

Title of the these

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Outline

1. Introduction

2. Academic Survey

3. Industrial Survey

4. Fuzzy C-Means Clustering

5. Testbed

6. Conclusion

1. IoT Devices

2. IoT Applications

3. IoT Wireless Communications

Outline

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1. IoT Devices

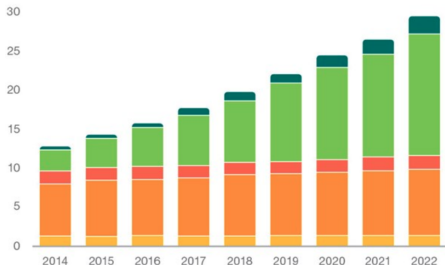
2. IoT Applications

3. IoT Wireless Communications

Massive IoT devices

IoT devices are useless without a good communication capability

Connected devices (billions)



	2016	2022	CAGR
Wide-area IoT	0.4	2.1	30%
Short-range IoT	5.2	16	20%
PC/laptop/tablet	1.6	1.7	0%
Mobile phones	7.3	8.6	3%
Fixed phones	1.4	1.3	0%
	16 billion	29 billion	10%



Figure 1. IoT devices [perera_mosden_2013].

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Applications diversification

Each application has its own communication requirements

Challenges/Applications	Grids	EHealth	Transport	Cities	Building
Resources constraints	✗	✓	✗	-	✗
Mobility	✗	-	✓	✓	✗
Heterogeneity	-	-	-	✓	✗
Scalability	✓	-	✓	✓	-
QoS constraints	-	-	✓	✓	✓
Data management	-	✗	✓	✓	-
Lack of Standardization	-	-	-	-	✓
Amount of attacks	✗	✗	✓	✓	✓
Safety	-	✓	✓	-	✓

Table 1. Main IoT challenges [kouicem_internet_2018] [1]



Figure 2. IoT Applications.

IoT platforms

IoT platforms is a chain of communication process

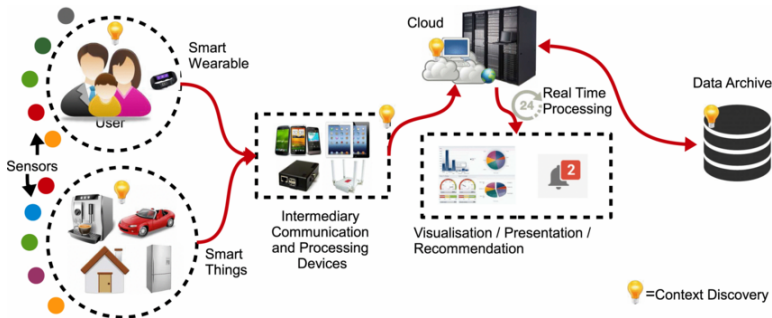


Figure 3. IoT platform.



Figure 4. IoT challenges.

Applications diversification

Requirements

Use Case	Packet rate [pkt/day]	Min success rate [Ps,min]	Payload Size [Byte]
Wearables	10	90	10-20
Smoke Detectors	2	90	
Smart Grid	10	90	
White Goods	3	90	
Waste Management	24	90	
VIP/Pet Tracking	48	90	50
Smart Bicycle	192	90	
Animal Tracking	100	90	
Environmental Monitoring	5	90	
Asset Tracking	100	90	
Smart Parking	60	90	
Alarms/Actuators	5	90	
Home Automation	5	90	
Machinery Control	100	90	
Water/Gas Metering	8	90	100-200
Environmental Data Collection	24	90	
Medical Assisted Living	8	90	
Micro-generation	2	90	
Safety Monitoring	2	90	
Propane Tank Monitoring	2	90	
Stationary Monitoring	4	90	
Urban Lighting	5	90	
Vending Machines Payment	100	90	
Vending Machines General	1	90	1K

Table 2. Application requirements for the use cases of interest [2] [1] [3]

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1. LoRa

IoT wireless communication

Wireless communication performance need to be evaluated to match applications requirements

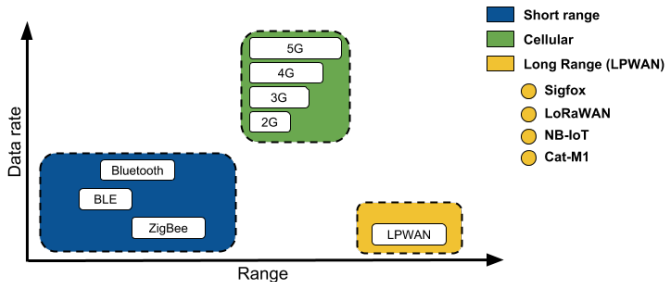


Figure 5. Short range, Cellular and Long range networks.

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1. LoRa

Wireless communication

Exp: LPWAN in a new technology that satisfy IoT applications requirements

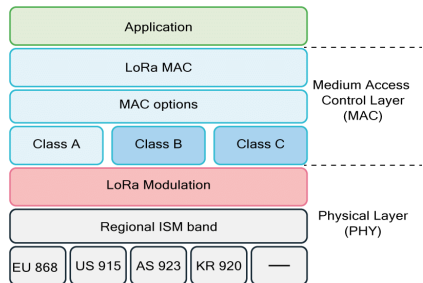


Figure 6. LoRa and LoRaWan stack.

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) [-7.5,-20dBm]

Metrics

- ➡ Data Rate (DR)
- ➡ Air Time (AT)
- ➡ PS_{max}
- ➡ Received Signal Strength Indication ($RSSI$) [-30,-120dBm]

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

Table 3. LoRa parameters selection [4]

Multi criteria decision making

Layer	Maximize (Reward)	Minimize (Cost)
Application	<i>Sec</i> security	Service Cost (<i>SC</i>)
Network	<i>Range</i> Packet delivery ratio (<i>PDR</i>) <i>PS</i> <i>DR</i>	Jitter (<i>Jit</i>) Traffic congestion (<i>TC</i>) Round-Trip Delay (<i>RTD</i>) Packet Error Rate (<i>PER</i>) Time Complexity (<i>O_{time}</i>) Space Complexity (<i>O_{space}</i>)
Radio	Mobility (<i>Mob</i>) Symbol Rate (<i>SR</i>) Bit Rate (<i>BR</i>) Signal-to-Interference Ratio (<i>SIR</i>) <i>RSSI</i> Signal-to-interference & noise ratio (<i>SINR</i>) <i>SNR</i>	Bit Error Rate (<i>BER</i>) <i>Ptx</i> Co-channel Interference (<i>CCI</i>) Duty cycle (<i>DC</i>) Time on Air (<i>ToA</i>) Path loss (<i>PL</i>)

Table 4. Network selection inputs and classification of parameters [bendaoud_network_2019]
[chowdhury_survey_2018]

Multi criteria decision making

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

$$ToA_{GFSK} = \frac{8}{DR} (NP + SW + PL + 2CRC)$$

(1)

$$Sen_{[dBm]} = -174 + 10 \log_{10} BW + NF + SNR$$

(2)

$$PL_{[B]} = |RSSI| + SNR + P_{TX} + G_{RX}$$

(3)

$$SNR_{[dB]} = 20 \cdot \log \left(\frac{S}{N} \right)$$

(4)

$$RSSI_{[dBm]} = T_{Xpower} \cdot \frac{Rayleigh_{power}}{PL}$$

(5)

$$SINR_{[dBm]} =$$

(6)

$$BR_{[bps]} = SF * \frac{4}{2SF} \frac{CR}{BW}$$

(7)

$$BER_{[bps]} = \frac{8}{15} \cdot \frac{1}{16} \cdot \sum k = 216 - 1^k \left(\frac{16}{k} \right) e^{20 \cdot SINR \left(\frac{1}{k} - 1 \right)}$$

(8)

$$PER_{[pps]} = 1 - (1 - BER)^{n_{bits}}$$

(9)

(10)

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

LoRa Frame

- ➔ **Modulation :**
 - ➔ Lora: 8 Symbols, 0x34 (Sync Word)
 - ➔ FSK: 5 Bytes, 0xC194C1 (Sync Word)
- ➔ **Length :**
- ➔ **Sync msg :**
- ➔ **PHY Header :** It contains:
 - ➔ The Payload length (Bytes)
 - ➔ **The Code rate**
 - ➔ Optional 16bit CRC for payload
- ➔ **Phy Header :** CRC It contains CRC of Physical Layer Header
- ➔ **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
- ➔ **RFU :** Reserved for Future Use
- ➔ **Major :** is the LoRaWAN version; currently, only a value of zero is valid
 - ➔ 00 LoRaWAN R1
 - ➔ 01-11 RFU
- ➔ **NwkID :** the short address of the device (Network ID): 31th to 25th
- ➔ **NwkAddr :** the short address of the device (Network Address): 24th to 0th
- ➔ **ADR :** Network server will change the data rate through appropriate MAC commands
 - ➔ 1 To change the data rate
 - ➔ 0 No change
- ➔ **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
- ➔ **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
- ➔ **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
- ➔ **FOptsLen :** is the length of the FOpts field in bytes ā 0000 to 1111
- ➔ **FCnt :** 2 type of frame counters
 - ➔ FCntUp: counter for uplink data frame, MAX-FCNT-GAP
 - ➔ FCntDown: counter for downlink data frame, MAX-FCNT-GAP
- ➔ **FOpts :** is used to piggyback MAC commands on a data message
- ➔ **FPort :** a multiplexing port field
 - ➔ 0 the payload contains only MAC commands
 - ➔ 1 to 223 Application Specific
 - ➔ 224 & 225 RFU
- ➔ **FRMPPayload :** (Frame Payload) Encrypted (AES, 128 key length) Data
- ➔ **MIC :** is a cryptographic message integrity code
 - ➔ computed over the fields MHDR, FHDR, FPort and the encrypted FRMPPayload.
- ➔ **CRC :** (only in uplink),
 - ➔ CCITT $x^{16} + x^{12} + x^5 + 1$
 - ➔ IBM $x^{16} + x^{15} + x^5 + 1$

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Notations

Related work

Set of devices, slices, gateways and flows

G	set of LoRa Gateways
S	set of Slices
D_s	cluster of devices associated to slice s

Parameters

F_c	packets with SF = c
$BW_{s,g}$	bandwidth assigned for slice s over GW g
P_g^{Tx}	transmission power of GW g

Constants

$i_{d,s}$	association index of device d to slice s
$i_{d,g}$	association index of device d to GW g
w_d	urgency factor for device d
w_s	priority of slice s
w_r	weight of reliability
w_{ld}	weight of load

Metrics

$DR_{d,s,g}$	data rate achieved by a device d
$SINR_{i,j}$	SINR with SF= i and SF= j
$G_{d,g}^{tx}$	power gain between a GW g and a device d
S_r^{rx}	Receiver sensitivity
RTD_d	instant packet delay for device d
PLR_d	packet loss rate of device d

$U_{d,s,g}$ utility for device d in slice s on GW g

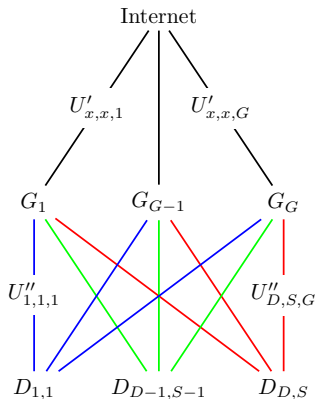


Figure 7. Slicing.

Notations

Related work

- $\mathbf{G} = \{1, \dots, \mathbf{G}\}$: Set of gateways
- $\mathbf{S} = \{1, \dots, \mathbf{S}\}$: Set of slices
- $\mathbf{D} = \{1, \dots, \mathbf{D}\}$: Set of devices
- $\mathbf{D}_s = \{1, \dots, \mathbf{D}_s\} \in \mathbf{D}$: Cluster of devices in slice s
- $\mathbf{F}_{d,s,g} = \{1, \dots, \mathbf{F}_{d,s,g}\}$: Virtual flow for device d in slice s through GW g
- $i_{d,s} \in \{0,1\}$ Association index of device d to slice s
- $i_{d,g} \in \{0,1\}$ Association index of device d to GW g
- $w_d \in [0,1]$ Urgency factor for device d
- $w_s \in [0,1]$ Priority of slice s
- $w_r \in [0,1]$ Weight of the impact of reliability (SINR)
- $w_{ld} \in [0,1]$ Weight of the impact of load (congestion)
- $\mathbf{DR}_{d,s,g}$ data rate achieved by a device d
- $\mathbf{G}_{d,g}^{\text{tx}}$ power gain between a GW g and a device d
- $\mathbf{S}_{d,s,g}^{\text{rx}}$ Receiver sensitivity
- \mathbf{RTD}_d instant packet delay for device d
- \mathbf{PLR}_d packet loss rate of device d
- $\mathbf{U}_{d,s,g}$ utility for device d in slice s on GW g

Constraints/Hypothesis

Related work

$$\max \sum_{d \in D} \sum_{s \in S} i_{d,s} \cdot U_{d,g,s} \quad , g \in G \quad (11)$$

$$C1 : \sum_{s \in S} i_{d,s} = 1, \forall d \in D$$

$$C2 : \sum_{d \in D} i_{d,g} \cdot P_{d,s,g}^{tx} \leq P_g^{tx \max}, \forall g \in G, \forall s \in S \quad (12)$$

$$C3 : \sum_{d=1}^N i_{d,s} \cdot i_{d,g} \cdot DR_{d,s,g} \leq BW_{s,g}, \forall s \in S, \forall g \in G$$

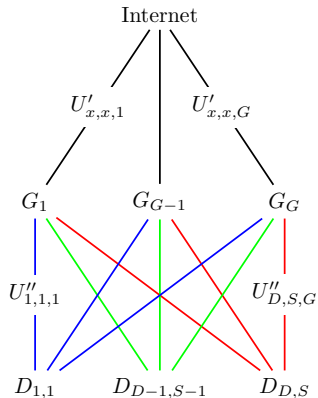


Figure 8. Slicing.

3 applications -> 3 slices -> 3 utility functions

1

$$\sigma_r = SINR_{d,s,g} / SINR_{max} \quad , \in [0, 1]$$

$$U_{HCC} = \delta_r (\sigma_r w_r + \sigma_{ld} w_{ld}) \quad \text{with} \quad \delta_r \in \{0, 1\}$$

$$U_{MCC} = \sigma_r w_r + \sigma_{ld} w_{ld}$$

$$U_{LCC} = \sigma_{ld} w_{ld}$$

$$U_{d,s,g} = U'_{d,s,g} + U''_{d,s,g}$$

$$E_{d,s,g} = \frac{p_i^{tx} + p_i^{rx}}{V + \epsilon p_a} \cdot d_{tx/rx}$$

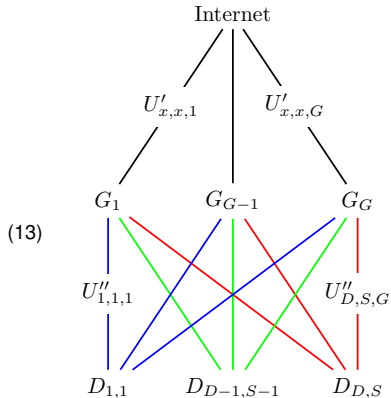


Figure 9. Slicing.

¹ Samir Dawaliby, Abbas Bradai, and Yanniss Pousset. Adaptive Dynamic Network Slicing in LoRa Networks. In: *Future Generation Computer Systems* 98 (Sept. 2019). 00004, pp. 697–707.

3 slice orchestration algorithms

Which slice for which application flow ?

- ADS-load
- DS-load
- FS-load

Utility Function

Related work

$$\begin{aligned}DR_{d,s,g} &= SF \cdot \frac{bw_{s,g}}{2^{SF}} \quad \text{bits/s} \\Rx_{d,s,g} &= \frac{Tx_{d,s,g} \cdot U_{d,s,g}^{rx} \cdot U_{d,s,g}^{tx}}{PL} \epsilon, \quad \text{with } \epsilon \sim N(0, \sigma^2) \\PL &= L_0 + 10 \cdot n \cdot \log_{10} \left(\frac{d}{d_0} \right) \\SINR_{i,j} &= \frac{Rx_i}{\sigma^2 + \sum_{n \in Pkt_j} Rx_n} \\\sigma_r &= \frac{SINR_{k,l,m}}{SINR_{max}}\end{aligned} \tag{14}$$

1 Clustering algorithm: BIRCH

Which slice for which device ?

T: max number of device per cluster,
B: max number of childes per cluster.

t_0 : number of clusters = number of devices;
 t_i : get D2 the set of closest devices to cluster D1
 \Rightarrow if $D1+D2 < T \rightarrow$ merge
 \Rightarrow eif $D2 < B \rightarrow$ create sub-cluster D2 of D1

$$CF : (D_s, LS, SS) = \left(D_s, \sum_{d=1}^{D_s} w_d, \sum_{d=1}^{D_s} w_d^2 \right) \quad (15)$$

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A Relay and Mobility Scheme for QoS Improvement in IoT

2

- ⇒ Only application requirements.
 - ⇒ Environment conditions, operator rules, User preferences.
- ⇒ Only one (simple) normalization function for all parameters.
 - ⇒ Use **Fuzzy logic** with different rules for normalization.
- ⇒ Only one objective function to fits all requirements.
 - ⇒ Use **Genetic algorithms** with 3 objective functions.
- ⇒ Only one application.
 - ⇒ Use **3 applications** with different requirements

²simiscuka_relay_2018.

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1. Fuzzy C-Means Clustering

2. Game Theory

3. Multi-Arm Bandits

4. Q-Learning

5. Markov Chain

6. Best Response Dynamics

7. Fictitious Play

8. Reinforcement Learning

9. Joint Utility Strategy

10. Trial and Error Learning

11. Regret Matching Learning

12. Imitation Learning

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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:**

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

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

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

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

➡ **Fuzzy membership matrix: U**

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

➡ **Clusterheads matrix: V**

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

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

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:

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

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

Input:

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

Output:

$$\mathbf{G} = \begin{matrix} & \text{app}_1 & \dots & \text{app}_c \\ \begin{matrix} \text{conf}_1 \\ \vdots \\ \text{conf}_n \end{matrix} & \begin{bmatrix} g_{11} & \dots & g_{1p} \\ \vdots & \ddots & \vdots \\ g_{n1} & \dots & g_{np} \end{bmatrix} \end{matrix}$$

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: $V_0 = [v_{11}, \dots, v_{cp}]$

Output: (\mathbf{U}, \mathbf{V})

$t = 0$

while $\|\mathbf{v}_j - \bar{\mathbf{x}}\| \geq e$ **or** $t \leq T$ **do**

$t = t + 1$

$\mathbf{U}_t = F_{\partial}(\mathbf{V}_{t-1})$

$\mathbf{V}_t = G_{\partial}(\mathbf{U}_{t-1})$

$(\mathbf{U}, \mathbf{V}) = (\mathbf{U}_t, \mathbf{V}_t)$

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.

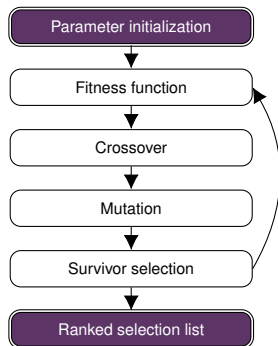
⇒ **Fitness/Crossover/Clustering:**

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

⇒ **Mutation:** $v \sim P$

* b is the mutation threshold (0.001).

$$\overline{g}_x = \begin{cases} \overline{g}_x \\ \overline{q}_{xj} / \sum_{l=1}^c \overline{q}_{xl}, \text{ with } \overline{q}_{xj} = \text{random}(\mathbb{R}), \forall j. \end{cases} \quad \begin{matrix} v \geq b \\ \text{otherwise} \end{matrix}$$



- 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: $\mathbb{P}(f_{1,1}) = 1, t = 1, \quad 2$
 - $\forall k \in K \alpha_{k,f_{1,1}} \leftarrow \alpha_0, \beta_{k,f_{1,1}} \leftarrow \beta_0$
- 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:

$$\forall i < t \mathbb{P}(x_t | f_{i,t}) = \begin{cases} \frac{\alpha_{k_t, f_{i,t}}}{\beta_{k_t, f_{i,t}} + \alpha_{k_t, f_{i,t}}} & \text{if } x_{k_t} = 1 \\ \frac{\beta_{k_t, f_{i,t}}}{\beta_{k_t, f_{i,t}} + \alpha_{k_t, f_{i,t}}} & \text{if } x_{k_t} = 0 \end{cases} \quad (16)$$

- Arm hyper parameters update:

$$\forall i < t \begin{cases} \alpha_{k_t, f_{i,t}} = \alpha_{k_t, f_{i,t}} + 1 & \text{if } x_{k_t} = 1 \\ \beta_{k_t, f_{i,t}} = \beta_{k_t, f_{i,t}} + 1 & \text{if } x_{k_t} = 0 \end{cases} \quad (17)$$

- Distribution of experts update:

- $\forall i < t, \mathbb{P}(f_{i,t}) \propto (1 - \rho) \cdot \mathbb{P}(x_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$
- $f_{t,t} : \mathbb{P}(f_{t,t}) \propto \rho \sum_{i=1}^{t-1} \mathbb{P}(x_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$
- $\alpha_{k_t, f_{t,t}} = \alpha_0, \beta_{k_t, f_{t,t}} = \beta_0$

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

$$\mu_{k,t} = \begin{cases} \mu_{k,t-1} & \text{probability } 1 - \rho \\ \mu_{\text{new}} \sim U(0,1) & \text{probability } \rho \end{cases} \quad (18)$$

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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

$$V(s, \pi) = \mathbb{E}_s^\pi \left(\sum_{k=0}^{\infty} \gamma^k \cdot r(s_k, a_k) \right), s \in \mathbb{S} \quad (19)$$

$$r(s_k, a_k) = G_k \cdot PRR(a_k) \quad (20)$$

$$\pi^* = \arg \max_{\pi} V(s, \pi) \quad (21)$$

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 $\forall k \in K$

$$\pi_k(t) \xrightarrow{t \rightarrow \infty} \pi_k^* \quad (22)$$

$$u_k(\pi_k(t), \pi_{-k}(t)) \xrightarrow{t \rightarrow \infty} u_k(\pi_k^*, \pi_{-k}^*) \quad (23)$$

Where:

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

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Selection framework

Methods

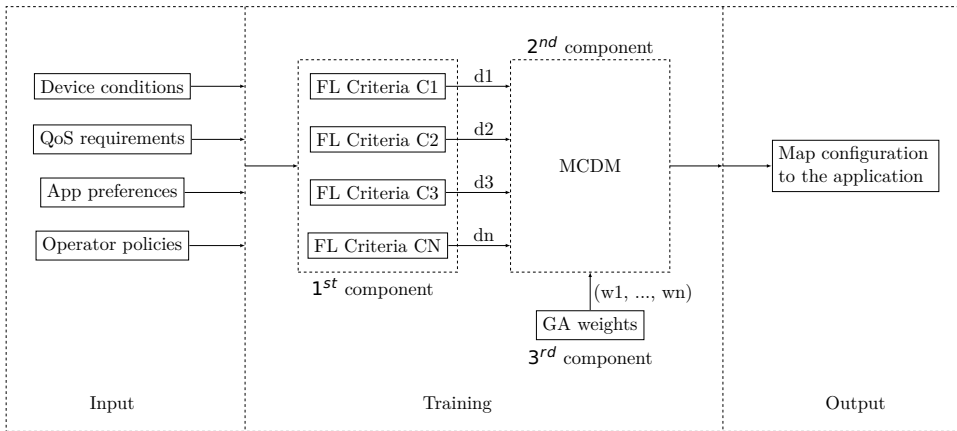


Figure 10. The proposed scheme for LoRa transmission parameters selection based on *GA*, *FL* and *MCDM*..

... (step 2)

Methods



... (step 3)

Methods



... (step 4)

Methods



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Experimentation

➡ a
➡ b

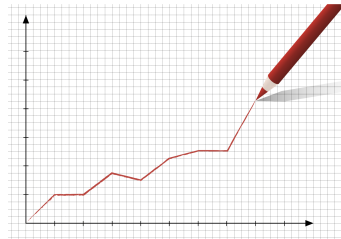


Figure 11. .

Experimentation

Experimentation

Inputs:

- ➡ Data structure
 - * Voice, Images and Text transmission.
- ➡ Environment conditions
 - * Rural/Urban
 - * Static/Mobile
 - * Temperature
 - * Interference/Noise
- ➡ QoS metrics:
 - * User layer: Cost
 - * Network metrics: DR, Payload length.
 - * Radio metrics: Receiver sensitivity, SNR, DR, Air time,
- ➡ MAC configuration (SF, CR, BW, Tx)

Outputs:

- ➡ (SF_i, CR_j, BW_k, Tx_l) optimal

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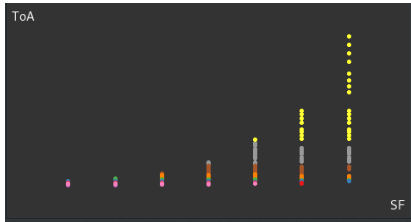


Figure 12. Impact of SF on ToA.

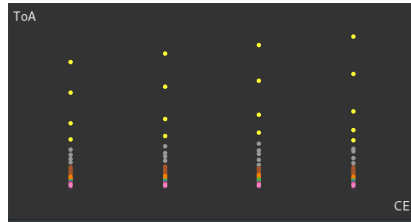


Figure 14. Impact of CR on ToA.

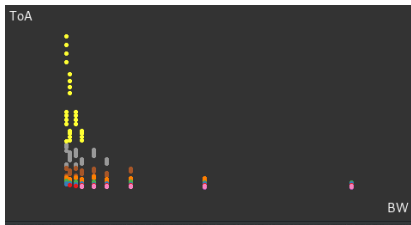


Figure 13. Impact of BW on ToA.

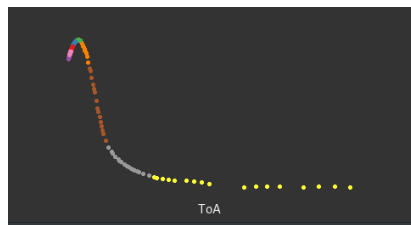


Figure 15. ToA distribution.

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⇒ a
⇒ b

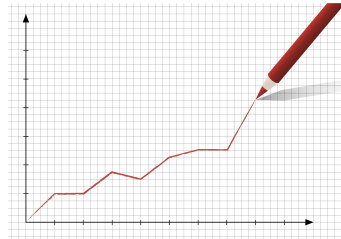


Figure 16. .

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Problem statement

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- a
- b

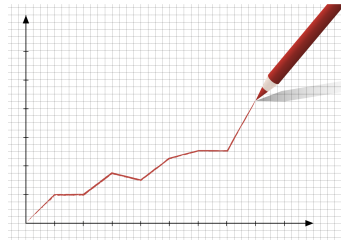


Figure 17. .

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... (step 1)

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... (step 2)

Methods



... (step 3)

Methods



... (step 4)

Methods

→ E

→

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Experimentation

- ➡ a
- ➡ b

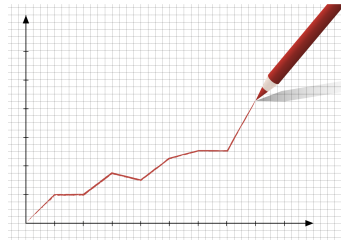


Figure 18. .

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- ➡ a
- ➡ b

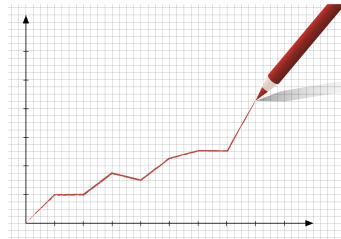


Figure 19. .

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- ➡ a
- ➡ b

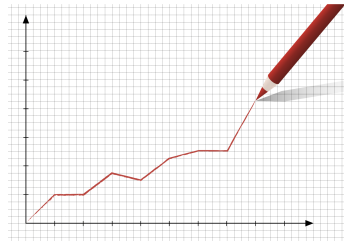


Figure 20. .

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Conclusion

Contributions	Memory	Computation	Dynamic	Optimality	Costs
Contribution 1	✓	✗	✗	✗	✓
Contribution 1	✗	✗	✗	✓	✗
Contribution 1	✓	✗	✓	✗	✗
Contribution 1	✓		✗	✗	✗
Contribution 1	✓	✓	✓	✓	✓

Table 7

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7. Appendix

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