Optimizing Sensor Data Transmission in Collaborative Multi-Sensor Environments

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***Abstract*—In the era of smart agriculture and smart industry, sensor networks have become indispensable for gathering crucial data to improve efficiency, reduce resource consumption, and enhance decision-making processes. In this context, sensor data transmission schedules are essential for real-time control in smart applications. This research explores the optimization of sensor data transfer schedules in environments where external sources can also contribute with informative updates in a non-controllable fashion. We propose an online method based on dynamic programming for AoI minimization that obtains optimal budgeted update instants in the presence of external assistance. Our findings reveal optimal transmission intervals, addressing data redundancy challenges and contributing to efficient sensor network utilization.**

***Index Terms*—Sensor networks; age of information; data transmission; resource optimization, collaborative sensing; smart industry.**

I. Introduction

In the era of smart agriculture and industry, sensor networks have become indispensable for gathering crucial data to improve efficiency, reduce resource consumption, and enhance decision-making processes [1], [2]. In these sophisticated setups, multiple sensors work collaboratively by continuously transmitting data to a central receiver [3]–[5]. However, a fundamental challenge arises when these sensors redundantly transmit similar data [6].

Consider a scenario where two sensors, A and B, are tasked with measuring the temperature in a plantation of trees. If sensor A has recently transmitted the temperature value to the receiver, it is unnecessary for sensor B to duplicate the effort, even if sensor B has not reported its reading for some time. This redundancy can lead to inefficient use of resources and may even contribute to information overload. To address this challenge, Age of Information (AoI) is used as a pivotal performance metric [7], quantifying how fresh or up-to-date the perception of the monitored process is [8]–[11].

AoI provides a precise and contextually relevant characterization of information freshness, particularly in domains like remote sensing and vehicular networks, where maintaining real-time data holds paramount importance [12]–[15]. While researchers traditionally emphasize the long-term average AoI, it is worth noting that various AoI variations, including Peak AoI and Discounted AoI, have been explored [16]–[19]. The dynamic nature of this field introduces nuanced distinctions, encompassing considerations related to discrete versus continuous time-axis models and the utilization of mathematical tools such as Markov chains or renewal theory [20]–[22].

Our research in the present paper diverges from the widely adopted infinite-horizon modeling approach and instead closely corresponds with the operational context of practical Internet of things (IoT) devices, which function within limited time periods. Within this defined temporal framework, the transmitter encounters constraints in its ability to transmit updates, primarily stemming from hardware and cost limitations [7].

In the context of this study, we perform an analysis similar to [23] where we consider AoI minimization within a finite time horizon, specifically addressing resource-constrained transmitter-receiver systems that exchange data over a channel. We recognize the practical relevance of scenarios where only the receiver possesses information about the communication's outcome, including the success of an update in reducing AoI [23]. Such variations are particularly pertinent in modern IoT scenarios, where transmissions must be sparse, and the cost of listening for feedback messages can be as substantial as transmitting data, as seen in technologies like LoRaWAN [24]. Moreover, our research extends its scope to consider the possibility of external assistance, wherein one sensor may transmit data on behalf of another.

We take inspiration from the analytical formulation of [23] to minimize the expected average AoI over a finite horizon corresponding to the assigned task, in the presence of correlated transmissions possibly coming from other sources [25]. In this context, we explore a stateful optimization for scheduling transmission instants. This dynamic programming-based strategy makes adaptive and context-aware transmission decisions to minimize the expected AoI.

In the upcoming sections, we will offer both theoretical insights and practical implementations. Our research represents a step forward in characterizing status update freshness for real-time control in smart applications.

The rest of this paper is organized as follows. In Section II, we review the related literature. Section III discusses the system model. We present numerical evaluations in Section IV. Finally, Section V concludes the paper.

II. Related Works

The application of AoI as a performance metric bears particular relevance in communication and control of cyber-physical systems, emphasizing the pivotal importance of timely data updates [3], [4], [7], [9], [12], [15], [23], [25]–[27]. As a result, various methodologies have been adopted in the literature, each potentially exhibiting different degrees of congruence with the content of the present paper.

The study in [26], places its primary focus on the development and analysis of transmission scheduling policies, particularly in the context of AoI. It addresses multiple sensors actively transmitting data related to diverse physical phenomena to a central monitoring system, resulting in a continuous influx of current data. However, the presence of channel limitations introduces practical constraints, similar to those encountered in our own research.

A similar analysis is conducted in [23], emphasizing the introduction of feedback mechanisms to enhance data clarity and the development of an optimal dynamic algorithm for specific requirements. This analysis involves a discrete-time system comprising state, transition, and reward components, addressing finite-horizon problems. Our investigation aligns with this approach, exploring scenarios within a finite time horizon. Furthermore, our study extends to consider the possibility of external assistance, where one sensor may transmit data on behalf of another, as considered in [25]. Prior studies have generally explored scenarios involving scheduling of transmission instants towards a guarantee of quality of service (QoS) [28], a role that in our scenario is played by AoI minimization.

The concept of average AoI within multi-source queueing models under a first-come-first-served (FCFS) serving policy is investigated in [4]. While this paper primarily focuses on information freshness within queueing models, our research extends this concept to optimize sensor data transmission schedules in environments with multiple sensors measuring similar parameters. We aim to understand how AoI behaves in multi-source queueing models to design efficient data transmission strategies, enhancing resource utilization and system efficiency.

The challenges of timely status updates in communication networks is investigated in [9], which aligns with our research concerns. The study focuses on applications requiring efficient transmission of status updates from sources like people and environmental sensors. Their introduction of a time-average age metric for performance evaluation aligns with our objectives in optimizing sensor data transmission schedules. Although their primary focus is on update rates, their insights seamlessly extend into our study, emphasizing the importance of real-time status updates and data transmission optimization in dynamic, resource-constrained environments.

In the main line of AoI investigation for queueing systems, [19] evaluates the timeliness of status updates for multiple source service systems. However, the focus of that paper is on competing sources sharing the same capacity, and they introduce a simplified technique for evaluating AoI in finite-state continuous-time queuing systems, akin in complexity to determining the stationary distribution of a finite-state Markov chain. Our approach takes a complementary view in that we do not consider external updates to interfere with the tracking of the process of interest, and conversely they both benefit the same AoI value.

Some existing work on AoI minimization for remote monitoring of correlated sources is also available in the literature. A simple probabilistic correlation model is considered in [5], whereas [25] generalizes this approach to a memoryless scenario that derives a Markov chain of manageable complexity. These models can support the derivation of scheduling policies that take correlation into account, with scalable complexity. A further reference is [15] that, motivated by AoI analysis from camera pictures with overlapping fields of view, considers the case of packets containing relevant information even when coming from a different source. Our study can be seen as a direct application of all these models since we assume an individualistic scheduling [3] of transmission updates from a single source, yet taking into account correlation with data sent from other sources, especially for what concerns the event that these packets allow for decreasing AoI of the source of interest without costing a transmission.

The general remark that correlation among multiple sources is beneficial to AoI and can be leveraged is also explored in [29], which delves into multiple independent sources but resonating with our focus on collaborative updates. Specifically, [29] examines the dynamics of status updates through a first-come-first-served M/M/1 queue, introducing a status-age timeliness metric to evaluate the effectiveness of real-time updates. Their research sheds light on the interplay between multiple sources and the need for an optimal update rate. The main difference with the presented approach is that they consider a queueing system, where the controllable parameter is the average injection rate, whereas in our study the horizon is finite, the data injection is controlled by the precise choice of the number of foreseen updates, and we investigate the actual finetuning of them.

In [30], a similar challenge of AoI minimization is addressed but for multi-hop networks, whereas we focus on a single link. They investigate different transmission policies to take advantage of spatial redundancy of the transmissions, yet the correlation of the information content is a direct consequence of the multi-hop structure, whereas in our scenario is controllable through the probability of external intervention.

Another related reference is [31], which challenges the conventional wisdom that compression conflicts with information freshness and timely data delivery. In particular, they show that correlation among multiple sources can be leveraged to eliminate the traditional trade-off between compression and AoI, especially with instantly decodable variants and techniques involving preset and dynamically created dictionaries. This can be therefore regarded as a complementary findings to our own that highlight the benefit of collaborative sensing.

Finally, we also mention [32], where the focus is on parameter estimation in statistical signal processing, highlighting the versatility of Monte Carlo (MC) methods in scenarios with challenging analytical expressions for estimators. In our study, we utilize MC simulations to optimize sensor data transmission schedules, recognizing their significance in enhancing resource utilization and system efficiency. By applying MC techniques in collaborative sensing within sensor networks, we aim to provide practical insights for effective data transmission management.

III. System Model and Analysis

We consider a sensor tasked with transmitting data to a central receiver, providing information pertaining to a specific monitored process. The principal objective is to deliver the data to the receiver with the utmost freshness [26], [27]. For the sake of the present analysis, we further consider that all transmissions are error free at the receiver's side. The impact of erasures that lead to increased AoI can be further taken into account by expanding our framework along the lines of [20], [22], [23].

The sensor has to monitor a physical process $\mathcal{P}$, having its own budget of M of updates that it can perform in a finite time horizon T, where $M \ll T$. This constraint on the update rate may arise due to various factors, but it is particularly convenient to associate it with the limited energy resources available at the transmitter's end [24]. This is especially pertinent in the case of remote battery-powered sensors situated in inaccessible locations, where battery replacement is infeasible or prohibitively costly. Alternatively, in the context of energy-harvesting devices, M can be linked to the average energy harvested over a recharge cycle [17], [20], [33]. We further consider time to be divided into slots having all the same duration.

We consider that other agents are able to intervene in the network operation by sending a status update that is relevant for the sensor of interest. This may

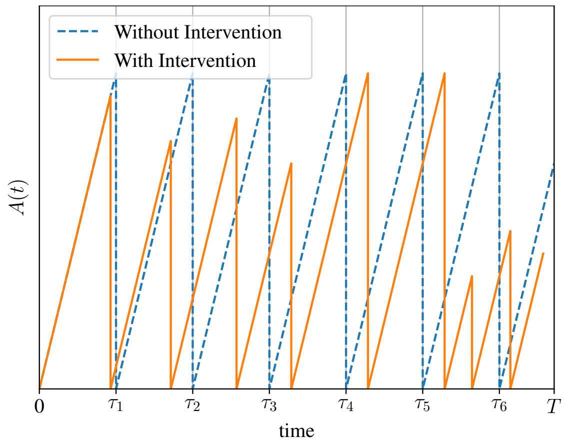

Fig. 1. An example timeline for the AoI evolution over time.

happen because they are tracking another process correlated with $\mathcal{P}$. Following [25], we concentrate the action of any of these external agents into a single parameter $\alpha \in [0, 1]$ that we call probability of external intervention. As argued in [25], assuming that the activity of other informative sources that are not directly under control happens with independent and identically distributed probability α is a very good approximation of many underlying process, even with correlated sources [21], if the proper numerical value is set.

In turn, the event of external intervention corresponds to an informative contribution to the tracking of $\mathcal{P}$, therefore we consider that any of these external events is counted as new information on the process of interest that benefits the AoI of the sensor of interest.

According to [7], we compute AoI $A(\cdot)$ as the difference between the current time slot and the last successful update. Mathematically we define the current time instant as t and τ_i as the last successful update. With this notation the AoI becomes

$$A(t) = t - \tau_i. \tag{1}$$

A potential timeline illustrating the evolution of AoI is presented in Fig. 1. The blue lines depict the temporal evolution of the Age of Information within an ideal system devoid of any external interventions, while the red line illustrates the timeline when external assistance is introduced as a possibility. We are interested in two different metrics, the Average AoI and the Peak AoI. The former, denoted as $\mathbb{E}[A]$, is computed as the time average of the AoI in a time frame T

$$\mathbb{E}[A(t)] = \frac{1}{T} \int_0^T A(t)dt. \tag{2}$$

Conversely, the Peak AoI is computed as the average of all the peaks reached by the AoI. Formally, if we denote $P_{\tau,i}$ the peak of the AoI reached at time instant i and we assume that in a time frame T there are exactly M updates the Peak AoI P_T is

$$P_T = \frac{1}{M-1} \sum_{i=1}^{M-1} P_{\tau,i}. \tag{3}$$

We want to minimize the expected AoI in an online fashion when subject to a probability of external intervention α. To accomplish this task we use a dynamic programming approach [34]. This is a sensible instrument to apply if we limit our study to relatively short time frames.

This approach implies to define a system state over discrete time instants $n = 0, \dots, T$ as $x[n] = \big(A[n], m[n]\big)$, where

- $A[n] \in \mathbb{Z}^+$ is the instantaneous AoI;
- $m[n] \in \mathbb{Z}^+$, $m[n] \leq M$ is the number of the update available to the sensor.

The dynamic programming framework also includes a control action $u(x[n])$ with a binary value corresponding to transmission activity, and the effect of external intervention, which is non-controllable by the sensor of interest and therefore treated as a noise.

This problem admits optimal control through backward induction [34]. Specifically, control $u(x[n])$ must be set to non-transmission whenever $m[n] = 0$, and to transmission when $n = T$ and $m[n] > 0$, i.e., there are transmission opportunities left at the end of the schedule. Quite evidently, the system state evolution to $x[n{+}1]$ just depends on $x[n]$, $u(x[n])$, and α. Thus, the optimal control action in the nth instant follows from Bellman equation, and backward induction can be applied from state n to state $n{-}1$ until the beginning of the schedule is reached. This approach was implemented in Matlab, with a pseudocode of our approach reported in Algorithm 1.

IV. Results and Discussion

We present numerical results obtained through our approach. First, the online optimization policy was derived, and the plots obtain the actual evaluation of the metrics of interest through a Monte Carlo simulation with a very high number of runs that make the confidence of the shown results above 99%.

All the following evaluations report different values of M and consider a different choice of α. To make homogeneous comparisons, instead of the direct probability α, we plotted the expected number of external interventions over the time horizon, i.e., αT. Although irrelevant for the following plots (the AoI values are normalized to a unit horizon), the actual granularity considered in the evaluation is $T = 1000$ slots.

In Fig. 2 we present the Average AoI values obtained by the online optimization, normalized to T^2 to consider a unit time horizon. As expected, increasing the number of external assistance interventions reduces drastically the metric of interest. Furthermore if the node has multiple opportunities for its own transmissions the Average AoI if further reduced.

Algorithm 1 Backward Induction

Require: $alphas$: values of external assistance probabilities; N_{max}: total number of slots; M: total number of opportunities; A_{max}: Maximum AoI value

Ensure: $bestmov$: Tensor of best moves to apply for each possible state of the system; $bestage$: Tensor of AoI values obtained through moves of $bestmov$

Initialize $bestage$ and $bestmov$ arrays ▷ both have dimensions (N_{max}, M, A_{max})
for α in $alphas$ **do**
  Initialize tensors $bestage$ and $bestmov$ for age and movement decision storage.
  $bestage[1, 1, 1 : A_{max}] \leftarrow \text{ZEROS}(A_{max}, 1)$
  $bestmov[1, 1, 1 : A_{max}] \leftarrow 0 : A_{max} - 1$
  for $m = 2$ to M **do**
    $bestage[1, m, 1 : A_{max}] \leftarrow \text{ONES}(A_{max}, 1)$
    $bestmov[1, m, 1 : A_{max}] \leftarrow (1 - \alpha) \cdot 0 : A_{max} - 1$
  end for
  $bestage[1, :, :] \leftarrow \text{REPMAT}(\text{RESHAPE}(0 : Amax - 1, [1, 1, A_{max}]), [1, M, 1])$
  for $n = 2$ to N_max **do** ▷ derive n from $n{-}1$
    for $a = 1$ to $A_{max} - n + 1$ **do** ▷ no more TXOPs
      $bestmov[n, 1, a] \leftarrow 0$
      $bestage[n, 1, a] \leftarrow (a - 1 + (n - 1) \cdot bestage]n - 1, 1, a + 1])/n$
    end for
    for $m = 2$ to M **do**
      for $a = 1$ to $Amax - n + 1$ **do** ▷ Determining the optimal movement and age
        $iftxage \leftarrow (\alpha(a - 1 + (n - 1) bestage[n{-}1, m{-}1, \min\{a{+}1, A_{max}\}]) + (1 - \alpha)(a - 1 + (n - 1) \cdot bestage[n - 1, m - 1, 1]))/n$
        $notxage \leftarrow (a - 1 + (n - 1) \cdot bestage[n - 1, m, \min\{a + 1, A_{max}\}])/n$
        if $iftxage \leq notxage$ **then**
          $bestmov[n, m, a] \leftarrow 1$
          $bestage[n, m, a] \leftarrow iftxage$
        else
          $bestmov[n, m, a] \leftarrow 0$
          $bestage[n, m, a] \leftarrow notxage$
        end if
      end for
    end for
  end for
end for
return $bestmov$, $bestage$

In Fig. 3 we report the Peak AoI obtained in the online optimization, with a similar normalization to before. The curves also present a similar trend to the ones of the previous figure, although they do not asymptotically converge towards zero as the number of expected external interventions increases.

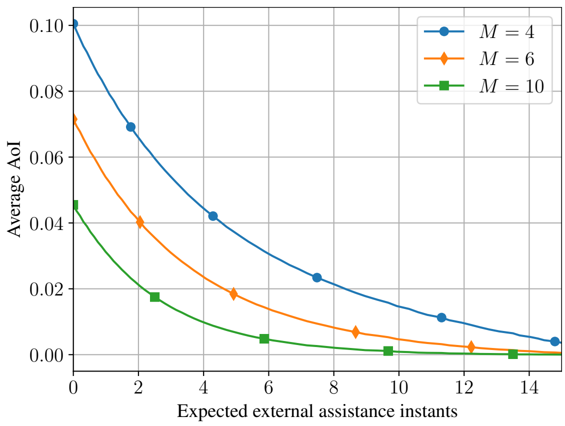

Fig. 2. Average Age of Information in the online optimization case.

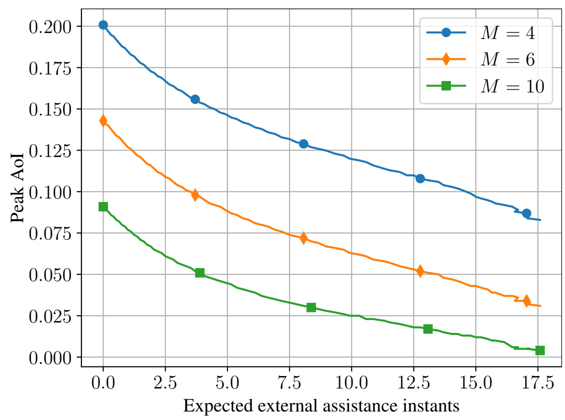

Fig. 3. Peak Age of Information in the online optimization case.

It is interesting to note that the effect of the external intervention to lower the normalized AoI (both average and peak) does not require a very high number of expected interventions to be noticeable. Clearly, when the number of external assistences becomes very high, the AoI values of the sensor of interest are considerably lowered (and, as a side effect, the optimality of the control action matters little, since the majority of the updates are non-controllable). Yet, the results show that even a moderate number of external updates can be extremely beneficial to lower AoI, which may suggest practical guidelines in sensing implementations of highly correlated measurement scenarios.

V. Conclusions

We analyzed the optimization of sensor data transmission in environments where external sources can also contribute with informative updates in a non-controllable fashion.

We proposed an online method based on dynamic programming for AoI minimization that obtains optimal budgeted update instants in the presence of external assistance. While increasing external assistance opportunities naturally results into a reduction of both Average AoI and Peak AoI, we argued that the quantitative effect of this trend can be particularly noticeable even with a relatively limited number of interventions [25].

This can suggest further extensions to distributed control scenario, possibly through participatory sensing [3], where the local control of the nodes is translated to a myopic choice instead of a global optimization with full network awareness, to see if these beneficial role of information correlation still applies in these more realistic contexts.

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