Using binary tree structure for efficient monitoring strategies in a dynamic set of sensors environment for Massiv IoT paradigm

Gwen Maudet, Mireille Batton-Hubert, Patrick Maille, Laurent Toutain

Using binary tree structure for efficient monitoring strategies in a dynamic set of sensors environment for Massiv IoT paradigm

Gwen MAUDET [1], Mireille BATTON-HUBERT[2], Patrick MAILLE[1], and Laurent TOUTAIN[1]

[1]IRISA, UMR CNRS 6074, F-35700, IMT Atlantique, Rennes, France
[2]Mines Saint-Etienne, Univ Clermont Auvergne, UMR CNRS 6158, F-42023, Saint-Etienne, France

***Abstract*—In current monitoring solutions, each application involves a customed deployment and requires significant configuration efforts to adapt to changes in the sensor field. In contrast, here we consider a massive deployment of battery-powered sensors temporarily intervening in the monitoring.**

In this paper, we propose a generic general-purpose monitoring solution that is not tied to the deployment of physical devices. We develop a method that allows to receive a homogeneous amount of information per unit of time, since it is a simple and very efficient way to monitor a physical quantity that varies in time. The proposed solution limits the management costs when the sensor field is changing. Considering that the sensors enter and exit following random processes, we develop analytical results linking the function parameters - the average amount of information per unit of time - and the monitoring quality metrics - diversity, management cost. Moreover, by comparing this solution to the existing literature, we show that this solution is the most suitable for the objectives that can be considered in the context of Massive IoT.

I. INTRODUCTION

A. Interoperability for more versatility

Progress in electronics and signal processing has enabled the development of miniaturized hardware. With the emergence of new low-power telecommunications networks, a new generation of applications has emerged: large-scale deployed sensors and actuators that can interact with their environment [1-3].

In a classical approach, a few very reliable sensors are placed at pertinent locations to provide only relevant information. Each solution is different and not very adaptable over time. In contrast, the Massive Internet of Things (mIoT) takes into account a large amount of cheap, energy autonomous sensors without prior information about their quality or position. This paradigm shift changes the game for the development of monitoring solutions, as it requires a high degree of flexibility in sensor management [4]. This makes it possible to develop versatile solutions that are independent of physical development.

At a scale as large as that predicted (,i.e. 500 billion objects), being able to automate and standardize the integration and management of these objects would remove a barrier to the adoption of the mIoT. Interoperability, defined by the ability to unify heterogeneous objects in a dynamic way, is therefore an important step for the development of such solutions [4-7].

gwen.maudet@imt-atlantique.fr

B. Overview of research on energy efficiency of wireless sensors

Sensors are usually powered by batteries and consume most of their energy when transmitting information. The greater the amount of information transmitted, the higher the power consumption of the sensor. It is of particular interest to manage sensor emissions appropriately in order to limit the energy drain on the sensors.

First, since the early 2000s, energy saving features have been proposed for devices [8,9]. Triggered and adaptive sensing methods adapt the sensor sampling rate to variations in the environment. However, in a mIot approach, we consider standardized sensors designed to send periodic messages. This emission period can only be updated during a short listening window when the sensor sends a message to the gateway.

In 2018, [10] proposes to aggregate the information provided by several surrounding sensors to a single sensor. The article uses the AHP and TOPSIS methods to determine the groups of sensors that will aggregate their information in order to optimize the transmissions. Other information aggregation methods, based on index tree structures, are proposed in [11,12]. Yet, mIoT solutions are primarily based on LPWANs as the least energy intensive network model. This is a star architecture, where direct sensor-to-sensor communications are not allowed.

In 2014, [13] introduces the concept of "Self-Organized Things". They introduce mechanisms that allow sensors to be put to sleep if their spatial area is already covered by other active sensors. In 2017, [14] proposes a energy-efficient hierarchical network architecture. In this paper, they propose an adaptation of the sleep times of the sensors, depending on the battery level, the standard variation of the returned values and the proximity to the other sensors. New results of [14] are depicted in 2019 [15], validating the relevance of exploiting the deep sleep mode. The latter approaches remain limited for applicability to mIoT paradigm. For instance, they rely on knowledge of sensor position and continuous modification of sensor sampling time.

More recently, [16] proposes a framework for developing monitoring policies adhering to the requirements that can be expected in mIoT. They also propose a first instantiation of these policies by adding a constraint: having strict periodical receptions coming each time from one of the sensors. We wish to build on this work, by proposing a more realistic/applicable solution in a very uncertain environment such as the one envisaged for the mIoT.

C. Development of the solution proposed in the paper

We wish to track the average variations of a physical quantity using a large amount of sensors entering and leaving an environment.

First, we wish to receive a temporally homogeneous receiving stream, since this is considered the simplest and most efficient way to track a physical quantity that varies over time [17].

In addition, the proposed solution must reach dynamic level of Conceptual Interoperability Model [18,19]. The sensors that enter and leave the environment must be dynamically managed by the monitoring system. No matter how many sensors are active, the solution must be able to retrieve the same amount of information over time.

This management of the sensors has a cost, which is quantified by the number of messages sent to the sensors. With each arrival and departure of a sensor, communications from gateway to device are made. Among other things, this has a negative impact on the QoS, which is why the objective is to minimize this management cost.

Finally, the solution must be easy to implement and must be robust against packet loss problems, which are considered in most LPWAN technologies.

This kind of solution could be used for a connected wine cellar for example, which would rely on connected objects supposedly embedded in each wine bottle (illustrating the mIoT paradigm). The objective would be to take advantage of the wine bottles present in the cellar, to control the interior temperature and to prevent a possible failure. The solution should not be too disrupted when a new bottle arrives or one leaves, while making the most of all the sensors present in the study area.

Here is the list of the contributions of this paper:

- Based on a structure where sensors are represented by the leaves of a almost complete full binary tree, we develop a period update function allowing the temporally homogeneous reception of messages at the desired target density, while limiting the management cost for sensor arrivals and departures.
- By proposing a scenario where sensors enter and exit following random processes, we establish analytical curves linking the monitoring performance metrics to the parameter set by the user.
- We compare our solution to the literature, confirming its relevance in a posed framework such as the one intended for mIoT.

The rest of the paper is as follows. section II introduces the essential notions setting the framework for the development of the solution proposed in the paper. In section III, we construct the period update function and prove some properties. We develop a scenario based on sensor inputs and outputs that follow random processes, in section IV. Simulations comparing the solution to the literature and confirming the developed analytical solutions are shown in section V. Finally, we conclude in section VI, by proposing perspectives for future work.

II. Problem statement

A. Hypothesis on sensors

We consider wireless sensors on battery, whose energy varies over time. These sensors emit messages periodically, sending information about a physical quantity towards the monitoring system. After each transmission of a sensor, it opens a listening window in order to receive information from the outside (LoRaWAN Class A standard). We exploit this listening time to send orders to redefine the transmission period of the sensor. In particular, in this paper, we focus on defining sensor emission management strategies, which we characterize by a period update function f defined by :

Definition 1. *H_t represents the transmission history up to time t, including the new message received at time t.*

*The **period update function** is defined by the function f :*

$$f : H_t \rightarrow \mathbb{R}^{+*} \tag{1}$$

$f(H_t)$ redefines the transmission period of a sensor that has just sent a message to the time t.

In our case, H_t represents the set of messages sent by sensors until t, where each message contains only the message content and the ID of the sending sensor.

We assume in this paper that sensors come and go during the monitoring. Thus, the monitoring system must automatically integrate sensors whose ID is not known. Also, we assume that when a sensor leaves the environment, then a message with empty content will be received by the monitoring system during its next transmission. From this, we can manage the following scenarios: (i) the sensor runs out of energy, (ii) it physically leaves the environment, or no longer describes the quantity to be monitored in a relevant way: failure leading to the sending of aberrant data, description of a locally isolated phenomenon.

B. Definition of the metric of monitoring

In this paper, we adopt the definition of diversity set out in [16] to represent our quality metric for monitoring the physical quantity. This metric relies on the freshness function [20-22], which quantifies the relevance of a data, relatively to its age Δ_t, compared to a reference time T.

Applying the notion of freshness to a sensor, considering its most recent emission, we will use the following definition of **diversity**.

Definition 2. *The diversity at time t is defined as the sum of the freshness of all sensors that were activated at that time.*

*For a period update function f, we define the **mean diversity** as the average of the diversities over a given monitoring time, denoted by D.*

In addition to this tracking quality metric, we are interested in minimizing the total number of period change orders. This metric encompasses the problems of downlink congestion, as well as additional energy costs. Moreover, the orders sent to the sensors may not be received. The fewer the number of orders, the simpler the solution is to implement while being robust to the hazards of packet loss.

It is possible to define an energy efficiency metric, containing transmissions, as it is the major vector of consumption [23]. As constructed thereafter, we define our period update function so that the number of emissions per time unit is a parameter of the function. This parameter must therefore be chosen to ensure sufficient monitoring quality, while limiting the power consumption of the sensors.

III. Development of the **2-level round-robin** monitoring method

A. Binary tree structure for the representation of sensors in the environment

Before developing the period update function which is the subject of this paper, we first focus on the representation structure of the sensors present in the environment.

We represent the sensor field as leaf nodes in a binary tree. We develop mechanisms to allow the inclusion of new sensors and their output. The considered structure is a tree that is *full* (each node contains 0 or 2 sons) and *almost complete* (all levels are filled except the last level). By these considerations, the present sensors can be grouped into two categories representing the two maximum depths of the tree:

- the so-called "large period" sensors are the leaf nodes whose depth in the tree is maximal. Consequently, a sensor of large period has a complementary (a sensor that have the same root of first degree).
- the so-called "small period" sensors, which are the leaf nodes whose depth is not maximum.

Note that these categories are subject to change when the sensor field is modified.

We identify each sensor by a unique ID locating it in the binary tree. The ID of a sensor contains only '0' and '1' and initially, a single sensor in the environment has an empty ID. The ID size of a sensor corresponds to its depth in the tree, so that the ID of small period have one character less than the sensors of large period.

The tree changes as soon as the sensor field changes, i.e. each time a sensor is added or removed. The ID of a sensor can change over time.

•*When a new sensor arrives in the environment*, a present sensor of small period passes of large period. The activating sensor is also of large period. The ID of each sensor becomes: the ID of the already active sensor + respectively '0' and '1'.

•*When a sensor leaves*, there are 2 cases :

· If the leaving sensor is of large period. In this case, as built, there is another sensor of large period complementary. This last one becomes of small period by removing the last character of its ID.

· If the leaving sensor is of small period, a sensor of large period in chosen to come in substitution to it, copying it ID. The complementary of the latter becomes of small period, removing the last character of its ID.

If all the sensors belong to the same category, then when a sensor is added, they will all be considered as small period; when a sensor is removed, all are considered large period.

B. Development of the period update function

We want to define a period update function so as to receive a homogeneous quantity of information through time. Thus, we define τ such that $\frac{1}{\tau}$ is the target quantity of reception per unit of time required, coming from one of the present sensors. In other words, over a sufficiently long time, the receptions are equivalent to the periodic reception of messages of regular interval τ.

We rely on the binary tree representation of the sensors to set the emission period of the sensors. In particular, we rely on the number of characters of the ID of a sensor to set its emission period. For a given τ, we define the function as:

Definition 3. *When receiving a new message:*

- it may be necessary to update (or set) the sensor IDs, as well as the large period and small period lists, to ensure that we obtain a representation of the sensors as leaf nodes of an almost complete full binary tree.

*After this, considering i the ID of the sensor in the tree which has emit a message at time t, $|i|$ the number of caracters of the ID. Then **2-level round-robin** with parameter τ redefines the sensor period as:*

$$f_\tau(i) = 2^{|i|} * \tau$$

C. Outstanding properties

Here, we prove that the amount of information per unit of time is invariant by adding and leaving sensors. Furthermore, we quantify an upper bound for the number of period changes upon arrival and departure of a sensor.

First, we need to introduce some notations, that will be used both for the below properties, and section IV. We assume a state where the sensor field is constant, i.e. the period of a sensor of ID i is exactly $2^{|i|} * \tau$. In reality, when a sensor ID is changed, its period of emission only changed during its next emission. Considering n sensors, k is denoted as the largest power of 2 that is less than n: $k = 2^{\lfloor \log_2(n) \rfloor}$. Moreover, we rely on the properties of the representation tree to determine the number of sensors present in each of both category:

- $n_2 = 2k - n$ sensors emit at period $k\tau$ and are of small period. To understand this, if we add n_2 additional sensors, they become complementary to each of the sensors of small period to make the binary tree perfect, with exactly $2k$ sensors.
- $n_1 = 2(n - k)$ sensors emit with an emission period of $2k$ and are of large period.

Proposition 1. *The sum of the inverses of the periods of the active sensors remains unchanged at the addition of a new sensor, and is equal to:*

$$\sum_{i \in \textit{ present sensors}} \frac{1}{p_i} = \frac{1}{\tau} \tag{2}$$

Proof. We consider n sensors. p_i is the emission period of sensor i. Thus, we can say that:

$$\begin{aligned}\textstyle\sum_{i \text{ present sensor}} \frac{1}{p_i} &= \tfrac{n_1}{2k\tau} + \tfrac{n_2}{k\tau} \\ &= \tfrac{2|\Pi(t)|-2k}{2k\tau} + \tfrac{2k-|\Pi(t)|}{k\tau} \\ &= \tfrac{1}{\tau}\end{aligned} \quad (3)$$

□

Changing the ID of a sensor results in a change of its emission period, ordered at its next emission. If the ID is changed several times before a new emission, the sensor changes it emission period only once. Then, we depict an upper bound for the number of period change orders when a new sensor arrives or leave an environment, characterized by the number of ID changes.

Proposition 2. *When a new sensor arrives, the number of ID changes (counting the ID definition of the incoming sensor) is, by using 2-level round-robin:*

$$r = 2$$

At the exit of a sensor, the number of ID changes of the other sensors r is, by using 2-level round-robin:

- $r = 1$ *if the sensor that dies is of large period,*
- $r = 2$ *if the sensor that dies is of small period,*

This represents an upper bound on the number of period changes.

We can note that if the sensor field does not vary frequently, then this upper bound gives a good approximation of the number of period changes.

IV. Characterization of the number of active sensors by a continuous time Markov chain

A. Modeling of sensor arrivals and departures by random processes

We propose a modeling of sensor arrivals and departures by random processes.

First, we model the time before the arrival of a new sensor by an exponential law of parameter λ.

Moreover, we consider that a sensor leaves the environment for two main reasons:

• The sensor has consumed all its energy and switches off. We assume that the sensor has an initial energy which follows an exponential law of parameter γc_e, characterizing the variability of the battery state when it arrives in the environment. The sensor consumes an energy c_e at each emission, and leaves the environment if its energy is null. This model is strictly equivalent to say that for a sensor which has a period p, the time before running out of battery follows an exponential law of parameter $\frac{\gamma}{p}$.

• The sensor leaves the environment for another reason. This includes a physical departure from the environment, a technical failure or other. Here, we consider that the maximum time that a sensor can stay before leaving is an exponential law of parameter μ. Each sensor follows this law.

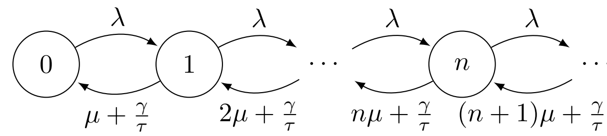

Fig. 1. Representation of the number of present sensors over time

B. Representation of the present sensors through time

The phenomenon "sensor entry", depicting the number of sensor inputs over time, is a Poisson process of intensity λ.

"out of battery", representing the number of sensors running out of battery over time, is a Poisson process of intensity $\frac{\gamma}{\tau}$ thanks to Proposition 1 and the additionality property of Poisson processes. "random exit", the number of sensors going out for other reasons, is a Poisson process that for n present sensors in the environment has an intensity $n\mu$.

This leads us to the definition of a continuous time Markov chain representing the number of sensors over time, illustrated in fig. 1.

C. Analytical expression related to monitoring metrics

We note Π_n the probability of having n active sensors in the steady state. By observing the transitions between $n-1$ and n states in the steady state, we obtain the following recurrence formulae:

$$\lambda \Pi_{n-1} = (n\mu + \frac{\gamma}{\tau})\Pi_n$$

This gives us the following formulae for the expression of the probability of being in state n in the steady state:

$$n \geq 1, \Pi_n = \left(\prod_{j=1}^{n} \frac{\lambda}{j\mu + \frac{\gamma}{\tau}}\right) \Pi_0$$

Also, since $\sum_{n=0}^{+\infty} \Pi_n = 1$, we get:

$$\Pi_0 = \frac{1}{1 + \sum_{n=1}^{+\infty} \left(\prod_{j=1}^{n} \frac{\lambda}{j\mu + \frac{\gamma}{\tau}}\right)}$$

The series $\left(\prod_{j=1}^{n} \frac{\lambda}{j\mu + \frac{\gamma}{\tau}}\right)_{n \in \mathbb{N}^*}$ converge, so $\Pi_0 \neq 0$ exist, hence the existence of a steady state.

The number of change IDs per unit of time considering n present sensors, is denoted $\dot{r}_n$. From Proposition 2, by splitting between small and large period sensors, $\dot{r}_n$ is:

$$\dot{r}_n = \left(\frac{\gamma}{\tau} \frac{2n_2}{2n_2 + n_1} + n_2\mu\right) \times 2 + \left(\frac{\gamma}{\tau} \frac{n_1}{2n_2 + n_1} + n_1\mu\right) \times 1 + 2\lambda \quad (4)$$

And so, the average ID changes per time unit, upper bound of the average number of period changes per unit of time, is:

$$\dot{r} = \sum_{n=1}^{+\infty} \Pi_n * \dot{r}_n \quad (5)$$

Considering the freshness function $u_T(\Delta_t) = e^{-\frac{\Delta_t}{T}}$, the average diversity if there are n sensors in the environment is:

$$D_n = Tn_1 \tfrac{1-e^{\frac{-2k\tau}{T}}}{2k\tau} + Tn_2 \tfrac{1-e^{\frac{-k\tau}{T}}}{k\tau} \quad (6)$$

The average diversity at equilibrium is therefore the sum of the diversities for each possible value of number of sensors present, weighted by the probability Π_n :

$$D = \sum_{n=1}^{+\infty} \Pi_n * D_n \quad (7)$$

V. SIMULATIONS

This section applies the 2-level round-robin method that is developed in the present paper. First, we show that it offers the best results in a context one can expect in mIoT, by comparing it to existing literature. Moreover, we confirm that the simulation fits the theoretical model from section IV-C. We show that we can rely on these theoretical results to express the link between the parameter τ and the quality metric, and thus determine the value of τ relevant to the monitoring needs.

A. Simulation frame

We consider a monitoring by the use of sensors over a given time. We evaluate the performance metrics after an initial duration. We consider that the sensors enter and leave the environment following the random processes defined in section IV-A. For both two methods, namely 2-level round-robin and periodic round-robin (from literature), and for a given parameter τ, we apply the period update function for each sensor message reception, and evaluate the overall performance after the simulation is completed. The parameters of the simulation are given in Table I, we use s as reference of time. Performance results are shown in figs. 2 and 3.

Parameter	Meaning	Value
	Beginning evaluation time	$10000s$
	Ending evaluation time	$100000s$
λ	parameter "sensor entry"	$0.1s^{-1}$
μ	parameter "random exit"	$0.001s^{-1}$
γ	parameter "out of battery"	0.01
Freshness function	Depletion over time	$e^{(-\frac{\Delta t}{T})}$
T	Relevance time of a data	$20s$

TABLE I
SIMULATION PARAMETERS

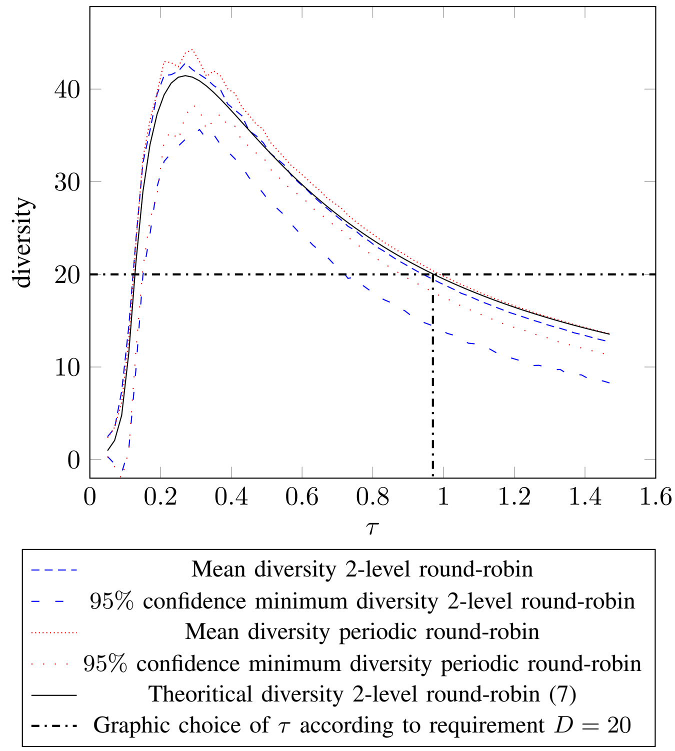

Fig. 2. -Mean diversity and 95% confidence minimum diversity based on the standard variation of diversities over time, comparing periodic round-robin and 2-level round-robin methods, for different values of $\tau \in [0.05, 1.5]$.
-Depletion of theoretical curve fitting the mean diversity of 2-level round-robin method.
-Example determining the parameter τ according to a requirement of mean diversity $D = 20$.

B. Comparison of 2-level round-robin with the literature

To the best of our knowledge, the only solution presented in the literature suitable for the context that one can expect for mIoT is [16]. The proposed function is parameterized by the maximum number of sensors transmitting in turn M and the target periodic reception τ. According to the considerations taken in the current paper, the method is valid only when M is equal to the total number of sensors present in the environment. We name this method **periodic round-robin**.

For a given τ, the periodic round-robin and 2-level round-robin methods return a same amount of information per unit of time (, i.e. $\frac{1}{\tau}$), and thus consume the same amount of energy by emissions. Hence, we compare these two methods according to a same value of τ.

First, from fig. 2, we notice that at a fixed τ, the average diversities of the two methods are close, although the periodic round-robin method proposes a slightly better diversity than 2-level round-robin. Moreover, since there is a strictly periodic reception of messages with periodic round-robin, the threshold allowing a 95% confidence minimum diversity is more centered around its mean than for 2-level round-robin, which does not guaranty strict periodic reception of messages.

Comparing only diversity, the method from literature gives the best results. However, looking at the number of period changes (from fig. 3), our solution is much better, with a much larger number of period changes for periodic round-robin.

The strict periodic reception imposed by the periodic round-robin method induces a high sensitivity to packet losses. Among other things, when a sensor is included in the solution, it must perfectly receive 2 consecutive messages of period modification order. Due to these latter arguments, periodic round-robin does not meet the requirements of mIoT (large amount of period change orders, not robust to packet loss), and has only slightly better performance in terms of diversity, compared to our new method. We can confidently state that our solution is the most adaptable in a framework such as the one we initially posed, modeling mIoT monitoring requirements.

C. Link between theoretical model and simulation, helping to determine the parameter τ

From the theoretical model proposed in section IV-C, we illustrate the link between the parameter of number of mes-

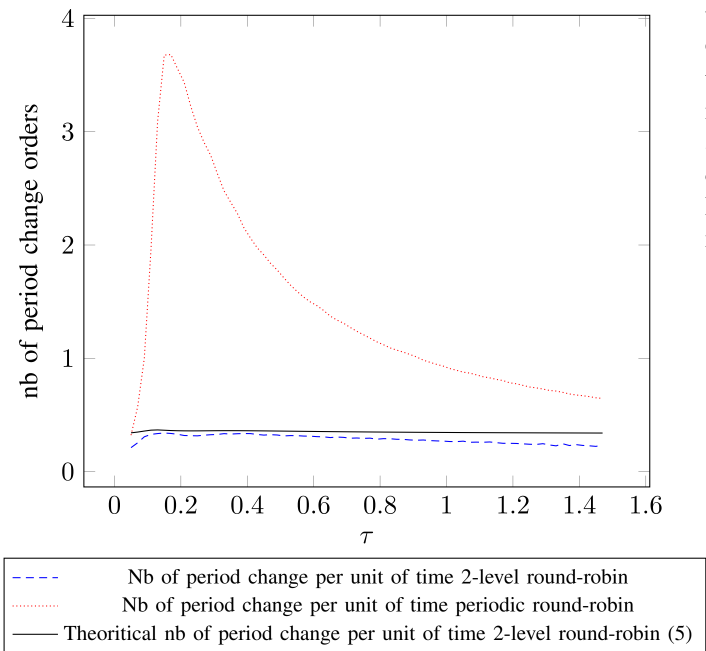

Fig. 3. Number of emission per time unit, comparing periodic round-robin and 2-level round-robin methods, for different values of $\tau \in [0.05, 1.5]$. Depletion of theoretical upper bound of the number of changes of 2-level round-robin method

sages sent per unit of time target $\frac{1}{\tau}$ and the average diversity - the number of order of maximum period modifications, in figs. 2 and 3. As constructed, the theoretical mean diversity (7) gives a similar result to the simulation. It is therefore possible, starting from a mean diversity objective, to choose without the help of the simulation to determine the value of τ for the 2-level round-robin method that will give the desired mean diversity. For example, if we want a mean diversity $D = 20$, we will choose a value of the parameter $\tau = 0.97$ (graphically depicted in fig. 2).

Moreover, thanks to the upper bound developed, we ensure that the number of orders of period modifications will not be too important (in particular in comparison with periodic round-robin), whatever the value of the parameter τ chosen.

VI. Conclusion et perspectives

This paper proposes an efficient monitoring solution that relies on miniaturized sensors on battery transmitting on a highly constrained network such as LoRaWAN Class A. Our method dynamically manages the inputs and outputs of sensors efficiently, while guaranteeing a homogeneous reception of information per time unit by a target reception parameter.

Our solution allows the efficient monitoring of an average physical quantity through the exploitation of highly constrained IoT objects in massive amount. This method, totally generic and easily applicable to LPWANs in mIoT context, validates the possibility of adopting such a paradigm for future monitoring solutions.

A lot of work remains to be done: (i) we have shown that it is possible to dynamically manage sensor inputs and outputs. Here, it would be relevant to look for some conditions in order to add and remove such sensors from information systems. Conditions would be based on a geographical position or on the relevance of the returned data, for instance. (ii) For the moment, we have considered that each message constitutes an atomic piece of information. However, each message contains different information, which is very dependent on the sensors. Incorporating these considerations into our monitoring policies is also a next step.

Acknowledgement

This work has been sponsored by the ValaDoE Chair.

References

[1] N. Varsier and J. Schwoerer, “Capacity limits of LoRaWAN technology for smart metering applications,” in *IEEE International Conference on Communications*, pp. 1–6, 2017.

[2] M. I. Nashiruddin and A. Hidayati, “Coverage and capacity analysis of LoRa WAN deployment for massive IoT in urban and suburban scenario,” in *5th International Conference on Science and Technology*, vol. 1, pp. 1–6, 2019.

[3] M. Carminati, “Trends and paradigms in the development of miniaturized sensors for environmental monitoring,” in *IEEE International Conference on Environmental Engineering*, pp. 1–5, 2018.

[4] D. Puccinelli and M. Haenggi, “Wireless sensor networks: applications and challenges of ubiquitous sensing,” *IEEE Circuits and Systems Magazine*, vol. 5, no. 3, pp. 19–31, 2005.

[5] G. Hurlburt, J. Voas, and K. Miller, “The internet of things: A reality check,” *IT Professional*, vol. 14, pp. 56–59, 05 2012.

[6] J. Gubbi, J. Buyya, S. Marusic, and M. Palaniswami, “Internet of things (IoT): A vision, architectural elements, and future directions,” *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645–1660, 2013.

[7] K. Janowicz, A. Haller, S. J. Cox, D. Le Phuoc, and M. Lefrançois, “Sosa: A lightweight ontology for sensors, observations, samples, and actuators,” *Journal of Web Semantics*, vol. 56, pp. 1–10, 2019.

[8] C. Alippi, G. Anastasi, M. Di Francesco, and M. Roveri, “Energy management in wireless sensor networks with energy-hungry sensors,” *IEEE Instrumentation Measurement Magazine*, vol. 12, no. 2, pp. 16–23, 2009.

[9] V. Raghunathan, S. Ganeriwal, and M. Srivastava, “Emerging techniques for long lived wireless sensor networks,” *IEEE Communications Magazine*, vol. 44, no. 4, pp. 108–114, 2006.

[10] S. Preeth, R. Dhanalakshmi, R. Kumar, and M. Shakeel P, “An adaptive fuzzy rule based energy efficient clustering and immune-inspired routing protocol for WSN-assisted IoT system,” *Journal of Ambient Intelligence and Humanized Computing*, 12 2018.

[11] J. Tang, Z. Zhou, J. Niu, and Q. Wang, “EGF-tree: An energy efficient index tree for facilitating multi-region query aggregation in the internet of things,” in *IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing*, pp. 370–377, 2013.

[12] J. Tang, Y. Xiao, Z. Zhou, L. Shu, and Q. Wang, “An energy efficient hierarchical clustering index tree for facilitating time-correlated region queries in wireless sensor network,” in *9th International Wireless Communications and Mobile Computing Conference*, pp. 1528–1533, 2013.

[13] O. Akgül and B. Canberk, “Self-organized things (SoT): An energy efficient next generation network management,” *Computer Communications*, vol. 74, 07 2014.

[14] N. Kaur and S. Sood, “An energy-efficient architecture for the internet of things (IoT),” *IEEE Systems Journal*, vol. 11, no. 2, pp. 796–805, 2017.

[15] U. Gupta, Y. Tripathi, H. Bhardwaj, S. Goel, A. Kaur, and P. Kumar, “Energy-efficient model for deployment of sensor nodes in IoT based system,” in *Twelfth International Conference on Contemporary Computing*, pp. 1–5, 2019.

[16] M. Maudet, M. Batton-Hubert, P. Maille, and L. Touain, “Emission scheduling strategies for massive-iot: implementation and performance optimization,” in *IEEE/IFIP Network Operations and Management Symposium*, 2022.

[17] J. Gruijter, D. Brus, M. Bierkens, and M. Kotters, *Sampling for Natural Resource Monitoring*. Springer, 01 2006.

[18] M. Tolk, "The levels of conceptual interoperability model (lcim)," *Proceedings IEEE Fall Simulation Interoperability Workshop*, 2003.

[19] W. Wang, A. Tolk, and W. Wang, "The levels of conceptual interoperability model: applying systems engineering principles to m&s," *ArXiv*, vol. abs/0908.0191, 2009.

[20] M. Bouzeghoub and V. Peralta, "A framework for analysis of data freshness," in *International Workshop on Information Quality in Information Systems*, pp. 59–67, 06 2004.

[21] A. Even and G. Shankaranarayanan, "Utility-driven assessment of data quality," *SIGMIS Database*, vol. 38, p. 75–93, May 2007.

[22] Y. Sun and B. Cyr, "Sampling for data freshness optimization: Non-linear age functions," *Journal of Communications and Networks*, vol. 21, pp. 204–219, 2019.

[23] T. Bouguera, J. Diouris, J. Chaillout, R. Jaouadi, and G. Andrieux, "Energy consumption model for sensor nodes based on LoRa and LoRaWAN," *Sensors*, vol. 18, no. 7, 2018.