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Abstract

In today's monitoring solutions, each application involves custom deployment and requires significant configuration efforts to accommodate sensor changes. In contrast, in this paper, a massive deployment of battery-powered sensors is considered and we propose a more versatile monitoring solution that is not tied to physical device deployment.

We characterize a monitoring strategy by formally defining a function that modifies the transmission period of a sensor that has just transmitted. Such a function can be customized to manage the tradeoff between overall monitoring accuracy and sensor energy consumption, for which we suggest a formalization through a generic metric of monitoring accuracy (to be weighed versus the monitoring network lifespan).

We introduce a specific two-parameter instantiation for the period update function, that ensures strictly periodic emissions from sensors even when new sensors join the system over time. We show through simulations how the two parameters–target emission period and number of jointly used sensors–can be chosen according to the objectives for the monitoring, by highlighting the Pareto front for accuracy and energy-efficiency.

1 Introduction

1.1 Context: flexible and generic solutions for the future of monitoring

Advances in electronics and signal processing have enabled the miniaturization of hardware. Thanks to the emergence of new energy-saving communication

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techniques, a new class of applications has arisen: miniaturized devices deployed on a large scale capable of sensing their environment [6], [15], [23].

In a classical approach, a few highly reliable sensors are placed at the points of relevance, so as to provide meaningful information. This solution is static and rigid in time. In contrast, the so-called massive Internet of Things (mIoT) considers a large quantity of cheap energy-autonomous sensors, with no prior information about their quality or position. This paradigm shift is a game-changer for the development of monitoring solutions, as it requires great flexibility in sensor management [11], [13], [18]. This allows the development of versatile solutions, independent of the physical development.

1.2 Overview of research on wireless sensor energy efficiency

Sensors are usually battery-powered, whose energy is consumed during the transmission of information. The more the data transmitted, the more accurately the environment is monitored but at the same time, the faster the energy is consumed. Due to these energy limitations, it is necessary to propose efficient management of sensor emissions, finding the compromise between monitoring quality and resource consumption.

First, from the early 2000s, energy-saving functionalities for devices have been proposed [2], [19]. Triggered and adaptive sensing methods allow the sensor's sampling rate to be adapted to variations in the environment.

In 2018, the authors of [17] propose to aggregate the information provided by multiple surrounding sensors to a single collector. The paper uses the fuzzy methods AHP and TOPSIS to determine cluster-heads that forward the aggregated information to the gateway. This energy-efficient solution significantly reduces the gateway traffic load. Other information aggregation methods, based on index tree structures, are proposed in [21], [22]. Those last approaches are particularly suitable for heterogeneous geographical distributions of sensors.

In 2014, [1] introduces the concept of "Self-Organized Things", where sensors are self-managed, following energy optimization mechanisms. Those mechanisms allow sensors to be put into sleep mode if their spatial coverage is already guaranteed by other active sensors. In 2017, [14] proposes a complete energy-efficient hierarchical architecture for IoT. The paper develop a continuous modification of the sensors' sleep times, based on the battery level, the standard variation of the returned values and the distance to other sensors. New results of [14] are proposed in 2019 [12], validating the relevance of the sleep mode usage.

The solutions presented above lack applicability in a context such as mIoT monitoring. Indeed, it is important to consider the following characteristics:

• mIoT solutions are mostly based on LPWANs, as the least energy intensive network model. This is a star architecture, where direct sensor-to-sensor communications are not allowed.

• Sensors are built to send periodic messages, and their transmission period can only be changed during a short window-time after a message is sent to the

gateway.
• One of the main goals we can expect from mIoT is automatic deployment. Therefore, it is needed to handle dynamic integration of sensors without having any prior knowledge about location.

To the best of our knowledge, there is no solution for the problem of optimally monitoring an environment under these hypotheses.

1.3 Positioning and development of the proposed solution

In this paper, we consider a large amount of "things" deployed in an area, that we want to use for monitoring purposes. The goal is to minimize the gap between the environment to monitor and its representation by the system. This is in general at the cost of more measures being sent by sensors, hence a tradeoff between the accuracy of the monitoring and the energy consumption.

The sensors we consider are transmitting messages periodically and are in sleep mode between each message, to save energy. Following the behavior of LoRaWAN class A objects, a listening window is open after each message sent, during which the monitoring system can modify the emission period. Sensors have limited energy in their battery, that is consumed over time. Note that the system does not know how many sensors will be in use, nor their respective positions, and will have to integrate them in the monitoring.

In this paper, we first introduce a standard formulation of a monitoring strategy, through the formal definition of a period update function, modifying the emission period of a sensor that has just transmitted. In addition, to measure the relevance of these functions, we propose a generic metric of monitoring quality, somehow quantifying the informative value of the messages received by all sensors, with the value of data depleting over time. By choosing the total monitoring duration as the overall energy efficiency indicator, this leads us to a clear definition of a multi-objective problem.

We apply our approach to a specific case where an additional constraint is imposed: taking into consideration that the simple but effective method for tracking a physical quantity over time is to obtain information at regular time intervals [10], we want the sensors to be programmed so that a message is sent periodically by one of them. We then develop a period update function that ensures the periodic transmission of messages from one (and only one) of the sensors, and dynamically adapts to new sensors entering the monitoring system. The function is configured by two parameters, namely the number of jointly emitting (through a cycle) sensors and the target emission period. We observe that the greater the number of sensors transmitting jointly, the greater the diversity of the data stream, but the more energy-consuming the solution. Therefore, we show that a compromise must be made between the diversity of the information received (i.e., the quality of the monitoring) and the total monitoring duration (i.e., the energy efficiency).

The contributions of this paper can be summarized as follows.

- We formalize the definition of a period update function.

- We propose a generic monitoring quality indicator, which together with the total network lifetime characterize a multi-objective problem.
- We construct a 2-parameter period update function, ensuring the strict periodic emission by one of the sensors. We compute analytical bounds on the monitoring duration according to the parameters used.
- We perform a numerical comparison in order to illustrate the approach and discuss the fitting parameters of the developed period update function.

The rest of the paper is organized as follows. Section 2 defines the studied mathematical problem and proposes a formal definition of the period update function. We propose a definition of the monitoring quality, which together with the total monitoring duration forms the two performance indicators of a period update function. In Section 3, we introduce a two-parameter period update function ensuring periodic emissions, and derive bounds for the total monitoring time according to the chosen parameters. Numerical investigations applying the proposed monitoring strategies are carried out in Section 4. Finally, we conclude and highlight the limits of the studied model in Section 5, suggesting directions for future works.

2 Problem statement and model

2.1 Assumptions and notations on sensors

We are interested in the monitoring of an environment with IoT sensors. Sensors are dynamically integrated in the management system at the time of their first emission, also called instant of **activation**. We consider a total of n sensors on battery indexed by their order of activation: 0 being the first sensor to be activated and $n-1$ the last.

The sensor i activates at time t_i, with an initial energy e_i. It sends messages periodically. Following each transmission, it is possible to modify the transmission period of the sending sensor, through a downlink message sent during the sensor reception window.

This paper revolves around how to define the new emission period to assign to each sensor after its emission, so as to ensure periodic emissions overall, while managing a tradeoff between the monitoring quality (through a measure of diversity) and energy efficiency (through the total lifetime of the monitoring network). We therefore use the notion of **period update function** f, defined in more detail hereafter, for that purpose.

A sensor is said to be **active** at a time t if, at that time, it is activated and has enough energy to emit again. Conversely, a sensor that is not active anymore at time t is said to be **dead**. We talk about the **end of monitoring** when there are no more active sensors. Thus, we consider for the whole paper that the n sensors activates without the monitoring stopping in the meantime.

In the strategy developed hereafter, we also consider a specific consumption model: only the consumption related to emissions and period changes is taken

into account (with respective energy cost of c_e and c_r), since the other consumptions can be considered as negligible [3], [4]. Finally, we assume that each sensor spends its energy until its battery is exhausted.

2.2 Formalization of the monitoring strategy: the period update function

A monitoring strategy defines the requirements for receiving data from active sensors in the environment. It is characterized by the period update function which, upon reception of a sensor message, redefines its emission period. The function takes as an argument the history of transmissions until then, and returns a new period of emission.

Definition 1. *Let us denote by H_t the transmission history up to and including time t, summarizing the gateway's knowledge.*

*A **period update function** is a function f:*

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

where $f(H_t)$ represents the new transmission period for a sensor that has just sent a message at time t.

For the function developed hereafter, each message sent by a sensor contains: its ID, the remaining energy in the battery, its transmission period; all that information is added to H_t for each new message sent.

The function f is used for each new received message. In particular, f defines the initial period of sensors. In practice, if the function f returns a different period from the sensor's current one, a downlink transmission from the gateway (with an energy cost c_r to the sensor) takes place to modify that period, so that after sending a message at time t, a sensor's period always equals $f(H_t)$.

2.3 Defining a monitoring quality metric

In most monitoring applications, the objective is to obtain a spatio-temporal coverage of the study area thanks to adapted sampling [7], [16]. However, here we assume that we do not know the position of the sensors. This is why we introduce the notion of **average diversity**: the amount of information from different sources weighted by their relative relevance. We characterize here the relevance of a data by its aging.

The **freshness** of a message evaluated at t [5], [9], [20] will represent the relevance of the transmitted information as a function its age. We model it through a positive decreasing function taking as argument the difference between the observation time t and the message sending time t', i.e., $\Delta_t = t - t' > 0$.

Sensors send messages to the management system, updating their emission period after an emission if told so by the gateway. We apply the notion of freshness to a sensor by considering its most recent emission, in order to propose the following definition of diversity.

Definition 2. *The diversity at time t is defined as the sum of the freshnesses of all sensors that have been activated at that time.*

For a given period update function f, we define the ***average diversity*** *as the average of the diversities over the entire monitoring duration. The average diversity related to a period update function f is denoted by $D(f)$.*

Below are two examples of freshness functions:

- $u_T(\Delta_t) = \mathbb{1}_{\Delta_t < T}$, for some value $T > 0$, meaning that the value of some received data remains constant during T then suddenly drops to 0.
- $v_T(\Delta t) = \exp\left(-\frac{\Delta t}{T}\right)$, with a smoother depletion of the information value over time.

The parameter T characterizes the relevance time of data: if T is large, then we consider that "old" data remains relevant.

To illustrate the meaning of the diversity measure, consider the freshness function $u_T(t)$: if a period update function f induces a diversity X, then that means that over a sliding window of size T, messages are received on average by X different sensors.

2.4 A multi-objective problem

In this paper, we are also interested in the overall energy efficiency, rather than in local efficiency: our metric for energy efficiency will be the total **monitoring duration**, that is the time between the activation of the first sensor and the end of the monitoring.

In this way, we characterize a bi-objective problem: we can quantify and compare the qualities of period update functions through our two performance metrics, for energy efficiency and monitoring quality.

3 Ensuring periodic emissions from at most M sensors

In this section, we develop a strategy to guarantee, by defining the period update function, that there is one (and only one) periodic emission, with a period τ, and that at most M sensors emit in turn (M and τ are chosen by the monitoring manager).

3.1 Definition of effectiveness

An effective method for tracking an average physical quantity over time is to collect regular samples [10]. Hence, starting from the instant of the first message received at time t_0, we want in this paper to receive exactly one message at regular time intervals from one of the active sensors. By introducing the time step parameter τ, that property will be named **effectiveness**, as formalized below.

Definition 3. *A period update function is said to be* ***effective over the instants of period*** τ *if the sensor emissions verify that:*

- *Starting at* t_0*, one and exactly one emission is made at each time step* τ *as long as there are active sensors.*
- *Apart from the activation, no sensor emits a message between each time interval* τ*.*

For such periodic update functions, we can quantify the energy efficiency relative to a fixed τ, called the sample span.

Definition 4. *Given an efficient period update function* f*, its* ***sample span*** $L(f)$ *is defined as the number of consecutive emissions at time steps* τ *until the end of the monitoring.*

The **monitoring duration** is then simply defined as $\tau L(f)$.

We develop below an analytical upper bound for the span (and thus, duration) of efficient period update functions.

Proposition 1. *If no sensor activates exactly at an instant of the form* $t_0 + k\tau$ *for an integer* k*, then any effective period update function will have a sample span upper-bounded by:*

$$L_{\max} := \frac{\sum_{i=0}^{n-1} e_i - nc_e - (2n-1)c_r}{c_e} \tag{2}$$

The proof is developed in Appendix B.

In the rest of this section, we develop a specific function, that we will denote by $f_{M,\tau}$, and that we will show is effective over the instants of period τ, while jointly using up to M sensors to provide some diversity.

3.2 Toward an effective period update function with controlled diversity

Considering the scenario of tracking an average physical quantity, we want to develop a periodic update function allowing to receive messages at regular intervals; the target time τ between two emissions will be the first parameter of our function.

In a context such as the one predicted for mIoT, it is possible to have some misplaced or faulty sensors. Moreover, in some cases, it may be necessary to receive spatially diversified information to get a more accurate global view. It may then be necessary to receive information from various sources (quantified by the average diversity). The second parameter of the function, that we will denote by M, will be the number of sensors transmitting in a round-robin fashion (when possible), to take into account this possible requirement.

For given parameters M and τ, we therefore want to define a period update function $f_{M,\tau}$ such that at most M sensors transmit in turn, will overall periodic emissions with period τ. If any, the other sensors will be set in sleep mode, and successively take over the dead sensors. Hence,

• when the number of active sensors is below M, all active sensors emit in turn. In that case, the active sensors have an emission period set to τ times the number of active sensors. If a new sensor activates, all the sensors then change their emission period to maintain that property.

• As soon as they are more than M active sensors, our proposed scheme works differently: M sensors emit periodically, with a period of $M\tau$, and the period of all the other sensors is set so that they successively take over dead sensors. When one such sensor takes over the death of another one, its period is set to $M\tau$, to ensure the same role.

An illustrative example of sensor emissions using the period update function is shown in Fig. 1.

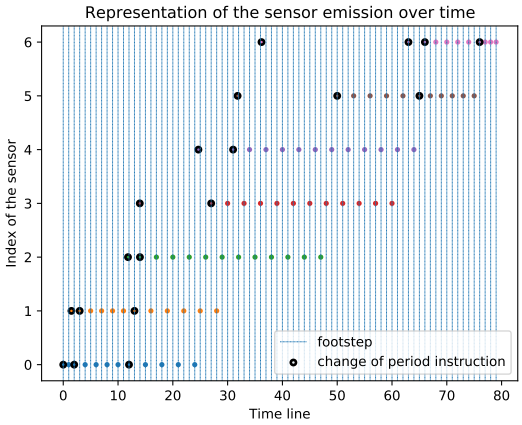


Figure 1: Illustration of sensor emissions using $f_{M,\tau}$ for $M = 3$ and $\tau = 1$. 7 sensors, of equal battery-capacities $e = 15$ and with emission and period change consumption $c_e = c_r = 1$, randomly activate between time 0 and 40. The emissions of sensor i appear as dots on the $y = i$ line. Black points indicate period changes after an emission, through the function $f_{M,\tau}$. As was the initial goal, there is exactly one emission on each blue vertical line, meaning that we receive exactly one message every τ. Note that when there are at least 3 active sensors, the emissions are only shared between 3 sensors emitting periodically.

3.3 Detailed definition of the period update function

First of all, we define the function in the case where the emitting sensor is already active. When the total number of active sensors does not exceed M i.e. an insufficient number of sensors has activated or a too important number

of sensors is out of battery. In this case, the function defines for each sensor a period $f(H_t) = |\Pi(t)|\tau$. When there are enough active sensors ($|\Pi(.)| > M$), then $f(H_t) = M\tau$. Thus, for already active sensors, the period update function is defined by:

$$f_{M,\tau}(H_t) = \min(M, |\Pi(t)|)$$

When a sensor activates, there are 2 different cases. If the number of active sensors is less than M, then new sensors get included in the *round-robin*. The activating sensor should emit τ after the sensor that has emitted just before. We firstly consider that the previous emission corresponds to a sensor already active. Thus, the period update function is defined by:

$$f_{M,\tau}(H_t) = \tau|\Pi(t)| - (t - \text{last emission})$$

The previous sensor emits on the instants of period τ. Thus, denoting "%" the operator remainder of the division algorithm, $(t-\text{last emission}) = (t-t_0)\%\tau$, so that:

$$f_{M,\tau}(H_t) = \tau|\Pi(t)| - (t - t_0)\%\tau \tag{3}$$

This last formula generalizes to the case where the previous emission does not come from an already active sensor.

We consider now the second case: there are already at least M active sensors. Then, a sensor that activates is put to sleep until a sensor dies. The sensor takes over from a sensor whose relay is not taken i.e. emits $M\tau$ after its last emission:

$$f_{M,\tau}(H_t) = \text{death time of a sensor } - t + M\tau$$

We now introduce an object allowing to keep in memory the deaths of each sensor. We define *death-date* the list sorted by ascending date of the dead sensors whose relay is not assured. The list is updated with each new message from a sensor.

Algorithm 1 defines the **death update algorithm**, updating the list *death-date*. This algorithm is executed each time a message is received, following the use of the period update function.

This lead us toa formal definition of $f_{M,\tau}$:

Definition 5. *The period update function $f_{M,\tau}$ used for a sensor just after it sent a message is defined by:*

- *if first message received from that sensor* ,
  $$f_{M,\tau}(H_t) = \begin{cases} \tau|\Pi(t)| - (t - t_0)\%\tau & \text{if } |\Pi(t)| \leq M \\ \textit{death-date[0]} - t + M\tau & \text{if } |\Pi(t)| > M \end{cases} \tag{4}$$
- *Else,* $f_{M,\tau}(H_t) = \min(M, |\Pi(t)|)\tau$

The death-date list, whose size is at most M, is updated to always contain the sorted list of sensor death instants whose relays are not covered. In particular, when a sensor activates while $|\Pi(t)| \geq M$, the death date of the sensor whose relay has just been taken is replaced by the predicted death of the new one.

Note that for the special cases $M = 1$ and $M = n$, combinatorial and memory space simplifications can be used to implement the function $f_{M,\tau}$.

Algorithm 1 Death update algorithm

i corresponds to the sensor ID, e_i the energy of the sensor just after it has emitted the message and p_i the period which is set by $f_{M,\tau}$. The function called "add" (and "update") add (and update) elements to the list while sorting it in ascending date order. The function "remove" is working if the element is still in death-date.

Require: death-date,time t , sensor index i, period p_i, remaining energy e_i

if $|\Pi(t)| \leq M$ **then**
  if $e_i < c_e$ **then**
    Remove sensor i from death-date
  else if $p_i \neq M\tau$ **then**
    Update death-date of sensor i with value $t + p_i + M\tau \left\lfloor \frac{e_i - c_e - c_r}{c_e} \right\rfloor$
  else if $p_i = M\tau$ **then**
    Update death-date of sensor i with value $t + p_i + M\tau \left\lfloor \frac{e_i - c_e}{c_e} \right\rfloor$
  end if
else
  if fst emission from i **then**
    add death-date of sensor i with value death-date[0] $+ M\tau(1 + \left\lfloor \frac{e_i - c_r}{c_e} \right\rfloor)$
    remove death-date[0] from death-date
  end if
end if

3.4 Properties and performance of $f_{M,\tau}$

The following propositions establish that $f_{M,\tau}$ behaves as we wanted it to and guarantees a minimum monitoring duration.

Proposition 2. *The $f_{M,\tau}$ period update function is effective on the instants of period τ.*

Proposition 3. *Considering sensors with the same initial energy e, the sample span of $f_{M,\tau}$ is at least:*

$$L_{\min}(f_{M,\tau}) := \frac{ne - nc_e - (2n - 1 + M(M-1))c_r}{c_e} \tag{5}$$

and at most:

$$L_{\max}(f_{M,\tau}) := \frac{ne - nc_e - (2n - \mathbb{1}_{M=1})c_r}{c_e} \tag{6}$$

Proof (sketch). As long as there are no more than M active sensors, in the worst scenario each new sensor that activates disrupts the existing schedule, forcing all other sensors to consume energy to change their emission period.

To get the upper bound, we on the contrary consider the most favorable scenario, that is when the first M sensors activate in the same time interval of length τ, and n is a multiple of M. If all sensors are activated (almost)

simultaneously, the scheduling is only disturbed once, which has little impact on the overall system energy. In that case, the solution is close to the global optimum $L_{\max}$ of Proposition 1. Except in that condition, at a fixed τ, an increase in the M parameter generally has a negative influence on the monitoring duration. □

Formal demonstrations of Propositions 2 and 3 are respectively developed in Appendices C and D

In addition to reducing monitoring time, choosing a large value of M can induce high downlink consumption, which in the worst case increases quadratically with respect to M. Downlink consumption congest the network, and can have a significant impact on Quality of Service [8].

4 Performance results

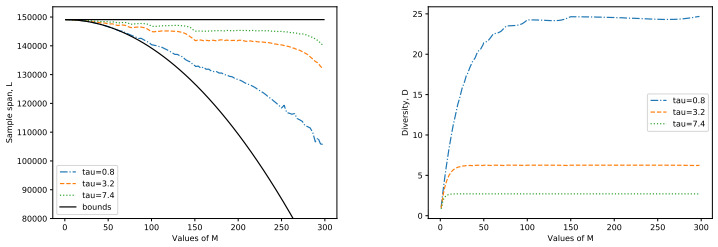
This section discusses the experimental analysis of the period update function $f_{M,\tau}$, carried out through simulations. We propose to study the performance by using the function $f_{M,\tau}$ for different values of the number of sensors jointly emitting M and of the target emission period τ. From the initial conditions defined in Table 1, we apply the period update function $f_{M,\tau}$ for each emission of sensor until the end of the monitoring, in order to determine monitoring duration and average diversity performance indicators.

Parameter	Meaning	Value
n	Number of sensors	300
$e_i = e$	Battery capacity	500
$c_e = c_r$	Emission and reception energy cost	1
$t_i - t_{i-1}$	Time between 2 consecutive activations	15π
T	Relevance time of a data	20
Freshness function	Depletion of the data over time	v_{20}

Table 1: Simulation parameters

4.1 Influence of the number M of sensors jointly transmitting

For a fixed target emission period τ, the parameter M influences both performance metrics, as Fig. 2 illustrates. The sample span (thus, the monitoring duration) decreases when M increases (Fig. 2(a)), confirming the trends of the bounds developed in Proposition 3. Between $M = 1$ and $M = 300$, we observe a relative decrease of 6.2% for $\tau = 7.4$ of the total monitoring time. It drops to 34.02% of relative difference for $\tau = 0.8$, since the sensors get scheduled more quickly and therefore are disturbed more times when new sensors activate.



(a) (b)

Figure 2: Representation of some performance indicators using the period update function $f_{M,\tau}$, varying the number of jointly emitting sensors M, for a few target emission periods τ. (a) corresponds to the sample span with analytical bounds, (b) the diversity.

At a fixed τ, larger values of M offer greater diversity, as more sensors update their value periodically (Fig. 2(b)), with diminishing diversity gains as M increases (hence a concave function).

4.2 "Diversity versus duration" trade-offs

We represent in Fig. 3 the monitoring time and average diversity metrics obtained with $f_{M,\tau}$, for different values of (M, τ). Of course, one would like to be as north-east as possible in the figure (high diversity and high monitoring duration). Interestingly, the Pareto front is not always attained with the same value of M: if the network designer preferences (or the application needs) favor the monitoring duration, smaller values of M should be preferred, while larger values should be chosen if diversity matters most.

If the need for diversity is not very strong, then choosing a small value of M and a relatively large τ time step (compared to the relevance time of data T) allows to extend considerably the total monitoring duration (and induce a low consumption of the downlink). On the other hand, if the need for diversity is more important, it is necessary to choose a larger value of M, and a small time step τ, leading to a more frequent energy consumption, at the price of a shorter monitoring duration. As an example, if the diversity requirement is $D > 10$, then choosing $M = 44$ and $\tau = 1.97$, ensure a monitoring duration of $2.9 * 10^5$.

Hence the methodology leading to Fig. 3 can be adapted to the specific parameters of a new scenario, and applied to determine the best-performing parameters M and τ for the needs of the application.

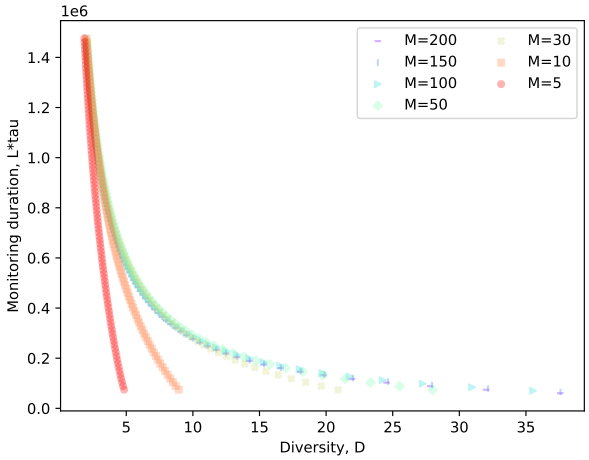


Figure 3: Performance of the update period function $f_{M,\tau}$, for several values of M (given in the legend) and τ (from 0.5 to 10 by 0.1 increments). Each point corresponds to the two-dimensional performance metrics (Diversity on the x-axis and monitoring duration on the y-axis), for fixed parameters M, τ of the update function.

5 conclusions and future works

This paper presents a method for scheduling sensor emissions in an initially uncoordinated environment, thanks to a 2 parameters emission scheduling strategy. Considering a massive number of deployed battery sensors, we show that a trade-off has to be made between a precise tracking and an extended monitoring time. We present a method to set the appropriate parameters of the proposed solution to find a compromise according to the preferences (energy efficiency vs. monitoring quality).

In addition, we provide new general bases for the development of centralized approaches based on requirement one can expect for mIoT. Starting from the first approach proposed in this paper, the forthcoming challenge will be to look for more dynamicity in monitoring strategies: (i) the hypothesis of strict regular message transmission should be relaxed in order to gain flexibility and robustness, (ii) In addition to the dynamic inclusion of sensors already managed in the proposed strategy, the solution must also adapt to unplanned departures, (iii) We supposed here that all the sensor data where equivalent. In a real system, messages can be very disparate; it is important to characterize this information heterogeneity to include it in monitoring policies.

Acknowledgement

This work has been sponsored by the ValaDoE Chair.

A Github repository

It is possible to access the github repository that helped us to create the different figures of the concerned document:

`https://github.com/gwenmaudet/emission_strategies_to_optimize_monitoring.git`

B Upper bound of all the period update functions effective over the instants of period τ

The following notation is introduced:

Definition 6. *Let f be an effective period update function. Then we denote by $r_i(f)$ the number of period changes of the sensor i.*

Proposition 4. *The sample span of a period update function f, effective over the instants of period τ is:*

$$L(f) = \sum_{i=0}^{n-1} \left\lfloor \frac{e_i - c_e - c_r r_i(f)}{c_e} \right\rfloor \tag{7}$$

Proof. We denote by $d_i(f)$ the number of emissions (excluding activation) on time steps τ without collisions with other emissions.

The consumption of a sensor is divided between: it first emission c_e, each period change $c_r r_i(f)$, and since f is effective, the collision-free emissions on the time steps τ $c_e d_i(f)$

$$e_i \geq c_e(1 + d_i(f)) + c_r r_i(f)$$

By definition of the behavior of the sensor, it sends messages until the battery is empty:

$$d_i(f) = \left\lfloor \frac{e_i - c_e + c_r r_i(f)}{c_e} \right\rfloor$$

The total number of emissions on the time steps τ corresponds to the number of emissions (excluding activation) of each sensor without collision i.e. by definition of $d_i(f)$:

$$L(f) = \sum_{i=0}^{n-1} d_i(f)$$

□

Lemma 1. *Let f and g be 2 effective period update functions. If $\forall i, r_i(f) \geq r_i(g)$, then the sample span of g is greater than that of f : $L(f) \leq L(g)$.*

Proof. We use directly Proposition 4. □

Demonstration of Proposition 1(page 7):

Proof. We will show that for a period update function, the minimum number of period changes for a sensor is:

$$r_i(f_{\max}) = 1 + \mathbb{1}_{i>0}$$

In order to exclude particular cases, let us suppose that the sensors do not activate at the instants of period τ i.e.

$$t_i \not\equiv t_0[\tau] \tag{8}$$

Then, let us consider g an effective period update function. We will show that $\forall i, r_i(g) \geq r_i(f_{\max})$.
-$i = 0$. Necessarily, g change at least one time the period of the sensor 0. Then $r_0(g) \geq r_0(f_{\max})$.
-$i > 0$. Let us suppose $r_i(g) < 2$, then $r_i(g) = 1$. We note p its period of emission. Since g is effective, its first emission after activation is on the time steps τ i.e. $t_i + p \equiv t_0[\tau]$. But from (8), $t_i \not\equiv t_0[\tau]$, so $p \not\equiv 0[\tau]$. Looking at the following emission, $t_i + 2p$, we come across an absurdity. Thus $r_i(g) \geq r_i(f_{\max})$.

Hence, $f_{\max}$ gives a minimum number of changes for each sensor. From Lemma 1, $f_{\max}$ gives a maximum bound to the sample span. The sample span is equal to:

$$L(f_{\max}) = \sum_{i=0}^{n-1} \left\lfloor \frac{e_i - c_e - c_r(1 + \mathbb{1}_{i>0})}{c_e} \right\rfloor$$

□

C demonstration of the effectiveness of the proposed period update function

We first introduce some tools to track the behavior of sensors over time, and then propose a proof of the effectiveness of the function $f_{M,\tau}$.

C.1 Sensor representation set and characterization over the instants of period τ

Definition 7. *A sensor i active at time t is represented by $E_i(t)$ such that:*

$$E_i(t) := \begin{cases} e_i(t) \geq c_e : \textit{remaining energy at time } t \\ p_i(t) > 0 : \textit{emission period} \\ \delta_i(t) > 0 : \textit{time before sending a message after } t \end{cases} \tag{9}$$

$E_i(t) := \emptyset$ if the sensor i is not active at time t (didn't activate yet or is dead).

We denote by $\Pi(t)$ the set of active sensors at time t, $|\Pi(t)|$ is the quantity of active sensors at time t i.e.

$$i \in \Pi(t) \Leftrightarrow E_i(t) \neq \emptyset$$

We define $E(t)$, so that:

$$E(t) := (E_i(t))_{i \in \Pi(t)}$$

The formalization of the state $E(.)$ will help to prove that the function $f_{M,\tau}$ is effective, i.e. the emissions of the sensors (except activations) are on the instants of period τ.

First of all, we can define $E(.)$ until the first emission of the first sensor:

$$\begin{gathered} t < t_0, E(t) = () \\ E(t_0) = (E_0(t_0)), E_0(t_0) = \begin{cases} e_0(t_0) = e_0 - c_e - c_r \\ p_0(t_0) = f(H_{t_0}) \\ \delta_0(t_0) = f(H_{t_0}) \end{cases} \end{gathered} \tag{10}$$

The initial emission period of the sensor is defined by f. The sensor consume energy for its first emission and the setting of its period: $c_e + c_r$. Then, from time t_0, the next emission occurs after a duration of $f(H_{t_0})$.

Moreover, $E(.)$ evolves over time, for each emission. We characterize the variations from state $E(t)$ to state $E(t + \Delta t)$.

A sufficient condition for the sensors to transmit at most once between t and $t + \Delta t$ is that their period is larger than the time step Δt, or more generally that the minimum of the period update function is greater than Δt.

$$f \geq \Delta t \tag{11}$$

We now characterize the evolution from t to $t + \Delta t$ under condition (11).

If i is a sensor that is active at time t, i.e. $i \in \Pi(t)$. Moreover, if the sensor does not transmit between t and $t + \Delta t$, $\delta_i(t) > \Delta t$. Then, the periods and energies states don't change. The duration before the next emission at time $t + \Delta t$ is decreased by Δt:

$$E_i(t + \Delta t) = \begin{cases} e_i(t + \Delta t) = e_i(t) \\ p_i(t + \Delta t) = p_i(t) \\ \delta_i(t + \Delta t) = \delta_i(t) - \Delta t \end{cases} \tag{12}$$

If i emits between t and $t + \Delta t$: $0 < \delta_i(t) \leq \Delta t$. Then, it consumes an energy c_e. Moreover, the function f is used to determine the new emission period of the sensor. It will consume an additional energy c_r if the defined period is different from the current one. The sensor is represented in $E(t + \Delta t)$ only if it is active at $t + \Delta t$ i.e. if it has enough energy to transmit again. In order to define a

simple form of $E_i(t+\Delta t)$, we define the energy remaining in the sensor i at time $t+\Delta t$. $e_i(t+\Delta t) = e_i(t) - c_e - c_r \mathbb{1}_{f(H_{t+\delta_t}) \neq p_i(t)}$ ($\mathbb{1}$ is the indicator function).

Then:

$$E_i(t+\Delta t) = \left[\begin{array}{ll} \emptyset & \text{, if } e_i(t+\Delta t) < c_e \\ \left\{ \begin{array}{l} e_i(t+\Delta t) \\ p_i(t+\Delta t) = f(H_{t+\delta_t}) \\ \delta_i(t+\Delta t) = \delta_i(t) - \Delta t + f(H_{t+\delta_t}) \end{array} \right. & \text{, else} \end{array} \right. \tag{13}$$

Finally, if a new sensor i activates between t and $t+\Delta t$, i.e. $i \notin \Pi(t)$, $i \in \Pi(t+\Delta t)$ and $t_i \in]t, t+\Delta t]$. In this case, f defines the emission period of i and:

$$E_i(t+\Delta t) = \left\{ \begin{array}{l} e_i(t+\Delta t) = e_i - c_e - c_r \\ p_i(t+\Delta t) = f(H_{t_i}) \\ \delta_i(t+\Delta t) = t_i - (t+\Delta t) + f(H_{t_i}) \end{array} \right. \tag{14}$$

In all these cases, if (11) is verified, then $\delta_{\cdot}(.) > 0$.

As explained above, the notations are used here to help the proof of efficiency of $f_{M,\tau}$. Thus, we use the following notations allowing simplification in the writings.

Definition 8. *We define the* ***characterization of the sensor set over the instants of period*** τ*:*

$$E_k := E(t_0 + k\tau)$$

In the same way, we define $(\Pi_k)_{k\in\mathbb{N}} := \{\Pi(t_0 + k\tau), k \in \mathbb{N}\}$.

For $i \in \Pi_k$*:*

$$E_{i,k} := E_i(t_0 + k\tau) = \left\{ \begin{array}{l} e_{i,k} = e_i(t_0 + k\tau) \\ p_{i,k} = p_i(t_0 + k\tau) \\ \delta_{i,k} = \delta_i(t_0 + k\tau) \end{array} \right.$$

.

From Definition 8, we mathematically define the **effectiveness**:

Definition 9. *A period update function is said to be* ***effective over the instants of period*** τ *if, using characterization of the sensor set over the instants of period* τ*:*

$$\begin{array}{ll} \forall k \in \mathbb{N}, |\Pi_k| > 0 \Rightarrow & \exists! i \in \Pi_k : \delta_{i,k} = \tau \\ & \forall j \in \Pi_k, j \neq i \Rightarrow \delta_{j,k} > \tau \end{array} \tag{15}$$

We then define its sample span L *by:*

$$L := \max\{k, |\Pi_k| > 0\} + 1 \tag{16}$$

C.2 Proof of the effectiveness of the function

Demonstration of Proposition 2 (page 10)

Proof. First, we consider that the description of the algorithm is sufficient to assert that

Assertion 1. death-date *is a list updated at each new emission such that it corresponds to the list sorted by ascending order of death of sensors whose relay is not already provided by other sensors.*

We will show by induction the statement called $P(k)$:
Looking at the instant $t_0 + k\tau$:

- If the number of active sensors does not exceed M, then the active sensors emit exactly on the next consecutive $j\tau$ instants, $1 \leq j \leq |\Pi_k|$.
- Otherwise, the $j\tau$ instants are covered for the first M instants by M sensors. The next emission of the other sensors occurs at least $M\tau$ after the death of the next sensor. There is exactly one that emits $M\tau$ after the death of the next sensor.

Mathematically, introducing $\mathbb{I}_k = \{i \in \Pi_k, \delta_{i,k} > M\tau\}$, $P(k)$ means:

$$\text{-If } |\Pi_k| \leq M, \forall j, 1 \leq j \leq |\Pi_k|, \exists! i \in \Pi_k : \delta_{i,k} = j\tau$$
$$\text{-Else, } \begin{cases} \forall j, 1 \leq j \leq M, \exists! i \in \Pi_k : \delta_{i,k} = j\tau \\ \exists! i \in \mathbb{I}_k : \delta_{i,k} = \text{next-death(k)} - (t_0 + k\tau) + M\tau \\ \forall i \in \mathbb{I}_k, \delta_{i,k} \geq \text{next-death(k)} - (t_0 + k\tau) + M\tau \end{cases}$$

Where next-death(k) represents the death time of the next sensor after $t_0 + k\tau$.

Initialization: We want to prove $P(0)$. $|\Pi_0| = 1 \leq M$. $f_{M,\tau}$ sets the period to τ, so that $\delta_{0,0} = \tau$, hence $P(0)$ is true.

Heredity: Assume $P(k)$ is true for some $k \geq 0$. We define $n := |\Pi_k|$.

Disjunction of cases.

-If $|\Pi_k| \leq M$ and $|\Pi_{k+1}| \leq M$.

• If there is no variation in the set of active sensors, $|\Pi_k| = |\Pi_{k+1}| = n \leq M$. By using $P(k)$, $\exists! i \in \Pi_k : \delta_{i,k} = \tau$ so that from the definition of $f_{M,\tau}$, we have $\delta_{i,k+1} = n\tau$. Moreover, $\forall j, 1 < j \leq n, \exists! i : \delta_{i,k} = j\tau$ so $\delta_{i,k+1} = (j-1)\tau$. Finally

$$\forall j, 1 \leq j \leq n, \exists! i : \delta_{i,k+1} = j\tau,$$

which means $P(k+1)$ is true.

• We now consider that m new sensors indexed $(l+r)_{r\in[1,m]}$ activate between states E_k and E_{k+1} and no sensor dies. l represents the number of sensors activated from the beginning of the monitoring. Since $|\Pi_{k+1}| \leq M$, $n+m \leq M$. We consider without loss of generality that $t_0 + k\tau < t_{l+1} < t_{l+2} ... < t_{l+m} \leq$

$t_0 + (k+1)\tau$. $\Pi_{k+1} = \Pi_k \bigcup \{(l+r)_{r\in[1,m]}\}$ so that $|\Pi(t_{l+r})| = n + r$. Since $t_{l+r} - t_0 - (t_{l+r} - t_0)\%\tau = k\tau$, from Eq. (14) we can simplify $\delta_{l+r,k+1}$:

$$\begin{array}{rcl} \forall r, 1 \leq r \leq m, & & \\ \delta_{l+r,k+1} & = & t_{l+r} - (t_0 + (k+1)\tau) \\ & & +(\tau|\Pi(t_{l+r})| - (t_{l+r} - t_0)\%\tau) \\ & = & \tau(|\Pi(t_{l+r})| - 1) \\ & = & (n + r - 1)\tau \end{array}$$

Now from induction hypothesis, $\exists! i \in \Pi_k : \delta_{i,k} = \tau$, so that $\delta_{i,k+1} = (n+m)\tau$. Moreover, $1 < j \leq n, \exists! i \in \Pi_k : \delta_{i,k} = j\tau \Rightarrow \delta_{i,k+1} = (j-1)\tau$. Finally:

$$\forall j, 1 \leq j \leq n + m, \exists! i \in \Pi_{k+1} : \delta_{i,k} = j$$

Which means $P(k+1)$ is true.

• If a sensor indexed l dies between $t_0 + k\tau$ and $t_0 + (k+1)\tau$, $\Pi_{k+1} = \Pi_k | \{l\}$ and $\delta_{l,k} = \tau$. Since $j > 1, \exists! i, \delta_{i,k+1} = (j-1)\tau$, $P(k+1)$ is true. It can be further shown that if between the states E_k and E_{k+1}, one sensor dies and several activates, $P(k+1)$ remains true.

-If $|\Pi_{k+1}| > M$.

• If there is no variation in the active sensors $\Pi_k = \Pi_{k+1}$. From $P(k)$, $\forall j, 1 \leq j \leq M, \exists! i \in \Pi_k : \Pi_k = j\tau$. Then, since the period of these sensors is $M\tau$ (definition of $f_{M,\tau}$), from the same reasoning as above $\forall j, 1 \leq j \leq M, \exists! i \in \Pi_{k+1} : \Pi_{k+1} = j\tau$. No sensor dies, so next-death(k) = next-death(k+1). Thus, about the other sensors (which do not emit on the first M instants): from Eq. (12), $\exists! i \in \mathbb{I}_{k+1} : \delta_{i,k+1} =$ next-death(k+1) $- (t_0 + (k+1)\tau) + M\tau$ and $\forall i \in \mathbb{I}_{k+1}, \delta_{i,k+1} \geq$ next-death(k+1) $- (t_0 + (k+1)\tau) + M\tau$. Hence, $P(k+1)$ is true.

• If m sensors, indexed $(l+r)_{r\in[1,m]}$ activates and no one dies. Then, if $|\Pi_k| < M$, the sensors activates in the same way as a case already studied above, until $|\Pi_k| = M$. Without loss of generality, we consider now that $(l+r)_{r\in[1,m]}$ activates while there are already M active sensors. Then $\forall j, 1 \leq j \leq M, \exists! i \in \Pi_{k+1} : \delta_{i,k+1} = \tau j$. Moreover, $f_{M,\tau}$ fix the period of $l+1$ to *death-date*[0] $- t_{l+1} + M\tau$ and delete *death-date*[0] from *death-date*. The same thing is done for all $l + r$. In that case, $\delta_{l+1,k+1} =$ *death-date*[0] $- (t_0 + (k+1)\tau) + M\tau$. and it is the same for the other sensors indexed $l + r$. Hence, $P(k+1)$ is true.

• If a sensor $l \in \Pi_k$ dies. Then, $\delta_{l,k} = \tau$ and $\Pi_{k+1} = \Pi_k / \{l\}$. Then next-death(k) = $t_0 + (k+1)\tau$. We consider,from hypothesis $P(k)$, i so that $\delta_{i,k} =$ next-death(k) $- (t_0 + k\tau) + M\tau = (M+1)\tau$ and $\delta_{i,k+1} = M\tau$. Hence :

$$\forall j, 1 \leq j \leq M, \exists! i \in \Pi_{k+1} : \Pi_{k+1} = j\tau$$

Moreover, next-death(k+1) is updated to the death date of the next sensor, and from assertion 1, $f_{M,\tau}$ fix the period of a sensor so that it emit $M\tau$ after the death of the next sensor i.e. $\exists! i \in \mathbb{I}_{k+1} : \delta_{i,k+1} =$ next-death(k+1) $- (t_0 + (k+1)\tau) + M\tau$. Moreover, all the other sensors will emit after that time: $\forall i \in \mathbb{I}_{k+1}, \delta_{i,k+1} \geq$ next-death(k+1) $- (t_0 + (k+1)\tau) + M\tau$. $P(k+1)$ is true.

$P(k+1)$ remains true if multiple sensors activates and one sensor die between $t_0 + k\tau$ and $t_0 + (k+1)\tau$. □

D Proofs of the bounds of the sample span of the defined function

Proposition 5. *The lower bound of the period update function $f_{M,\tau}$, for sensors with same energy e is:*

$$\begin{aligned} \tfrac{n}{2} > M, L(f_{M,\tau}) &\geq \sum_{i=0}^{M-1} \left\lfloor \tfrac{e-c_e-(i+1+\mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ &+ (n-2M) * \left\lfloor \tfrac{e-c_e-2c_r}{c_e} \right\rfloor \\ &+ \sum_{i=0}^{M-1} \left\lfloor \tfrac{e-c_e-(i+2)c_r}{c_e} \right\rfloor \end{aligned} \tag{17a}$$

$$\begin{aligned} M \geq \tfrac{n}{2}, L(f_{M,\tau}) &\geq \sum_{i=0}^{n-M-1} \left\lfloor \tfrac{e-c_e-(M-i+\mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ &+ \sum_{i=n-M}^{M-1} \left\lfloor \tfrac{e-c_e-(2M-n+\mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ &+ \sum_{i=M}^{n-1} \left\lfloor \tfrac{e-c_e-(i-n+M+2)c_r}{c_e} \right\rfloor \end{aligned} \tag{17b}$$

Proof. Let a sensor indexed i. It modifies $1 + \mathbb{1}_{i>0}$ times its emission period to adjust itself with respect to the other sensors during its first two emissions.

$|\Pi(.)|$ varies at each activation and death of a sensor. We will study the case where sensor i is subject to the most period changes. If i activates while $|\Pi(.)| \leq M$, it can modify its emission period for any new sensor activating, until there are M active sensors i.e. at most $M - i - 1$ additional times. In that case, the sensor i emits at least once between each activation. This is the case if the time between two activations is greater than the period of i. Focusing on the sensor indexed 0:

$$\forall i, 1 \leq i \leq M-1, t_i - t_{i-1} > \tau i$$

Furthermore, if we consider that a sensor i activates when there are no more than M remaining active sensors, it can change its emission period for each sensor death from the time when there are M remaining sensors. Considering that the sensors are activated at sufficiently spaced instants, and that they have the same initial energy, then the activation index corresponds to the death index of the sensors. Thus, the sensor i will change its emission period at the death of sensors if $i \geq n - M$. It will thus change at most $i - (n - M)$ additional times.

However, depending on the chosen value of M, the results are different. It is necessary to split in 2 cases:

If M is small relative to n i.e. $M < \frac{n}{2}$.

The sensors will have a different number of period changes following these 3 intervals Fig. 4:

- $0 \leq i \leq M-1, r_i = M - i + \mathbb{1}_{i>0}$.
- $M-1 \leq i \leq n-M, r_i = 2$.
- $n-M \leq i \leq n-1, r_i = i - (n-M) + 2$.

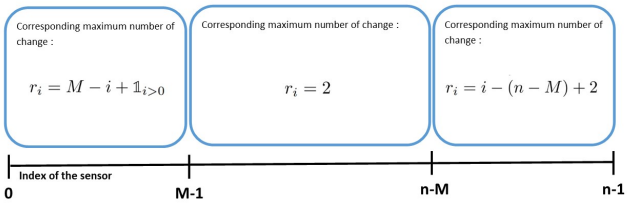


Figure 4: Representation of the number of period changes depending on the index of the sensor when $M < \frac{n}{2}$

Using Definition 6, we can define the number of emissions on the time steps τ without duplicates, and thus have a lower bound formula for the sample span:

$$\begin{aligned} L(f_{M,\tau}) \geq & \quad \sum_{i=0}^{M-1} \left\lfloor \frac{e - c_e - (M - i + \mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ + & \quad (n - 2M) * \left\lfloor \frac{e - c_e - 2c_r}{c_e} \right\rfloor \\ + & \quad \sum_{i=n-M}^{n-1} \left\lfloor \frac{e - c_e - (i - n + M + 2)c_r}{c_e} \right\rfloor \end{aligned}$$

Hence, by changing indices in the sums, we get the formula (17a).
If M is close to n i.e. $M \geq \frac{n}{2}$.

In this case, the intervals $[0, M-1]$ and $[n-M, n-1]$ overlap. We study the 3 following intervals (Fig. 5):

- si $0 \leq i \leq n - M, r_i = M - i + \mathbb{1}_{i>0}$.
- si $n - M \leq i \leq M - 1, r_i = 2M - n + \mathbb{1}_{i>0}$.
- si $M - 1 \leq i \leq n - 1, r_i = i - (n - M) + 2$

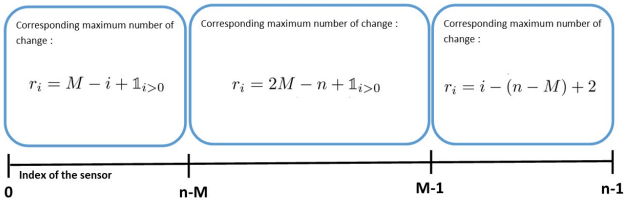


Figure 5: Representation of the number of period changement depending on the index of the sensor when $M \geq \frac{n}{2}$

We can then get the minimization:

$$\begin{aligned} L(f_{M,\tau}) \geq & \quad \sum_{i=0}^{n-M-1} \left\lfloor \frac{e - c_e - (M - i + \mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ + & \quad \sum_{i=n-M}^{M-1} \left\lfloor \frac{e - c_e - (2M - n + \mathbb{1}_{i>0})c_r}{c_e} \right\rfloor \\ + & \quad \sum_{i=M}^{n-1} \left\lfloor \frac{e - c_e - (i - n + M + 2)c_r}{c_e} \right\rfloor \end{aligned}$$

□

This leads us directly to the simplified expression Eq. (5).

Proposition 6. *We can define an analytical expression for the upper bound of the period update function $f_{M,\tau}$, for sensors with the same initial energy e:*

$$L(f_{M,\tau}) \leq \sum_{i=0}^{n-1} \left\lfloor \frac{e - c_e - c_r(1 + \mathbb{1}_{M>1 \text{ or } i>0})}{c_e} \right\rfloor$$

Proof. We consider that the first M sensors are activated in the first time interval τ i.e.

$$\forall i, 1 \leq i \leq M, t_i \in [t_0, t_0 + \tau]$$

Let us consider the first M sensors. In this case, considering the first sensor of index 0 : $f_{M,\tau}$ modifies its emission period a first time to τ, then modifies it to $M\tau$ if $M \neq 1$. For the sensors of index $0 < i < M$, their first emission period is $\tau|\Pi(t_i)| - (t - t_0)\%\tau$. Their second period is exactly τM. Each sensor performs exactly $r_i = 2$ period changes.

Moreover, for the following sensors, they also change their emission period a first time to emit following the death of a sensor, then the period is fixed to $M\tau$. Finally, since all the sensors turned on at the same time and consumed a similar amount of energy, if $n \equiv 0[M]$, then the cycles of M sensors will be renewed each time at the same time, and thus the M last sensors will die at the same time in turn (no additional period change consumption). In this case, all sensors must change their emission period twice except for the 0 sensor if $M = 1$. In the latter case, the upper bound on monitoring time is reached with respect to the period update functions effective over the instants of period τ.

Hence:

$$L(f_{M,\tau}) \leq \sum_{i=0}^{n-1} \left\lfloor \frac{e - c_e - c_r(1 + \mathbb{1}_{M>1 \text{ or } i>0})}{c_e} \right\rfloor$$

□

This lead us to the approximation Eq. (6), and then we proved Proposition 3 (page 10)

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