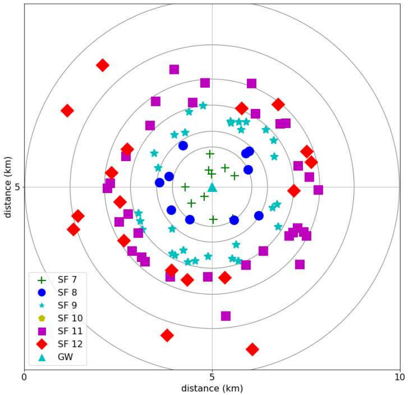


Figure 9: without CE

Network Performances

Strategy Evolution in outer regions

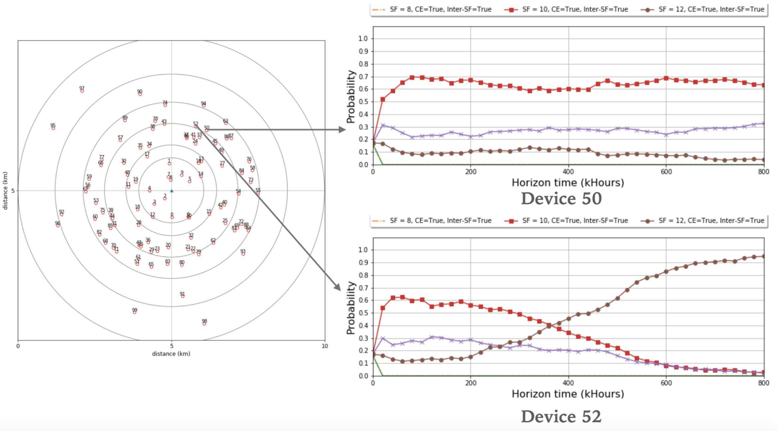


Figure 10: SF distribution

Network Performances

Various ratios of intelligent devices: 0%, 50% and 100%

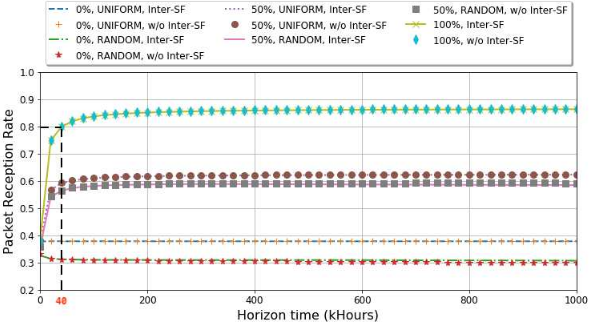


Figure 11: Packet Reception rate

Network Performances

Comparison between centralized optimal solution, uniform SF selection, random SF selection

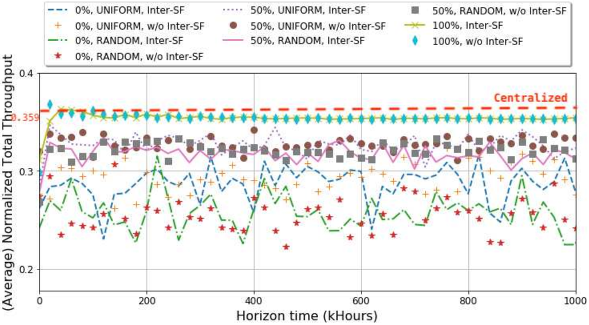


Figure 12: Normalized Throughput

Future Work

- Devices should learn not only SF but also sub-channel and transmission power selection to improve performances and reduce the energy consumption of the network.
- We need to explore ways to improve the convergence rate of the algorithm.