Emission scheduling strategies for massive-IoT based monitoring: implementation and performance optimization

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

Battery-powered sensor emission strategies to optimize monitoring

Gwen MAUDET [1], Mireille BATTON-HUBERT[3], Patrick MAILLE[2], and Laurent TOUTAIN[1]

[1]IMT Atlantique, IRISA, OCIF
[2]IMT Atlantique, IRISA, Dionysos
[3]EMSE

***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, to 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 for example be customized to manage the tradeoff between overall monitoring accuracy and sensor energy consumption, for which we suggest a formalization through a generic indicator of the 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.

I. Introduction

A. 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 techniques, a new class of applications has arisen: miniaturized devices deployed on a large scale capable of sensing their environment [1-3].

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 [4-6]. This allows the development of versatile solutions, independent of the physical development.

B. 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 [7,8]. Triggered and adaptive sensing methods allow the sensor's sampling rate to be adapted to variations in the environment.

In 2018, the authors of [9] 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 [10,11]. Those last approaches are particularly suitable for heterogeneous geographical distributions of sensors.

In 2014, [12] 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, [13] 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 [13] are proposed in 2019 [14], 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 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

gwen.maudet@imt-atlantique.fr

hypotheses.

C. 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 [15], 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 II 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 III, 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 IV. Finally, we conclude and highlight the limits of the studied model in Section V, suggesting directions for future works.

II. Problem statement and model

A. 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**. The **end of the monitoring** is when there are no more active sensors.

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 [16,17]. Finally, we assume that each sensor spends its energy until its battery is exhausted.

B. 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:*

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

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 $f(H_t)$.

C. 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 [18,19]. 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 [20-22] 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.

D. 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.

III. 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).

Note that for reasons of space, the formal proofs of Propositions 1 to 4 are developed in the separate document [23].

A. Definition of effectiveness

An effective method for tracking an average physical quantity over time is to collect regular samples [15]. 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 sampling interval.

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 for any effective period* *update function, the maximum sample span $L(f)$ (removing the integer parts) is:*

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

B. Functioning of $f_{M,\tau}$

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 first parameter τ of the function is defined by the target time between two emissions.

In a context such as the one predicted for the 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 want to receive information from various sources (quantified by the average diversity). The second parameter of the function is M to take into account this possible requirement, defined as the number of sensors transmitting in turn.

For given parameters M and τ, the period update function $f_{M,\tau}$ is defined such that at most M sensors transmit in turn, spaced by a time τ. If any, the other sensors are in sleep mode and successively take over the sensors when one dies.

• As long as the number of active sensors does not exceed M, all the active sensors are emitting in turn. In that case, the sensor already active have an emission period set at τ multiplied by the number of active sensors. If a new sensor activates, all the sensors change their emission period, since the number of active sensors change.

• As soon as they are more than M active sensors, it works differently. M sensors emit periodically, with a period of M multiplied by τ. The period of each other sensor is set so that it takes over successively when one of the M sensors dies. When the 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.

C. Definition of the period update function

In order to build an understandable definition of $f_{M,\tau}$, we refer to the notations of [23]. $\Pi(t)$ is the set of elements active at time t so that $|\Pi(t)|$ represents the number of active elements. A sensor is included in the set of elements $\Pi(t)$ when it activates and is removed as soon as it can no longer transmit.

Moreover, we define *death-date* the list sorted by ascending date of sensor deaths whose relay is not assured. The list is updated at each message thanks to the **death update algorithm**. *death-date* is defined so that the first element of the list (i.e., *death-date[0]*) corresponds to the next sensor death whose relay is not already assured.

We use the notation % to indicate the rest of the division algorithm. This leads us to this definition of $f_{M,\tau}$.

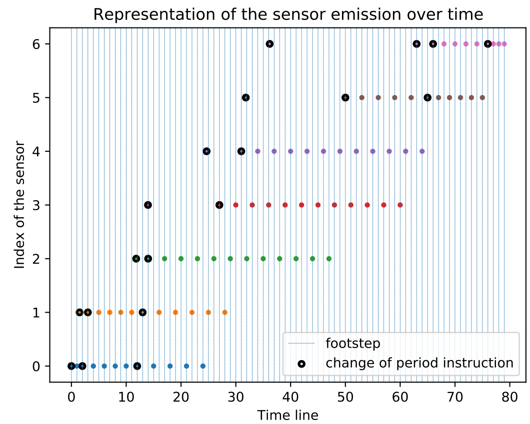


Fig. 1. Illustration of sensor emissions using $f_{M,\tau}$ for $M = 3$ and $\tau = 1$. We considered 7 sensors randomly activating between 0 and 40, of equal battery-capacities $e = 15$, with emission and period change consumption $c_e = c_r = 1$. The emissions of a sensor indexed i appear on the horizontal with ordinate line i. The points circled in black mean that the function $f_{M,\tau}$ changes the period of the sensor in question. There is exactly one emission on each blue vertical line, meaning that we receive exactly one message at each time $\tau = 1$. Moreover, as soon as there are at least 3 active sensors, the emissions are shared between 3 sensors emitting periodically.

Definition 5. *the period update function $f_{M,\tau}$ is defined by:*

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

(3)

*death-date is updated by using the **death update algorithm** after each use of the $f_{M,\tau}$ function.*

To apply the period update function $f_{M,\tau}$, it is necessary to keep in memory the list *death-date*, whose size is at most M, and to update it when it is necessary. As long as the number of active sensors is less than M, the list is updated at each transmission: find the date of death of the sensor in the list, then update it and insert it in the sorted list. When a sensor activates while $|\Pi(t)| \ge M$, death update algorithm replaces the death date of the sensor whose relay has just been taken by the predicted death of the new one.

For $M = 1$ and $M = n$, combinatorial and memory space simplifications can be done for the implementation of the function $f_{M,\tau}$.

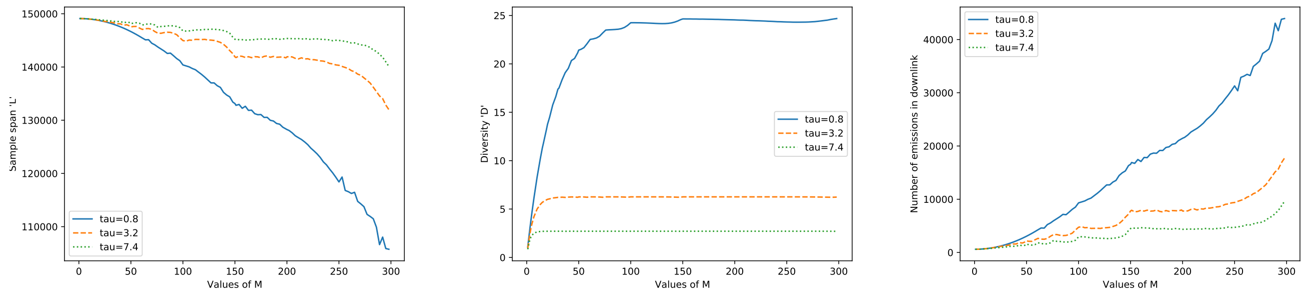
D. Properties and boundaries of $f_{M,\tau}$

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 lower bound of the sample span of $f_{M,\tau}$ is, by simplifying (removal of integer parts):*

$$L(f_{M,\tau}) \ge \frac{ne - nc_e - (2n-1+M(M-1))c_r}{c_e} \tag{4}$$

The bound is reached if some conditions are verified. Namely, as long as there are no more than M active sensors,



(a) (b) (c)

Fig. 2. Representation of some performance indicators using the period update function $f_{M,\tau}$, varying the number of jointly emitting sensors M, for different target emission periods τ. (a) corresponds to the sample span, (b) the diversity, and (c) the total number of downlink emissions.

Parameter	Value
n	300
$e_i = e$	500
$c_e = c_r$	1
$t_i - t_{i-1}$	15π
T	20
Utility function	v_{20}

TABLE I
SIMULATION PARAMETERS

the time between two activations must be greater than the period of the sensors:

$$\forall i \in [1, M-1], t_i - t_{i-1} > \tau i \tag{5}$$

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.

Proposition 4. *Considering sensors with the same initial energy e, the upper limit of the sample span of $f_{M,\tau}$, is, by simplification (suppression of the integer parts):*

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

This bound is reached under some conditions; the first M sensors must activate in the same time interval of length τ and all sensors can be separated into subsets of exactly M sensors:

$$\begin{gathered} \forall i \in [1, M], t_i \in [t_0, t_0 + \tau] \\ n \equiv 0[M] \end{gathered} \tag{7}$$

If all sensors are activated 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 $L_{\max}$ Proposition 1.

Apart from this condition, at a fixed τ, an increase in the M parameter generally has a negative influence on the monitoring duration.

IV. Numerical simulations

This section discusses the experimental analysis of the period update function $f_{M,\tau}$. We propose to compare the performances 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 I, 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.

A. Influence of the number of sensors jointly transmitting M on indicators

For a fixed target emission period τ, the parameter M influence the performance Fig. 2. The sample span (i.e., the monitoring duration) decreases when M increases Fig. 2(a), confirming our suppositions based on 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. We reach 34.02% of relative difference for $\tau = 0.8$, because the condition (5) is valid for a greater number of sensors.

At a fixed τ, larger values of M offer greater diversity, as more sensors update their value periodically Fig. 2(b), even if the diversity varies much less strongly for high values of M.

B. Optimal solutions for the multi-objective problem

Considering the two-objective problem, there is only a subset of relevant solutions, all other solutions are suboptimal. The set of optimal solution (i.e., the pair of parameters) consists of the points closest to the upper right corner of Fig. 3, constituting a Pareto front.

For extreme values of the number of jointly transmitting sensors M ($M \leq 10$, or $M \geq 150$), the period update function give suboptimal performances. However, depending on the needs, a discussion must be made on the parameters to find the fitting solution. If the need for diversity is not very strong, then a small value of M and a relatively large τ time step (compared to relevance time of data T) allows to extend considerably the total monitoring duration. 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, and thus to a shorter monitoring duration. We notice that choosing a big value of M

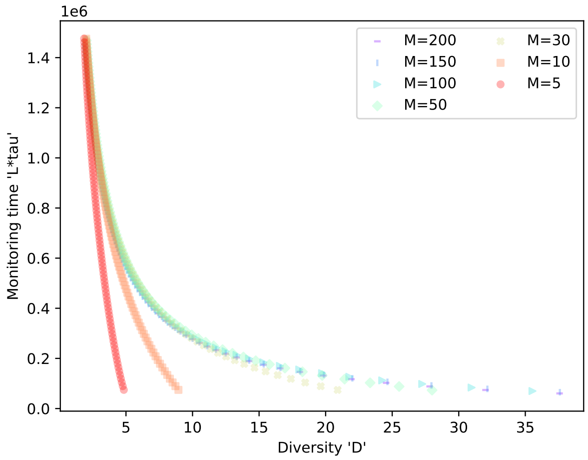


Fig. 3. Each point in the graph represents the performance of an update function of period $f_{M,\tau}$, for several values of M (in the legend) and values of τ between 0.5 and 10, spaced by 0.1. Each point corresponds to a chosen parameterization for the update function, whose x-axis corresponds to the diversity and y-axis the total network lifespan.

induces a high downlink consumption Fig. 2(c), which must be minimized, since it has a significant impact on Quality of Service [24]. Thus, when possible, it is preferable to choose a smaller number of joint transmitting sensors in order not to saturate the network.

V. Conclusions and Future Works

This paper presents a method for scheduling sensor emissions in an initially uncoordinated environment. We show that it is possible to optimize the monitoring by choosing the appropriate parameters, relative to the quality requirements. In particular, we proove that only a limited number of sensors should actively participate in the monitoring, so as to ensure sufficient diversity without overly disturbing the scheduling.

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 relevant to include the available metadata in monitoring policies.

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