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***Abstract*—In current sensor-based monitoring solutions, each application involves a customized deployment and requires significant configuration efforts to adapt to changes in the sensor field. This becomes particularly problematic for massive deployments of battery-powered monitoring sensors.**

In this paper, we propose a generic solution for sensor emission scheduling to ensure overall regular sensor data emissions over time (at a rate chosen by the user), with limited management costs incurred by sensors' arrivals and departure. Our objectives include monitoring quality–which we quantify through a "diversity" metric encompassing that information value depletes with time–and some management cost–quantified by the number of orders sent to sensors. Modeling arrivals and departures as random processes, we compute those performance metrics as functions of the overall data reception period selected, and evaluate them against an alternative scheduling method existing in the literature. We show that our solution provides similar monitoring quality (diversity), but with significantly reduced management costs, making it better suited for Massive IoT contexts.

I. Introduction

A. New versatile monitoring solutions

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 projected (500 billion connected objects), automating and standardizing 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].

B. Existing methods for managing emissions from energy autonomous sensors

Sensors are usually powered by batteries and consume most of their energy when transmitting information. 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.

In 2018, [10] proposes to aggregate to a single sensor all the information provided by the surrounding sensors in order to limit the number of sends to the system. The article uses the TOPSIS AHP method for the determination of the sensor clusters. Other information aggregation methods, based on index tree structures, are proposed in [11,12].

In 2014, [13] introduces the concept of "Self-Organized Things". The authors 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. The authors 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.

All of the studies mentioned above discuss different techniques to save energy from IoT sensors. However, none of them encompass hypothesis one can expect for mIoT. First, it is considered standard sensors are emitting periodically on a star topology, where it is possible to redefine their emission period only when they send a message. Moreover, these sensors are deployed with a minimum of human assistance: we have no information about them, like positioning. Finally, one of the main objectives of having a massive amount of sensors is the adaptability to changes in the field of sensors: managing the arrival of new sensors, the departure, the deactivation, etc.

More recently, [16] proposes a framework for developing monitoring policies adhering to these requirements. The paper gives a first instantiation, imposing one constraint: having strict periodical receptions coming each time from one of the sensors. We wish to build on that work, by proposing a more realistic/applicable solution for mIoT.

C. Paper contributions and organization

Assume we wish to track the variations over time of a physical quantity, using a large amount of sensors entering and leaving the monitoring system. Our goal in this paper is to receive a temporally homogeneous data stream, since this is considered the simplest and most efficient way to track the evolution of a physical quantity [17].

In addition, the proposed solution must reach the dynamic level of the Conceptual Interoperability Model [18,19]: sensors that enter and leave the environment must be dynamically managed by the monitoring system. No matter how many sensors are active, our goal is to rely on all the present sensors in order to receive the same (average) number of messages over time. This management of the sensors has a cost, which is quantified by the number of order sent to reconfigure sensor emission periods. Finally, the solution must be easy to implement in order to be robust against packet loss issues, common in most LPWAN technologies.

A typical example scenario is that of a connected wine cellar, which would rely on connected objects supposedly embedded in wine bottles (illustrating the mIoT paradigm). The objective would be to take advantage of the bottles (sensors) present in the cellar to control the interior temperature and to detect a possible change. The solution should not be too disrupted when new sensors arrive or leave, while making the most of all the sensors present in the study area.

The main contributions of this paper are summarized below:

i) Based on a representation of sensors as the leaves of an almost complete full binary tree, we develop a period update function allowing the temporally homogeneous reception of messages at the desired target rate, while limiting the number of period change orders upon sensor arrivals and departures.

ii) Through a model with random sensor arrivals and departures, we compute performance metrics as a function of the target reception rate set by the user.

iii) We compare our solution to existing sensor management methods, and confirm its relevance in a posed framework such as the one intended for mIoT.

The rest of the paper is organized 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 establish its properties. section IV develops the stochastic model used to compute performance metrics. Simulations comparing our solution to other existing methods and confirming the analytical results are shown in section V. We conclude in section VI, by proposing perspectives for future work.

II. Problem statement

A. Hypothesis on sensors

We consider wireless sensors on battery, sending information periodically about a physical quantity towards the monitoring system. After each transmission, the sensor opens a short listening time, to receive information from the outside (LoRaWAN Class A standard), which we use to send sensor period change orders. In particular, in this paper, we focus on defining sensor management strategies that aim to enable optimal monitoring while limiting sensor energy consumption. We characterize a sensor emission management strategy by a **period update function** f, which manages the sensor emission period over time. The function takes as argument the transmission history and the new message received, returning a target transmission period. If this transmission period is different from the current one, an order of period change is made to the sensor during its listening window.

In our case, each message contains only the message content and the ID of the sending sensor. One of the objectives of this document is to manage the comings and goings of sensors during monitoring. Receiving a message with an unknown sensor ID means that it is a new sensor. Also, when a sensor leaves the environment, we assume that a message with empty content is received by the monitoring system during its next transmission.

These assumptions help us handling new scenarios. Sensors can enter the system at any time, the monitoring system recognizes them as soon as they transmit and integrates them into the management solution. Also, the departure of a sensor can be caused by several reasons, which are now taken into account in the policies we propose: (i) the sensor runs out of energy, (ii) it physically leaves the environment, or no longer describes the quantity in a relevant way (failure, description of an isolated phenomenon).

B. Definition of metrics

By contrast with all already existing monitoring quality metrics, where objectives are around the maximization of coverage area [20,21], here we assume the position of the sensors is unknown. Hence, to characterize the quality of a data, we rely on the freshness function which quantifies the relevance of a data, relatively to its age Δ_t, compared to a reference time T [22-24].

Applying the notion of freshness to a sensor, considering its most recent emission, we will use the following definition of **diversity** (developed in [16]).

Definition 1. *The diversity at time t is defined as the sum of the freshness of all sensors that were activated at that time.*

We define the ***mean diversity*** *as the average of the diversities over a given monitoring time, denoted by D.*

An understandable way to explain this would be to say that the diversity at time t is the number of information coming from different sources, all weighted by their age-related relevance.

In addition to this monitoring quality metric, we are interested in looking at the management cost, quantified by the **number of period change orders**. When the gateway is giving orders of period change, it cannot intercept messages sent by other sensors. Moreover, the redefinition of the transmission period implies an additional energy cost for the sensors. Hence, this has direct impact on energy efficiency metric and

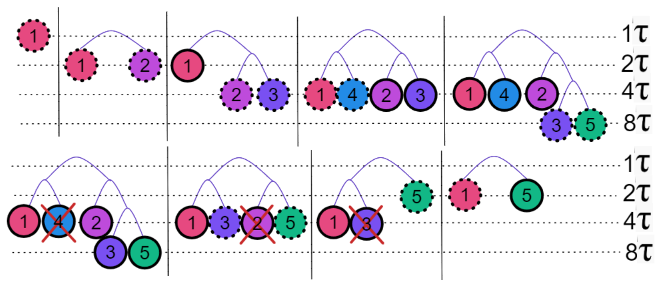

Fig. 1. Binary tree representation according to appearances and disappearance of sensors; each sensor is represented with a colored circle with an ID. A dotted line around a sensor means that its position was changed in the tree. The part above represents the inclusion of 5 sensors one by one, indexed from 1 to 5; the below one shows the departure of 3 sensors (symbolized by a cross).
Horizontal dotted lines represent target emission periods so that a sensor crossing a line have the corresponding emission period.

quality metric: lower lifetime of sensors, lower packet delivery ratio.

A sensor emission management method induces a data-flow received by the gateway. We are therefore interested in quantifying the metrics defined above in relation to the same **number of sensor emissions per time unit**, which should be minimized to lower the overall consumption of the sensors. Note that for the method developed in the paper, the number of sensor emissions per time unit is a parameter chosen by the user.

Hence, the objective for the user is then to guarantee a sufficient diversity of reception, minimizing the number of sensor emissions per time unit while limiting the number of period changes orders.

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

[1]

A. Representation of the present sensors in a binary tree

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, as leaf nodes in a binary tree.

First, a sensor alone has an initial dept of 0 (on the root). Then, when a second sensor arrives, the new tree is composed of a 2 branches tree where each sensor is on a leaf. A schematic principle is proposed in fig. 1.

More generally, sensors are represented as leaves of a binary tree that is full: each node contains 0 or 2 sons. Moreover, we constrained the tree to be almost complete (all levels are filled except the last level) so that the tree doesn't get too unbalanced.

By these considerations, the present sensors can be grouped into two categories representing the two maximum depths of the tree, that we define as respectively **maximum depth** and **minimum depth** categories.

The tree changes as soon as the sensor field changes, i.e. each time a sensor is added or removed.

•*When a new sensor arrives in the environment*, a minimum depth sensor changes position by increasing its depth by one, with the new sensor as a complementary sensor (only 2 branches to link them), both as maximum depth thereafter.

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

· If the leaving sensor is of maximum depth. In this case, as built, there is another sensor of maximum depth complementary. This last one becomes of minimum depth by decreasing its depth by one.

· If the leaving sensor is of minimum depth. A sensor of maximum depth come in substitution to it. The complementary of the latter becomes of minimum depth, decreasing its depth by one.

B. Development of the period update function

[2]

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 their depth in the binary tree. For a given τ, we define the function as:

Definition 2. *When receiving a new message:*

- it may be necessary to update the binary tree, if the sensor ID is new, or if the message content is empty (meaning that the sensor is gone).

*After this, considering a sensor which dept in the tree is d, emitting a message at time t. Then **2-level round-robin** with parameter τ redefines the sensor period as: $f_\tau(d) = 2^d * \tau$.*[3]

Note that the metric of number of period change orders is increased only if the sensor need to modify its emission period.

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 period of a sensor of depth d is exactly $2^d * \tau$. In reality, when a sensor position 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, $k = 2^{\lfloor \log_2(n) \rfloor}$. Then, according to the binary tree representation, we can say that:

[1] From Patrick: pourquoi "development" dans le titre?

[2] From Patrick: pourquoi "development"?

[3] From Patrick: Eviter le symbole *, préférer soit rien soit $\times$

•$n_{\text{min}} = 2k - n$ sensors emit at period $k\tau$ and are of minimum depth. To understand this, if we add n_{min} additional sensors, they become complementary to each of the sensors of minimum depth to make the binary tree perfect, with exactly $2k$ sensors.
•$n_{\text{max}} = 2(n-k)$ sensors emit with an emission period of $2k$ and are of maximum depth.

Proposition 1. *The sum of the inverses of the periods of the active sensors*[4] *remains unchanged at the addition of a new sensor, and is equal to:*

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

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

$$\begin{aligned} \sum_{i \text{ present sensor}} \tfrac{1}{p_i} &= \tfrac{n_{\text{max}}}{2k\tau} + \tfrac{n_{\text{min}}}{k\tau} \\ &= \tfrac{2n-2k}{2k\tau} + \tfrac{2k-n}{k\tau} \\ &= \tfrac{1}{\tau} \end{aligned}$$

□

Changing the position of a sensor in the tree results in a change of its emission period, ordered at its next emission. If the position 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 sensor position changes in the tree.

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

At the exit of a sensor, the number of position changes of the other sensors is, by using 2-level round-robin: $r = 1$ if the sensor that dies is of maximum depth and $r = 2$ if the sensor that dies is of minimum depth.

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. Modeling the entrances/departures of sensors

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

[4]From Patrick: Formulation bizarre, pourquoi ne pas juste dire qu'à tout moment, le temps moyen entre deux envois est τ?

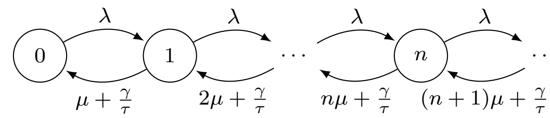

Fig. 2. Representation of the number of present sensors over time

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 $\frac{\gamma}{p}$. "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.
• 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. "random exit", the number of sensors going out for other reasons over time, is a Poisson process that for n present sensors in the environment has an intensity $n\mu$.

This leads to the definition of a continuous time Markov chain representing the number of sensors over time, illustrated in fig. 2.

B. 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:

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

Thanks to $\sum_{n=0}^{+\infty} \Pi_n = 1$, this gives us the following formulae for the expression of the probability of being in state n in the steady state:

$$\begin{aligned} n \geq 1, \quad \Pi_n &= \left(\prod_{j=1}^{n} \tfrac{\lambda}{j\mu + \frac{\gamma}{\tau}} \right) \Pi_0 \\ \Pi_0 &= \frac{1}{1 + \sum_{n=1}^{+\infty} \left(\prod_{j=1}^{n} \frac{\lambda}{j\mu + \frac{\gamma}{\tau}} \right)} \end{aligned}$$

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 position changes per unit of time considering n present sensors, is denoted[5] $\dot{r}_n$[6]. From Proposition 2, by splitting between small and maximum depth sensors, the

[5]From Patrick: denoted **by**
[6]From Patrick: notation bizarre : pour moi le point au-dessus d'une grandeur marque la dérivée par rapport au temps de cette grandeur

sensors that die in minimum depth lead to 2 position changes, and 1 for maximum depth. Thus $\dot{r}_n$ is:

$$\begin{aligned}\dot{r}_n = \quad & 2\left(\frac{\gamma}{\tau}\frac{2n_{\text{min}}}{2n_{\text{min}}+n_{\text{max}}} + n_{\text{min}}\mu\right) \\ + \quad & \left(\frac{\gamma}{\tau}\frac{n_{\text{max}}}{2n_{\text{min}}+n_{\text{max}}} + n_{\text{max}}\mu\right) + 2\lambda\end{aligned}$$

And so, the average position changes per time unit of sensors in the tree, upper bound of the average number of period changes per unit of time, is:

$$\dot{r} = \sum_{n=1}^{+\infty} \Pi_n * \dot{r}_n \tag{1}$$

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:

$$D_n = Tn_{\text{max}}\frac{1-e^{\frac{-2k\tau}{T}}}{2k\tau} + Tn_{\text{min}}\frac{1-e^{\frac{-k\tau}{T}}}{k\tau}$$

[7] 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 :

$$D = \sum_{n=1}^{+\infty} \Pi_n * D_n \tag{2}$$

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 that can be expected from mIoT, by comparing it to other existing methods. Moreover, we confirm that the simulation fits the theoretical model from section IV-B.

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 all methods, 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. 3 and 4.

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

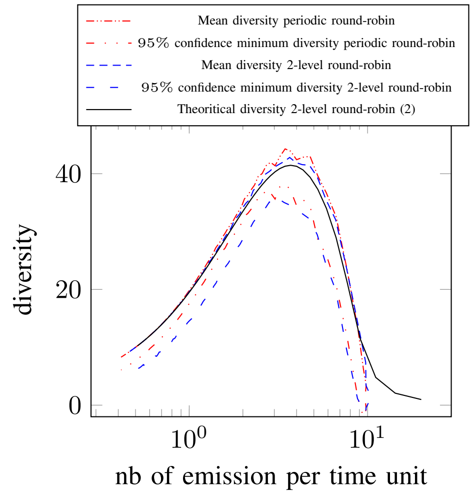

Fig. 3. Mean diversity and 95% confidence minimum diversity based on the standard variation of diversities over time, comparing periodic round-robin and 2-level round-robin methods, according to the average number of emission per time unit. Depletion of theoretical curve fitting the mean diversity of 2-level round-robin method.

B. Performance evaluation

To the best of our knowledge, the only solution presented in the literature suitable for the context one can expect for mIoT is [16]. Here, we do not make a comparison with other methods, because they are quite out of the scope of this paper: they rely on greater knowledge of the sensors. Moreover, for the most part, they modify the emission period of the sensors at each emission, which tends to disqualify them directly.

The function proposed by [16] allows the strict periodic emission from one of the present sensors of a period τ, in the form of a round-robin between all the present sensors. We name this method **periodic round-robin**. This method would give an optimal diversity value, since it makes different sensors transmit in turn, while guaranteeing a strict periodic reception of messages.

We want to compare all these methods with respect to the same number of sensor emissions per unit of time. In our case, this is directly related to the parameter of the two methods: the number of sensor emissions per time unit corresponds to $\frac{1}{\tau}$. We propose to compare them with respect to the diversity, and the number of period change orders.

First, from fig. 3, we notice that the average diversities of the two methods are close. 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. Therefore, periodic round-robin provides better results if a user has a minimum diversity requirement of 95%.

Focusing exclusively on the diversity under the simplified consideration of the simulation, periodic round-robin

[7]From Patrick: Comment obtiens-tu cette expression ? Via une intégrale ? Ou bien tu utilises des propriétés de la loi exponentielle ?

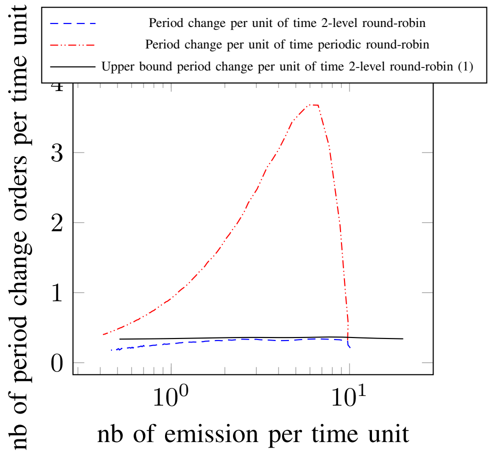

Fig. 4. Number of period change per time unit, according to the number of emission per time unit. Theoretical upper bound of the number of changes of 2-level round-robin method

is slightly better than 2-level round-robin. However, from fig. 4, the 2-level round-robin method involves a low rate of period change. For periodic round-robin, the number of orders performed by the gateway is exorbitant; about the same amount of transmission as performed by the sensors. Using arguments given in section II-B, the periodic round-robin solution lowers the QoS significantly, makes the sensors consume more, and induces a diversity that will actually be lower in real conditions.

Moreover, the strict periodic reception imposed by the periodic round-robin method induces a high sensitivity to packet losses. When a sensor is included in the environment, it must perfectly receive 2 consecutive messages of period modification order. On the contrary, the two-level round-robin does not rely on the perfect reception of the sensors' orders: if an order is not well received, another order will be sent the next time.

Hence, 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.

From the theoretical model proposed in section IV-B, we illustrate the link between the parameter of number of messages sent per unit of time target $\frac{1}{\tau}$ and the average diversity - the number of order of maximum depth modifications, in figs. 3 and 4. As constructed, the theoretical mean diversity (2) 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. 3).

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 allows having an optimal diversity of sensor receptions ensuring a limited cost of adaptation to sensor field changes.

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.

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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] G. Maudet, M. Batton-Hubert, P. Maille, and L. Toutain, "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] S. Pourshahabi, N. Talebbeydokhti, G. Rakhshandehroo, and M. Nikoo, "Spatio-temporal multi-criteria optimization of reservoir water quality monitoring network using value of information and transinformation entropy," *Water Resources Management*, vol. 32, 08 2018.

[21] C. Castello, J. Fan, A. Davari, and R. Chen, "Optimal sensor placement strategy for environmental monitoring using wireless sensor networks," in *42nd Southeastern Symposium on System Theory*, 2010.

[22] 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.

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

[24] 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.