

Energy-Efficient Internet of Things Monitoring with Content-Based Wake-Up Radio

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Abstract—The use of Wake-Up Radio (WUR) in Internet of Things (IoT) networks can significantly improve their energy efficiency: battery-powered sensors can remain in a low-power (sleep) mode while listening for wake-up messages using their WUR and reactivate only when polled. However, polling-based WUR may still lead to wasted energy if values sensed by the polled sensors provide no new information to the receiver, or in general have a low Value of Information (VoI). In this paper, we design a content-based WUR that tracks the process observed by the sensors and only wakes up the sensor if its estimated update's VoI is higher than a threshold communicated through the poll. If the sensor does not reply to the polling request, the Gateway (GW) can make a Bayesian update, knowing that either the sensor value substantially confirms its current estimate or the transmission failed due to the wireless channel. We analyze the trade-off between the tracking error and the battery lifetime of the sensors, showing that content-based WUR can provide fine-grained control of this trade-off and significantly increase the battery lifetime of the node with a minimal Mean Squared Error (MSE) increase.

Index Terms—Wake-Up Radio, Scheduling, Remote monitoring, Energy efficiency

I. INTRODUCTION

The explosion of the Internet of Things (IoT) has led to new developments in remote monitoring applications [1], [2], which use distributed sensors to keep track of remote environments and wide areas, as well as manufacturing plants and cities. Since the inception of the IoT, however, energy has been a major issue for system design [3]: battery-powered nodes face significant constraints in terms of computational and communication capabilities, and often resort to uncoordinated random access schemes like ALOHA to avoid the signaling overhead.

However, the limits of random access schemes are well-known: unless the traffic is extremely light, these schemes suffer from packet collisions and congestion [4], and do not allow the Gateway (GW) to request new data from a specific sensor [5]. The challenge is then to avoid the significant energy consumption incurred by nodes constantly listening for request messages, without tying the schedule to a fixed duty cycle.

One possible solution to this problem is provided by Wake-Up Radio (WUR) technology, standardized as part

This work was supported by the European Union as part of the Italian National Recovery and Resilience Plan of NextGenerationEU, under the partnership on “Telecommunications of the Future” (PE0000001 - program “RESTART”) and the “Young Researchers” grant REDIAL (SoE0000009).

of IEEE802.11ba [6]: the system includes an extremely low-power radio only capable of receiving simple signals and making some basic calculations, which is kept in listening mode, while the sensor's main processor and Primary Communication Radio (PCR) are only turned on when needed. Typically, the WUR is used to reduce the downlink response time of a node whose PCR is in sleep mode to save energy [7], achieving both a relatively low latency and a limited energy consumption. The standard defines the physical and Medium Access Control (MAC) parameters for communication with the WUR, as well as the wake-up procedure for the PCR when a WUR signal is received from the GW along with the power management scheme to be implemented and associated Duty Cycle (DC) specifications and synchronization schemes. Crucially, it defines the channelization of wake-up frames to be sent to WUR. The standard explains the usage of ID-based wake-up messages to be sent to each node, waking up their PCRs.

However, the basic WUR design defined in IEEE802.11ba, hereforth referred to as ID-based WUR, does not take into account the Value of Information (VoI) from the polled sensors. Hence, the concept of content-based WUR was proposed in [8]. In content-based WUR, the polling packet carries not only the ID of the target node, but also a condition on the VoI of the data to be collected (generally, in the form of a range of interesting values). The target node then wakes the PCR and replies to the poll on if its data satisfies the VoI requirement. Hence, in this work, we design a scheme for joint ID- and content-based WUR, defining the optimal estimate response and proposing a scheduling policy that can take into account the VoI of the update using Kalman filter estimates to increase the network lifetime while trading off some Mean Squared Error (MSE) performance. The proposed solution can improve the former by about 40% in some cases, while only increasing the MSE by 10%.

The rest of this paper is organized as follows: first, in Sec. II, we present the basic system model for kalman filter estimation and energy consumption. We then present the censored update computation and the scheduling policy in Sec. III. Results in a realistic setting are provided and discussed in Sec. IV. Sec. V concludes the paper and presents some possible avenues of future work on the subject.

II. SYSTEM MODEL

We consider a system with N distributed sensors, monitoring a physical process over a wide area. The sensors are equipped with uplink radios with wake-up functionality, and can be polled at will by the GW. In the following, we will denote vectors using bold letters, e.g., \mathbf{x} , and matrices using bold capital letters, e.g., \mathbf{A} . Individual elements of vectors and matrices will be denoted using the same letter, with the element index as a subscript, e.g., x_n or $A_{m,n}$.

A. Process Model and Kalman Filter Estimation

We model the physical process monitored by the N sensors as a linear dynamic process running in discrete time. The state of the process at step k is the $P \times 1$ column vector $\mathbf{x}(k) = [x_1, \dots, x_P]^T$. The dynamic system update is defined by

$$\mathbf{x}(k) = \mathbf{A}\mathbf{x}(k-1) + \mathbf{v}(k), \quad (1)$$

where $\mathbf{A} \in \mathbb{R}^{P \times P}$ is the update matrix for the system and $\mathbf{v}(t) \sim \mathcal{N}(0, \mathbf{Q})$ is the Gaussian perturbation noise of the system, determined by the covariance matrix is $\mathbf{Q} \in \mathbb{R}^{P \times P}$. Each sensor n then measures value $y_n(k)$, and we collect the measurements at timestep k in the $N \times 1$ column vector $\mathbf{y}(k)$:

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{w}(k), \quad (2)$$

where $\mathbf{H} \in \mathbb{R}^{N \times P}$ is the observation matrix and $\mathbf{w}(t) \sim \mathcal{N}(0, \mathbf{R})$ is the measurement noise vector, with covariance matrix $\mathbf{R} \in \mathbb{R}^{N \times N}$. As the GW knows the process statistics, it can know or estimate \mathbf{A} , \mathbf{H} , \mathbf{Q} , and \mathbf{R} . It also has an initial estimate of the process at step 0, $\hat{\mathbf{x}}(0)$, and an initial estimation covariance matrix $\mathbf{P}(0)$, defined as:

$$\mathbf{P}(0) = \mathbb{E}[(\mathbf{x}(0) - \hat{\mathbf{x}}(0))^T(\mathbf{x}(0) - \hat{\mathbf{x}}(0))]. \quad (3)$$

In the following, we will use the symbol $\mathbf{z}(k)$ to denote the estimation error $\mathbf{x}(k) - \hat{\mathbf{x}}(k)$. We can then use a Kalman filter, the Minimum MSE (MMSE) estimator for linear processes, to obtain the *a priori* estimate after each step:

$$\begin{cases} \hat{\mathbf{x}}(k|k-1) = \mathbf{A}\hat{\mathbf{x}}(k-1); \\ \mathbf{P}(k|k-1) = \mathbf{A}\mathbf{P}(k-1)\mathbf{A}^T + \mathbf{Q}. \end{cases} \quad (4)$$

If sensor n is polled, it can then report its measured value. Due to the wireless channel conditions, this update might be lost, in which case the *a priori* estimate remains the best possible estimate of the state. Conversely, if the update is successfully received, the Kalman filter observation is simply $y_n(k)$. In the following, we will use symbol $\mathbb{1}_n$ to denote a one-hot row vector of length N , whose values are all 0 except for the n -th, which is equal to 1. We also define the innovation covariance matrix $\mathbf{S}(k|n)$:

$$\mathbf{S}(k) = \mathbf{H}\mathbf{P}(k|k-1)\mathbf{H}^T + \mathbf{R}. \quad (5)$$

The Kalman gain is then:

$$\mathbf{g}(k|n) = \frac{\mathbf{P}(k|k-1)\mathbf{H}^T \mathbb{1}_n^T}{S_{n,n}(k)}. \quad (6)$$

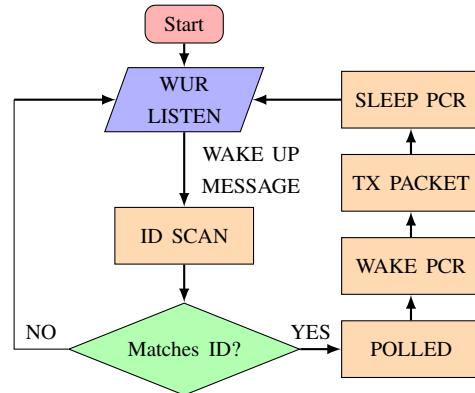


Fig. 1: ID-based WUR sensor operation.

The *a posteriori* estimate is then:

$$\begin{cases} \hat{\mathbf{x}}(k|n) = \hat{\mathbf{x}}(k|k-1) + \mathbf{g}(k|n)(y_n(k) - \hat{x}_n(k|k-1)); \\ \mathbf{P}(k|n) = (\mathbf{I}_P - \mathbf{g}(k|n)\mathbb{1}_n\mathbf{H})\mathbf{P}(k|k-1), \end{cases} \quad (7)$$

where \mathbf{I}_P is the $P \times P$ identity matrix. We consider a scenario in which the process dynamics are significantly slower than the time it takes to poll a sensor, i.e., the process is much slower than polls. Hence, to avoid draining the battery of all the sensors in every single timestep, the GW can choose to poll $M \leq N$ sensors sequentially. The updated estimate from (7) after each poll then becomes the *a priori* estimate to determine the next polled sensor.

B. Communication and Energy Model

We consider a system in which one GW communicates with N wake-up capable receivers. The communication model is then a simple Packet-Erasure Channel (PEC) with erasure probability ε_n , which includes three possible failure events:

- 1) The wake-up message might be lost due to wireless channel conditions or interference from outside the sensor network, and the sensor might not wake up and transmit its update;
- 2) The wake-up message might be misunderstood by another sensor, who then wakes up along with the intended node and causes a packet collision by transmitting out of turn;
- 3) The wireless channel conditions or interference from outside the network might not allow the GW to correctly decode the packet transmitted by the sensors even if no other sensors transmit.

As sensors are geographically spread out over the environment, their failure probabilities will be different. We assume that these probabilities are known to the receiver, or can be estimated beforehand.

III. ENERGY-AWARE VOI-BASED POLLING

Using the communication and energy model defined, we consider the three sensor operations that consume energy: the reception of a wake-up message E_w , the measurement of a new observation of the physical process monitored by the sensor E_s , and the transmission of an update E_t . WUR

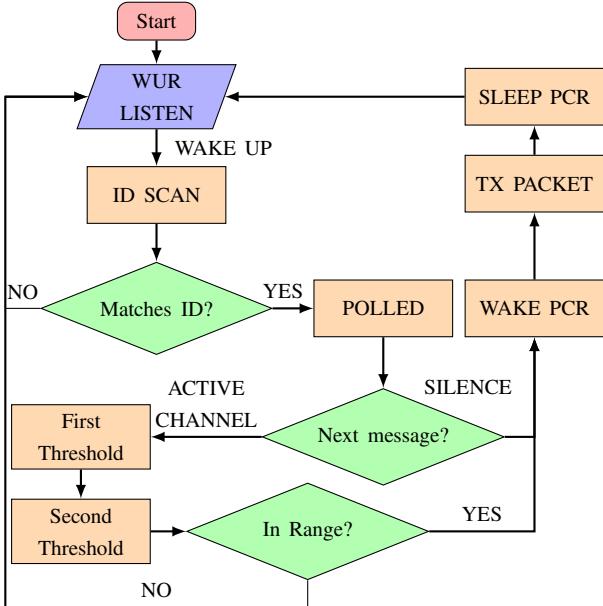


Fig. 2: Content-based WUR sensor operation.

systems are designed to reduce the energy necessary for the wake-up radio, E_w , as much as possible [9]. The power consumption of the WUR can be as low as $2\mu\text{W}$ [10], much lower than the power required to keep the main sensor computing unit and radio in sleep mode, which may be close to 1mW even for low-energy LoRa devices [11]. Moreover, E_s is usually much lower than E_t , which may require up to 100mJ in LoRa devices, depending on the packet length and spreading factor [11].

Hence, we can consider the energy expenditure of the sensor: in a standard wake-up model, shown in Fig. 1, the sensor needs only a limited amount of energy E_w to receive a wake-up radio message and check if its ID matches the target one, while it consumes a much larger E_t to wake up the PCR and transmit a message. We can then envision a content-based scheme, depicted in Fig. 2, which adds two more messages to the wake-up procedure. The two messages correspond to two thresholds, a and b which are compared to the measured value. If $b \leq a$, the sensor will wake up its PCR and transmit any value outside the range $[b, a]$, while if $b > a$, it will transmit values only inside the interval $[a, b]$. If no further message is received after the ID message, the sensor falls back to a simple ID-based wake-up and transmits the sensed values directly. The total cost of the scheme is then $3E_w + E_s$, rather than $E_w + E_s$ as in standard WUR.

The scheme relies on sensors being able to obtain measurements using relatively low energy, and the PCR being the most significant factor when measuring energy consumption. However, this assumption is realistic and shared by other well-known content-based WUR schemes [8], [12], [13].

A. Censored Kalman Update

As the energy consumption of the WUR is designed to be orders of magnitude lower than the PCR's, we can then use the content-based wake-up to improve the battery lifetime of

the sensors by avoiding the transmission of updates with a lower VoI. In the following, we consider the simpler case in which $N = P$ and $\mathbf{H} = \mathbf{I}_P$, i.e., the case in which each sensor observes a component of the system state, with no influence from others, leaving the general case for future work. In particular, we consider information that confirms the GW's estimate to be less relevant than surprising updates that may significantly change it, i.e., we set the thresholds $a = \hat{x}_n(k) - \theta$ and $b = \hat{x}_n(k) + \theta$. If the measured value $y_n(k)$ is outside the specified silent range, i.e., $y_n(k) \notin [\hat{x}_n(k) - \theta, \hat{x}_n(k) + \theta]$, the sensor transmits it, and the update occurs as described above for a normal Kalman filter. If the GW does not receive an update, this can either be due to a channel error or to the sensor remaining silent. The probability of sensor n remaining silent, an event we denote as ξ , is then:

$$p_n(\xi) = \Phi\left(-\theta R_{n,n}^{-\frac{1}{2}}\right) - \Phi\left(\theta R_{n,n}^{-\frac{1}{2}}\right) = 1 - 2\Phi\left(\theta R_{n,n}^{-\frac{1}{2}}\right), \quad (8)$$

where $\Phi(x)$ is the Cumulative Density Function (CDF) of the standard Gaussian distribution. We can then easily compute the probability that an update is missing because the sensor was silent, and not because the packet was lost, as:

$$p_n(\xi|\chi) = \frac{p_n(\xi)}{p_n(\xi) + (1 - p_n(\xi))\varepsilon_n}, \quad (9)$$

where χ indicates that there was no successful update from the sensor. The probability of having no update is then:

$$p_n(\chi) = \varepsilon_n + (1 - \varepsilon_n)p_n(\xi). \quad (10)$$

If the sensor is silent, the prior estimate $\hat{\mathbf{x}}(k|k-1)$ is simply maintained. On the other hand, we need to consider the effect of the new information on the estimate covariance. We then consider each element $P_{m,n}(k)$ in the covariance matrix $\mathbf{P}(k|k-1)$:

$$P_{m,n}(k) = \mathbb{E}[z_n(k)z_m(k)|\mathbf{P}(k|k-1)], \quad (11)$$

and then compute $P_{m,n}(k|\xi)$, i.e., each individual element of the covariance matrix in case the sensor was silent. In the following, we omit the timestep index for readability's sake. In order to compute the expected value from (11), we need to apply Bayes' theorem to compute the *a posteriori* Probability Density Function (PDF) of z_n :

$$p(z_n|\xi) = \frac{\phi\left(\frac{z_n}{\sqrt{P_{n,n}}}\right)\left(\Phi\left(\frac{\theta-z_n}{\sqrt{R_{n,n}}}\right) - \Phi\left(\frac{-\theta-z_n}{\sqrt{R_{n,n}}}\right)\right)}{p_n(\xi)}, \quad (12)$$

where $\phi(x)$ is the PDF of the standard Gaussian distribution. By the definition of the covariance matrix, the conditional expected value of z_m is simply:

$$\mathbb{E}[z_m|z_n] = \frac{P_{m,n}(k|k-1)z_n}{P_{n,n}(k|k-1)}. \quad (13)$$

The value of $P_{m,n}(k|\xi)$ is then:

$$\begin{aligned} P_{m,n}(k|\xi) &= \int_{-\infty}^{\infty} p(z_n|\xi)z_n \mathbb{E}[z_m|z_n] dz_n, \\ &= \frac{P_{m,n}}{P_{n,n}} \int_{-\infty}^{\infty} p(z_n|\xi)z_n^2 dz_n. \end{aligned} \quad (14)$$

TABLE I: Simulation Parameters

Parameter	Symbol	Value
Number of episodes	L	100
Timesteps per episode	K	1000
Number of nodes	N	50
Number of polls per step	M	{1,2,5,10,20,50}
Value threshold	θ	{0.5, 1, 1.5, 2, 2.5, 3} $\times \sigma$
Transmission energy	E_t	50 mJ
Sensing energy	E_s	10 mJ
Wake-up energy	E_w	10 mJ
Sleep energy	E_0	1 mJ
Battery size	E_{\max}	9000 mAh, 5 V (162 kJ)

This integral does not have an analytical solution, as it involves the Gaussian CDF, but it can be computed numerically. The calculation can then be repeated for each element of the n -th column of $\mathbf{P}(k)$, so as to obtain $\mathbf{P}(k|\xi)$, but the integral only needs to be solved once, as the only element that changes is $P_{m,n}(k|k-1)$. The overall update if no packet is received is:

$$\begin{cases} \hat{\mathbf{x}}(k|\chi) = \hat{\mathbf{x}}(k|k-1); \\ \mathbf{P}(k|\chi) = p_n(\xi|\chi)\mathbf{P}(k|\xi) + (1 - p_n(\xi|\chi))\mathbf{P}(k|k-1). \end{cases} \quad (15)$$

B. Poll Scheduling

Using the system model definition, we need to define the next polling sensor that would minimize the MSE while also maximizing the network lifetime. Hence, the scheduling strategy using the previous estimates $\{\hat{\mathbf{x}}(k-1), \mathbf{P}(k-1)\}$ can be defined as

$$a(k) = \arg \max_{n \in \{1, \dots, N\}} \text{tr}(\mathbf{P}(k|k-1)) - p_n(\chi) \text{tr}(\mathbf{P}(k|\chi) - (1 - p_n(\chi)) \text{tr}(\mathbf{P}(k|n)). \quad (16)$$

This strategy selects the sensor which offers the highest expected reduction in the overall MSE, considering the possibility of a failed or censored update. After each sensor is polled, the scheduling should be computed again with the new estimate covariance matrix, and the value of already polled sensors is set to 0.

This polling strategy is, hence, a one-step optimal heuristic [14], as it greedily computes the next sensor to be polled without considering correlations. More advanced scheduling schemes that take correlations and longer-term trends into account are left for future developments.

IV. SIMULATION SETTINGS AND RESULTS

In this section, we verify the performance of the scheduling scheme by setting up a Monte Carlo simulation. We generate a stable synthetic linear process, i.e., a process whose system matrix eigenvalues are lower than 1, and apply the scheduling approach for a relatively long time.

A. Simulation Settings

We consider two different linear systems, which we allow to freely evolve over 100 episodes of 1000 timesteps each. The Monte carlo simulation is run for both classical ID-based WUR and the content-based scheme proposed in this

paper, considering different values of the censoring threshold θ , which is expressed as a function of the estimated *a priori* uncertainty on the sensor reading, i.e., $\sqrt{P_{n,n}(k)}$ for sensor n . In all cases, we consider the special case in which $N = P$ and $\mathbf{H} = \mathbf{I}_P$. We consider two systems with $N = 50$ sensors for which elements of the update matrix \mathbf{A} are known. In the first system, $\mathbf{A}^{(1)}$ is:

$$A_{i,j}^{(1)} = \begin{cases} \frac{3}{4}, & \text{if } i = j; \\ -\frac{1}{8}, & \text{if } i \neq j, \text{mod}(i - 2j, 4) = 0; \\ 0, & \text{otherwise;} \end{cases} \quad (17)$$

where $\text{mod}(m, n)$ is the integer modulo function. In the second system, $\mathbf{A}^{(2)}$ is:

$$A_{i,j}^{(2)} = \begin{cases} \frac{4}{5}, & \text{if } i = j; \\ -\frac{1}{9}, & \text{if } i \neq j, \text{mod}(\lceil i - 2.3j, 4 \rceil) = 0; \\ 0, & \text{otherwise.} \end{cases} \quad (18)$$

The other parameters remain the same for both systems. The measurement noise covariance matrix is set to $\mathbf{R} = \mathbf{I}$ and the perturbation noise covariance matrix \mathbf{Q} is defined as:

$$Q_{i,j}^{(i,j)} = \begin{cases} \frac{11+\text{mod}(i,5)}{5}, & \text{if } i = j; \\ 1, & \text{if } i \neq j, \text{mod}(i - j, 6) = 0; \\ 0, & \text{otherwise.} \end{cases} \quad (19)$$

Note that, in both systems, the sensors with higher indices have a slightly higher variance. Additionally, the transmission error probabilities are set to $\varepsilon_n = 0.02 \lceil \frac{n-1}{25} \rceil$ and the Kalman filter is initialized at step 0 with $\hat{\mathbf{x}}(0) = \mathbf{x}(0) = 0$ and $\mathbf{P}(0) = \mathbf{I}$. Overall, we particularly choose these values so as to consider two systems with distinct correlated processes: system 1 is highly interdependent, i.e., state components affect each other strongly, leading to a higher correlation, while system 2 is sparser, with a lower correlation between state components. The full simulation parameters are listed in Table I.

As discussed above, the main trade-off in the system is between tracking accuracy and energy efficiency. In order to measure the former, we use the standard MSE over the state estimate and average it over all episodes:

$$\text{MSE} = \frac{1}{LKN} \sum_{\ell=1}^L \sum_{k=0}^K (\mathbf{x}^{(\ell)}(k) - \hat{\mathbf{x}}^{(\ell)}(k))^T (\mathbf{x}^{(\ell)}(k) - \hat{\mathbf{x}}^{(\ell)}(k)), \quad (20)$$

where $\mathbf{x}^{(\ell)}(k)$ denotes the state of the system in step k of the ℓ -th episode. On the other hand, we measure energy efficiency through the sensor lifetime, i.e., the average duration of the sensor batteries:

$$\mathcal{L} = \frac{1}{N} \sum_{n=1}^N \left(\frac{E_{\max}}{f_t(n)E_t + f_w(E_s + 3E_w) + (1 - f_w)E_0} \right), \quad (21)$$

where $f_t(n)$ is the fraction of the total timesteps in which sensor n transmitted an update and f_w is the fraction of the total timesteps in which sensor n was polled (including the ones in which the update was not transmitted). If we consider

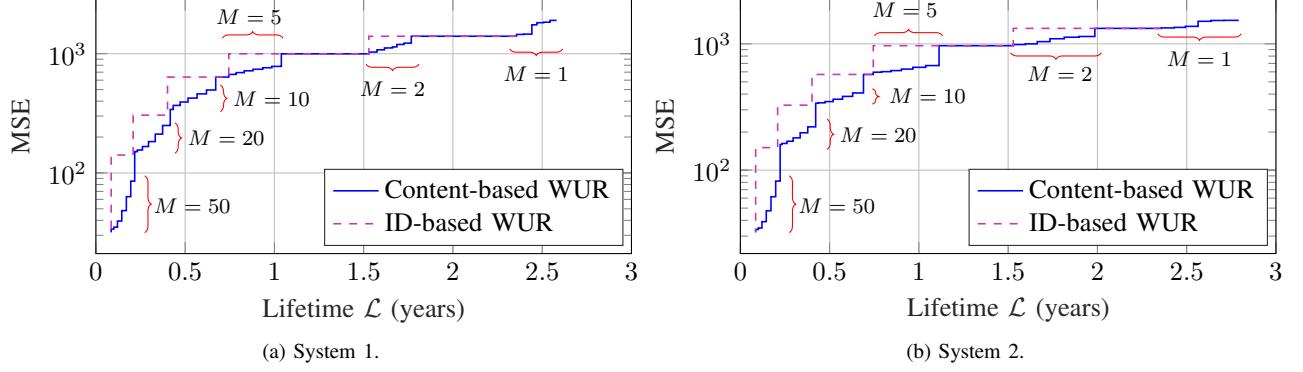


Fig. 3: Pareto curves for the lifetime and accuracy of the schemes in the two scenarios.

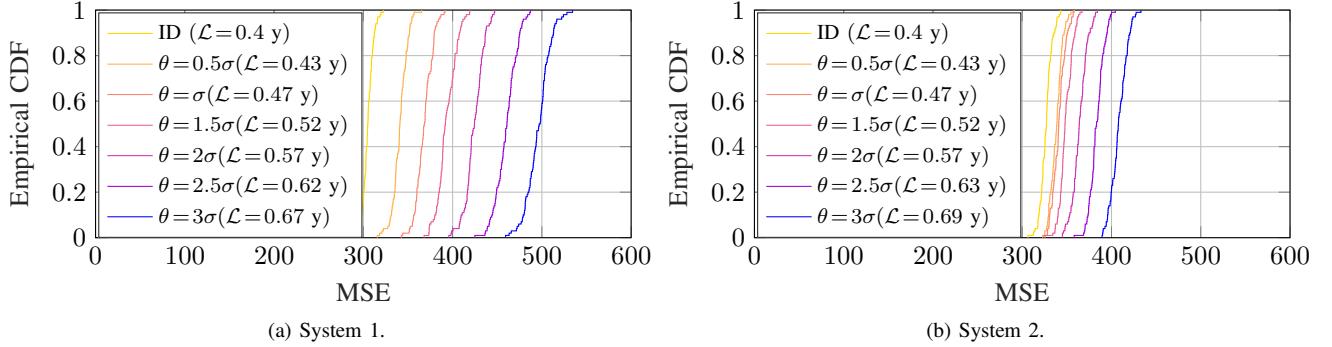


Fig. 4: Tracking MSE CDF with $M = 10$ for the two systems.

ID-based WUR, we have $f_t = f_w$, but the energy required to receive the wake-up signal is $E_s + E_w$ instead of $E_s + 3E_w$.

Finally, we consider a timestep of 1 s for system state evaluation, in which the GW chooses to poll a set of M sensors chosen by the scheduler over a single step. We assume that M is fixed over each episode, and use it as a system parameter to control the trade-off between accuracy and battery lifetime.

B. Results

The trade-off between tracking accuracy and battery lifetime can be visualized using a Pareto curve, which shows the boundary of the performance feasibility region. Any point on the curve is Pareto efficient, i.e., improving one of the performance metrics would require sacrificing the other. Fig. 3 shows the Pareto curves for the two schemes in the two simulation scenarios. Each large step for ID-based WUR represents the accuracy and lifetime obtained with M polled sensors, and each small step in content-based WUR represents the accuracy and lifetime achieved for a different value of θ , with M polled sensors. So, in this case, optimal performance would be on the lower right of the plot. We can easily notice that the content-based scheme is significantly more flexible and outperforms the ID-based scheme given a fixed M sensors are polled: while the two Pareto curves share some points (if we set $\theta = 0$, the content-based scheme is the same as the legacy one), the content-based scheme can control the trade-off better, achieving intermediate performance points that trade some accuracy for a higher network lifetime. This is particularly evident in the second scenario, shown in Fig. 3b,

in which increasing θ leads to a significantly smaller accuracy degradation. If we consider $M = 50$, content-based WUR can increase the network lifetime by around 100% at the cost of an MSE increase of around 50% in both scenarios. This relative advantage diminishes for smaller values of M , but the absolute change in the MSE due to higher thresholds also decreases, while the battery lifetime increase is approximately the same. Additionally, the content-based scheme can reach a lifetime of over 2.5 years at the lowest accuracy setting, while the ID-based scheme would need to reduce the polling frequency below 1 poll per second to do so.

We can analyze the accuracy-lifetime trade-off more in depth by considering the empirical CDF of the MSE for different values of θ , shown in Fig. 4. In this analysis, we set $M = 10$, considering the intermediate part of the graph. Firstly, we can note that the network lifetime increases in a predictable fashion, as expected from the settings of the scheme: as θ is a function of the predicted sensor reading standard deviation σ , the probability of a censored update scales in a similar fashion to the Gaussian complementary CDF function. However, there are some minor differences between the lifetimes in the two scenarios that can be attributed to the definition of σ : which is $\sqrt{P_{n,n}(k)}$ instead of $\sqrt{R_{n,n}}$, which depends on the state of the Kalman filter. The figures clearly show that the MSE is relatively stable across episodes and steps for all settings, as well as the trend we discussed in the two scenarios: the difference between settings is more significant in scenario 1, as the average MSE increases by

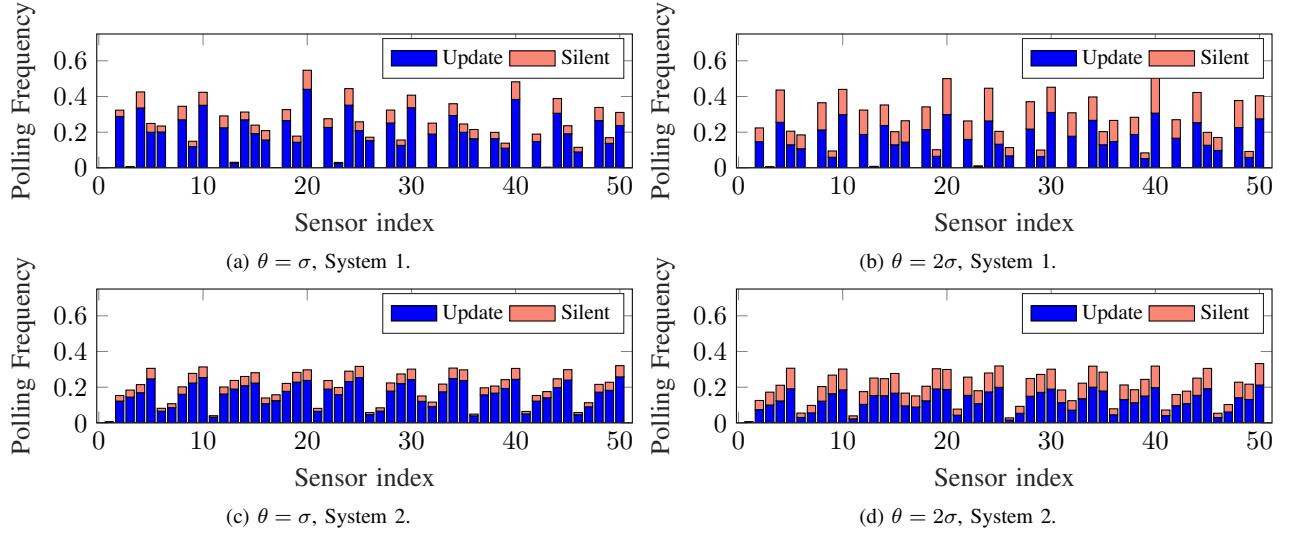


Fig. 5: Polling frequency for each sensor with $M = 10$.

10% for each increase in the threshold with respect to the ID-based WUR scheme's. On the other hand, scenario 2 can fare much better: setting $\theta = 2\sigma$, the MSE only increases by approximately 10%, but the network lifetime increases by more than 40%. This is because of the structure of the two scenarios: correlation between sensors is generally lower, leading to a more uniform covariance matrix, while in the first scenario, some sensors have a much larger impact on the variance, and the consequences of a censored update from them on the MSE become more important.

Finally, we can look at the sensor selection, shown in Fig. 5: we can note that the polling frequency confirms that some “central” sensors have a relatively large impact on the overall estimation process, and therefore deplete their battery faster, while scenario 2 is much more uniform. As expected, the threshold has a limited effect on which sensors are polled, having a relatively low impact on the estimate itself, but increasing it significantly reduces the transmitted updates.

V. CONCLUSION AND FUTURE WORK

In this work, we presented a content-based WUR scheme that is able to control the trade-off between accuracy and network lifetime at a finer scale than standard ID-based WUR. To do so, the GW transmits threshold values along with the wake-up request and the sensor only communicates when the value is outside the range, i.e., when the update's VoI is significant. The implicit communication when the sensor is silent reduces the need for explicit updates and increases the overall network lifetime, with limited MSE degradation.

The promising results shown in this paper can be extended in several direction: firstly, a dynamic optimization of the threshold values to better represent VoI may be considered. Another interesting optimization is on the schedule, which may be designed with long-term consequences in mind, considering individual sensors' batteries as well as the average lifetime.

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