Efficient Message Scheduling for Dynamic Massive IoT Monitoring

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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 LPWAN sensors emissions scheduling, to ensure overall regular sensor data emissions over time (at a rate chosen by the user), while limiting management costs incurred by sensors' arrivals and departure. Our objectives include monitoring quality that we evaluate through a "diversity" metric encompassing that information value depletes with time, plus 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 alternative scheduling methods. We show that our solution is 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 for 2030 [1]), 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].

[1]https://emarsonindia.com/wp-content/uploads/2020/02/Internet-of-Things.pdf

B. Literature on management of 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 and Model

A. A dynamic set of battery-powered 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, which we use to send sensor period change orders. These considerations respect the specifications of LPWANs and keep being suitable for all type of star topology networks.

In this paper, we focus on defining sensor management strategies that approach 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 returns a new transmission period to be applied by the sensor that sent the latest message. If this transmission period is different from the current one, an order of period change is sent to the sensor during the listening window.

In our case, each message sent by sensors contains the message content and the ID of the sending sensor. One of the objectives of this paper is to manage arrivals and departures 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 model it as a message with empty content received by the monitoring system on its next transmission.

These assumptions help us handling new scenarios. When a new sensor first emits, the monitoring system recognizes it and integrates it into its management policy. Also, the departure of a sensor can be caused by several reasons, 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 (sensor that would be identified as irrelevant).

B. Performance metrics

By contrast with already existing monitoring quality metrics, where objectives are around the maximization of the coverage area [20,21], here we assume the position of the sensors is unknown and we will want to get information from a large number of sensors. To characterize the quality of data, we rely on its *freshness*, which we quantify through a function that decreases as data ages [22,23].

In this paper, we use as a performance metric the sum of the freshness values of the latest data from each sensor, which we will call **diversity** (as also developed in [16]).

Definition 1. *The* diversity *at time t is the sum of the freshness of the latest emission of all sensors that are (or were) in the environment.*

Diversity at time t can be interpreted as the current value of information, accumulated from different sources: since the goal is to track the evolution of a physical quantity (e.g., temperature), only the latest emission from each sensor needs to be considered, and each piece of data is weighted by its age-related relevance (freshness).

In addition to this monitoring quality metric, we are interested in 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; plus, the redefinition of the transmission period can imply an additional energy cost for the sensors. Therefore, a large number of period change commands has a direct impact on monitoring quality: sensors die sooner and packages are more likely to be lost.

The objective for the user will be to find a satisfying trade-off between those metrics, by ensuring an accurate monitoring (high diversity) while controlling the management costs (number of period change orders). Note that setting (fixed) short emission periods for all sensors might satisfy both objectives, but this would accelerate battery depletion, ultimately degrading the diversity metric as sensors die.

III. The **2-level round-robin** monitoring method

This section presents our proposed solution to compute individual sensors' emission periods, while maintaining a constant "overall" period τ of data receptions. The basic idea is to have all sensors emit with a "similar" (up to a factor 2) period, while needing to send only one or two period change orders for each sensor arrival or departure. This is in contrast to [16], where all sensors had the exact same period, but each arrival/departure involved an order sent to each sensor.

A. Construction of the period update function

To ensure the emission periods of all sensors never differ by more than a factor 2, we will represent sensors as the leaves of a *full balanced binary tree*, and impose that a sensor with depth d in the tree have an emission period set to $2^d\tau$. Figure 1 illustrates how the tree evolves as sensors enter and leave the system.

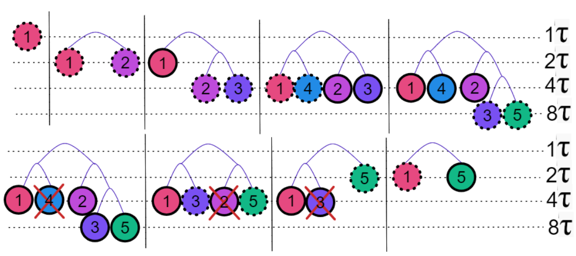

Fig. 1. Evolution of the binary tree representation as sensors enter *(top)* or leave *(bottom)* the system; each sensor is represented with a colored circle with an ID, and horizontal dotted lines represent the emission periods of the sensors at that depth. A dotted line around a sensor means that its position (and height) was changed in the tree (hence a period change order is needed). The top part represents the successive arrivals of sensors indexed from 1 to 5; the bottom one shows the successive departure of sensors 4, 2, and 3 (departures are symbolized by a cross).

The binary tree being balanced means that all levels are filled except possibly the last one, hence leaves only exist in the last (and possibly penultimate) level(s). The active sensors can therefore be grouped into two categories, whether their representation in the tree is in the last or second-last level in the tree, that we define as respectively **high-depth** and **low-depth** categories. We should note that if all the sensors belong to the same category, by convention we consider them all high-depth.

•*When a new sensor arrives in the environment*, if all sensors are high-depths, we now consider all of them being low-depths, so that in all cases there is a low-depth sensor. Hence, one of these (low-depth sensors) changes position by increasing its depth by one, and the new sensor becomes its *sibling* (with a same parent), both being high-depth thereafter.

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

· If the leaving sensor is of high-depth, by construction it has a sibling, which becomes of low-depth by decreasing its depth by one. This is the case for the exits of sensors 2 and 3 in fig. 1.

· If the leaving sensor is of low-depth, it is substituted with a high-depth sensor, whose displacement is treated like the departure of a high-depth sensor (described above). This is the case for the departure of sensor 4 in fig. 1.

For a sensor i that just sent a message, the period update function f that we suggest is then simply $f(H) = 2^{d_i}\tau$, with d_i the depth of node i in the current version of the tree that the gateway maintains thanks to the history H of messages received so far.

B. Properties

We show here that our suggested period update function meets the objectives initially set, regarding the reception at a global rate of τ, with a limited number of period change orders over time. To that goal, we make the approximation that the period of a sensor of depth d is exactly $2^d\tau$ at any moment, while in reality, when a sensor changes positions in the tree (because of another sensor's arrival or departure), its emission period is only modified after its next emission.

For n sensors, let us denote by k the minimum depth of the tree, $h = \lfloor \log_2(n) \rfloor$. Then, according to the binary tree representation, we can say that:

• $n_{\text{min}} = 2^{h+1} - n$ sensors emit at period $2^h\tau$ and are of low-depth. To understand this, if n_{min} additional sensors are added in the environment, they become complementary to each of the sensors of low-depth in order to make the binary tree *perfect*, with exactly 2^{h+1} sensors.

• $n_{\text{max}} = 2(n - 2^h)$ sensors emit with an emission period of 2^{h+1} and are of high-depth.

Proposition 1. *At any moment, the average time between two sensor emissions is τ. Mathematically, if S denotes the current set of sensors in the tree, and p_i the emission period of sensor i, we have*

$$\sum_{i \in S} \frac{1}{p_i} = \frac{n_{\text{max}}}{2^{h+1}\tau} + \frac{n_{\text{min}}}{2^h\tau} = \frac{2n - 2^{h+1}}{2^{h+1}\tau} + \frac{2^{h+1} - n}{2^h\tau} = \frac{1}{\tau}.$$

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 its emission period only once. Therefore, counting the number of position changes in the tree of a sensor provides us with an upper bound for the actual number of period change orders over time, a useful insight on the management cost of our method. From our tree construction, those position changes are quantified below.

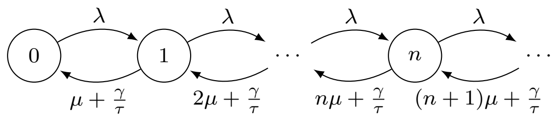

Fig. 2. Markov modeling of the number of active sensors over time

Proposition 2. *When a new sensor arrives, the number of position changes in the tree (counting the position definition of the incoming sensor) is $r = 2$.*

When a sensor leaves the environment, the number of position changes is $r = 1$ if the sensor that dies is of high-depth and $r = 2$ if it is of low-depth.

IV. A Markovian model for performance evaluation

In this section, we develop a model to analyze as a Markov chain the evolution over time of the number n of jointly used sensors. This will be used to estimate the steady-state values of our performance metrics.

A. Modeling sensor arrivals and departures

We model sensor arrivals as a Poisson process, with an average arrival rate of λ sensors per time unit.

Regarding departures, we assume that a sensor can leave the environment for two main reasons:

- The sensor has consumed all its energy and switches off. We consider that the sensor has an initial energy which follows an exponential law with mean c_e/γ, with c_e the energy consumed for each emission, and γ a parameter characterizing the variability of the battery state when joining the environment. To have a continuous-time Markov chain, we slightly relax the periodic-emission assumption from sensors, by assuming that each sensor i with period p_i emits messages according to a Poisson process with rate $1/p_i$ (note that in our simulations, emissions are really). With this model, the time before running out of battery follows an exponential law of parameter $\frac{\gamma}{p_i}$. At any moment, the time before one sensor leaves because of battery depletion is then exponentially distributed, with parameter $\sum_{i \in S} \frac{\gamma}{p_i} = \gamma/\tau$, thanks to Proposition 1.
- The sensor leaves the environment because it has been physically removed, turned off, or has undergone a technical failure. For each sensor, the time before this occurs is modeled through an exponential law of parameter μ, hence with n sensors the time before one departure for this reason is exponentially distributed with parameter $n\mu$.

With those assumptions, the continuous-time process describing the number n of sensors in the system is a Markov chain, whose transition diagram is displayed in fig. 2.

B. Performance metrics estimation

We now use the Markov chain previously described to derive the steady-state distribution on n, and corresponding expected values for our performance metrics (approximating the actual ones).

Denoting by π_n the steady-state probability of having n active sensors, we have $\lambda \pi_{n-1} = (n\mu + \frac{\gamma}{\tau})\pi_n$ for all $n \geq 1$, leading to $\pi_n = \left(\prod_{j=1}^{n} \frac{\lambda}{j\mu + \frac{\gamma}{\tau}}\right)\pi_0$ with $\pi_0 = \frac{1}{1+\sum_{n=1}^{+\infty}\left(\prod_{j=1}^{n} \frac{\lambda}{j\mu+\frac{\gamma}{\tau}}\right)}$.

The number $\dot{r}_n$ of position changes of sensors in the tree per time unit if there are n sensors is, by splitting between low and high-depth sensors (from Proposition 2): $\dot{r}_n = 2\left(\frac{\gamma}{\tau}\frac{2n_{\text{min}}}{2n_{\text{min}}+n_{\text{max}}} + n_{\text{min}}\mu\right) + \left(\frac{\gamma}{\tau}\frac{n_{\text{max}}}{2n_{\text{min}}+n_{\text{max}}} + n_{\text{max}}\mu\right) + 2\lambda$.

An upper bound for the average number of period change orders sent per time unit is then $\dot{r} = \sum_{n=1}^{+\infty} \pi_n \dot{r}_n$.

Considering the freshness function $u_T(x) = e^{-\frac{x}{T}}$, the average diversity for one sensor of emission period p is $T/p(1-e^{-p/T})$. Then, we can estimate the average diversity D_n for n sensors as

$$D_n = T n_{\text{max}} \frac{1-e^{\frac{-2^{h+1}\tau}{T}}}{2^{h+1}\tau} + T n_{\text{min}} \frac{1-e^{\frac{-2^{h}\tau}{T}}}{2^{h}\tau},$$

and the (steady-state) average diversity D as

$$D = \sum_{n=1}^{+\infty} \pi_n D_n. \tag{1}$$

V. Simulation results

This section compares the 2-level round-robin method developed in this paper to other existing strategies, highlighting that it is the best fitted method under the hypotheses and objectives considered. Moreover, we show that the analytical study can help find the user parameter τ maximizing the diversity.

A. Comparative performance evaluation

1) Simulation frame: We consider an initially empty system, with sensors entering and leaving as per the random processes described in section IV-A, except emissions are really periodic. We assume two consecutive phases: in the first one, many sensors enter the environment, while in the second one, sensors enter the environment more rarely. We start observing the environment (i.e., computing the metrics) after an initialization time.

For all three methods, we apply the period update function after each sensor message reception, and evaluate the overall performance after the simulation is completed. The parameters of the simulation are given in Table I.

Recall our two metrics are diversity (that varies over time) and management cost (overall number of period update orders). Rather than the average diversity value over time, we display here its 5th percentile, that is, the diversity value that is guaranteed 95% of the time. For the management cost, we just count the period update orders sent per time unit.

2) Other scheduling methods for comparison: To the best of our knowledge, the only solution from the literature that is suitable for the context one can expect for mIoT is from [16]. Indeed, other existing methods tend to be outside our scope: they rely on much greater knowledge of the sensors. Moreover, for the most part, the methods modify the emission period of

Parameter	Meaning	Value
	Initialisation time	$20000s$
	Duration of the first phase	$50000s$
	Duration of the second phase	$50000s$
λ_1	Sensor arrival rate - first phase	$0.1s^{-1}$
λ_2	Sensor arrival rate - second phase	$0.001s^{-1}$
$1/\gamma$	Average battery level	1000 emissions
μ	Departure rate (other than battery depletion)	$0.00002s^{-1}$
Freshness	Value depletion with time x	$e^{-x/T}$
T	Relevance time of data	$100s$

TABLE I
SIMULATION PARAMETERS

the sensors at each emission, which tend to disqualify them since our objective is to minimize the number of orders given by the monitoring system.

The function proposed by [16] allows to receive strictly periodic transmissions globally with a period τ, through a synchronized round-robin scheduling over all active sensors. Let us call that method **periodic round-robin**; its main drawback regards managements costs, since for each arrival or departure all the active sensors have to change their emission period.

Moreover, we propose to compare to the simplest sensor management method, that fixes the same (given) emission period p to all newly arrived sensors. That method, that we call **static**, minimizes the number of period change order, but does not adapt to the changing number of present sensors.

3) Performance evaluation: fig. 3(a) illustrates a simulation trajectory, showing the diversity over time for the 3 management methods, with parameters $\tau = 0.1s$ for the two round-robin methods, and $p = 150s$ for the static one. The curves show how the period update function manages sensor emissions, in particular how it adapts to sensor field changes. We graphically show our overall diversity metric, that is the 5th-percentile over the observation period: 95% of the time, the instantaneous diversity exceeds that value.

The overall performance metrics of the three methods for different parameters are shown in fig. 3(b,c), for different parameter values (τ on the bottom x-axis for round-robin methods, and p for static on the top).

From fig. 3(b), the best methods under the simulation conditions are the round-robin ones, each insuring the best monitoring quality for τ around 0.1s. The static method performs a little less well in our simulations, even with the most favorable fixed period p. One reason for this is that it does not adapt to the number of present sensors, hence may overuse the sensors when there is a high density, rather than saving their energy for later.

Note also that the periodic round-robin and the 2-level round-robin provide fairly similar diversity over time, although the periodic round-robin leads to a more stable diversity, due to the periodic round-robin method ensuring strict periodic message receptions.

However, those strict periodic receptions come with a high management cost, as illustrated in fig. 3(c). For $\tau = 0.1$, periodic round-robin implies 59 times more period update messages to the sensors than 2-level round-robin. This is due to our tree structure, that limits the number of period change orders to 1 or 2 for each arrival or departure, instead of n for periodic round-robin.

B. Search for the optimal parameter

We show here how to choose the parameter τ to have the best monitoring quality, in a steady-state situation (we take here the second phase of our simulation, as an example). In fig. 4(a), we show the instantaneous diversity over time when $\tau = 5$, with a steady-state behavior around the theoretical expected value computed in (1) from the Markovian model. In fig. 4(b), we compare that theoretical mean diversity from (1) with the simulated fifth percentile for different values of τ.

From these results, if sensor arrivals and departures are reasonably modeled with Markovian models, then we can approximate the mean diversity in the steady state, for a given user parameter τ. This can be used to choose a well-performing τ, which should also be close to optimal for the fifth percentile, as suggested by fig. 4 (b).

VI. CONCLUSIONS AND PERSPECTIVES

This paper proposes a data emission strategy for monitoring solutions relying on miniaturized battery-powered sensors, transmitting on a highly constrained network. Our method guarantees the quality of the monitoring (in the sense of a diversity metric), with a limited cost of adaptation to sensor field changes.

Our solution can for example be used to monitor an average physical quantity with a large number of IoT objects. It is generic and easily applicable to LPWANs in the mIoT context, and validates the possibility of adopting such a paradigm for future monitoring solutions.

A lot of work remains to be done: (i) it could be relevant to not always use all the sensors that are present, e.g., turn some off because of their geographical position or the quality of the data they return, 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 sensor. Incorporating these considerations into our monitoring policies is also a next step.

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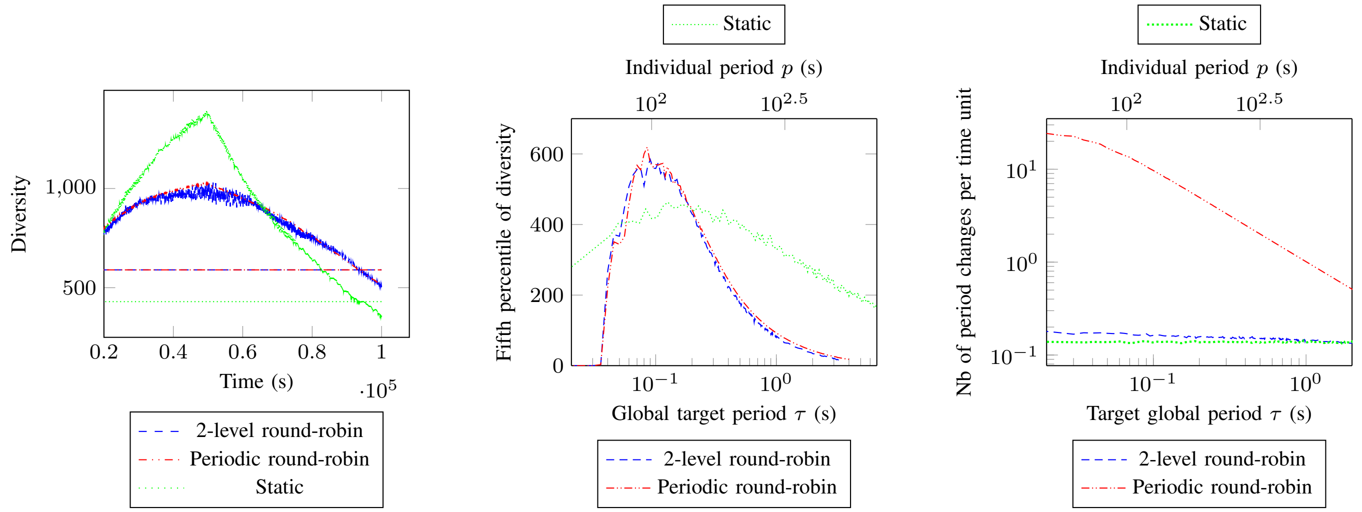
REFERENCES

[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.

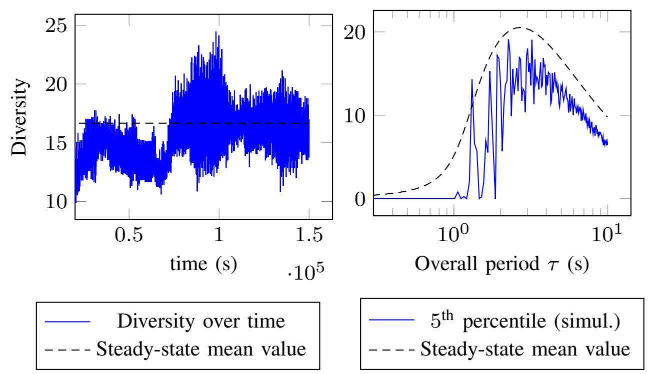
[2] M. I. Nashiruddin and A. Hidayati, “Coverage and capacity analysis of LoRa WAN deployment for massive IoT in urban and suburban scenario,” in *5th International Conference on Science and Technology*, vol. 1, pp. 1–6, 2019.

[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.



(a) (b) (c)

Fig. 3. (a): Diversity over time for a simulation, with global period $\tau = 0.1$s for round-robin methods and individual period $p = 150$s for the static method, and diversity guarantee (fifth percentile) for each method (horizontal lines). (b,c): Performance metrics for the three methods, versus their parametrization.



(a) (b)

Fig. 4. Simulation versus theoretical results, with constant parameters for sensor arrivals and departures. One simulation trajectory of diversity over time is shown in (a), with the corresponding steady-state mean value for the Markovian model, for $\tau = 5$. In (b) we compare the fifth percentile of simulated diversity with the theoretical mean diversity: both reach their maximum for approximately the same global period τ.

[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.