

Title these

Pourquoi faire une these ?

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Outline

1. Introduction

2. Academic Survey

3. Industrial Survey

4. FCM for LoRa setting

5. Testbed

6. Conclusion

Massive IoT devices

Emergence of new IoT devices that need a wide area wireless communications

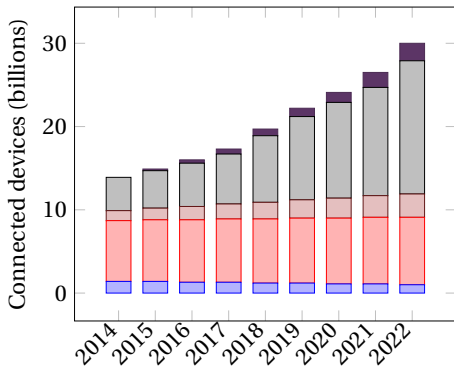
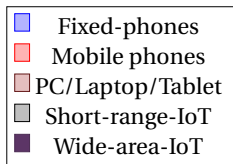


Figure 1. Diversity of IoT devices [1].

2012: Sigfox

2015: Long Range (LoRa)

Open access

2016: Narrow Band-Internet of Things (NB-IoT)

Low Power Wide Area Networks (LPWAN)

IoT wireless communication

Wireless communication offers different Quality of Service (QoS) performances

1) **Cellular networks:**

➡ 2G, ..., 5G

2) **Short range networks:**

➡ Zigbee, Bluetooth, Wifi

3) **Long range networks:**

➡ LoRa, Sigfox, NB-IoT

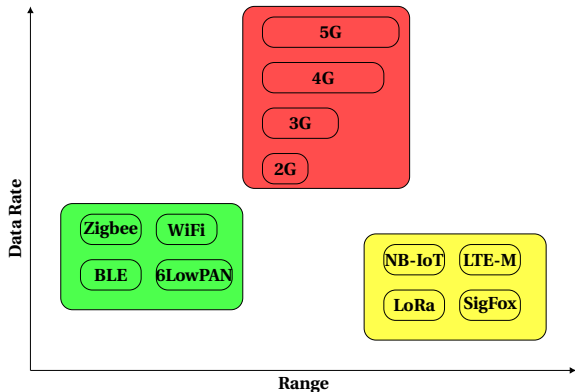


Figure 2. Short range, Cellular and Long range networks.

IoT wireless communication

Wireless communication performance need to be evaluated to match applications requirements

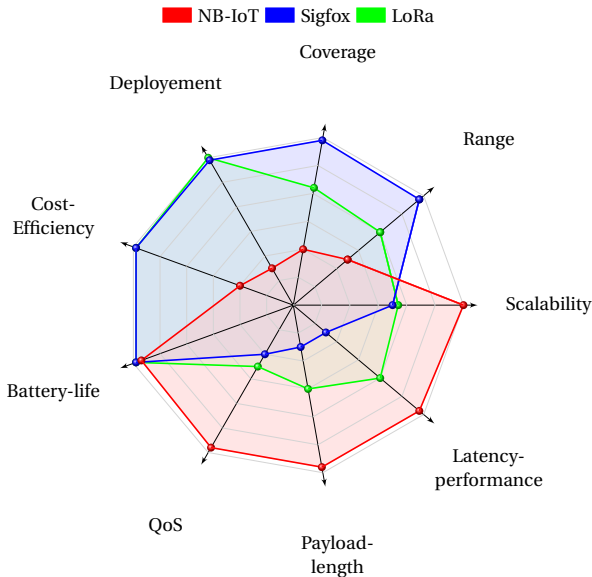


Figure 3. LPWAN comparison.

Applications diversification

Each application has its own communication requirements



Figure 4. IoT applications [2].

Applications	PR [pkt/day]	PDR min [%]	PS [Byte]
Wearables	10	90	10-20
Smoke Detectors	11	90	10-20
Smart Grid	10	80	10-20
Waste Management	24	60	10-20
Smart Bicycle	192	80	50-100
Animal Tracking	100	70	50-100
Environmental	5	90	50-100
Water/Gas Metering	8	85	100-200
Medical Assisted	8	90	100-200
Safety Monitoring	2	95	100-200

Table 1. Applications requirements in IoT [2], [3]

Applications diversification

Each application has its own communication requirements



Figure 4. IoT applications [2].

Applications	PR [pkt/day]	PCR min [%]	PS [Byte]
Wearables	10	90	10-20
Smoke Detectors	1	90	10-20
Smart Grid	10	80	10-20
Waste Management	24	60	10-20
Smart Bicycle	192	80	50-100
Animal Tracking	100	70	50-100
Environmental	5	90	50-100
Water/Gas Metering	8	85	100-200
Medical Assisted	8	90	100-200
Safety Monitoring	2	95	100-200

Table 1. Applications requirements in IoT [2], [3]

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Genetic algorithm

⇒ $G = [g_{11}, \dots, g_{nc}]$, $g_{ij} \in [0, 1]$, $1 \leq i \leq n$, $1 \leq j \leq c$.

⇒ **n**: received packets, **c**: applications.

⇒ $G_0 = [g_{11}, \dots, g_{nc}]$, $g_{ij} = q_{ij} / \sum_{l=1}^c q_{il}$, $\forall i, j$.

⇒ $q_{ij} = \text{random}(\mathbb{R})$, $\forall i, j$.

⇒ $G_t = [g_1, \dots, g_n]$

⇒ **Selection (roulette wheel):**

1) $f(r_i) = \beta(1 - \beta)^{r_i - 1}$

* $\beta \in [0, 1]$ biggest section probability allowed.

* $r_i \in [1, n]$ rank of g_i

2) $\overline{g_x} = \{g_{x^1}, \dots, g_{x^z}\}$, $F(r_{i-1}) \leq h_{x^e} \leq F(r_i)$, $1 \leq e \leq z \leq n$, $\forall i$

* $h_{x^e} \in [0, 1]$, $h \sim \text{Uniform}$

* z : number of selected packets.

⇒ **Fitness/Crossover/Clustering:**

* $\overline{g_x} = \text{FCM}(\mathbf{X})$

⇒ **Mutation:** $v \sim P$

* b is the mutation threshold (0.001).

$$\overline{g_x} = \begin{cases} \overline{g_x} & v \geq b \\ \overline{q_{xj}} / \sum_{l=1}^c \overline{q_{xl}}, \text{ with } \overline{q_{xj}} = \text{random}(\mathbb{R}), \forall j. & \text{otherwise} \end{cases}$$

- 1) The Fuzzy C-Means Clustering algorithm takes in parameter a matrix of n packets received by the gateway by each end-devices with their p metrics (RSSI, ToA, BER, ...).
- 2) The algorithm builds two other matrices, U which contains the membership degree of each packet to the c applications, and V , which contains the optimal p metrics that best fit the c applications.
- 3) The genetic algorithm starts by randomly generating a matrix with the same dimensions as matrix U .
- 4) The algorithm selects z packets and applies the Fuzzy C-Means Clustering algorithm on these z packets.
- 5) β is a parameter that represents the biggest probability that a packet could have to be selected.
- 6) r is a parameter that defines its rank, a packet of rank 1 has the probability β to be selected, a packet of rank r has a probability $f(r)$ to be selected.
- 7) $F(r)$ is the cumulative function of $f(r)$,
- 8) To select a set of packets to be sent to the FCM, a random variable between 0 and 1 is generated for each packet received. The probability to select packets decrease progressively until achieving all the packets.
- 9) Once the selected packets are chosen, we apply the FCM algorithm on the selected packets.

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Game theory

- ⇒ $P = \{p_1, \dots, p_n\}, \quad p_i \in \mathbb{N}, 1 \leq i \leq n.$
 - ⇒ n : number of players.
- ⇒ $S = \{s_1, \dots, s_n\}, 1 \leq i \leq n$
 - ⇒ s_i is the strategy set of the i^{th} player.
- ⇒ $r_i(s_i, s_{-i}) = u_i : S \rightarrow R_+$
 - ⇒ $s_{-i} = (s_1, \dots, s_{i-1}, s_{i+1}, \dots, s_n) \in S_1 \times \dots \times S_{i-1} \times S_{i+1} \times \dots \times S_n$

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Multi-Armed-Bandit Algorithm

For each step $t = 1, \dots, T$

- ⇒ **Arms: $K = 1, \dots, K$**
- ⇒ **Reward: X_t^k with $\mu_t^k = \mathbb{E}[X_t^k]$**
 - ⇒ **Bernoulli rewards: $X_{k_t} \sim B(\mu_{k_t, t})$**
 - ⇒ **Best reward: X_t^* with $\mu_t^* = \max_{k \in K} \mu_t^k$**
 - ⇒ **The reward k_t is revealed $X_{k_t} \in [0, 1]$**
- ⇒ **Minimize the pseudo regret:**
 - ⇒ $R(T) = \sum_{t=1}^T \mu_t^* - \mathbb{E} \left[\sum_{t=1}^T X_{k_t} \right]$
 - ⇒ **where**
 - * $\mu_t^* = \max_k \mu_{k, t}$

Bandit Algorithm

Growing number of Thompson Sampling $f_{i,t}$:

▮ i denotes the starting time

▮ t the current time.

Let $P(f_{i,t})$ be the probability at time t of the Thompson sampling starting at time i .

▮ Initialization: $\mathbb{P}(f_{1,1}) = 1, t = 1, 2$

▮ $\forall k \in K \alpha_{k,f_{1,1}} \leftarrow \alpha_0, \beta_{k,f_{1,1}} \leftarrow \beta_0$

▮ Decision process: at each time t :

▮ $\forall i < t, \forall k : \theta_{k,f_{i,t}} \sim \text{Beta}(\alpha_{k,f_{i,t}}, \beta_{k,f_{i,t}})$

▮ Play (Bayesian Aggregation):

✱ $k_t = \arg \max_k \sum_{i < t} \mathbb{P}(f_{i,t}) \theta_{k,f_{i,t}}$

▮ Instantaneous gain update:

$$\forall i < t \mathbb{P}(x_t | f_{i,t}) = \begin{cases} \frac{\alpha_{k_t, f_{i,t}}}{\beta_{k_t, f_{i,t}} + \alpha_{k_t, f_{i,t}}} & \text{if } x_{k_t} = 1 \\ \frac{\beta_{k_t, f_{i,t}}}{\beta_{k_t, f_{i,t}} + \alpha_{k_t, f_{i,t}}} & \text{if } x_{k_t} = 0 \end{cases} \quad (1)$$

▮ Arm hyper parameters update:

$$\forall i < t \begin{cases} \alpha_{k_t, f_{i,t}} = \alpha_{k_t, f_{i,t}} + 1 & \text{if } x_{k_t} = 1 \\ \beta_{k_t, f_{i,t}} = \beta_{k_t, f_{i,t}} + 1 & \text{if } x_{k_t} = 0 \end{cases} \quad (2)$$

▮ Distribution of experts update:

▮ $\forall i < t, \mathbb{P}(f_{i,t}) \propto (1 - \rho) \cdot \mathbb{P}(x_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$

▮ $f_{t,t} : \mathbb{P}(f_{t,t}) \propto \rho \sum_{i=1}^{t-1} \mathbb{P}(x_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$

▮ $\alpha_{k_t, f_{t,t}} = \alpha_0, \beta_{k_t, f_{t,t}} = \beta_0$

Bandit Algorithm

THOMPSON SAMPLING (TS)

→ success counter: $\alpha_k = \#(x_{k_t} = 1) + \alpha_0$

→ failure counter: $\beta_k = \#(x_{k_t} = 0) + \beta_0$

→ At each t :

* $\theta_k \sim \text{Beta}(\alpha_k, \beta_k)$

* $k_t = \arg \max_k \theta_k$

*
$$\begin{cases} \alpha_k = \alpha_k + 1 & \text{if } x_{k_t} = 1 \\ \beta_k = \beta_k + 1 & \text{if } x_{k_t} = 0 \end{cases}$$

SWITCHING ENVIRONMENT

$$\mu_{k,t} = \begin{cases} \mu_{k,t-1} & \text{probability } 1 - \rho \\ \mu_{new} \sim U(0, 1) & \text{probability } \rho \end{cases} \quad (3)$$

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Q Learning

$$Q(s_{t+1}, a_t) = Q(s_t, a_t) + \gamma (R(s_t, a_t) - Q(s_t, a_t))$$

⇒ $Q(s_{t+1}, a_t)$ = new Q-Value

⇒ $Q(s_t, a_t)$ = old Q-Value

⇒ γ = learning constant

⇒ $R(s_t, a_t)$ = immediate reward received after executing action a in state s at time t

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Marcov chain

$$V(s, \pi) = \mathbb{E}_s^\pi \left(\sum_{k=0}^{\infty} \gamma^k \cdot r(s_k, a_k) \right), s \in \mathbb{S} \quad (4)$$

$$r(s_k, a_k) = G_k \cdot PRR(a_k) \quad (5)$$

$$\pi^* = \arg \max_{\pi} V(s, \pi) \quad (6)$$

Marcov chain

Learning iterative steps:

- ▮ **Choose** action $a_k(t) \sim \pi_k(t)$
- ▮ **Observe** game outcome
 - ▮ $a_{-k}(t)$
 - ▮ $u_k(a_k(t), a_{-k}(t))$
- ▮ **Improve** $\pi_k(t+1)$

Thus, we can expect that $\forall k \in K$

$$\pi_k(t) \xrightarrow{t \rightarrow \infty} \pi_k^* \quad (7)$$

$$u_k(\pi_k(t), \pi_{-k}(t)) \xrightarrow{t \rightarrow \infty} u_k(\pi_k^*, \pi_{-k}^*) \quad (8)$$

Where:

- ▮ $\pi^* = (\pi_1^*, \dots, \pi_k^*)$ is the NE strategy profile

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Clustering

	mutual info	v measure	adjusted rand	completeness	fowlkes mallows	homogeneity
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Agglomerative						
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MeanShift						
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AffinityProp						
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DBSCAN						
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OPTICS						
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FeatureAgg						
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Spectral						
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MiniKMeans						
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KMeans						
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SpectralBi						
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SpectralCo						
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Birch						
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FCM						
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LoRa parameters selection

How to select the optimal configuration

Parameters:

- Bandwidth (BW)
- Spreading Factor (SF)
- Coding Rate (CR)
- Transmission Power (P^{tx})
- Payload size (PS)
- Signal Noise Rate (SNR)

Metrics:

- Data Rate (DR)
- Time on Air (ToA)
- Payloadsize(PS)_{max}
- Received Signal Strength Indication (RSSI)
- Bit Error Rate (BER)

Setting	Values	Rewards	Costs
BW	7.8 \Rightarrow 500kHz	DR	RSSI, Range
SF	$2^6 \Rightarrow 2^{12}$	RSSI, Range	DR, SNR, PS _{max} , P^{tx}
CR	4/5 \Rightarrow 4/8	SNR	PS _{max} , P^{tx} , ToA
P^{tx}	-4 \Rightarrow 20dBm	SNR	P^{tx}
PS	59 \Rightarrow 230B	PS	P^{tx} , ToA

Table 2. LoRa parameters selection [4]

QoS metrics

Time on Air (ToA)

$$\rightarrow \text{ToA}_{\text{GFSK}} = \frac{8}{DR} (NP + SW + PL + 2CRC)$$

$$\rightarrow \text{ToA}_{\text{LoRa}} = \frac{2^{SF}}{BW} \left((NP + 4.25) + \left(SW + \max \left(\left\lceil \frac{8PS - 4SF + 28 + 16CRC - 20IH}{4(SF - 2DE)} \right\rceil (CR + 4), 0 \right) \right) \right)$$

Receiver Sensitivity (RS)

$$\rightarrow \text{RS}_{[\text{dBm}]} = -174 + 10 \log_{10} BW + NF + SNR$$

Path loss (PL)

$$\rightarrow \text{PL}_{[\text{dB}]} = |RSSI| + SNR + P_{TX} + G_{RX}$$

Signal Noise Rate (SNR)

$$\rightarrow \text{SNR}_{[\text{dB}]} = 20 \cdot \log \left(\frac{RS}{noise} \right)$$

Bit Rate (BR)

$$\rightarrow \text{BR}_{[\text{bps}]} = SF * \frac{4}{\frac{2^{SF}}{BW}}$$

Bit Error Rate (BER)

$$\rightarrow \text{BER}_{[\text{bps}]} =$$

$$\frac{8}{15} \cdot \frac{1}{16} \cdot \sum k = 216 - 1^k \left(\frac{16}{k} \right) e^{20 \cdot \text{SNR} \left(\frac{1}{k} - 1 \right)}$$

Where:

- NP = 8, if LoRa . 5, if GFSK
- SW = 8, if LoRa . 3, if GFSK
- CRC = 0 if downlink packet. 1 if uplink packet
- IH = 0 if header. 1 if no header present
- DE = 1 if data rate optimization. 0 if not
- PS = PHY_Payload bytes
- SF = 7, 8, 9, 10, 11, 12
- BW = bandwidth
- CR = Indicates the Coding Rate


LoRa Frame

Preamble		Sync msg	PHY Header	PHDR-CRC						
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MAC Header					
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major			
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major	Dev Address		
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major	NwkID	NwkAddr	ADR
0	1	2	3	4	5	6	7	8	9	10

PHY Payload									CRC	
MAC Payload								MIC	CRC Type	Polynomial
Frame Header						FPort	Frame Payload	MIC	CRC Type	Polynomial
FCtrl				FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
ADRACKReq	ACK	FPending /RFU	FOptsLen	FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
11	12	13	14	15	16	17	18	19	20	21

Figure 5. LoRa Frame.

LoRa Frame

Preamble		Sync msg	PHY Header	PHDR-CRC						
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MAC Header					
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major			
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major	Dev Address		
Modulation	length	Sync msg	PHY Header	PHDR-CRC	MType	RFU	Major	NwkID	NwkAddr	ACK 
0	1	2	3	4	5	6	7	8	9	10

PHY Payload									CRC	
MAC Payload								MIC	CRC Type	Polynomial
Frame Header						FPort	Frame Payload	MIC	CRC Type	Polynomial
FCtrl				FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
ADRACKReq	ACK	FPending /RFU	FOptsLen	FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
11	12	13	14	15	16	17	18	19	20	21

Figure 5. LoRa Frame.

LoRa Frame

➔ Modulation :

- ➔ Lora: 8 Symbols, 0x34 (Sync Word)
- ➔ FSK: 5 Bytes, 0xC194C1 (Sync Word)

1) Length :

2) Sync msg :

3) PHY Header : It contains:

- ➔ The Payload length (Bytes)
- ➔ **The Code rate**
- ➔ Optional 16bit CRC for payload

4) Phy Header : CRC It contains CRC of Physical Layer Header

5) MType : is the message type (uplink or a downlink)

- ➔ whether or not it is a confirmed message (reqst ack)
- ➔ 000 Join Request
- ➔ 001 Join Accept
- ➔ 010 Unconfirmed Data Up
- ➔ 011 Unconfirmed Data Down
- ➔ 100 Confirmed Data Up
- ➔ 101 Confirmed Data Down
- ➔ 110 RFU
- ➔ 111 Proprietary

6) RFU : Reserved for Future Use

7) Major : is the LoRaWAN version; currently, only a value of zero is valid

- ➔ 00 LoRaWAN R1
- ➔ 01-11 RFU

8) NwkID : the short address of the device (Network ID): 31th to 25th

9) NwkAddr : the short address of the device (Network Address): 24th to 0th

10) ADDR : Network server will change the data rate through appropriate MAC commands

- ➔ 1 To change the data rate
- ➔ 0 No change

11) ADRACKReq : (Adaptive Data Rate ACK Request): if network doesn't respond in 'ADR-ACK-DELAY' time, end-device switch to next lower data rate.

- ➔ 1 if (ADR-ACK-CNT) >= (ADR-ACK-Limit)
- ➔ 0 otherwise

12) ACK : (Message Acknowledgement): If end-device is the sender then gateway will send the ACK in next receive window else if gateway is the sender then end-device will send the ACK in next transmission.

- ➔ 1 if confirmed data message
- ➔ 0 otherwise

13) FPending / RFU ↑ : (Only in downlink), if gateway has more data pending to be send then it asks end-device to open another receive window ASAP

- ➔ 1 to ask for more receive windows
- ➔ 0 otherwise

14) FOptsLen : is the length of the FOpts field in bytes ā 0000 to 1111

15) FCnt : 2 type of frame counters

- ➔ FCntUp: counter for uplink data frame, MAX-FCNT-GAP
- ➔ FCntDown: counter for downlink data frame, MAX-FCNT-GAP

16) FOpts : is used to piggyback MAC commands on a data message

17) FPort : a multiplexing port field

- ➔ 0 the payload contains only MAC commands
- ➔ 1 to 223 Application Specific
- ➔ 224 & 225 RFU

18) FRMPayload : (Frame Payload) Encrypted (AES, 128 key length) Data

19) MIC : is a cryptographic message integrity code

- ➔ computed over the fields MHDR, FHDR, FPort and the encrypted FRMPayload.

20) CRC : (only in uplink),

- ➔ CCITT $x^{16} + x^{12} + x^5 + 1$
- ➔ IBM $x^{16} + x^{15} + x^5 + 1$

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Machine Learning

- ▮ **Labels:** Supervised learning
 - 1) **Categorical data:** Classification
 - 2) **Quantitative data:** Regression
- ▮ **No labels:** Unsupervised learning
 - 1) **Hard clustering**
 - ▮ Binary memberships
 - 2) **Fuzzy clustering**
 - ▮ Fuzzy membership degree of each object
 - 3) **Hierarchical clustering**
 - ▮ Hierarchical membership degree of each object

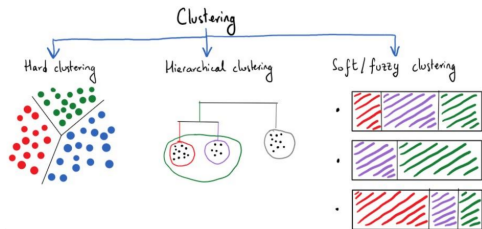


Figure 6. 3 types of clustering.

Fuzzy C-Means Clustering

1) **Input:** $X = [x_{11}, ..., x_{np}]$, with $x_{ik} \in \mathbb{R}$, $1 \leq k \leq p$, $1 \leq i \leq n$

➡ **X:** Set of received packets with their performance metrics.

➡ **n:** received packets, **p:** performance metrics, **c:** applications.

2) **Method:**

➡ **Objective function:**

$$\rightarrow \min_{(\mathbf{U}, \mathbf{V})} \left\{ F_m(\mathbf{U}, \mathbf{V}) = \sum_{j=1}^c \sum_{i=1}^n \mathbf{u}_{ij}^m d(\mathbf{x}_i, \mathbf{v}_j)^2 \right\}$$

$$\ast \text{ Constraint: } \sum_{j=1}^c \mathbf{u}_{ij} = 1, \forall i$$

$$\ast \text{ Distance: } d(\mathbf{x}_i, \mathbf{v}_j) = \|\mathbf{x}_i - \mathbf{v}_j\|$$

$$\ast \text{ Degree of fuzzification: } m \geq 1$$

➡ **Fuzzy membership matrix: U**

$$\rightarrow \mathbf{u}_{ij} = \left[\sum_{j'=1}^c \left(\frac{d(\mathbf{x}_i, \mathbf{v}_{j'})}{d(\mathbf{x}_i, \mathbf{v}_j)} \right)^{\frac{2}{m-1}} \right]^{-1}, \forall j, i \sim \mathbf{U}_t = F_{\partial}(\mathbf{V}_{t-1}) \quad (1)$$

➡ **Clusterheads matrix: V**

$$\rightarrow \mathbf{v}_j = \left(\sum_{i=1}^n \mathbf{u}_{ij}^m \mathbf{x}_i / \sum_{i=1}^n \mathbf{u}_{ij}^m \right), \forall j \sim \mathbf{V}_t = G_{\partial}(\mathbf{U}_{t-1}) \quad (2)$$

3) **Output:** $\mathbf{U} = [u_{11}, ..., u_{nc}]$, $\mathbf{V} = [v_{11}, ..., v_{cp}]$, with $u_{ij}, v_{jk} \in [0, 1]$, $1 \leq j \leq c$, $1 \leq i \leq n$, $1 \leq k \leq p$

➡ **V:** Clusterheads matrix.

➡ **U:** Fuzzy membership matrix.

4) **Validation: (Performance Index)**

$$\rightarrow \min_{(c)} \left\{ P(c) = \sum_{j=1}^c \sum_{i=1}^n \mathbf{u}_{ij}^m \left(d(\mathbf{x}_i, \mathbf{v}_j)^2 - \|\mathbf{v}_j - \bar{\mathbf{x}}\|^2 \right) \right\}, \quad \bar{\mathbf{x}} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i$$

Fuzzy C-Means Clustering

Initialization:

- Fuzzy C-Means Clustering
 - **c**: number of applications
 - **m**: weighting exponent (Fuzziness degree)
- Iteration
 - **T**: maximum number of iterations (Typ.: 100)
 - **e**: termination threshold (Typ. 0.01)

Algorithm 1: FCM

Input: $X = [x_{11}, \dots, x_{np}]$

Output: (**U**, **V**)

$t = 0$

while $F_m(\mathbf{U}_t, \mathbf{V}_t) \geq e$ **do**

$t = t + 1$

 Update \mathbf{U}_t from Equation 1

 Update \mathbf{V}_t from Equation 2

(U, V) = (U_t, V_t)

➤ Input:

$$\mathbf{X} = \begin{matrix} & \text{metric}_1 & \dots & \text{metric}_p \\ \begin{matrix} \text{conf}_1 \\ \vdots \\ \text{conf}_n \end{matrix} & \begin{bmatrix} x_{11} & \dots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{np} \end{bmatrix} \end{matrix}$$

➤ Output:

$$\mathbf{U} = \begin{matrix} & \text{app}_1 & \dots & \text{app}_c \\ \begin{matrix} \text{conf}_1 \\ \vdots \\ \text{conf}_n \end{matrix} & \begin{bmatrix} u_{11} & \dots & u_{1c} \\ \vdots & \ddots & \vdots \\ u_{n1} & \dots & u_{nc} \end{bmatrix} \end{matrix}$$

$$\mathbf{V} = \begin{matrix} & \text{metric}_1 & \dots & \text{metric}_p \\ \begin{matrix} \text{app}_1 \\ \vdots \\ \text{app}_c \end{matrix} & \begin{bmatrix} v_{11} & \dots & v_{1p} \\ \vdots & \ddots & \vdots \\ v_{c1} & \dots & v_{cp} \end{bmatrix} \end{matrix}$$

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Experiments

Simulation settings

Setting	Values
BW _[kHz]	[125,250,500]
SF _[#]	[7,8,9,10,11,12]
PS _[B]	[60, 230]
SNR _[dbm]	[-40,-30,-20,-10,0]

Table 3. LoRa transmission parameters

- Transmission settings: (SNR, PS, SF, BW)
 - Environment: Signal Noise Rate (SNR)
 - Application: Payload size (PS).
 - Radio: Spreading Factor (SF), Bandwidth (BW), (Coding Rate (CR)).
- QoS metrics: (SNR, PS, SF, BW) -> (ToA, BER, RSSI)
 - Time on Air (ToA)
 - Bit Error Rate (BER)
 - Received Signal Strength Indication (RSSI)
- Clustering: (ToA, BER, RSSI) -> (U1, U2, U3)

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Results

Comparison

- ➡ **Cluster 2** have RSSI values between -135 dBm and -110 dBm, and BER lower than 0.2%.
- ➡ **Cluster 1** could be used for applications with a high sensitivity to BER and lower sensitivity to RSSI.
- ➡ **Cluster 0** has the worst RSSI compared to the two other clusters and also the worst BER.

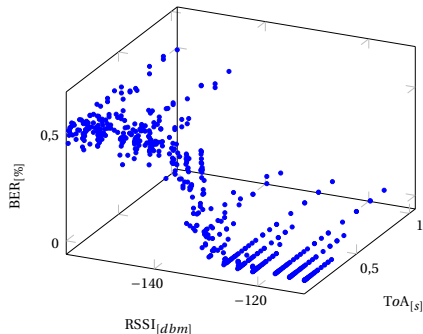


Figure 7. RSSI vs ToA and BER.

Results

Comparison

- ➡ **Cluster 2** have RSSI values between -135 dBm and -110 dBm, and BER lower than 0.2%.
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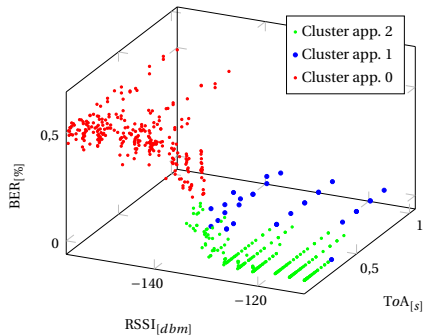


Figure 8. RSSI vs ToA and BER.

Results

Comparison

- The best candidate settings that match applications with high QoS requirements are the green points and they are scattered for all SF levels [7,12].
- when we increase the SF, settings are more mapped to cluster 1 and 2, this is mainly due to the short transmission delay (ToA).
- Settings with a high BER are mapped to cluster 0 when SF is close to 7, the reason is that SF 7 is more vulnerable to noise (SNR).

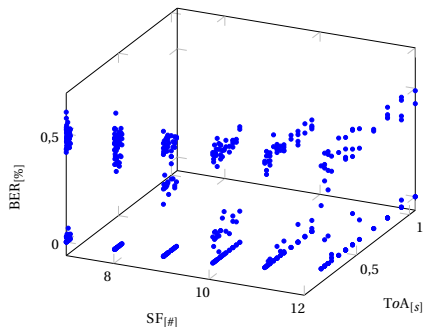


Figure 9. SF vs ToA and BER.

Results

Comparison

- The best candidate settings that match applications with high QoS requirements are the green points and they are scattered for all SF levels [7,12].
- when we increase the SF, settings are more mapped to cluster 1 and 2, this is mainly due to the short transmission delay (ToA).
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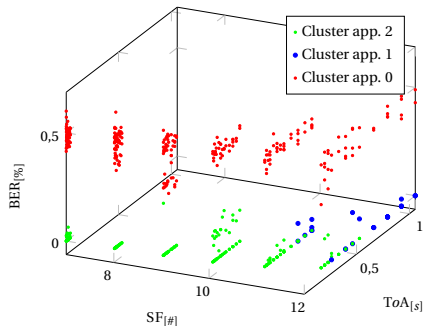


Figure 10. SF vs ToA and BER.

Results

Comparison

BW	SF	PS	SNR	BER	RSSI	ToA	C ₂	C ₁	C ₀
125	11	30	-20	0	-137	0.39	0.91	0.045	0.045
125	7	10	-10	0.05	-127	0.02	0.015	0.492	0.492
125	11	70	0	0	-117	0.46	0.492	0.492	0.015
250	12	70	-20	0.03	-137	0.92	0.734	0.153	0.113
250	11	10	-10	0	-127	0.33	0.104	0.791	0.104
250	12	90	-20	0	-134	0.46	0.965	0.004	0.030
500	7	50	-20	0.5	-131	0.00	0.003	0.030	0.965
500	12	10	-20	0	-131	0.16	0.003	0.965	0.030
250	12	110	-20	0.1	-134	0.52	0.469	0.061	0.469
500	12	110	-20	0.1	-131	0.26	0.113	0.734	0.153

Table 4. Samples of membership values of LoRa transmission settings

Performance metrics:	value
time (s):	0.0102
homogeneity score:	0.984
mutual info score:	0.9729

Table 5. Clustering performance

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Problem statement

Introduction

- a
- b

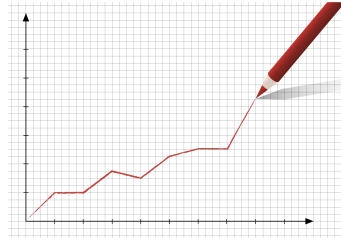


Figure 11. .

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... (step 1)

Methods



... (step 2)

Methods



... (step 3)

Methods



... (step 4)

Methods

▮ E

▮

Results

Comparison

Table 6

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Experimentation

Experimentation

- a
- b

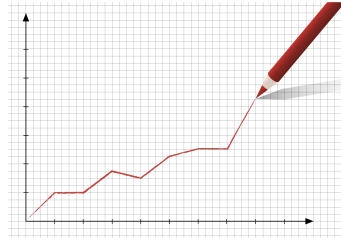


Figure 12. .

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Results

Comparison

- ➡ a
- ➡ b

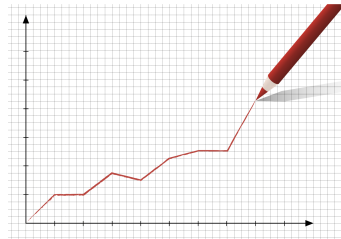


Figure 13. .

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Discussion

- ➡ a
- ➡ b

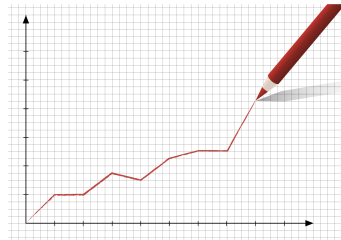


Figure 14. .

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Conclusion

- The main challenge of this work was to build a tool that can **easily be plugged** in **LoRaWAN** network servers **to** map transmission settings to applications requirements.
- Our contribution was to test the effectiveness of applying the **FCM clustering algorithm** to select the transmission setting that best fit a given application requirement.
- Each cluster **represents** a set of applications with the same **QoS** requirements.
- The proposed process has been developed to present and design a solution that consider **radio parameters** (**SF**, **BW** and **PS**), **environment conditions** (**SNR**) and performance metrics (**ToA**, **BER** and **RSSI**) required by applications.
- We plan to **integrate this approach** in one of the open source **LoRaWAN** network servers like the ChirpStack network server to test their performance in a real environment.

Conclusion

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- We plan to **integrate this approach** in one of the open source **LoRaWAN** network servers like the ChirpStack network server to test their performance in a real environment.

Thank you !

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7. Appendix

References

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