Massive Deployment Evaluation of Adaptive LPWA Networks Using Turbo-FSK

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***Abstract*—Originally, Low Power Wide Area (LPWA) Networks were predetermined for long range, low power and low data rate transmissions. The existing LPWA technologies trade-off by definition between these parameters and therefore, they can not cover the different scenarios of Machine-to-Machine communications. Moreover, heterogeneity and large-scale are still two main challenges that are not always considered in LPWA studies. In this paper, we evaluate different massive deployment strategies using a flexible radio based on Turbo-FSK: selfish approach where each node selects its own configuration according to its needs and centralized approach where the Base Station selects the best strategies to improve the network performance. Then, we evaluate these deployments with large-scale simulations in terms of reliability, network capacity, battery lifetime and end-to-end latency. The results show the advantages and drawbacks of homogeneous and heterogeneous deployments in different LPWA contexts (e.g., Smart Metering and Agri-systems).**

***Index Terms*—Adaptive Networks, Low Power Wide Area (LPWA), Massive Access, Medium Access Control (MAC), PHY.**

I. Introduction

To tackle the problem of massive Machine-to-Machine (M2M) communications in cellular networks [1], Low Power Wide Area (LPWA) Networks were proposed for large-scale applications needing long range communication and low power consumption [2]. The most important LPWA technologies which are proprietary (such as Sigfox, LoRa or RPMA) or standardized (such as NB-IoT or LTE-M) have been focused to trade mainly between range, throughput and battery lifetime [3]. Therefore, these technologies can be used for specific LPWA contexts, but none of them can cover the huge range of the Internet of Things (IoT) scenarios one at a time [3]. Indeed, the Quality of Service (QoS) of each application vary according to the traffic load (e.g., heterogeneity) and network density (e.g., massive access) [4].

The proprietary solutions are based on physical layer (PHY) approaches tailored for some scenarios of the IoT and designed with a simple Medium Access Control (MAC) protocol declining from ALOHA access. Sigfox uses an ultra-narrow band radio to reduce the probability of interference by limiting its throughput (i.e. 0.1 to 1 kbps in UpLink and 0.6 kbps in DownLink) [5]. Thus, it can achieve long range transmissions at the cost of very low data rate and flexibility. LoRa and RPMA propose a different approach based on spread signals which benefit from the spectral diversity. Thus, these technologies can adapt their throughput by adjusting the spreading factor (i.e. 0.24 to 37.5 kbps with LoRa and 0.06 to 30 kbps with RPMA). However, these techniques lack of an efficient MAC protocol to adapt to network density scale up and congestion rises when the traffic load increases [6].

Alternatively, NB-IoT is a promising LPWA solution for the standardized technologies [7]. It provides a narrow band access and achieves a maximum coupling loss of 164 dB. Therefore, it is expected to support a massive number of nodes with low throughput requirements (i.e. 0.3 to 250 kbps). However, it has an important signaling overhead (due to LTE backward compatibility) which can increase the energy consumption. Moreover, it does not support Device-to-Device (D2D) communications, reducing the scope of many IoT scenarios.

Besides the heterogeneity of applications and physical layers, massive access evaluation is still a challenge for M2M simulations. Most of LPWA studies considering large-scale remains on theoretical analysis (e.g., [3] [5] [6] [8]) and there are few simulators that can be used to evaluate multiple layers of wireless communications (i.e. from the PHY to the application layers) under large-scale scenarios [9]. OMNET++ is one of the most known, but it is mainly used to evaluate networking protocols. NS-3 is another interesting simulator for massive access evaluation, because it has several validated models for wireless networks. In [10], the authors evaluated the scalability of LoRa with NS-3 by implementing the LoRaWAN PHY/MAC protocols and an orthogonal interference model. However, the base station is evaluated with the LoRa model class A, which accepts only one spreading factor at once. Therefore, this approach does not evaluate the heterogeneity of LoRa with a more realistic non-orthogonal model [8] and neither the energy consumption of the nodes.

In this work, our contribution focuses on massive deployment strategy of LPWA networks using Turbo-FSK [11]. For that purpose, we have developed a large scale network simulator that provides the network performance (abacus) depending on application requirements (e.g., number of users, traffic intensities). Our simulation is adapted to flexible PHY and multiple waveforms and it provides spectrum model with an accurate interference model. The MAC and upper layer performance can be evaluated in terms of reliability, network capacity, latency and energy consumption for massive access scenarios. In this paper, thanks to this simulation framework, we evaluate the different Turbo-FSK configurations with different traffic loads and deployment strategies. Thus, we show the importance of heterogeneity management in LPWA networks.

The reminder of this work is organized as follows: Section II describes the challenges for adaptive LPWA networks and provides a description of our flexible PHY layer based on Turbo-FSK. Section III evaluates the different deployment strategies by simulation. Section IV analyses Turbo-FSK flexibility for different LPWA heterogeneous scenarios. Finally, Section V concludes this paper and presents the future work.

II. Adaptive LPWA Networks with Turbo-FSK

A. Flexible PHY/MAC Layer

As mentioned in the introduction, the first generation of LPWA technologies had the challenge to propose a PHY Layer able to provide long range and low energy consumption. The second generation needs to propose a new PHY/MAC layer capable to adapt to any scenario it is facing. Such technology has to propose the following functionalities:

- A flexible PHY and hybrid MAC capable to manage heterogeneous traffics (i.e. periodic to sporadic or synchronous to asynchronous).
- A flexible network architecture to adapt to different topologies (i.e. star to device-to-device communications) and density (i.e. sparse to dense).
- A decision module with cognitive functionalities to learn from the network, exploit the PHY/MAC flexibility and adapt to the current context.

In [12], we introduced a new flexible PHY layer for LPWA which can use three different waveforms with the same radio: i) Turbo-FSK which can achieve long range with low Peak-to-Average Power Ratio (PAPR) and hence, good energy efficiency, ii) OFDM which can provide high data rate and iii) SC-FDM to tackle the trade-off between the last two. On the one hand, SC-FDM and OFDM waveforms are interesting for short range and high data rate communications especially when they exploit large bandwidth thanks to their high spectral efficiency. Thus, they provide two high data rate solutions: SC-FDM focusing on energy efficiency and OFDM on high performance. On the other hand, Turbo-FSK waveform achieves the best communication range but is limited in terms of data rate. This waveform should be preferred for low power long range communications.

B. Turbo-FSK Physical Layer Overview

Turbo-FSK was proposed in [11] to increase the robustness of long range and low power transmissions with low complexity at the transmitter. This waveform combines an orthogonal modulation frequency (FSK) with a linear modulation (PSK) at the transceiver, and a channel coding based on turbo-code adapted to FSK. Thus, we can achieve a PAPR equal to 0 dB with a performance close to the Shannon limit for the lower spectral efficiency. Indeed, authors showed in [11] that Turbo-FSK waveform performs better (around 4 dB in terms of signal-to-noise ratio) than LoRa technology which is based on the concatenation of CSS with a Hamming code.

This waveform is composed by three main parameters: the number of carriers (N) for the FSK modulation, the order of the PSK constellation (M) and the repetition factor (k) which consists on the number of parallel concatenated convolutional codes. These parameters can be combined in different ways to achieve different performance and to adapt the Turbo-FSK waveform to different situations. Note that Turbo-FSK can be implemented using the OFDM framework (based on Fast Fourier Transform (FFT) and prefix cyclic) [12].

In this paper, we consider 4-FSK, 16-FSK, 32-FSK to define the bandwidth of the signal; 1-PSK (i.e. pure FSK), 4-PSK, 16-PSK, 32-PSK; and 2, 3 or 4 repetitions. Moreover, for each possible configuration we consider the following assumptions in our simulations:

- Sampling frequency of 1.92 MHz
- Tones spacing Δf of 15 kHz
- FFT size of 128
- Prefix cyclic size of 9 samples
- A packet contains 1008 information bits
- Ideal synchronization and channel estimation

For sake of simplicity, we define different Modulation and Coding Schemes (MCS) with the notation (N-FSK, M-PSK, k for repetition factor). Thus, a configuration using 4-FSK, 1-PSK with 4 repetitions (N=4, M=1, k=4) will be represented as (4,1,4). For instance, 4-FSK will present a bandwidth of 60 kHz (i.e. narrow band signal) for low data rate and higher spectral efficiency, whereas 32-FSK will have a bandwidth of 480 kHz (i.e. wide band signal) for higher data rate and low power consumption.

C. Deployment Strategies

In our last study [13], we evaluated the flexibility of Turbo-FSK for the decision module in adaptive LPWA networks. To do so, we analyzed different MCS in terms of range, network capacity, reliability and battery lifetime and we selected the optimal MCS using Turbo-FSK. However, we did not evaluated the effect of the heterogeneity and the large scale on the network. Hence, in this paper, we evaluate the impact of homogeneous and heterogeneous Turbo-FSK strategies for large scale deployments:

1) Homogeneous Networks with Turbo-FSK : This strategy consists to keep one single configuration for the whole network in order to trade between range, network capacity and energy consumption. For instance, we showed in [13] that (4-FSK, 32-PSK, 2 rep.) achieved the maximum capacity at the expense of energy consumption and range, whereas (32-FSK, 1PSK, 4 rep.) achieved the highest range with low power consumption but the worst network throughput. Therefore, a heterogeneous deployment (i.e. mixing different Turbo-FSK configurations) may be a solution to achieve long range with different traffic loads. For comparison with heterogeneous approaches, we will consider the following homogeneous configurations: (4,1,4), (4,4,3), (4,32,2), (32,1,4), (16,16,3) and (32,32,2). Note that these configurations are limited in range according to its Maximum Coupling Loss (MCL). Thus, we define three levels of range: short, medium and long.

2) Heterogeneous Network deployments : In this study, we consider different strategies for heterogeneous networks where the MCS is chosen according to different approaches:

- **Selfish with MCS random selection** (Figure 1) where each node chooses its own configuration randomly. With this approach, we simulate the case where nodes can choose a configuration adapted for their own needs, e.g. increase the battery lifetime or the data rate.

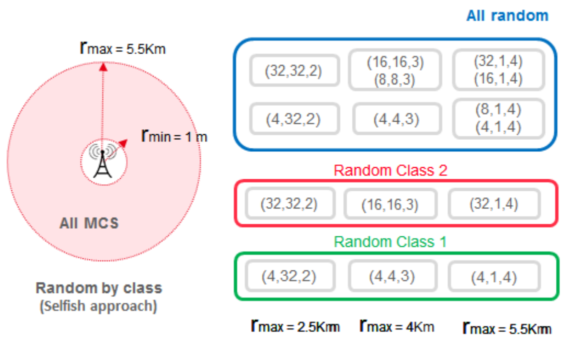

Fig. 1. Deployment setup for selfish heterogeneous networks

- **Centralized with feedback** (Figure 2) where nodes choose a predefined MCS according to its budget link (MCS ordered selection). In this case, we consider that the Base Station (BS) is capable to collect all the data and choose the best configuration for all the network. Thus, we simulate the case where the nodes had already received the feedback from the BS who wants to increase the resilience and capacity of the network.

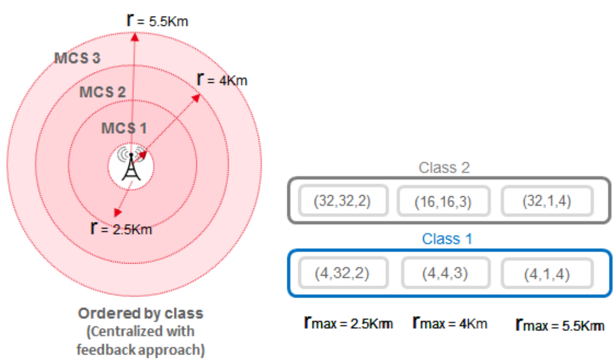

Fig. 2. Deployment setup for cognitive heterogeneous networks

III. Massive Access Simulations for Turbo-FSK LPWA Networks

A. Simulation Framework

The main goal of our study is to evaluate large scale performance of heterogeneous networks by simulation. To do so, we implemented several models using an event-driven simulator (WSNet [14]) to exploit and evaluate the PHY/RF flexibility with Turbo-FSK:

1) Application Layer: We consider a pseudo-periodic model where nodes send a packet randomly at each new period. This random periodic traffic is suited to simulate sporadic applications, such as smart metering or agri-systems.

2) MAC Layer: We implemented a random access MAC protocol where the frequency is selected randomly in a defined band (e.g. 868 MHz) with a sub-carrier of $\Delta f = 15$ kHz. The MAC layer selects the waveform depending on the application requirements (i.e. data rate, reliability, network capacity and energy consumption). Thus, we can exploit the flexibility of the transceiver model using the different Turbo-FSK waveform configurations.

3) Reconfigurable Transceiver: We implemented a PHY layer based on the Turbo-FSK waveform where nodes can use any of the configurations to communicate. Moreover, we integrated an energy model able to measure the energy consumption [12] at each radio state (i.e. sleep, idle, transmission or reception) during a simulation and estimate the battery lifetime (BL) [15] as follows:

$$BL(days) = x * \frac{T_{appli}}{3600 * 24}, \quad x = \frac{E_{battery} - E_{cutoff}}{E_{conso} + E_{leaked}} \quad (1)$$

where T_{appli} represents the application period in seconds, x is the number of times this application can run with the available energy, $E_{battery}$ is the available energy from battery (we consider 13500 Joules while using 2 AAA batteries of 1250 mAh under 1.5 V each), E_{cutoff} represents the energy cutoff at the end of lifetime (we consider 10 % of battery energy), E_{leaked} is the energy leakage per year as $E_{leaked} = 0.05 * E_{battery} * \frac{T_{appli}}{60*60*24*365}$ and E_{conso} is the total energy consumed during the application period.

In the case of the base station, we consider a powerful receiver that can demodulate several signals simultaneously in the band of interest. Therefore, the received signals depend only on the Signal-to-Noise Ratio (SNR) and Packet Delivery Ratio (PDR) [12]. Note that the error rate models were obtained by simulation using an Extend Typical Urban (ETU) fading channel.

4) Channel Model: For the simulations, we consider a pathloss model using an Okumura-Hata model in open rural [12]. Then, we implemented a spectrum model inspired from [16] in order to model the frequency-dependent aspects of wireless communications. Thus, we can accurately evaluate the interference of heterogeneous simulations.

5) Interference Model: In WSNet, we are not simulating the whole PHY layer of a Turbo-FSK waveform, but we take into account the channel occupancy of the waveform. We measure the interference ambiguity between two packets as the amount of energy coming from the interference in a time-frequency proportion of the received packet as follows:

$$P_I = \delta f * PSD * \frac{\delta t}{T_{paquet}} \quad (2)$$

where T_{paquet} is the packet duration at reception, δf is the bandwidth of the interference, δt represents the duration of the interference and the PSD (W/Hz) is the Power Spectral Density of the interference. Then, we estimate the Signal-to-Interference-plus-Noise Ratio (SINR) according to the received power P_{RX}, the noise (N) and interference (P_I) as:

$$SINR = \frac{P_{RX}}{N + \Sigma P_I} \quad (3)$$

Finally, for each waveform and configuration, we have a look up table (based on measurements from [12]) that gives us the Bit Error Rate (BER) w.r.t. the SINR of the packet. Thus, we can estimate the PDR for any size of packet.

B. Simulation Setup and Parameters

With this framework, we are able to evaluate large-scale LPWA networks based on Turbo-FSK. To do so, we consider a disk deployment where nodes remain static at random positions around a base station. The maximum radius is fixed at r_{max} = 5.5 km for all the simulations and the MCS selection strategy changes according to the analyzed deployment. For each simulation, nodes send one data packet of 100 Bytes randomly in a period defined by the simulation time. We consider a physical band of 1 MHz starting at 868 MHz and the transmission power is fixed to 14 dBm for all the nodes. Then, we run different simulations by changing the network size (1 to 30000 nodes) or the application period (1 to 10000 seconds). Each simulation setup is tested 50 times. Finally, the different deployments are evaluated from the MAC point of view (i.e. by considering the trade-off between reliability, latency, network throughput and battery lifetime).

C. Comparison Between Homogeneous and Selfish Heterogeneous Deployments

In this section, we evaluate the selfish approach where nodes select its own configuration by following two rules (Figure 1):

- *All Random* where nodes choose a MCS configuration randomly (9 possibilities). This configuration lets us evaluate the coexistence of all the MCS.
- *Random by Class* where nodes select a MCS randomly depending on their class. To do so, we define 2 different classes with 3 MCS each. Class 1 is composed of MCS with 4 sub-carriers (4-FSK based) to achieve high spectral efficiency and long range. Class 2 is composed of MCS with 32 sub-carriers (32-FSK and 16-FSK based) to achieve higher data rate and low power consumption. Note that Class 1 exploits narrow band properties (i.e. bandwidth of 60 kHz), while Class 2 benefits of wide band channel diversity (i.e. bandwidth of 480 kHz).

We evaluate these strategies and compare them with the case of homogeneous networks in terms of Packet Delivery Ratio (PDR), network throughput and battery lifetime. In the homogeneous networks simulations, nodes are positioned according to the MCL of the selected MCS. For instance, a homogeneous network using (4,32,2), (4,4,3) or (4,1,4) will have a r_{max} of 2.5 km (short range), 4 km (medium range) or 5.5 km (long range). These values were obtained for an open rural scenario with the Okumura pathloss model and the ETU channel, but they can be adapted to other channel scenarios.

First, we analyze the PDR as a function of the number of nodes with an application period of one second (Figure 3).

We observe that the PDR decreases when the number of nodes increases. A homogeneous deployment using (4,32,2) provides the best PDR because of its high spectral efficiency but its coverage is limited due to its short range. For heterogeneous deployment, when the network reaches 1000 nodes, Random Class 1 shows a better reliability with 33% of PDR, while Random Class 2 presents a PDR of 15%. However, the PDR decreases considerably with 30000 nodes down to 1.2%

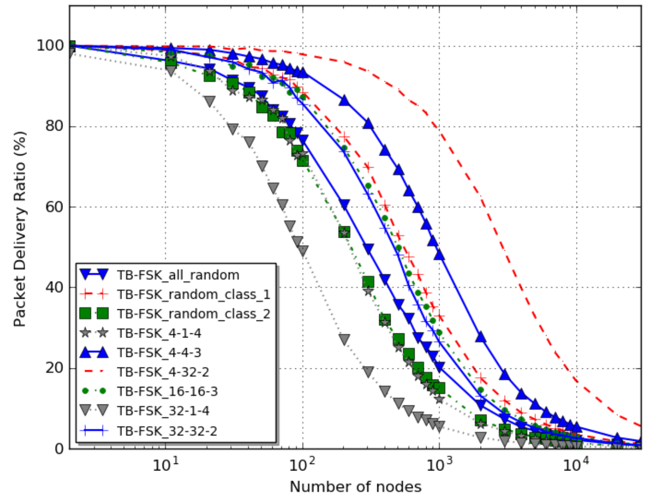

Fig. 3. PDR as a function of the number of nodes sending a 100-Bytes packet each second in selfish heterogeneous and homogeneous networks

for Class 1 and 0.4% for Class 2. Moreover, the All Random class presents a better PDR (20% with 1000 nodes) compared to Class 2 because of the spectral efficiency contribution of narrow band MCS (i.e. 4-FSK). According to these results, if we are looking to ensure high reliability (90% of PDR) with a one second application period, Random Class 1 and 2 may achieve it for 90 nodes and 30 nodes respectively. To push theses limits, it would be necessary to adapt the PHY and MAC layers. For instance, at the PHY, increase the bandwidth may be necessary for applications needing high data rate (i.e. using 32-FSK modulations); and power control at the center may also increase the coexistence with nodes at the edges. At the MAC layer, we may increase the application period to increase the capacity or improve the MCS selection by the BS (centralized cognitive strategy).

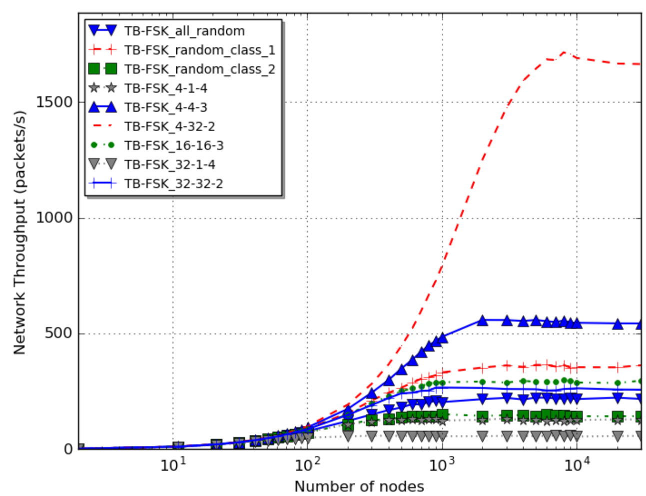

Fig. 4. Network throughput (packets/second) as a function of the number of nodes sending a 100-Bytes packet each second in selfish heterogeneous and homogeneous networks

Furthermore, if we analyze the network throughput as a function of the number of nodes with one second period (Figure 4), we observe that Random Class 1 shows a higher throughput (361 packets/s) compared to Random Class 2 (150 packets/s) and all random class (221 packets/s). This is because of the better spectral efficiency of 4-FSK based configurations. Note that the highest throughput remains constant at one point even when we increase the number of nodes. This is because without power control at the user side, the capture effect of the powerful base station still enables to demodulate the closest signals in the band of interest.

Compared to homogeneous networks, we observed that selfish heterogeneous networks improve the overall performance of the network and make some tradeoffs. On the one hand, homogeneous networks have its advantages at short range. For example a homogeneous network with (4,32,2) achieves the highest throughput (1714 packets/s) and PDR (79% for 1000 nodes) but cannot reach long range (< 2.5 Km). On the other hand, homogeneous networks with (32,1,4) achieves long range (< 5.5 km) but the throughput (57 packets/s) and PDR (5.5% for 1000 nodes) decrease due to the higher duration of packets and the higher number of collisions. Hence, heterogeneous networks exploit short range configurations to improve the reliability and capacity and long range configurations to extend the coverage.

Figure 5 shows the average battery lifetime of 30000 nodes as a function of the application period for homogeneous and selfish heterogeneous networks.

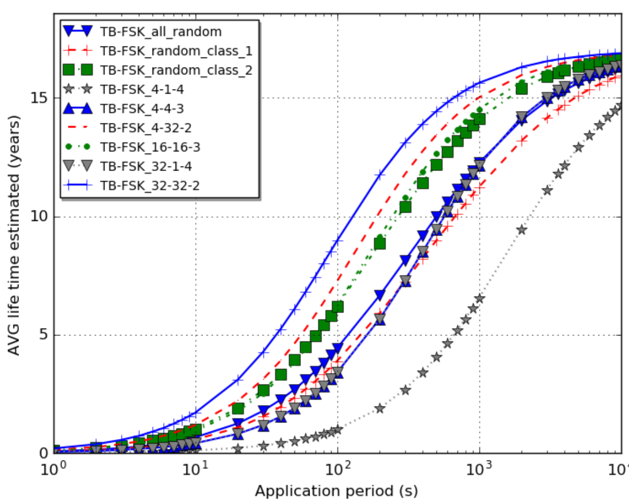

Fig. 5. Average Battery Lifetime as a function of the application period in a network of 30000 nodes in selfish heterogeneous and homogeneous networks

We observe that the battery lifetime increases when the application period is longer and converge to the maximum capacity of the battery. Moreover, wide band configurations (e.g. using 32-FSK, Random Class 2) are more energy efficient than narrow band configurations (e.g. using 4-FSK, Random Class 1) because larger bandwidth increases the data rate and makes the packet durations shorter. Nevertheless, nodes that decide to increase their battery lifetime (by exploiting larger bandwidth) will intrinsically decrease the network throughput.

To conclude, we have compared the selfish approach in heterogeneous networks with homogeneous networks and shown the trade off between range, network capacity and energy consumption. While keeping the maximal coverage, heterogeneous networks improve the overall performance of the network by exploiting short range configurations to improve the reliability and capacity and long range configurations to extend the coverage. Moreover, by comparing the 3 heterogeneous classes (i.e. All Random, Random Class 1 with high spectral efficiency and Random Class 2 with low power consumption), we show that the Class 1 is more robust to network saturation and should be prioritized to release congestion in short periods whereas channel aggregation with Class 2 is interesting for offloading with high data rate and for high battery lifetime, but not for the overall performance of the network. Therefore, Class 2 can be freely used in sparse networks (i.e. few number of nodes or high application periods), but its use has to be limited in dense networks.

D. *Improvement of Heterogeneous Network Deployment With Centralized Strategy*

In the previous section, we have considered a selfish approach where each node can take its own decision to either achieve higher battery lifetime or higher data rate. However, this is not optimal from the network point of view because the nodes do not consider the interference their choice can produce. For this, we propose a centralized approach controlled by the BS which has a global perception of the network state. The BS decides the MCS of each node according to its position and to the selected class (Figure 2) and distributes its decision by feedback at the beginning of the simulation.

In Figure 6, we evaluate the PDR as a function of the number nodes sending a 100-Bytes packet each second.

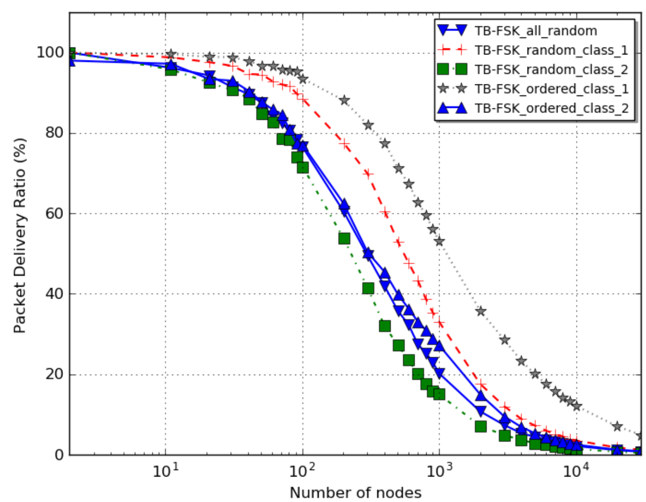

Fig. 6. PDR as a function of the number of nodes sending a 100-Bytes packet each second in heterogeneous networks

We observe that Ordered Classes are more reliable that Random Classes. We note a difference of 20% (resp. 12%) in PDR between Random and Ordered Class 1 (resp. Class 2). Ordered Class 1 improves Random Class 1, even when the number of nodes using (4,1,4) is higher in Ordered Class 1. While the distribution of MCS is uniform in Random Class 1, the proportion in Ordered Class 1 is 47% with (4,1,4), 32.5% with (4,4,3) and 20.5% with (4,32,2).Therefore, one can imagine that the probability of collision is higher with Ordered Class 1, but the interference of nodes at the edge (using

(4,1,4)) is reduced. Moreover, Ordered Class 1 achieves better resilience (e.g. 53% of PDR for 1000 nodes) than Ordered Class 2 (e.g. 27% of PDR for 1000 nodes).

Figure 7 shows the PDR as a function of the application period for a 30000 nodes network.

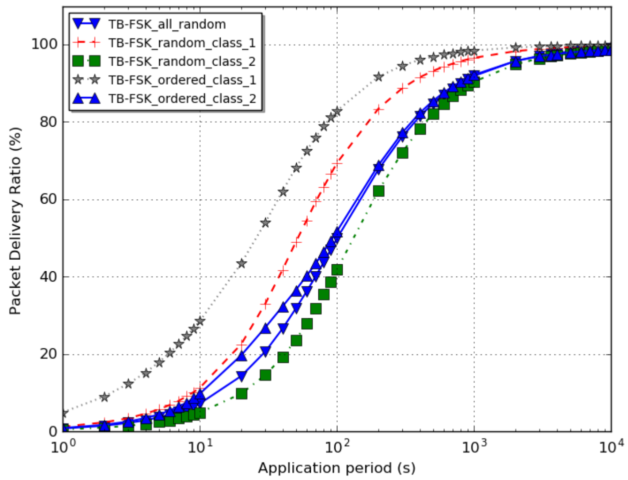

Fig. 7. PDR as a function of the application period in heterogeneous networks of 30000 nodes

We observe that the threshold of 90% of PDR is reached at 1000s for all the classes. In particular, Ordered Class 1 (Resp. Random Class 1) can support 30000 devices sending a 100-Bytes packet each 200 seconds (Resp. 350 seconds). However, this difference is reduced when the application period increases. Therefore, a centralized approach could be interesting for ultra-reliable dense networks whereas the selfish approach could be enough for sparse networks (e.g. daily period) by reducing the traffic overhead and the energy consumption.

In Figure 8, we evaluate the throughput as a function of the number of nodes sending a packet each second.

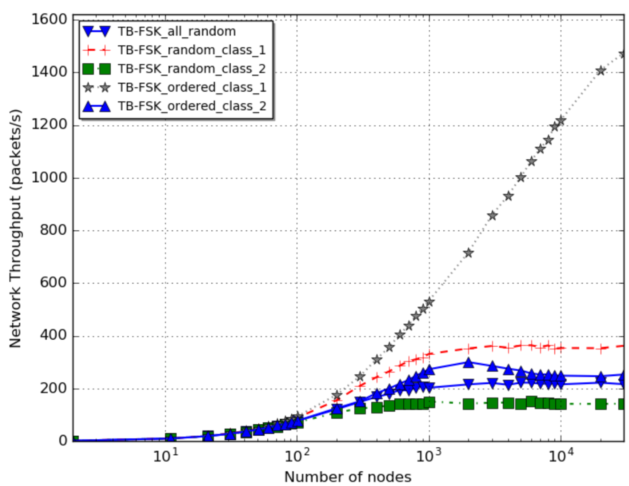

Fig. 8. Network throughput (packets/second) as a function of the number of nodes sending a 100-Bytes packet each second in heterogeneous networks

We observe that Ordered Class 1 achieves a higher throughput (1473 packets/s) than Ordered Class 2 (299 packets/s). Moreover, the saturation is reached with 2000 nodes for Ordered Class 2 whereas for Ordered Class 1, it is not reached even with 30000 nodes. This is because after 1000 nodes, only the packets from nodes close to the BS (i.e. using (4,32,2)) are received and the throughput of Ordered Class 1 follows the throughput of homogeneous networks using (4,32,2).

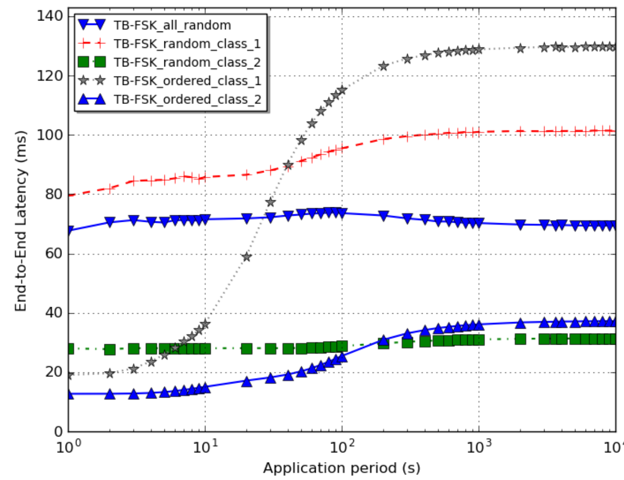

Fig. 9. Average end-to-end latency as a function of the application period in heterogeneous networks of 30000 nodes

This conclusion can be confirmed by observing the average end-to-end latency (Figure 9) as a function of the application period with 30000 nodes. As we consider uplink communications without retransmission, the latency mainly depends on the packet duration. The (4,32,2) or (4,1,4) packets respectively last 19.03 ms and 228.33 ms. Therefore, the average latency can indicate the MCS used by successful communications. For instance, when the application period is between 1 to 10 seconds, we observe the latency around 20 ms with Ordered Class 1. This is because only nodes close to the BS using (4,32,2) are successfully communicating. However, the average latency increases to 120 ms when the application period becomes higher than 100 seconds. This means that the packets coming from nodes at edge are received as well.

Figure 10 shows the throughput as a function of the application period with 30000 nodes.

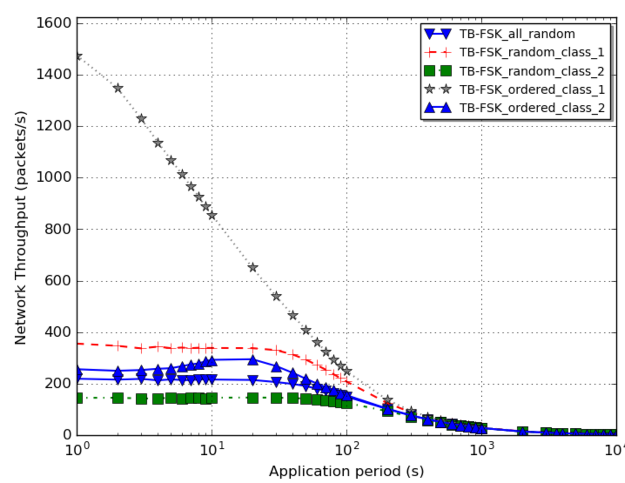

Fig. 10. Network throughput (packets/s) as a function of the application period in heterogeneous networks of 30000 nodes

We note that the throughput converges for all classes with a 1000 seconds application period. Therefore, the centralized with feedback approach is only necessary for ultra-dense networks to increase the throughput.

Concerning the energy consumption, Figure 11 compares the average battery lifetime between the selfish and centralized approaches as a function of the application period. As expected, Random and Ordered Class 2 have the longest battery lifetime. The difference between them is due to the higher proportion of nodes using (32,32,2) in Random Class 2 (33.33%) than Ordered Class 2 (20.5%).

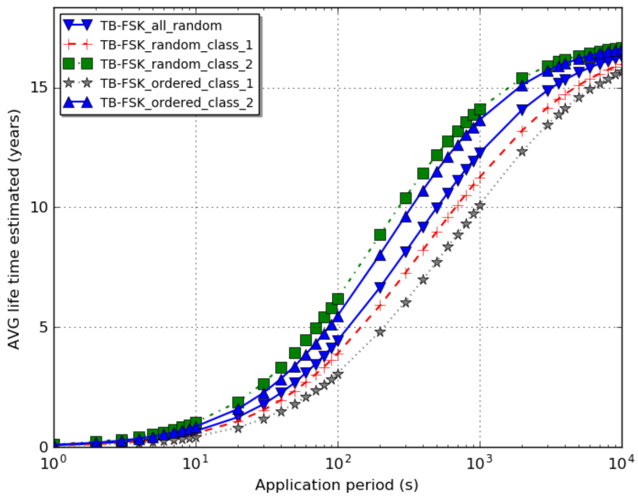

Fig. 11. Average Battery Lifetime as a function of the application period in heterogeneous networks of 30000 nodes

From this analysis, we can conclude that Ordered Classes improve the performance of Random Classes in terms of reliability and network throughput. Ordered strategies are interesting for ultra-reliable dense networks whereas Random ones for reducing traffic overhead and energy consumption in sparse networks.

IV. Turbo-FSK Analysis for LPWA Applications: Smart Metering and Agri Systems

Among the different LPWA scenarios, Smart Metering and Agri-systems are two applications with different requirements:

- Smart Metering requires an adaptive communication to support heterogeneous traffics: Automatic Meter Reading (AMR) and Advanced Metering Infrastructure reading (AMI). AMR only requires uplink communications for daily periodic transmissions with low resilience and low traffic. AMI requires bidirectional communications for near-real time periodic transmission (less than 60 seconds) with high resilience, low latency (less than 1 second) and low to medium traffic intensity. In terms of coverage, we consider the case of smart metering deployed in a rural area (to cover 30 nodes/km^2 and with a range up to 5 km).
- Agri Systems define several kinds of monitoring (e.g. crop/seed, livestock, intruder detection) and therefore, different levels of QoS. The required period can be between few to 60 seconds with high resilience for low to high traffic. In this scenario, the coverage is in rural wide area for a range between 1 to 5 km and a density of 400 nodes/km^2.

For this analysis, we run several simulations with our different homogeneous and heterogeneous approaches by considering these two scenario requirements (i.e. in terms of range and density). Then, we evaluate the minimum application period that can support the required number of nodes with high reliability (PDR $>$ 90%). The results of these simulations are shown in Table I. The range is defined according to the MCL of each MCS strategy (homogeneous or heterogeneous) and the number of nodes is calculated from the required density and the range. For instance, if we consider a deployment with a range of 5.5 km and a density of 30 nodes/km^2, the network should support 2851 nodes.

For rural AMR metering applications (with daily period), we can observe that all the heterogeneous and homogeneous deployments with long range configurations (e.g. (4,1,4) or (32,1,4)) achieve an application period smaller than the required period, even with 90% of PDR. Hence, 32-FSK based strategies should be prioritize to increase the battery lifetime.

For rural AMI metering applications (with 60 seconds period), we observe that none of the long range homogeneous deployments are adapted for this application. Only short range configurations (e.g. (32,32,2) and (4,32,2)) can achieve a good application period, but their coverages are limited for rural environment and the BS infrastructure needs to be densified. To increase the cell coverage while keeping good reliability, we proposed Class 1 and Class 2 for heterogeneous networks. In Table I, we can observe that the 32-FSK strategies (Random or Ordered Class 2) needs at least 80 seconds to support the required density for rural AMI, which is higher than the 60 seconds needed. On the other hand, Classes 2 are compliant with the application requirements and Ordered Class 1 achieves the shortest application period with 17s.

For Agri-systems applications, the density is set to 400 nodes/km^2 at short-medium range (e.g. $<$5 km), 1 to 60 seconds application period and low power consumption. We can observe that none of the homogeneous/heterogeneous deployments support the required traffic intensity with high reliability, whereas the 60 seconds period requirement can only be supported by (4,32,2) homogeneous network with a limited range. For low power consumption, Ordered Class 2 is the most adapted but it needs 1000 seconds to support 400 nodes/km^2 with high reliability. This performance can be improved by densifying the network (i.e. increase the number of BS), increasing the bandwidth or exploiting other bands.

Note that we can evaluate other LPWA applications with this simulation framework, such as manufacturing automation or smart building. To do so, we can adapt the mobility of nodes, the packet generation period and the packet size.

V. Conclusion and Future work

In this study, we evaluated the performance of massive access heterogeneous networks using Turbo-FSK. To do so,

TABLE I
COMPARISON OF MINIMUM APPLICATION PERIOD OF HOMOGENEOUS AND HETEROGENEOUS STRATEGIES FOR OPEN RURAL DEPLOYMENTS AND 1 MHZ OF BAND AT 868 MHZ

MCS	Radius range (km)	Smart Metering Rural: Number of Nodes for 30/km^2 density	Smart Metering Rural: Application period (sec)	Agri-systems: Number of Nodes for 400/km^2 density	Agri-systems: Application period (sec)
(32,32,2)	2.5	589	9	7854	120
(16,16,3)	4	1508	20	20106	260
(32,1,4)	5.5	2851	220	38013	2800
(4,32,2)	2.5	589	1.5	7854	18
(4,4,3)	4	1508	10	20106	130
(4,1,4)	5.5	2851	80	38013	1000
All Random	5.5	2851	80	38013	1100
Random Class 1	5.5	2851	35	38013	450
Random Class 2	5.5	2851	100	38013	1250
Ordered Class 1	5.5	2851	17	38013	220
Ordered Class 2	5.5	2851	80	38013	1000

we evaluated a selfish approach where each node selects its own configuration according to its needs and a centralized approach where the BS selects the best strategies to improve the network performance based on different decision criteria (i.e. increase the network capacity with Class 1 having high spectral efficiency or increase the data rate and the energy efficiency with Class 2 having high throughput). We showed that the centralized approach with a narrow band strategy (i.e. Class 1) is interesting in dense networks (e.g. high number of nodes or low application periods, such as AMI metering) but not necessary when the networks congestion is low (e.g. sparse networks or applications with daily periods, such as AMR metering). In the second case, we may prefer a wide band strategy (Class 2) to keep a good battery lifetime.

These results show the interest of deployment adaptation in LPWA networks under large-scale heterogeneous conditions. However, to fulfill the adaptive networks challenges, our future work will focus to evaluate cognitive capabilities for centralized or distributed strategies. In the centralized approach, the BS needs to learn from the network to identify its global performance and status (i.e. dense or sparse). Based on this analysis, it can help nodes with low reliability (e.g. nodes at the edges having low PDR) and propose them a better communication strategy (e.g. sending a feedback to force 4-FSK configurations or creating a dedicated channel for signaling and traffic control). In the distributed approach, nodes could activate their cognitive capabilities to detect the channel availability and adapt to the application (e.g. optimizing its energy consumption, sending a critical packet, performing real-time transmissions). Then, they will take the best strategy to communicate (e.g. by performing listen-before talk to avoid interference and by choosing the adapted MCS configuration).

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