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Toward a self reconfigurable LoRaWAN network for smart city applications

Low Power Wide Area Networks (LPWAN)

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Outline

Outline

Massive Internet of things (IoT) devices

Emergence of new IoT devices that need wide area wireless communications

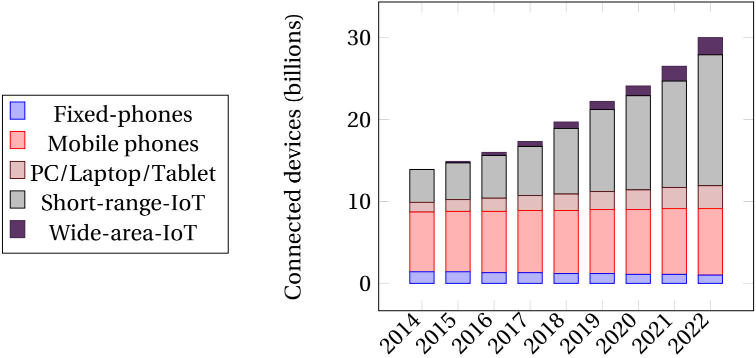

Figure 1. Diversity of IoT devices [1].

- **2012:** Sigfox
- **2015:** Long Range (LoRa)
  - Licence open source
- **2016:** Narrow Band-Internet of Things (NB-IoT)

} Low Power Wide Area Networks (LPWAN)

LoRaWAN architecture

LoRa vs LoRaWAN

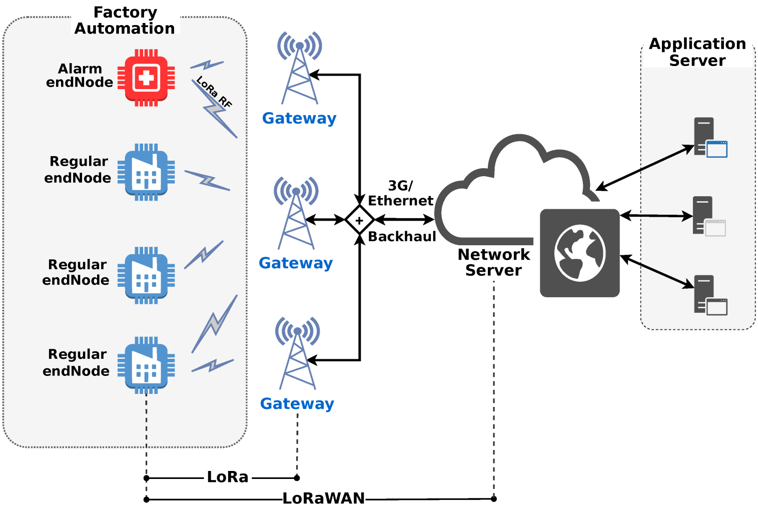

Figure 2. LoRaWAN architecture [2].

Wireless technologies

LoRa is a new technology that could satisfy smart building applications requirements

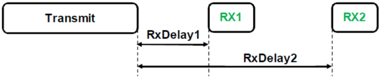

Figure 3. Class A (Baseline).

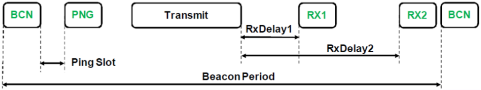

Figure 4. Class B (Beacons).

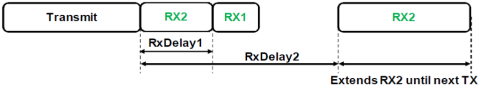

Figure 5. Class C (Continuous).

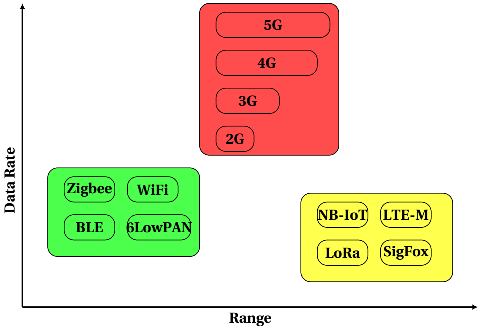

Figure 6. Short range, cellular and long range networks.

Requirements of IoT applications in smart cities

Wireless communication performance need to be evaluated to match applications requirements

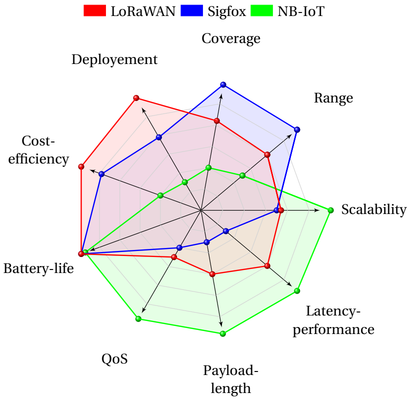

Figure 7. LPWAN characteristics [3].

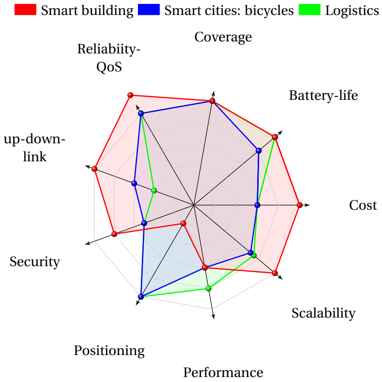

Figure 8. Applications requirements [4].

Outline

Research issue

Each application has its own communication requirements

Figure 9. IoT applications [5].

- Packet Rate (PR)
- Packet delivery Ratio (PDR)
- Payload size (PS)

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

Table 1. Applications requirements in IoT [6, 7]

Research issue

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Table 1. Applications requirements in IoT [6, 7]

How to adapt the network to these applications ?

Outline

Smart construction

Toward a self reconfigurable LoRaWAN for smart building applications

1) Collect data from a construction site
2) Manage traffic behavior
3) Adapt transmission settings to applications
4) Online reconfiguration of the network

Figure 10. Smart construction [8].

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Related works

Year	Paper	Parameters	Metrics	Algorithm	Comments
2015	[9]	Type of data	Minimize ToA & E^{tx}	A-TRED mechanism	Critical data get lower ToA
2017	[10]	SF, P^{tx},BW	minimize E^{tx}	Heuristic	Mesh topology is better in dense network
2017	[11]		RSSI, PRR, LQI, BER	Kalman filter + Fuzzy system	Evaluate link: Good or poor quality
2017	[12]	SF,P^{tx}	PRR,SNR	ADR algorithm	Trade-off between DR and E^{tx}
2018	[13]	# devices	PRR,E^{tx}	ADR^{+} algorithm	ADR+ is more scalable than ADR
2018	[14]	SF	Throughput	Gradient Projection	The throughput is higher compared to ADR
2019	[15]	BW	SNR, PDR	Dynamic MLE algorithm	Ressource allocations fit slice requirements

Table 2. Adaptive data rate

Outline

1. Introduction
2. **State of the art**
    1. Literature review
    2. **Limitations**
3. Online reconfiguration
4. Conclusion

Adaptive Data Rate (ADR)

Algorithm 1: ADR

```
i ← 0
history[j] ← 0 ∀j ∈ [0,19]
SINR_margin ← 10 dB
SNR_threshold ∈ {-7.5,-10.0,-12.5,-15.0,-17.5,-20.0}
SF ∈ {7,8,9,10,11,12}
P_tx ∈ {2, 5, 8, 11,14, 20} dBm
Function RECEIVEPACKET(mSNR):
    history[i] = mSNR
    i++
    if i=20 then
        ADJUSTADR()
        i ← 0
Function ADJUSTADR():
    margin ← max(history) - SNR_threshold[SF-7] - SINR_margin
    N_step ← round(margin/3)
    while N_step != 0 do
        if N_step > 0 then
            decrease SF by steps until SF=7
            decrease P_tx by steps until P_tx=2 dBm
            N_step −−
        else
            increase P_tx by steps until P_tx=20 dBm
            N_step ++
```

Outline

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Scalability of LoRaWAN

LoRaWAN throughput is limited by ALOHA pure protocol and energy consumption

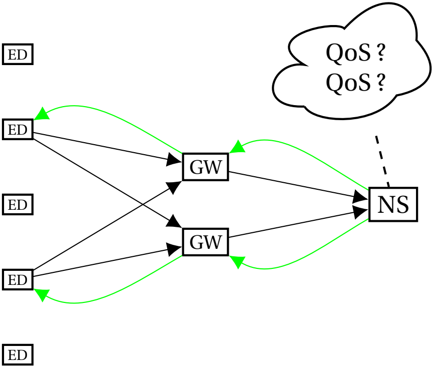

Figure 11. LoRaWAN throughput.

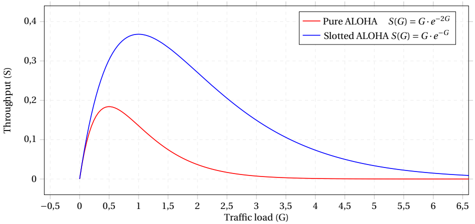

Figure 12. LoRaWAN throughput.

Scalability of LoRaWAN

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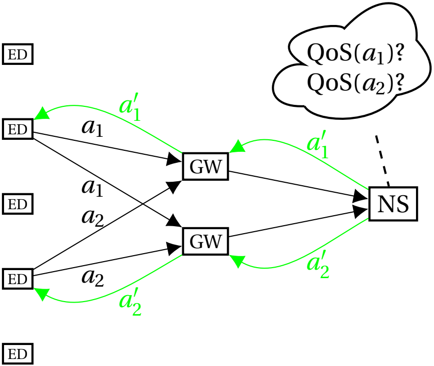

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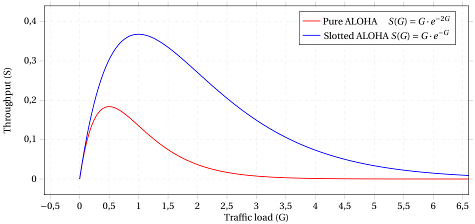

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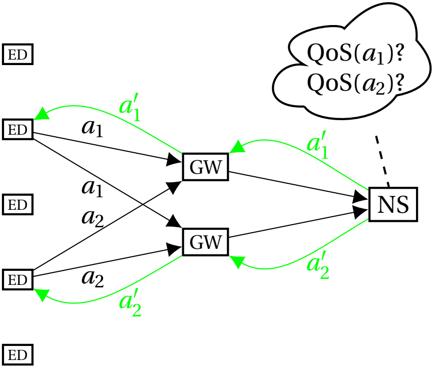

Figure 11. LoRaWAN throughput.

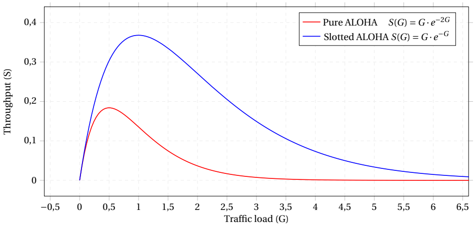

Figure 12. LoRaWAN throughput.

$$S = \sum_{sf \in SF} \frac{S(sf)}{|SF|} \tag{1}$$

with:

$$\begin{aligned} S(sf) &= G(sf) \cdot e^{-2 \cdot G(sf)} \\ G(sf) &= \lambda \ . \ ToA(sf) \end{aligned} \tag{2}$$

Scalability of LoRaWAN

LoRaWAN throughput is limited by ALOHA pure protocol and energy consumption

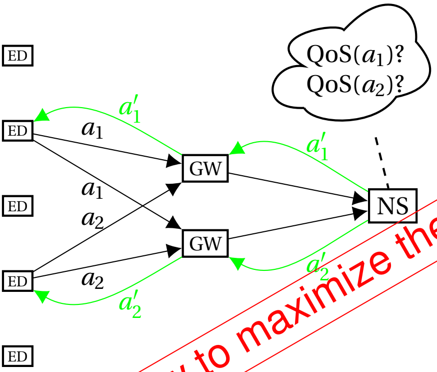

Figure 11. LoRaWAN throughput.

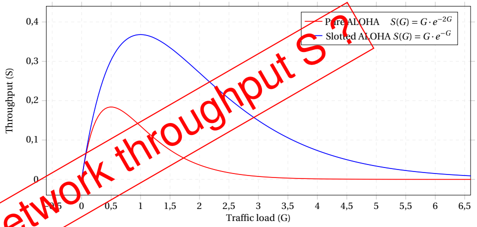

Figure 12. LoRaWAN throughput.

How to maximize the network throughput S ?

$$S = \sum_{sf \in SF} \frac{S(sf)}{|SF|} \tag{1}$$

with:

$$\begin{aligned} S(sf) &= G(sf) \cdot e^{-2 \cdot G(sf)} \\ G(sf) &= \lambda \ . \ ToA(sf) \end{aligned} \tag{2}$$

Outline

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Markov Decision Process (MDP)

Notations

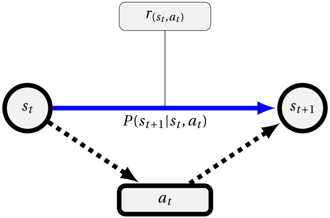


Figure 13. MDP process.

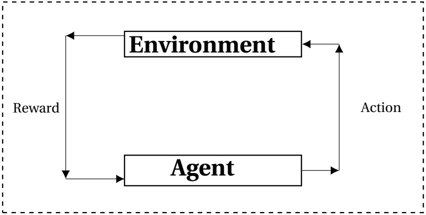


Figure 14. MDP process.

- S={s_0,...,s_n} is a finite set of states which in our study it is a set of link state levels.
- A={a_0 ,...,a_n} is a finite set of actions which in our study is shown as set possible transmission settings.
- P=Pr(s_{t+1} =s' | s_t=s) is the transition probability from state s at step t to state s' at the next step due to an action a.
- R(s,a) is the expected reward received after transitioning from state s to state s' due to action a.
- $\gamma \in [0, 1]$ is called a discount factor which represents the difference in importance between current and future rewards.

Markov Decision Process (MDP)

Mathematical description

- State value function:

$$
\begin{aligned}
V_t^{\pi}(s) &\doteq \mathbb{E}^{\pi}\left[G_t(s) \mid s_t = s\right] \\
&= \mathbb{E}^{\pi}\left[\sum_{a' \in A(s)} G_t(s,a') \mid s_t = s\right] \\
&= \mathbb{E}\left[\sum_{a' \in A(s)} Q_t^{\pi}(s,a') \mid s_t = s\right] \\
&= \sum_{a' \in A(s)} \pi(a' \mid s) \cdot Q_t^{\pi}(s,a')
\end{aligned} \tag{3}
$$

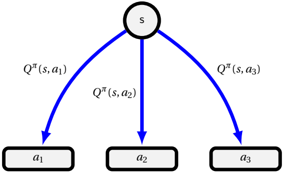


Figure 15. State value function.

- Action value function:

$$
\begin{aligned}
Q_{t+1}^{\pi}(s,a) &\doteq \mathbb{E}^{\pi}\left[G_{t+1}(s,a) \mid s_t = s, a_{t+1} = a\right] \\
&= \mathbb{E}^{\pi}\left[\sum_{s' \in S_{t+1}} R_{t+1}(s,a) + \gamma \cdot G_t(s') \mid s_t = s, a_{t+1} = a\right] \\
&= \mathbb{E}\left[\sum_{s' \in S_{t+1}} R_{t+1}(s,a) + \gamma \cdot V_t^{\pi}(s') \mid s_t = s, a_{t+1} = a\right] \\
&= \sum_{s' \in S_{t+1}} P(s' \mid s,a) \cdot \left[R_{t+1}(s,a) + \gamma \cdot V_t^{\pi}(s')\right]
\end{aligned} \tag{4}
$$

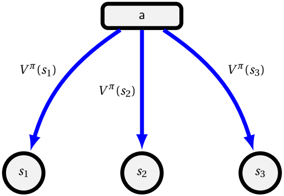


Figure 16. Action value function.

Markov Decision Process (MDP)

Mathematical description

- Transition matrix:

$$[\mathbf{P}] = \begin{array}{l} \\ \textbf{action 1} \\ \textbf{action 2} \\ \vdots \\ \textbf{action n} \end{array} \begin{array}{c} \begin{array}{ccc} \textbf{State 1} & \dots & \textbf{State c} \end{array} \\ \begin{bmatrix} u_{11} & \cdots & u_{1c} \\ u_{21} & \cdots & u_{2c} \\ \vdots & \ddots & \vdots \\ u_{n1} & \cdots & u_{nc} \end{bmatrix} \end{array}$$

- Reward function:

$$R_{t+1} = U_{t+1} - U_t \tag{5}$$

$$U_t = \frac{S_t}{S^{\max}} \tag{6}$$

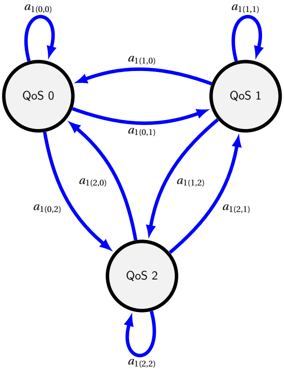


Figure 17. State value function.

Outline

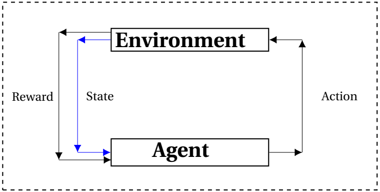


Figure 18. h.

$$Q_{t+1}(s,a) \leftarrow (1-\alpha)\cdot Q_t(s,a) + \alpha \left(r_{t+1} + \gamma \cdot \max_{a'} Q_t(s',a') \right) \tag{7}$$

$$\pi^*(s) = \arg \max_{a \in A(s)} Q(s,a) \quad \forall s, \pi \tag{8}$$

Algorithm 2: Q-learning algorithm

Input: $Q(s,a) \leftarrow 0, a_{init}, s_{init}$
Output: $Q(s,a)$
$a \leftarrow a_{init}, s \leftarrow s_{init}$
while *True* **do**
  R[s, a] $\leftarrow \Delta\ U_t$ (Equation 5)
  s' $\leftarrow$argmax P[a]
  $Q[s,a]$ $\leftarrow$(Equation 7)
  $a \leftarrow \arg\max_{a'} Q(a')$ (Equation 8)
  $s \leftarrow s'$

Q Learning

- Membership degree: μ

$$\mu = \begin{array}{c} \\ a_1 \\ \vdots \\ a_c \end{array} \begin{array}{c} \begin{array}{ccc} QoS_0 & \dots & QoS_p \end{array} \\ \begin{bmatrix} \alpha_{s_0,a_1} & \dots & \alpha_{s_p,a_1} \\ \vdots & \ddots & \vdots \\ \alpha_{s_0,a_c} & \dots & \alpha_{s_p,a_c} \end{bmatrix} \end{array}$$

- Reward: R_{t+1}

$$\mu = \begin{array}{c} \\ a_1 \\ \vdots \\ a_c \end{array} \begin{array}{c} \begin{array}{ccc} QoS_0 & \dots & QoS_p \end{array} \\ \begin{bmatrix} \alpha_{s_0,a_1} & \dots & \alpha_{s_p,a_1} \\ \vdots & \ddots & \vdots \\ \alpha_{s_0,a_c} & \dots & \alpha_{s_p,a_c} \end{bmatrix} \end{array}$$

$$Q_{t+1}(s_p, a_c) = \underbrace{\left(1 - \alpha_{s_d,a_c}\right) \cdot Q_t\left(s_p, a_c\right)}_{exploitation} + \underbrace{\alpha_{s_d,a_c} \cdot \left[R_{t+1}(s_p, a_c) + \gamma \cdot \max_{\mathbf{a}} Q_t\left(s'_p, a_{\{1,\dots,c\}}\right)\right]}_{exploration}$$

$$Q_t = \begin{array}{cc} & \\ \alpha_{s_d,a_1} & a_1 \\ \vdots & \\ \alpha_{s_d,a_c} & a_c \end{array} \begin{array}{c} \begin{array}{ccc} QoS_0 & \dots & QoS_p \end{array} \\ \begin{bmatrix} Q_t(s_1, a_1) & \dots & \dots \\ \vdots & \ddots & \vdots \\ \dots & \dots & Q_t(s_p, a_c) \end{bmatrix} \end{array}$$

$$Q_{t+1} = \begin{array}{cc} & \\ \alpha_{s_d,a_1} & a_1 \\ \vdots & \\ \alpha_{s_d,a_c} & a_c \end{array} \begin{array}{c} \begin{array}{ccc} QoS_0 & \dots & QoS_p \end{array} \\ \begin{bmatrix} Q_{t+1}(s_1, a_1) & \dots & \dots \\ \vdots & \ddots & \vdots \\ \dots & \dots & Q_{t+1}(s_p, a_c) \end{bmatrix} \end{array}$$

- s_d is the Quality of Service (QoS) level of the application running on the device

Outline

Multi-Armed Bandit

Mathematical/Algorithmic description

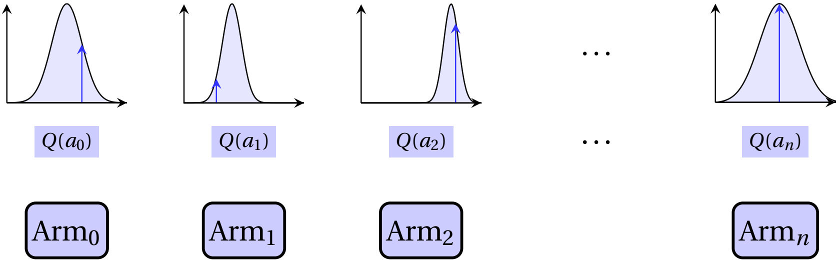


Figure 19. Multi-Armed Bandit.

- Reward function:

$$G_t(a) \doteq \sum_{i=1}^{t} R_t(a) \tag{9}$$

- Action value function:

$$\begin{aligned} Q_t^{\pi}(a) &\doteq \mathbb{E}^{v}\Big[G_t(a)\Big] \\ Q_t^{\star} &= \max_a Q_t(a) \end{aligned} \tag{10}$$

Thompson sampling

Bayes equation

$$P(R_{t+1} \mid Q_t) = B_{G_t}(Q_t) = Q_t^{G_t} \cdot (1 - Q_t)^{N_t - G_t} \tag{11}$$

$$P(Q_{t+1} \mid R_t) = \frac{P(R_t \mid Q_t)}{P(R_t)} \times P(Q_t) \tag{12}$$

with $P(Q_t) = \mathrm{Beta}_{\alpha,\beta}(Q_t)$

$$\begin{aligned} P(Q_{t+1} \mid R_t) &= \frac{P(R_t \mid Q_t)}{P(R_t)} \times \mathrm{Beta}_{\alpha,\beta}(Q_t) \\ &= \frac{P(R_t \mid Q_t)}{P(R_t)} \times \frac{Q_t^{\alpha-1} \cdot (1 - Q_t)^{\beta-1}}{C(\alpha,\beta)} \\ &= \frac{Q_t^{\alpha'-1} \cdot (1 - Q_t)^{\beta'-1}}{P(R_t) \cdot C(\alpha,\beta)} \\ &= \frac{Q_t^{\alpha'-1} \cdot (1 - Q_t)^{\beta'-1}}{C(\alpha',\beta')} \\ &= \mathrm{Beta}_{\alpha',\beta'}(Q_t) \end{aligned} \tag{13}$$

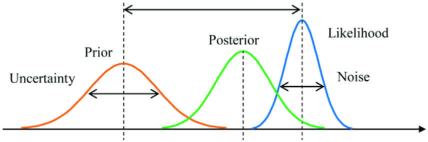


Figure 20. Prior vs Posterior distribution.

where:

- $\alpha' = G_t + \alpha$
- $\beta' = N_t - G_t + \beta$
- $C(\alpha,\beta) = \int Q_t^{\alpha-1} \cdot (1 - Q_t)^{\beta-1} \, dQ$

$$\pi_{t+1}(a) = \mathrm{Beta}_{\alpha',\beta'}(Q_t(a)) \tag{14}$$

UCB & EXP3

1) UCB:

Algorithm 3: UCB

$N_0(a) \leftarrow 0 \quad \forall a$

while *true* **do**

$\quad a = \text{argmax}_a \, Q(a) + \sqrt{\frac{\ln(t)}{N_t(a)}}$

$\quad$ Receive r

$\quad Q(a) \leftarrow \frac{N_t(a) \cdot Q(a) + r}{N_t(a) + 1}$

$\quad t \leftarrow t + 1, N_{t(a)} \leftarrow N_t(a) + 1$

2) EXP3:

$$\begin{aligned} \pi_{t+1}(a) &= (1-\gamma) \cdot \frac{w_{t+1}(a)}{\sum_{a' \in A} w_{t+1}(a')} + \gamma \cdot \frac{1}{|A|} \\ w_{t+1}(a) &= w_t(a) \cdot \exp\left(\frac{\gamma \cdot R_{t+1}(a)}{|A| \cdot \pi_t(a)}\right) \end{aligned} \tag{15}$$

Where:

- $\gamma \in [0, 1]$ controls the exploration and the probability to choose an action a at round t.

Outline

Experiments

- Table bellow summarizes the simulation settings used in our work.

Parameters	Values
# uplink channels	1
# BS or GW	1
# ED	$[10^3, 2.10^3, ..., 10.10^3]$
# pkt sent by ED	50
Simulation Area	$14 km^2$
Payload size	[20,30,40,50,70,80,100] B
Packet Rate	1 packet per [1,2,...,10] mn
Bandwidth	125 kHz
Transmission Power	[11,12,13,14] dBm
Coding Rate	[1,2,3,4]
Spreading Factor	[7,8,9,10,11,12]
Carrier Frequency	868.1 MHz
Capture Effect	6.0 dB

Table 3. Simulation setting

Outline

Results

- Such behavior is explained by the fact that ADR tries to maximize the DR of each devices without caring about the global throughput.
- Reinforcement learning algorithms offer a higher throughput compared to ADR when the number of devices exceeds 1000.
- With less than 1000 devices, learning algorithms didn't get enough data to be able to be trained well.

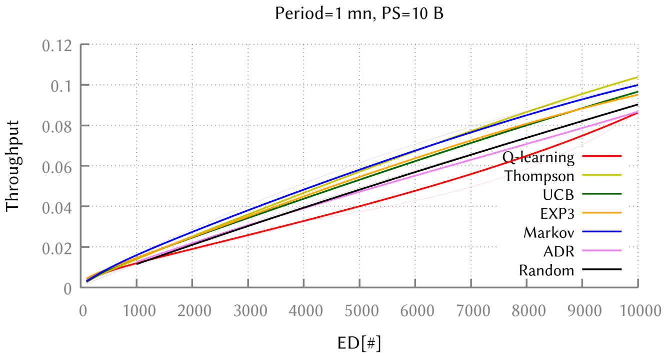


Figure 21. Throughput vs number of end-devices.

Results

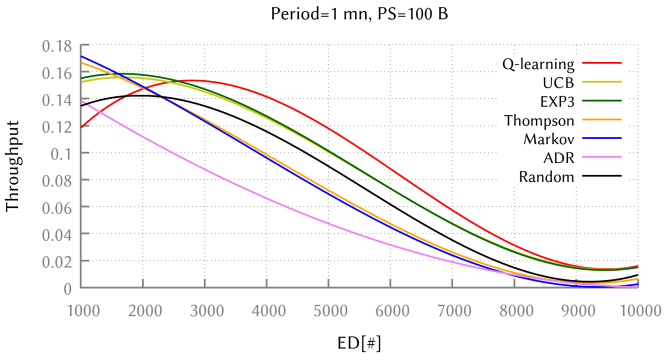


Figure 22. Throughout vs number of end-devices.

- Thompson and Markov offer a higher throughput when the number of devices is less than 10^3.
- Such behavior is explained by the fact that Markov algorithm has an a prior knowledge about the environment through the transition matrix.
- Thompson bring the same performances as Markov since Bayes theorem used in this algorithm can predict the mean of each arm with less samples.
- Q-learning algorithm requests more devices to update its policy more frequently to be able out perform other learning algorithms.

Results

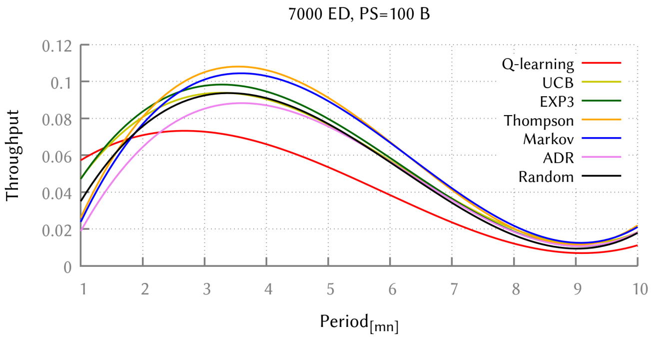


Figure 23. Throughput vs packet rate.

- When the frequency is higher, the probability of collision is higher also.
- When 7000 devices use the same channel to send packets of 100 bytes, the advisable packet rate is between 1 packet per 3 and 4 minutes.
- For Q-learning a higher transmission frequency above 1 packet per minute is required to get a higher throughput than other algorithms.

Results

- Using a small packet size allows to mitigate collisions since the time during which the channel is used is reduced.
- The amount of data that should be sent will be reduced and then the throughput is reduced also.
- This figure shows the best trad-off between the throughput and size of packets that should be sent regarding the number of nodes and packet rate.

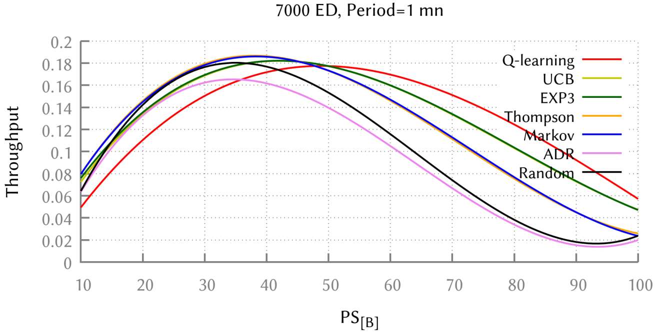


Figure 24. Throughput vs packet size.

Results

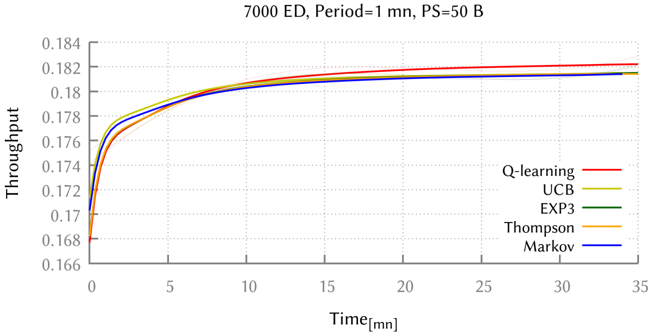


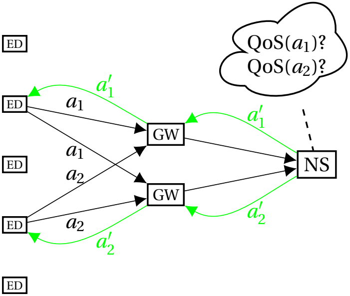
Figure 25. Throughput vs Time.

- Q-learning algorithm starts with lower throughput than other learning algorithms.
- However, it out perform other multi armed bandit algorithms by time.

Outline

1. Introduction
2. State of the art
3. Online reconfiguration
4. **Conclusion**

Conclusion



- The main challenges of this work is how to maximize the throughput when new applications' requirements arise.
- we addressed the reconfigurabilty problem of transceivers' parameters.
- We introduced a new approach for dynamic reconfiguration using Fuzzy C-Means (FCM) clustering,
- As a future work, we will focus on a thorough analysis of the impact of reinforcement learning parameters adapted to our context.

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Outline